MACHINE LEARNING APPLIED TO ACTIVE FIXED-INCOME PORTFOLIO MANAGEMENT: A LASSO LOGIT APPROACH

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Abstract

The use of quantitative methods constitutes a standard component of the institutional investors' portfolio management toolkit. In the last decade, several empirical studies have employed probabilistic or classification models to predict stock market excess returns, model bond ratings and default probabilities, as well as to forecast yield curves. To the authors' knowledge, little research exists into their application to active fixed-income management. This paper contributes to filling this gap by comparing a machine learning algorithm, the Lasso logit regression, with a passive (buy-and-hold) investment strategy in the construction of a duration management model for high-grade bond portfolios, specifically focusing on US treasury bonds. Additionally, a two-step procedure is proposed, together with a simple ensemble averaging aimed at minimising the potential overfitting of traditional machine learning algorithms. A method to select thresholds that translate probabilities into signals based on conditional probability distributions is also introduced. A large set of financial and economic variables is used as an input to obtain a signal for active duration management relative to a passive benchmark portfolio. As a first result, most of the variables selected by the model are related to financial flows and economic fundamentals, but the parameters seem to be unstable over time, thereby suggesting that the variable relevance may be time dependent. Backtesting of the model, which was carried out on a sovereign bond portfolio denominated in US dollars, resulted in a small but statistically significant outperformance of benchmark index in the out-of-sample dataset after controlling for overfitting. These results support the case for incorporating quantitative tools in the active portfolio management process for institutional investors, but paying special attention to potential overfitting and unstable parameters. Quantitative tools should be viewed as a complementary input to the qualitative and fundamental analysis, together with the portfolio manager's expertise, in order to make better-informed investment decisions.

Keywords: machine learning, probabilistic or classification models, Lasso logit regressions, active fixed-income management, absolute excess return, Sharpe ratios, duration management.

JEL classification: C45, C51, C53, E37, G11.

Resumen

El uso de métodos cuantitativos es fundamental en la gestión de carteras de inversores institucionales. En la última década, se han realizado diversos estudios empíricos que emplean modelos probabilísticos o de clasificación para predecir los rendimientos del mercado de valores, modelar calificaciones de riesgo y probabilidades de incumplimiento de bonos, así como pronosticar la curva de rendimientos. Sin embargo, existe una escasa investigación sobre la aplicación de estos modelos en la gestión activa de renta fija. Este documento busca abordar esta brecha al comparar un algoritmo de aprendizaje automático, la regresión logística Lasso, con una estrategia de inversión pasiva (comprar y mantener) en la construcción de un modelo de gestión de duración para carteras de bonos gubernamentales, con enfoque específico en los bonos del Tesoro de Estados Unidos. Además, se propone un procedimiento de dos pasos, junto con un promedio simple entre variables de características estadísticas similares, con el objetivo de minimizar el posible sobreajuste de los algoritmos tradicionales de aprendizaje automático. Asimismo, se introduce un método para seleccionar umbrales que conviertan probabilidades en señales basadas en distribuciones de probabilidad condicional. Se utiliza un amplio conjunto de variables financieras y económicas para obtener una señal de duración y se comparan otras estrategias de inversión. Como resultado, la mayoría de las variables seleccionadas por el modelo están relacionadas con flujos financieros y fundamentos económicos, aunque los parámetros no parecen ser estables a lo largo del tiempo, lo que sugiere que la relevancia de las variables es dinámica y se requiere una evaluación continua del modelo. Además, el modelo logra un exceso de retorno estadísticamente significativo en comparación con la estrategia pasiva. Estos resultados respaldan la inclusión de herramientas cuantitativas en el proceso de gestión activa de carteras para inversores institucionales, con especial atención en el posible sobreajuste y en los parámetros inestables. Las herramientas cuantitativas deben considerarse como un complemento del análisis cualitativo y fundamental, junto con la experiencia del gestor de carteras, para tomar decisiones de inversión fundamentadas de manera más sólida.

Palabras clave: aprendizaje automático, modelos probabilísticos o de clasificación, regresiones logísticas Lasso, gestión activa de renta fija, exceso de retorno, ratios de Sharpe, gestión de duración.

Códigos JEL: C45, C51, C53, E37, G11.

1. Introduction and literature review

A vast empirical econometric literature has been devoted in the last decade to the prediction of financial market variables using classification-based qualitative models combined with machine-learning (ML) techniques. Most of the studies have been applied to predict the direction of excess returns in the stock market and, to a lesser extent, in the FX markets. In the equity space, for example, Nyberg (2011) uses a dynamic error correction probit model, incorporating a binary recession indicator, for the prediction of S&P excess returns, finding better sign predictions and higher investment returns than in previous probit and ARMAX (Autoregressive Moving Average with Exogenous Inputs) models. In Kara, Acar, Omer and Baykan (2011), two models based on machine-learning techniques (Artificial Neural Networks and Support Vector Machines –SVM-) are applied to the prediction of daily directional movements in the Istanbul Stock Exchange National 100 Index, showing superior experimental performance of the first class of models. This result contrasts with the ones shown by Kumar and Thenmozhi (2006), who try to predict the direction of S&P CNX NIFTY Market Index using several machine learning tools, resulting in a superior performance of SVM compared to random forest, artificial neural networks and other traditional discriminant analysis and logit models. Rapach, Strauss and Zhou (2013) apply Least Absolute Shrinkage and Selection Operator (Lasso) to predict global equity market returns using lagged returns in different countries. Nasekin (2013) uses adaptive Lasso quantile regression in an empirical application designed as a "Lasso quantile trading (hedging) strategy" in comparison to other strategies related to the S&P500. Other authors use hybrid approaches to combine the strengths of parametric (logistic regressions) and nonparametric models or tree-based models (such as Classification and Regression Trees –CART-). This is the case of Zhu, Philpotts, Sparks and Stevenson (2011), with the application to North American stock selection of defensive companies. In the same vein, Zaidi and Amirat (2016) combine logistic regression and artificial neural networks to predict Kingdom of Saudi Arabia stock market trends. Additionally, some researchers apply machine learning to the design of trading strategies in the stock market, such as Beaudan and He (2019) who use a logistic regression algorithm to build a time-series dual momentum trading strategy on the S&P500 index with successful risk-adjusted overperformance. Another application can be found in Roy, Mittal, Basu and Abraham (2015), where a Lasso method based on a linear regression model is proposed as a method to predict stock market behavior. Finally, Gu, Kelly and Shu (2020) perform a comparative analysis of machine learning methods for the measurement of asset risk premia, identifying neural networks and regression trees as the best performing tools for predicting stock returns.

Regarding the FX markets, literature is less abundant compared to the stock market, but a good example can be found in Sermpinis et al. (2012), where the authors investigate the use of different machine learning methods, mainly neural networks, for forecasting and trading the EUR/USD exchange rate, finding significant outperformance evidence.

With regard to the application of machine learning techniques to fixed-income markets, a limited amount of research has been conducted, most of which has primarily been focused on the modelling and prediction of yield curves. Some examples can be found in Castellani and Santos (2006), who do not find significant outperformance of data-driven artificial intelligence approaches in building reliable predictions for US 10-year Treasury bonds, and Dunis and Morrison (2007), who find mixed evidence for the advanced time series models, compared to more traditional ones. In Nunes et al. (2018) several artificial neural network models are applied for forecasting the main benchmarks of the European yield curve, concluding that the multilayer perceptron achieved the higher outperformance for yield forecasting and, in general, neural network models tend to improve results, comparing favorably as Dunis and Morrison results, in spite of the different dataset used. Another example of yield curve forecasting with neural network models can be found in Rosadi, Nugraha and Dewi (2011), where no outperformance is observed for neural networks models in the prediction accuracy of the yield curve compared to more traditional methods, such as Nelson Siegel or Vector-Autoregression (VAR), at least for long term bonds. This result contrasts with those in Sambasivan and Das (2017) who, applying a Gaussian process to model the yield curve, find superior performance in forecasting the yields in the medium and long term segments of the yield curve.

With regard to the empirical analysis using classification-based qualitative models, it has predominantly been devoted to the modelling of bond ratings or predicting bond defaults. Some examples can be found in Westgaard and Wijst (2001), for default rates estimation of a retail bank portfolio, or Bandyopadhyay (2016) where traditional Z-score discriminant analysis is complemented with logistic regression analysis to achieve a more accurate default prediction.

Nevertheless, to the best of the authors' knowledge, few research examples can be found on the application of classification models to the active management of bond portfolios. In Larsen and Wozniak (1995) regression models are applied for market timing in active portfolio management of different combinations of stocks, bonds and cash, finding superior performance over passive fixed-weight strategies. Berardi, Ciraolo and Trova (2004) estimate a logistic econometric model for forecasting default probabilities of US dollar-denominated emerging market bonds. They construct a naïve trading strategy, based on the signals of the out-of-sample forecasts of the logit model, which obtain risk-adjusted returns outperforming those derived from a buy-and-hold indexed strategy. As an example of the application of machine learning techniques, Pollege and Posch (2013) use a Lasso algorithm to find the optimal set of explanatory variables in the design of an arbitrage strategy to benefit from the non-zero basis between European Sovereign Credit Default Swaps (CDS) and cash bonds.

Despite the significant attention given to machine-learning techniques by academia, their adoption in the asset management industry has not been as widespread as in other sectors. The performance of active exchange-traded funds (ETFs) using ML in their investment strategies tends to be mixed as shown by Bartram et al. (2021). Lopez De Prado (2018) concludes that these mixed results are mainly due to the fact that financial datasets violate standard assumptions of ML applications.

2. Methodology

The present study adopts a simple approach for modelling the future performance of a fixed-income portfolio, assuming that its expected market value can be explained by a set of potential variables. Following Nyberg (2011), the goal is to predict the future direction, not the level, of the fixed-income portfolio market value[1] ($Let\ y_t^* = 1$ if we observe a positive total return, i.e. if $I_t - I_{t-1} > 0\ where\ \ I_t\ is\ the\ index\ value\ at\ time\ t;\ y_t^* = 0,$ otherwise). Logistic Lasso approach is applied to handle the high number of predictors[2]. This approach predicts y^* conditioned on a set of k explanatory variables $[\boldsymbol{x}]$ as reflected in equation (1):

$$E(y^*/_x) \quad = g(\boldsymbol{x\beta}, \varepsilon) \tag{1}$$

assuming $g(\boldsymbol{x\beta}, \varepsilon)$ to have the same structure as a traditional logit regression but with a penalized version of the log-likelihood function. A simple Logistic Lasso is selected because given the literature in other areas different from fixed-income asset management it is not clear that complex models, such as XGBOOST or neural networks, are more accurate than simpler ones. For example, Palomares-Salas, De La Rosa, Ramiro Melgar and Moreno (2009) found that ARIMA models

[1] Portfolio is used interchangeably to refer to the benchmark index used in this paper: The Bloomberg-Barclays fixed-income index for US bonds (section 3).
[2] We opted for Lasso over Ridge and Stepwise Regression primarily due to our dataset's high multicollinearity. Lasso handles this issue more effectively, selecting and regularizing variables simultaneously. In contrast, Stepwise Regression's sequential approach may lead to suboptimal results depending on the order of incorporation.

outperformed neural networks for short-term wind speed forecasting, while Rahman, Chowdhury, and Amrin (2022) found that an ARIMA model performed better than an XGBoost model for predicting COVID-19 in Bangladesh. However, different results were achieved in Fang, Yan, An, and Wu's (2022) study for the USA.

2.1. Hyperparameter, lambda or regularization parameter

The penalizing component included in the definition of equation 1 is the sum of the absolute value of the k parameters incorporated in the model scaled by a hyperparameter[3] λ such that the final log-likelihood is given by equation (2):

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n}\left[y_i x_i \boldsymbol{\beta} - \boldsymbol{log}\left(\mathbf{1} + \boldsymbol{e}^{x_i\boldsymbol{\beta}}\right)\right] + \lambda \sum_{j=1}^{k}\left|\beta_J\right| \tag{2}$$

The penalty used in Lasso logit regression works as a variable selection and shrinkage procedure: when λ is sufficiently large it forces some of the coefficient estimates to be exactly equal to zero. From a Bayesian perspective, Park and Casella (2008) conclude that λ can be interpreted as the prior-uncertainty of the model parameters. For example, when λ is small it could be interpreted as the true model a priori, i.e.the one that includes most of the variables. Usually when only a few predictors have large coefficients, one can expect Lasso to have a good performance but when all the coefficients are roughly of equal size, or when the number of predictors is much larger than the number of observations (n)[4], Pereira (2016) suggests that other regularization techniques are more appropriate (for example, ridge regressions, elastic net, etc.).

To deal with potential overfitting, which can be more severe in more complex machine learning algorithm such as XGBoost due to the subjectivity associated with the selection of hyperparameters, the Lasso hyper-parameter λ[5] is selected using the Cross-validation algorithm. Cross-validation is a resampling method that uses different portions of the data to train and test a model on different iterations. The same data that were used to fit the model are divided into K (K=10 in this study) approximately equally sized and mutually exclusive subsamples called folds. For each fold k, the model is refit on the data using 100 different λ in the other K-1 folds. Finally, λ is selected so as to minimize the Cross-validation deviance[6] defined in the algorithm as minus twice the log-likelihood on the left-out data.

The estimation exercise is done by dividing the database in two parts: a training set (in-sample) and a testing set (out-of-sample). The training set starts in January 2004 and ends recursively at the end of 2011 throughout 2020; leaving the testing sample, also recursively, from 2012 throughout 2021. For example, the first loop has a training set from 2004 to 2011[7] and leaves the 2012 for testing (out-of-sample).

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[3] In the literature, the hyperparameter is also known as regularization parameter or just lambda. This paper will use these terms interchangeably.

[4] This is not the case in this dataset, there are 201 variables and 275 observations.

[5] Only one hyper-parameter in the simple Lasso approach compares to more complex models that have more than one hyper-parameters to choose.

[6] Cross-validation deviance is a statistical technique commonly used in model evaluation to assess the predictive performance of a statistical or machine learning model. It is particularly useful when working with complex models that may have a high risk of overfitting or poor generalization to new data. Cross-validation deviance involves dividing the available dataset into multiple subsets or "folds." The model is then trained on a combination of folds and tested on the remaining fold. This process is repeated several times, with each fold serving as a testing set exactly once. The deviance, which quantifies the model's fit to the data, is calculated for each fold. By averaging the deviances across all folds, a robust estimate of the model's performance can be obtained. Cross-validation deviance provides researchers with a reliable measure of a model's ability to generalize to unseen data, enabling them to make informed decisions regarding model selection and refinement.

[7] The two-step procedure, as explained in Section 2.2, involves the division of the trained set into two sub-samples. The first sub-sample contains no more than 10 years of data, while the second sub-sample encompasses a period of 4 years. The length of the test sample is always fixed at one year. The rationale behind this approach is to approximate the widely accepted five-year business cycle duration reported in existing literature. By combining the sub-sample comprising four years of data with the one-year test data, this approximation is achieved.

2.2. The two-step procedure: an error correction approach and a simple ensemble averaging

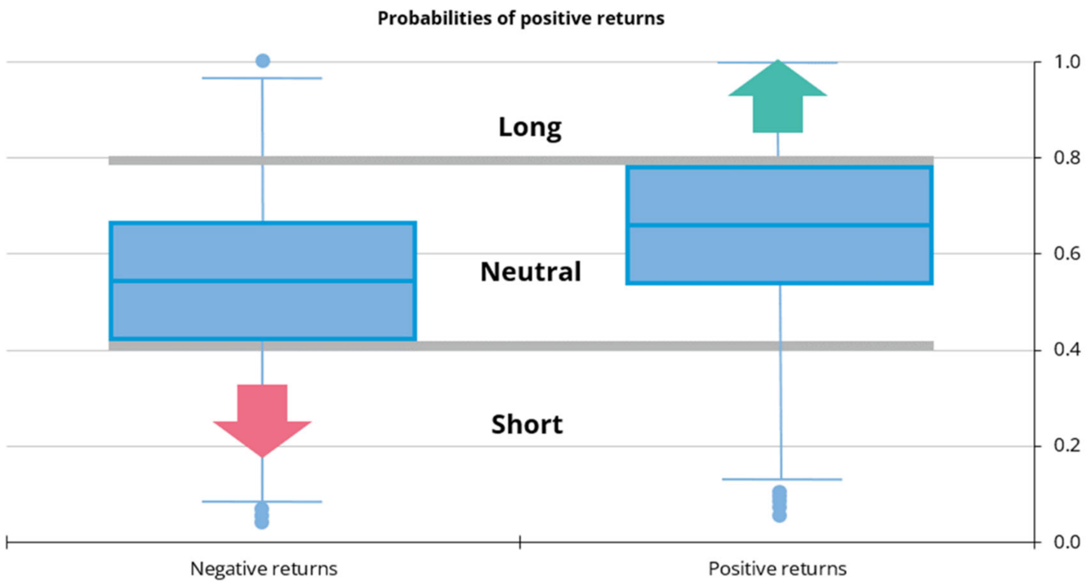
The method proposed to overcome potential worse out-of-sample performance in Lasso logit algorithm consists of a two-step procedure. In the first step, a Lasso logit model is estimated with a long time span (ten years, in order to include around two economic cycles) that is interpreted as the long-term relationship between financial and economic variables and the portfolio performance. In the second step, another model is estimated, a simple logit regression with the error committed in t - 1 and the prediction made by the Lasso logit estimated with the long time span as explanatory variables, this step is estimated for the last four years (around a standard economic cycle). If the error committed in t-1 is statistically significant, the probability eventually used will be the one obtained in the second step; otherwise, it will be the one obtained in the first step.

Additionally, another model proposed to overcome possible overfitting or model misspecification is a simple ensemble averaging. Ensemble averaging is the process of creating multiple models and combining them to produce a desired output, as opposed to creating just one model. The ensemble of models frequently performs better than any individual model, because the various errors of the different models tend to "average out". An advanced methodology that can address misspecification and model uncertainty is the Bayesian Model Averaging approach, as discussed by Fragoso, Bertoli, and Louzada (2018). However, in the present study, a simpler approach is adopted, where three distinct models are estimated, each pertaining to a specific type of statistical property observed in the data, namely level, first difference, and monthly growth stationary variables. The final estimation is obtained by taking a simple average of the three estimates.

2.3. Thresholds based on conditional probability distributions to translate probabilities into portfolio duration signals

It is proposed an algorithm to translate probabilities into three portfolio duration signals (short, neutral and long). The algorithm checks the distribution of probabilities given by the model in the in-sample period conditioned on the observed direction of the portfolio market value (i.e. if it had positive or negative returns). Short signals are derived from probabilities lower than the 25th percentile of the distribution when the index went down and long signals when probabilities are

Chart 1. Thresholds based on conditional probability distributions.



Source: Own elaboration.

higher than the 75th percentile, but in this case conditioned on cases where the index went up (Chart 1). Neutral signals are assigned to probabilities between those two previously defined thresholds (i. e. higher than the 25th percentile when the index presented negative returns and lower than the 75th percentile when positive returns were observed). The proposed mapping is also compared to a "naïve" threshold or "rule of thumb" (up to 33% short position, 33%-66% neutral and more than 66% long).

The active market-timing strategy implemented to incorporate the aforementioned signals derived from the model involves the following approach:

Assuming three indices with different durations, namely BEUSG4 index with an average duration of 7.43 years, BEUSG1 with a duration of 1.8 years, and BEUSGA with a duration of 6.07 years, BEUSGA represents the neutral duration, so when the signal is "long / short" the duration is increased / decreased by 1 year. Thus, to take a long position, the duration needs to be adjusted to 7.07 years. This is achieved by investing 74% in the BEUSGA4 index (with a duration of 7.43 years) and 26% in BEUSGA (with a duration of 6.07 years). The same calculation applies for taking a short position, where the duration should be reduced to 5.07 years (BEUSG1: 23% and BEUSGA: 77%).

2.4. Model-based strategies compared to passive investment

Five models and two additional strategies will be compared to a passive investment in this study:

2.4.1. **LassoDefault:** A Lasso Logit model that selects the hyperparameter using cross-validation, as described in section 2.1.
2.4.2. **LassoDefaultTwoStep**: A Lasso Logit model that utilizes the two-step procedure outlined in section 2.2.
2.4.3. **LassoSimpleEnsemble**: This model employs a Lasso Logit approach for each group of variables, as defined in section 2.2. There are three models in total: one for data in levels, one for first differences, and one for monthly growth stationary variables.
2.4.4 **LassoSimpleEnsembleTwoStep**: Similar to the LassoSimpleEnsemble model, but it also applies the two-step procedure described in section 2.2.
2.4.5. **Always long strategy**: A strategy that consistently invests 10% more than the passive investment.

In addition to these models, two additional strategies will be evaluated:

2.4.6. **Ladder strategy**: This strategy evenly allocates 1/3 of the investment across BEUSG1, BEUSGA, and BEUSG4 indices, with a duration of 5.1 years.
2.4.7. **Barbell strategy**: This strategy invests in the extremes by allocating 50% of funds to BEUSG1 and 50% to BEUSG4 indices, while excluding BEUSGA.

All these models and strategies will be compared against a passive investment algorithm, which aims to invest in the benchmark or replicate its total return while minimizing tracking error. In this study, passive investment refers to maintaining a neutral position or investing in the same constituents with identical weights as the benchmark (BEUSGA) throughout all periods.

3. Data description

A large set of financial and economic indicators are used as input information to obtain a signal for active duration management relative to a passive benchmark portfolio. The series used in the estimation of this model are listed in the Annex (Table 12). The selection of these indicators was driven by a focus on maximizing the available variables without adhering to a specific rule or hypothesis testing. Our aim was to include as many variables as possible to capture a broad range of market dynamics and information. We start with 250 indicators, almost half of which are macroeconomic series, 18% are financial data and 9% fixed-income market variables (Table 14). In addition, these indicators include mixing frequencies, 107 of which are updated on a monthly basis, 85 are updated daily, and 24 are updated quarterly.

The economic and financial variables should start from 2004, on a monthly basis, in order to encompass a 10 year out-of-sample period so as to include the Global Financial Crisis (GFC). Only 201 out of 250 analyzed variables fulfill the requirement imposed by this study. Table 12 provides the details of the final indicators.

Most indicators are local data series and they have been commonly used in the previously described literature. A good example, albeit with a smaller number of indicators, can be found in Abouseir et al. (2020). It is also worth noting that in our study we have only tested a single lag.

As regards the missing values, an imputation method is applied, in which the last non-missing observed value is used to assign a particular missing value. This approach allows us to maintain the term structure of the data and minimize any potential biases introduced by working only with complete observations, for more information about potential drawbacks of dropping missing values in finance see Kofman and Sharpe (2003). For daily and weekly data, we take the average value of the corresponding month to ensure consistency in the frequency of the variables. It is worth noting that we have explored alternative approaches, including the entire exclusion of missing values and found that the results remain unchanged. Additionally, the variables are standardized in order to ease the comparion of scores measured on different scales. It is important to note that only the in-sample values are standardized, not the out-of-sample data.

Before using the data as input for the model an Augmented Dickey-Fuller test is run for every variable to check if they are stationary. If they are not stationary, a first difference or a percentage change transformation is applied. Finally, variables are allocated to three different groups: 1) stationary variables in levels without transformation, 2) first difference of stationary variables, and 3) percentage change of stationary variables. These three groups are going to be used for simple ensemble averaging.

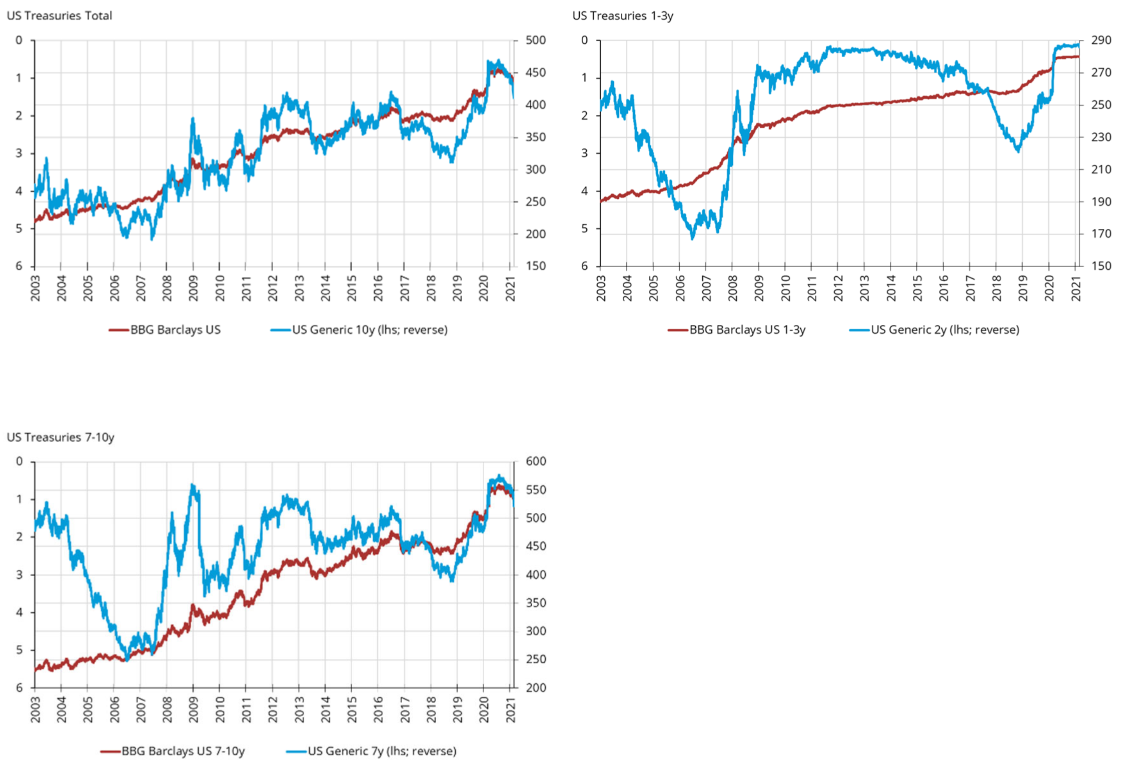
With respect to the dependent variable, as a good proxy for a high-grade bond portfolio (the focus of this study), the Bloomberg Barclays USD Treasuries Total Return Index -from now on the neutral or passive index- is used, which includes all US domestic government debt with maturities higher than one year. It is denominated in USD and it is unhedged. The index has a monthly rebalancing frequency and market value weighting. The effective duration of the index, and therefore of the passive investment portfolio, is approximately 6 years. This total return index has been selected for two reasons. Firstly, it represents the whole yield curve of the US Treasury market and has a high correlation with the 10-year US Generic Government Bond (see Chart 2). Secondly, this index is transparent in their constituents and their weights.

In order to construct the portfolio to be compared with the passive investment benchmark in terms of performance and risk ratios (see section 4), two more indexes are used (see Charts 3 and 4) to implement the position signals given by the model (long/neutral/short). The Bloomberg Barclays USD Treasuries 1-3-year Total Return Index –from now on the short index- is used to build the short portfolio. It includes all US domestic government debt with maturities between one and three years. This index has an effective duration of approximately 1.8 years. The Bloomberg Barclays USD Treasuries 7-10-year Total Return Index - from now on the long index - will be used for building the long portfolio. It includes all US domestic government debt with maturities between seven and ten years. It has an effective duration of approximately 7.4 years.

Both indexes are also denominated in USD, are unhedged, have a monthly rebalancing frequency and their weighting is based on market value.

To backtest the model we use a sovereign bond portfolio denominated in USD dollars invested in different proportions in the three indexes described above. This is done to follow the duration management model signals in each period. Whenever the model produces a short signal, the portfolio will be proportionately allocated to the short index and the passive index, with 23%/77% respective weightings. The short portfolio would therefore have a duration of approximately 5 years, one year shorter than the passive investment portfolio. When the model gives a neutral signal, the portfolio will be fully invested in the neutral index, thus, having a 6 years duration. Finally, when the model gives a long signal, the portfolio will be invested in the long index and the passive index with a 74%/26% weighting respectively. The long portfolio would have then a duration of approximately 7 years, one year longer than the passive investment portfolio.

Charts 2-4. Benchmark Indices and Generic Treasury Bonds.



Source: Own elaboration based on Bloomberg data.

Table 1 shows time-lagged correlations between monthly growth rates (Month-Over-Month, MoM) and the benchmark index. The financial variables are the most contemporaneously correlated, specifically fixed-income series. However, economic variables increase its importance when the forecasting horizon is higher than one month. This result supports the empirical evidence found by Cerniglia and Fabozzi (2020) that the variance-covariance matrix depends on the forecast horizon analyzed. In the short-term, financial variables have the greatest impact on fixed-income markets, while macroeconomic variables seem to impact more in the long-run behaviour of fixed-income portfolios.

Table 1. Correlation table. Month-Over-Month (MoM).

MoM							
			Lags				
	0		1		2		3
BBG US Ser-E Gov > 1Y Bond Index	100%	S&P 500	26%	MOVE	20%	US JPM Ts Investor Sentiment	12%
iBoxx US Ts 7-10Y TRI	98%	DAX	24%	London Metal Exchange Index	18%	Generic Spain 30y Government Bond	11%
iBoxx US Ts 5-7Y TRI	96%	IBEX 35	20%	BBG USDJPY 3M Hedging Cost	18%	Conference Board Consumer Conf	11%
iBoxx US Ts 3-5Y TRI	91%	CBOE Volatility Index	18%	Langer US National Economy Exp	16%	US Capacity Utilization % of Total	11%
iBoxx US Ts 1-3 TRI	77%	Federal Reserve Balance Sheet	17%	iBoxx Euro Spain Sovereign TRI	13%	Langer US Nat. Eco. Expect. Diffus. Index	11%
iBoxx Euro Germany Sovereign TRI	75%	USD INFL SWAP ZC 10Y	16%	BBG Commodity	12%	ECB Survey of Professional Forecasters	10%
iBoxx Euro Germany Covered TRI	66%	Private Housing Authorized by Bldg Permits	16%	Federal Reserve Balance Sheet	12%	Phil. Fed Survey of Professional Forecasters	9%
iBoxx Euro Spain Sovereign TRI	41%	Generic 1st 'CO' Future	14%	iBoxx US Ts 7-10Y TRI	11%	U. of Michigan Current Eco. Conditions Index	8%
iBoxx EUR Spain Covered	35%	Nat. Assoc. of Home Builders Market Index	13%	EUR-JPY X-RATE	10%	Market News International Chic	8%
Gold Spot $/Oz	26%	iBoxx US Trs 1-3 TRI	13%	iBoxx EUR Spain Covered	10%	Private Housing Authorized by Bldg Permits	8%

MoM							
			Lags				
	0		1		2		3
Fixed Income	100%	Equity	26%	Uncertainty	20%	Survey	12%
Fixed Income	98%	Equity	24%	Commodity	18%	Financials	11%
Fixed Income	96%	Equity	20%	Financials	18%	Economics	11%
Fixed Income	91%	Uncertainty	18%	Economics	16%	Economics	11%
Fixed Income	77%	Monetary	17%	Fixed Income	13%	Economics	11%
Fixed Income	75%	Financials	16%	Commodity	12%	Survey	10%
Fixed Income	66%	Economics	16%	Monetary	12%	Survey	9%
Fixed Income	41%	Commodity	14%	Fixed Income	11%	Economics	8%
Fixed Income	35%	Economics	13%	Currency	10%	Economics	8%
Commodity	26%	Fixed Income	13%	Fixed Income	10%	Economics	8%

Source: Own elaboration.

4. Results

Firstly, it is compared the naïve threshold or "rule of thumb" method with the proposal based on conditional probabilities. Table 2 shows the confusion matrix using the "naive" threshold, rows show the signals predicted by the model, while columns show the actual benchmark's movements (negative or positive returns). This "naive" threshold gives only one correctly identified long signal in the out-of-sample period (2012-2021). The signals given by this approach are too small (1 out of 120 months) compared to the proposed thresholds based on conditional probabilities (22 out of 120 months). Based on this low active ratio, this study will only use the threshold obtained by the proposed approach, discarding the "naive" threshold so that we obtain a more "active" model.

Table 2. Confusion matrix.

Lasso with rule of thumb thresholds

	Loss	Gain	Total_Signals
Short	0%	0%	0%
Neutral	49%	51%	99%
Long	0%	100%	1%
Total_observed	49%	51%	100%

HIT Ratio	100%
Active	1%

Source: Own elaboration.

Secondly, performance analysis is carried out for the LassoDefault model. This model has a hit ratio[8] of 58% in the in-sample period (2004-2011), but only because it correctly predicts the direction of returns when they are positive (74%). It is not able to identify the negative returns, where only 43% of the time correctly predicts a bearish move. It is very active in the in-sample

[8] Hit ratio is defined as the sum of correct long and short signals given by the model divided by the number of periods in which the model delivers a signal.

period where it gives a long/short signal 42% of the time (Table 3). In the out-of-sample period, the LassoDefault's hit ratio drops 8pp to 50%, not better than a random model, and gives signals only 27% of the time. The performance loss comes from a decrease of accuracy when the model predicts positive returns (long signals), down from 74% to only 52%. There is an increase in the accuracy of negative returns, but not enough to achieve a hit ratio higher than a random model (up to 45% from 43%) (Table 4). The two-step procedure it is not able to increase the performance of the model in the out-of-sample period (Table 5).

Tables 3-5. Model performance.

Lasso default (CrossValidation - insample)

	Loss	Gain	Total_Signals
Short	43%	57%	22%
Neutral	40%	60%	58%
Long	26%	74%	20%
Total_observed	38%	62%	100%

HIT Ratio	58%
Active	42%

Lasso default (CrossValidation - outsample)

	Loss	Gain	Total_Signals
Short	45%	55%	9%
Neutral	50%	50%	73%
Long	48%	52%	18%
Total_observed	49%	51%	100%

HIT Ratio	50%
Active	27%

Lasso default Two Step (CrossValidation - outsample)

	Loss	Gain	Total_Signals
Short	44%	56%	8%
Neutral	50%	50%	73%
Long	48%	52%	19%
Total_observed	49%	51%	100%

HIT Ratio	50%
Active	27%

Source: Own elaboration.

The "poorly" out-of-sample performance of the LassoDefault could be explained by possible overfitting when choosing the lambda's value in the Cross-validation exercise. To try to overcome this potential overfitting, the simple ensemble model is compared. This model has a really good performance in the in-sample period, with a hit ratio of 88%, but it gives few signals (only 27% of the time). The accuracy between negative and positive returns looks more balanced (a hit ratio of 82% when the index has losses and 93% when the returns are positive) (Table 6). The simple ensemble model behaves well also in the out-sample period. The hit ratio decreases but it maintains a level that is above the 50% threshold (59%), in this model the accuracy is concentrated in the short signals, where 67% correctly identified a loss trend and 56% the positive returns. The model is slightly less active than in the in-sample period, down to 18% from 27% (Table 7). In this case, the two-step procedure is able to increase slightly the performance to achieve a hit ratio of 62%, with correct short signals 71% of the time, and correct long signals 57% of the time (Table 8).

Tables 6-8. Model performance.

Lasso Simple Ensemble (CrossValidation - insample)

	Loss	Gain	Total_Signals
Short	82%	18%	12%
Neutral	38%	62%	73%
Long	7%	93%	16%
Total_observed	38%	62%	100%

HIT Ratio	88%
Active	27%

Lasso Simple Ensemble (CrossValidation - outsample)

	Loss	Gain	Total_Signals
Short	67%	33%	5%
Neutral	49%	51%	82%
Long	44%	56%	13%
Total_observed	49%	51%	100%

HIT Ratio	59%
Active	18%

Lasso Two Step Simple Ensemble (CrossValidation - outsample)

	Loss	Gain	Total_Signals
Short	71%	29%	6%
Neutral	48%	52%	83%
Long	43%	57%	12%
Total_observed	49%	51%	100%

HIT Ratio	62%
Active	18%

Source: Own elaboration.

Previously it has been shown that the Lasso regression with default options is worse than the model with the simple ensemble model. However, it is possible that a model with a low hit ratio may outperform a model with a high hit ratio if the former produces signals whenever there are significant movements in returns. This could happen if the LassoDefault identifies a period of extreme return movements compared to the simple ensemble (many mistakes with small losses but hitting very big and extreme returns). In Table 9 both models (with the two-step procedure applied to each) are compared to the passive investment strategy, as well as the Ladder and Barbell portfolios. As illustrated there, the LassoDefault model is not able to beat the passive investment in the out-of-sample period either in absolute returns or in Sharpe Ratio terms. The passive investment has also better risk ratios than the LassoDefault. The LassoDefault suffers the worst Drawdown over the models analyzed. The two-step procedure (Lasso Default (Two-step)) doesn't improve the model. The Sharpe Ratio and the Conditional Value-at-Risk at the 95% confidence level (CVaR95) remain virtually the same, the accumulated return is the only indicator that improves slightly when the two-step procedure is applied (+22bps).

The analysis presented in Table 9 (see also Chart 5) reveals that the Simple Ensemble model surpasses passive investment in terms of performance metrics like annual returns, Sharpe ratio, and accumulated return. It also showcases a positive excess return and a superior information ratio. However, this model fails to improve upon the risk ratios when stacked against the Ladder and Barbell alternative strategies, though these strategies carry their own demerits - negative excess returns and the poorest information ratios. Interestingly, compared to the "Always Long" strategy, the Simple Ensemble model exhibits a lower annual return, but it outperforms in terms of the Sharpe ratio and risk metrics. It shows a significantly lower tracking error, maximum drawdown, VaR 5%, and CVaR, highlighting its ability to manage risk more effectively despite lower returns compared to the “Always Long” strategy. Thus, it appears that the Simple Ensemble model offers a more balanced performance-risk profile than either the "Always Long" strategy or the alternative Ladder and Barbell strategies.

Table 9. Performance and risk ratios (annualized figures[9]).

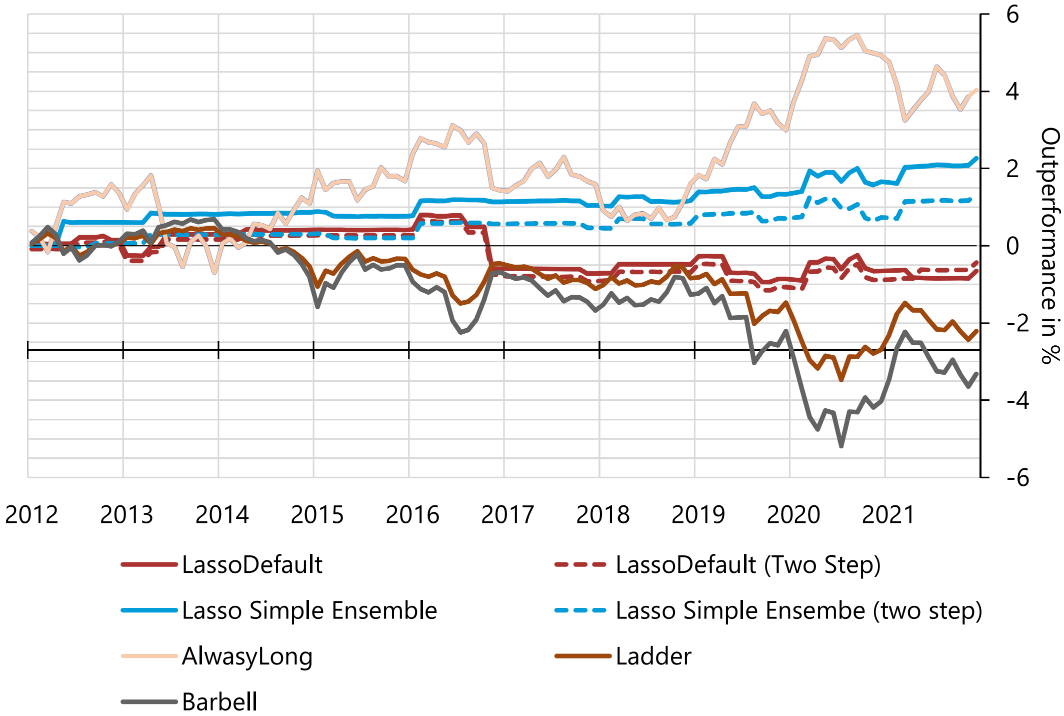
	Performance Ratios					Risk Ratios				
	Annual Returns	Sharpe Ratio	Accum. Return	Exc. Return[1]	Info. Ratio	SE	Tracking Error	MaxDD	VaR 5%	CVaR
Passive Investment	2.18	0.58	23.47	n/a	n/a	3.78	n/a	-7.72	-16.48	-23.28
Lasso Default	2.13	0.55	22.82	-0.05	-0.10	3.91	0.46	-7.75	-15.51	-25.01
Lasso Default (Two step)	2.15	0.55	23.04	-0.03	-0.06	3.92	0.46	-7.73	-15.51	-25.01
Lasso Simple Ensemble*	**2.37**	**0.61**	**25.74**	**0.18**	**0.53**	**3.85**	**0.35**	**-7.36**	**-14.66**	**-22.91**
Lasso Simple Ensemble (Two Step)*	2.29	0.60	24.83	0.11	0.39	3.82	0.28	-7.56	-14.66	-22.91
Always Long	2.55	0.53	27.51	0.37	0.32	4.80	1.16	-9.61	-23.80	-31.46
Ladder	1.98	0.61	21.26	-0.20	-0.31	3.22	0.65	-5.73	-15.50	-25.17
Barbell	1.88	0.64	20.16	-0.30	-0.31	2.96	0.98	-5.73	-14.56	-22.18

*Note: * p < 0.1. Period 2012-2021.*

[1] *Excess returns compared to Passive Investment's accumulated returns.*

Source: Own elaboration.

Chart 5. Outperformance.



Source: Own elaboration.

In the extended analysis of the performance, the alpha generated across the whole sample is significant at the 5% level (Table 10). Importantly, this alpha is primarily attributable to the identification of extreme movements in the dataset. For returns that are below 1.28σ, the alpha is lower (0.05) and not statistically significant (p-value = 0.27). However, when focusing on returns exceeding the 1.28σ threshold, a much higher alpha of 0.88 is found, significant at the 5% level. As the return thresholds increase (1.64σ and 1.96σ), the alpha drops to 0.31 and 0.60, respectively, and their p-values suggest less statistical significance. This underlines the importance of extreme movements in generating alpha in this context. These insights are further confirmed by conducting a regression that specifically identifies these extreme movements

[9] Except for MAXdd, which represents the cumulative loss incurred when buying at the highest price and selling at the lowest.

(Table 10). The model is estimated to generate 94 basis points (bp) of excess return in the top 20% of the data considered "extreme" (greater than 1.28 standard deviations). According to the regression table, the alpha at the 80th percentile (greater than 1.28σ) is 0.94 with a standard error of 0.10, which is statistically significant at the 1% level (p-value = 0.010). The constant term, representing the alpha when not considering these extreme data points, is 0.09 with a standard error of 0.03, but it is not statistically significant (p-value = 0.429). These findings further demonstrate the model's capability in identifying and capitalizing on extreme market movements to generate significant alpha.

Table 10. Lasso Simple Ensemble Two-Step: alpha.

	alpha (%)[1]	p-value	n
Whole sample	0.18	0.05	120
returns < 1.28σ	0.05	0.27	101
returns > 1.28σ	**0.88**	**0.05**	**19**
returns > 1.64σ	0.31	0.17	13
returns > 1.96σ	0.60	0.18	8

alpha (%)[1]	coefficient	Std. Err.	p-value
percentile 80 (> 1.28σ)	0.94	0.10	0.010
constant	0.09	0.03	0.429

[1] *Annualized figures.*

Source: Own elaboration.

Table 11 shows the set of variables that the machine learning algorithm is selecting every year, jointly with their betas. Only two variables appear recurrently in the whole out-of-sample exercise, one related to economics (US import prices) and another related to financial flows (Japanese two-year government bond). US capacity utilization appears 9 out of 10 years, jointly with the 7 year Japanese bond and the Euro Swap Overnight Index Rate (OIS) for one week. Remarkably the betas are not stable year over year. For instance, it seems that at the end of the out-sample period US capacity utilization is losing forecasting power compared to US 1y1y inflation forward rate. This result goes in line with the increase in inflation uncertainty observed in 2021 when the COVID-19 measures started to be loosened and the demand began to lift out.

Table 11. Set of variables selected by year.

Variable	Type	Year incl.	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean beta
US Capacity Utilization	ECON	9		0,38	0,42	0,31	0,42	0,38	0,37	0,27	0,19	0,07	0,31
Unemployment	ECON	1									-0,27		-0,27
Japan (7 year Issue)	FINANCIAL	9		-0,23	-0,33	-0,25	-0,25	-0,29	-0,25	-0,28	-0,26	-0,17	-0,26
Dax Index	FINANCIAL	7				-0,02	-0,18	-0,28	-0,27	-0,23	-0,30	-0,26	-0,22
Japan (2 year Issue)	FINANCIAL	10	-0,05	-0,24	-0,22	-0,24	-0,26	-0,34	-0,23	-0,28	-0,24	-0,10	-0,22
Home Builders Market Index	ECON	8		-0,26	-0,32	-0,14	-0,14	-0,10	-0,10	-0,12	-0,17		-0,17
JPMorgan Investor Sentiment Survey Active (long)	SURVEY	4		-0,05	-0,14	-0,17	-0,24						-0,15
VIX	FINANCIAL	1										0,13	0,13
Euro Swap 1 week	FINANCIAL	9	0,02	0,13	0,15	0,17	0,18	0,20	0,10	0,14	0,11		0,13
Adjusted Retail Sales	ECON	6		-0,12	-0,18	-0,20	-0,13	-0,12	-0,04				-0,13
US Import Prices	ECON	10	-0,19	-0,13	-0,06	-0,10	-0,21	-0,09	-0,12	-0,15	-0,07	-0,08	-0,12
5-year US Open Interest	FINANCIAL	8		-0,22	-0,16	-0,16	-0,17	-0,08	-0,09	0,00	-0,02		-0,11
Japan (5 year Issue)	FINANCIAL	3	-0,32	-0,01							-0,01		-0,11
US Retail Sales	ECON	2				-0,01	-0,20						-0,11
Economic Condition Michigan	SURVEY	2		-0,10	-0,04								-0,07
OIL Open Interest	COMMODITIES	2				0,00	0,13						0,07
US Export Prices	ECON	5			-0,06	-0,06	-0,08	-0,10		-0,02			-0,06
US Inflation Forward Rate 1y1y	FINANCIAL	8		0,01	0,00	0,02	0,09	0,10	0,02	0,06	0,09		0,05
PMI Services	SURVEY	4					-0,01		-0,03	-0,11	-0,04		-0,04
US Manufacturers New Orders	ECON	4			-0,04	-0,11			-0,01	-0,02			-0,04
JPMorgan Investor Sentiment Survey All (long)	SURVEY	4		-0,03	-0,02	-0,04	-0,08						-0,04
Eurostoxx Implied Volatility	FINANCIAL	1										0,03	0,03
US 3 month	FINANCIAL	1				-0,03							-0,03
Global Implied Volatility	FINANCIAL	3							0,02	0,05	0,01		0,03
OIL	COMMODITIES	1									-0,02		-0,02
US Industrial Production	ECON	1					0,02						0,02
Man. Activity (Kansas)	ECON	3			-0,01	-0,01	-0,01						-0,01

Source: Own elaboration.

5. Conclusions and further research

This paper tries to fill the gap related to the application of machine learning in the context of active fixed-income management. It compares the performance of a machine learning algorithm, "The Lasso logit regression", with a passive investment and proposes a simple ensemble alternative and a two-step model to reduce overfitting problems. It also presents an algorithm to select thresholds that map probabilities into signals based on conditional probability distributions.

The algorithm proposed to translate probabilities into signals is more active than the "rule of thumb" alternative and gives superior performance. The approach involves categorizing model-generated probabilities in the 'in-sample' dataset into two groups: those linked to positive benchmark returns and those tied to negative benchmark returns. When positive benchmark returns are observed, the conditional distribution of model probabilities is used to establish the higher threshold (indicating long signals) at the 75th percentile. In contrast, for short position signals, probabilities associated with negative benchmark returns are chosen, and the 25th percentile within this conditional distribution is identified. Any probabilities falling between these upper and lower thresholds are considered "neutral".

The machine learning algorithm that only applies the Lasso logit regression with default options is not able to beat the passive investment strategy, even applying the two-step procedure the performance is not improved. The algorithm that seems to work well is the simple ensemble alternative, which achieves the best risk and return ratios. This algorithm splits the dataset into three different sets of variables, based on their statistical properties (being stationary or not) and then a lasso logit regression is applied to every set. The two-step procedure applied to the simple ensemble improves the risk ratios of the model, achieving the highest Sharpe Ratio, Information Ratio and lowest Maximum Drawdown.

The variables selected by the machine learning behave as expected a priori. For the evolution of our monthly fixed-income portfolio, economic variables and financial flows are the most relevant ones. For most of the years the following variables are selected: US capacity utilization, Japanese bonds, import prices and Euro swap OIS. But a signal of caution is observed because the relevance of the variables is not stable and changes over time. Nevertheless, this makes sense, as an example the inflation expectations have increased their forecasting power in 2021 compared to US capacity utilization. Something that one should expect because of the increasing inflation uncertainty post COVID-19 in 2021.

The alpha generated by the Lasso Simple Ensemble after applying the two-Step procedure is positive and statistically significant at 10%, but the most interesting result is that most of the alpha comes from correctly identifying "extreme" movements (returns movements higher than 1,3 standard deviations).

These results provide evidence to support the advantages of incorporating quantitative tools in the active portfolio management process for institutional investors but taking into account that some overfitting could occur. All in all, applying machine learning algorithms should be done as a complementary input to the qualitative or fundamental analysis together with the portfolio manager's expertise, in order to make better-informed investment decisions.

There are some limitations that could be explored in further research. First of all, the amount of money invested (divested) when there is a long (short) signal (+10%/-10%) could be tied to the probabilities, maybe applying the Kelly criterion, in order to find if there are some improvements compared to the fixed 10% approach. The lack of stability in the parameters of the model could be an additional line of research, including some feature selection algorithms like Bayesian Model

Averaging. Another extension could be to include as inputs for the model some technical indicators[10] that are widely used in investment decisions, like Bollinger Bands, Relative Strenght Index (RSI), Moving Average oscillator, Ichimoku, among others. It could also be interesting to test other types of machine learning algorithms like XGBoost, among others, to investigate if they are less prone to overfitting issues.

[10] For definitions, see https://tabtrader.com/academy/articles/trading-indicators.

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ANNEX

Table 12. Data description. Final indicators **in bold**.

Variable	Classification	Start year	Periodicity	Max	Min	Mean	Indicator
US Govt 2yr-3yr-5yr Butterfly	Butterfly	2003	Intraday	10,7	-80,1	-22,9	Rate
US Govt 2yr-5yr-10yr Butterfly	Butterfly	1999	Intraday	80,9	-75,7	-0,3	Rate
US Govt 5yr-10yr-30yr Butterfly	Butterfly	1999	Intraday	87,9	-58,9	-0,7	Rate
BBG Commodity	Commodity	1999	Daily	238,0	59,5	121,0	Price
Crude Oil Open Interest Combined	Commodity	1999	Daily	3.785.409,0	439.268,0	2.068.316,0	Net balance
Generic 1st 'CO' Future	Commodity	1999	Daily	146,1	14,2	63,4	Price
Gold Spot $/Oz	Commodity	1999	Daily	2.063,5	252,6	956,5	Price
LMEX LONDON METALS INDEX	Commodity	2000	Daily	4.556,6	958,3	2.662,2	Price
EUR-JPY X-RATE	Currency	1999	Daily	169,5	89,5	127,1	Currency
EURO 1 MO	Currency	1999	Daily				Rate
EURO 10 YR	Currency	1999	Daily				Rate
EURO 12 MO	Currency	1998	Daily				Rate
EURO 2 MO	Currency	1999	Daily				Rate
EURO 3 YR	Currency	1999	Daily				Rate
EURO 5 YR	Currency	1999	Daily				Rate
EURO 7 YR	Currency	1999	Daily				Rate
Euro Spot	Currency	1999	Daily	1,6	0,8	1,2	Currency
EUR-USD OPT VOL 1M	Currency	1999	Daily	28,9	3,8	9,6	Index (state)
CFTC CME Euro Fx Total Open Interest/Combined	Currency	1999	Weekly on Tuesday	795.353,0	33.215,0	305.334,0	Net balance
Citi Economic Surprise - United States	Economics	2003	Intraday	270,8	-144,6	4,3	Index
Citi Economic Surprise Index - Eurozone	Economics	2003	Intraday	212,4	-304,6	4,4	Index
Adjusted Retail & Food Services Sales	Economics	1999	Monthly	18,2	-14,7	0,4	Rate
Adjusted Retail Sales Less Autos and Gas Stations	Economics	1999	Monthly	12,1	-14,2	0,4	Rate
Adjusted Retail Sales Less Autos	Economics	1999	Monthly	12,2	-15,1	0,4	Rate
ADP National Employment Report	Economics	2002	Monthly	4.485,5	-19.408,9	47,4	Net balance
Capital Goods New Orders Nondefense Ex Aircraft & Parts	Economics	1999	Monthly	9,2	-10,8	0,1	Rate
Capital Goods Shipments Ex Air	Economics	1999	Monthly	5,2	-8,1	0,1	Rate
Census Bureau US Construction	Economics	1999	Monthly	2,8	-3,7	0,3	Rate
Challenger US Job Cut Announce	Economics	2000	Monthly	1.576,9	-77,4	31,6	Rate
Chicago Fed National Activity	Economics	1999	Monthly	6,0	-17,7	-0,1	Confidence/survey
Conference Board Consumer Confidence	Economics	1999	Monthly	144,7	25,3	95,0	Confidence/survey
Conference Board Consumer Confidence Expectations	Economics	1999	Monthly	119,2	27,3	88,0	Confidence/survey
Conference Board Consumer Confidence Present Situation	Economics	1999	Monthly	186,8	20,2	105,4	Confidence/survey
Conference Board US Leading Index	Economics	1999	Monthly	3,1	-7,6	0,1	Confidence/survey
Dallas Fed Manufacturing Outlook Level of General Business Activity	Economics	2004	Monthly	48,0	-72,2	2,2	Rate
Federal Reserve Consumer Credit	Economics	1999	Monthly	29,3	-64,0	10,3	Net balance
FHFA US House Price Index Purchase Only	Economics	1991	Monthly	-	-	-	Rate
ISM Manufacturing PMI SA	Economics	1999	Monthly	61,4	34,5	52,8	Confidence/survey
ISM Manufacturing Report on Business Employment	Economics	1999	Monthly	62,3	28,0	50,8	Confidence/survey
ISM Manufacturing Report on Business New Orders	Economics	1999	Monthly	71,3	25,9	55,7	Confidence/survey
ISM Manufacturing Report on Business Prices	Economics	1999	Monthly	92,1	17,1	60,0	Confidence/survey
ISM Services PMI	Economics	1999	Monthly	61,3	37,8	54,6	Confidence/survey
Kansas City Federal Reserve SA	Economics	2001	Monthly	25,0	-30,0	4,7	Confidence/survey
Langer US National Economy Expectations Diffusion Index	Economics	1999	Monthly	63,0	8,5	42,0	Confidence/survey
Market News International Chicago Business Barometer	Economics	1999	Monthly	68,6	32,5	54,8	Confidence/survey
Markit US Composite PMI SA	Economics	2018	Monthly				Confidence/survey
Markit US Manufacturing PMI SA	Economics	2018	Monthly				Confidence/survey
Markit US Services PMI Busines	Economics	2018	Monthly				Confidence/survey
Merchant Wholesalers Inventories Total	Economics	1999	Monthly	2,1	-2,0	0,3	Rate
Merchant Wholesalers Sales Total	Economics	1999	Monthly	9,0	-16,4	0,4	Rate
National Association of Home Builders Market	Economics	1999	Monthly	90,0	8,0	50,5	Difference, employees
NFIB Small Business Optimism Index	Economics	1999	Monthly	108,8	81,6	97,6	Index
Philadelphia Fed Business Outlook Survey	Economics	1999	Monthly	37,0	-46,8	7,5	Confidence/survey
Private Housing Authorized by Building Permits	Economics	1999	Monthly	2.263,0	513,0	1.335,0	Level
Private Housing Units Started	Economics	1999	Monthly	24,0	-26,4	0,3	Rate
Private Total Housing Authorized by Building Permits	Economics	1999	Monthly	18,6	-21,9	0,2	Rate
Retail Inventories Seasonally	Economics	1999	Monthly	1,6	-6,2	0,2	Rate
Retail Sales Less Food Service	Economics	1999	Monthly	10,4	-12,4	0,3	Rate
S&P CoreLogic Case-Shiller 20-City Composite Home Price Index	Economics	2000	Monthly	-	-	-	Index
S&P CoreLogic Case-Shiller 20-City Composite Home Price MoM	Economics	2000	Monthly	-	-	-	Rate
S&P CoreLogic Case-Shiller 20-City Composite Home Price YoY	Economics	2001	Monthly	-	-	-	Rate
S&P CoreLogic Case-Shiller U.S	Economics	1987	Monthly	-	-	-	Index
S&P CoreLogic Case-Shiller U.S YoY	Economics	1988	Monthly	-	-	-	Rate
U-3 US Unemployment Rate Total	Economics	1999	Monthly	14,8	3,5	5,9	Rate
UMich Expected Change in Prices During the next 5-10y	Economics	1999	Monthly	3,4	2,2	2,8	Confidence/survey
UMich Expected Change in Prices During the next year	Economics	1999	Monthly	5,2	0,4	3,0	Confidence/survey
University of Michigan Consumer Expectations Index	Economics	1999	Monthly	108,6	47,6	78,6	Confidence/survey
University of Michigan Consumer Sentiment Index	Economics	1999	Monthly	112,0	55,3	86,2	Confidence/survey
University of Michigan Current	Economics	1999	Monthly	121,2	57,5	98,2	Confidence/survey
US Auto Sales Total Annualized	Economics	1999	Monthly	21,8	8,6	15,8	Rate
US Average Hourly Earnings All Employees Total Private MoM	Economics	2006	Monthly				Rate
US Average Hourly Earnings All Employees Total Private YoY	Economics	2007	Monthly				Rate
US Average Weekly Hours All Employees	Economics	2006	Monthly				Index Level
US Capacity Utilization % of Total Capacity	Economics	1999	Monthly	82,3	64,2	77,0	Rate
US CPI Urban Consumers Less Food & Energy YoY	Economics	1999	Monthly	4,5	0,6	2,0	Rate
US CPI Urban Consumers Less Food & Energy Index	Economics	1999	Monthly	279,1	175,7	222,4	Index
US CPI Urban Consumers Less Food & Energy MoM	Economics	1999	Monthly	0,9	-0,4	0,2	Rate
US CPI Urban Consumers MoM SA	Economics	1999	Monthly	1,4	-1,8	0,2	Rate
US CPI Urban Consumers NSA	Economics	1999	Monthly	261,6	165,0	215,7	Index
US CPI Urban Consumers YoY NSA	Economics	1999	Monthly	5,6	-2,1	2,1	Rate

US Durable Goods New Orders Industries	Economics	1999	Monthly	23,0	-18,8	0,2	Rate
US Durable Goods New Orders Total ex Transportation	Economics	1999	Monthly	6,3	-10,3	0,1	Rate
US Empire State Manufacturing	Economics	2001	Monthly	39,0	-78,2	7,9	Confidence/survey
US Employees on Nonfarm Payrolls Total Private MoM	Economics	1999	Monthly	4.807,0	-19.731,0	62,5	Difference
US Employees on Nonfarm Payrolls Total MoM	Economics	1999	Monthly	4.846,0	-20.679,0	69,6	Difference
US Employees on Nonfarm Payrolls Manufacturing Industry	Economics	1999	Monthly	342,0	-1.304,0	-18,7	Difference, employees
US Existing Homes Sales MoM SA	Economics	1999	Monthly	23,7	-22,5	0,2	Rate
US Existing Homes Sales SAAR	Economics	1999	Monthly	7,3	3,5	5,3	Difference
US Export Price By End Use All Commodities MoM	Economics	1999	Monthly	2,7	-3,5	0,1	Rate
US Export Price By End Use All Commodities YoY	Economics	1999	Monthly	17,6	-8,3	1,3	Rate
US Foreign Net Transactions	Economics	1999	Monthly	157,8	-134,9	42,6	Net balance
US Import Price Index by End Use All MoM	Economics	1999	Monthly	3,2	-7,4	0,2	Rate
US Import Price Index By End Use Ex-Petroleum MoM	Economics	1999	Monthly	1,3	-1,7	0,1	Rate
US Import Price Index by End Use All YoY	Economics	1999	Monthly	-	-	-	Rate
US Industrial Production Industry Groups Manufacturing	Economics	1999	Monthly	7,7	-15,8	0,1	Rate
US Industrial Production MoM	Economics	1999	Monthly	6,2	-12,7	0,1	Rate
US Job Openings By Industry Total	Economics	2000	Monthly	-	-	-	Level
US Labor Force Participation	Economics	1999	Monthly	67,3	60,2	64,7	Rate
US Manufacturers New Orders Excluding Transportation	Economics	1999	Monthly	4,8	-8,9	0,2	Relative change
US Manufacturers New Orders Total	Economics	1999	Monthly	10,3	-13,5	0,2	Net balance
US Manufacturing & Trade Inventories Total	Economics	1999	Monthly	1,3	-2,3	0,2	Rate
US New One Family Houses Sold Annual Total MoM	Economics	1999	Monthly	21,0	-33,6	0,2	Rate
US New One Family Houses Sold Annual Total Units/Persons	Economics	1999	Monthly	1.389,0	270,0	708,4	Level
US New Privately Owned Housing	Economics	1999	Monthly	2.273,0	478,0	1.287,0	Level
US Pending Home Sales Index YoY	Economics	2002	Monthly	29,3	-34,6	1,1	Rate
US Personal Consumption Expenditures Chained 2012 $ MoM	Economics	1999	Monthly	8,5	-12,2	0,2	Rate
US Personal Consumption Expenditure Core Price Index MoM	Economics	1999	Monthly	0,7	-0,6	0,2	Rate
US Personal Consumption Expenditures Nominal $ MoM	Economics	1999	Monthly	8,6	-12,6	0,4	Rate
US Personal Consumption Expenditure Core Price Index YoY	Economics	1999	Monthly	3,6	0,6	1,7	Rate
US Personal Consumption Expenditures Chain Type Price Index MoM	Economics	1999	Monthly	1,0	-1,2	0,2	Rate
US Personal Consumption Expenditures Chain Type Price Index YoY	Economics	1999	Monthly	4,2	-1,5	1,8	Rate
US Personal Income MoM SA	Economics	1999	Monthly	12,4	-4,7	0,4	Rate
US PPI Final Demand Less Foods and Energy MoM	Economics	2010	Monthly				Rate
US PPI Final Demand Less Foods Energy and Trade Services MoM	Economics	2013	Monthly				Rate
US PPI Final Demand Less Foods Energy and Trade Services YoY	Economics	2014	Monthly				Rate
US PPI Final Demand Less Foods and Energy YoY	Economics	2010	Monthly				Rate
US PPI Final Demand MoM SA	Economics	2009	Monthly				Rate
US PPI Final Demand YoY NSA	Economics	2010	Monthly				Rate
US Real Average Hourly Earning	Economics	2007	Monthly				Rate
US Real Average Weekly Earning	Economics	2007	Monthly				Rate
US Trade Balance of Goods and Services	Economics	1999	Monthly	-17,7	-69,0	-44,3	Net balance
US Trade in Goods Balance Total	Economics	1999	Monthly	-23,8	-86,1	-57,0	Net balance
US Treasury Federal Budget Debt Summary	Economics	1999	Monthly	214,3	-864,1	-57,8	Difference
US Treasury International Capital	Economics	1999	Monthly	317,0	-194,6	36,6	Net balance
US U-6 Unemployed & Part Time	Economics	1999	Monthly	22,9	6,8	10,7	Rate
Bureau of Labor Statistics Employment Cost	Economics	1999	Quarterly	1,2	0,2	0,7	Rate
Delinquencies As % Of Total Loans	Economics	1979	Quarterly	-	-	-	Rate
FHFA US Purchase-Only	Economics	1991	Quarterly	-	-	-	Rate
FOF Federal Reserve US Households	Economics	1946	Quarterly	-	-	-	Difference
Foreclosures As % Of Total Loans	Economics	1979	Quarterly	-	-	-	Rate
GDP US Chained 2012 Dollars	Economics	1999	Quarterly	33,4	-31,4	2,1	Rate
GDP US Personal Consumption	Economics	1999	Quarterly	41,0	-33,2	2,4	Rate
US GDP Personal Consumption	Economics	1999	Quarterly	3,4	-0,8	1,7	Rate
US GDP Price Index QoQ SAAR	Economics	1999	Quarterly	4,2	-1,8	1,9	Rate
US Labor Productivity Output	Economics	1999	Quarterly	10,6	-4,8	2,0	Rate
US Nominal Account Balance	Economics	1960	Quarterly	-	-	-	Net balance
US Nominal Output Gap as a Percentage of GDP	Economics	1999	Quarterly	2,1	-10,1	-1,4	Rate
US Unit Labor Costs Nonfarm Business Sector	Economics	1999	Quarterly	15,6	-13,4	1,5	Rate
MBA US US Mortgage Market	Economics	1999	Weekly on Friday	112,1	-38,8	0,5	Rate
US Continuing Jobless Claims	Economics	1999	Weekly on Friday	24.912,0	1.649,0	3.282,0	Level (state)
US Initial Jobless Claims	Economics	1999	Weekly on Friday	6.867,0	201,0	397,7	Level (state)
Langer US Weekly Consumer Comf	Economics	1999	Weekly on Sunday	69,0	23,0	43,3	Confidence/survey
DAX INDEX	Equity	1999	Daily	14.109,0	2.203,0	7.628,0	Price
IBEX 35 INDEX	Equity	1999	Daily	15.946,0	5.364,0	9.684,0	Price
S&P 500 INDEX	Equity	1999	Daily	3.934,8	676,5	1.657,3	Price
Bloomberg USDEUR 3 Month Hedging Cost	Financials	1999	Daily	3,6	-2,0	0,7	Rate
Bloomberg USDJPY 3 Month Hedging Cost	Financials	1999	Daily	6,9	0,1	2,1	Rate
BONOS Y OBLIG DEL ESTADO	Financials	1999	Daily	7,5	0,8	4,2	Rate
EUR Eonia Forward 1Y1Y	Financials	2000	Daily	7,5	-0,8	1,7	Rate
EUR SWAP (EONIA) 1WK	Financials	1999	Daily	5,0	-0,5	0,7	Rate
USD INFL FORWARD RATE 1Y1Y	Financials	1999	Daily	5,6	-2,1	0,7	Rate
USD INFL SWAP ZC 10Y	Financials	2004	Daily	3,1	0,8	2,4	Rate
USD INFL SWAP ZC 5Y	Financials	2004	Daily	3,3	-0,6	2,1	Rate
USD SWAP OIS 18M	Financials	2001	Daily	5,6	0,0	1,6	Rate
USD SWAP OIS 1M	Financials	2001	Daily	5,4	0,0	1,4	Rate
USD SWAP OIS 1W	Financials	2001	Daily	5,3	0,0	1,4	Rate
USD SWAP OIS 1Y	Financials	2001	Daily	5,7	0,0	1,5	Rate
USD SWAP OIS 2M	Financials	2001	Daily	5,4	0,0	1,4	Rate
USD SWAP OIS 2W	Financials	2001	Daily	5,4	0,0	1,4	Rate
USD SWAP OIS 2Y	Financials	2001	Daily	5,6	0,0	1,7	Rate
USD SWAP OIS 3M	Financials	2001	Daily	5,4	0,0	1,4	Rate
USD SWAP OIS 3Y	Financials	2002	Daily	4,6	0,0	1,2	Rate
USD SWAP OIS 4M	Financials	2001	Daily	5,5	0,0	1,4	Rate
USD SWAP OIS 4Y	Financials	2002	Daily	5,0	0,0	1,4	Rate
USD SWAP OIS 5M	Financials	2001	Daily	5,5	0,0	1,4	Rate
USD SWAP OIS 5Y	Financials	2002	Daily	5,7	0,0	2,4	Rate
USD SWAP OIS 6M	Financials	2001	Daily	5,5	0,0	1,4	Rate
USD SWAP OIS 9M	Financials	2001	Daily	5,6	0,0	1,5	Rate
USD SWAP SEMI 30/360 10Y	Financials	1999	Daily	7,9	0,5	3,7	Rate
USD SWAP SEMI 30/360 7YR	Financials	1999	Daily	7,8	0,4	3,4	Rate
US Breakeven 10 Year	Financials	1999	Intraday	2,8	0,0	2,0	Rate
Bloomberg CFTC CBT 10-Yr US Tr	Financials	1999	Weekly on Tuesday	608.492,0	-756.316,0	-20.779,0	Net balance
Bloomberg CFTC CME Euro Fx Net	Financials	1999	Weekly on Tuesday	211.752,0	-226.560,0	-4.222,0	Net balance
CFTC CBT 10-Year US Treasury N	Financials	1999	Weekly on Tuesday	5.736.552,0	541.198,0	2.556.514,0	Net balance
CFTC CBT 2-Year US Treasury No	Financials	1999	Weekly on Tuesday	4.423.693,0	32.328,0	998.523,0	Net balance
CFTC CBT 5-Year US Treasury No	Financials	1999	Weekly on Tuesday	5.580.720,0	285.337,0	1.939.930,0	Net balance

AUSTRALIAN GOVERNMENT	Fixed Income	1999	Daily	7,3	0,6	4,3	Yield
BELGIUM KINGDOM	Fixed Income	1998	Daily	-	-	-	Rate
BUNDESREPUB. DEUTSCHLAND	Fixed Income	1999	Daily	5,6	-0,9	2,6	Rate
IBOXX (EUR) DESOV OA TR	Fixed Income	1999	Daily	248,2	96,4	170,5	Price
IBOXX (EUR) ES SOV TR	Fixed Income	1999	Daily	289,0	95,5	176,0	Price
IBOXX (EUR) JUMBO OA TR	Fixed Income	1999	Daily	209,0	96,8	159,8	Price
IBOXX (EUR) SPAIN COVRD TR	Fixed Income	2003	Daily	255,1	122,2	186,2	Price
iBoxx US Trs 1-3 TR	Fixed Income	1999	Daily	185,4	100,6	150,4	Price
JAPAN (7 YEAR ISSUE)	Fixed Income	1999	Daily	1,9	-0,4	0,6	Rate
JAPAN (10 YEAR ISSUE)	Fixed Income	1999	Daily	2,0	-0,3	0,9	Rate
JAPAN (1 YEAR ISSUE)	Fixed Income	1999	Daily	0,8	-0,4	0,1	Rate
JAPAN (2 YEAR ISSUE)	Fixed Income	1999	Daily	1,1	-0,4	0,1	Rate
JAPAN (5 YEAR ISSUE)	Fixed Income	1999	Daily	1,6	-0,4	0,4	Rate
US Generic Govt 12 Mth	Fixed Income	1999	Daily	6,4	0,0	1,4	Rate
USD Trsyies 3-5Y Tot	Fixed Income	1999	Daily	243,5	98,0	174,1	Price
USD Trsyies 5-7Y Tot	Fixed Income	1999	Daily	283,2	96,1	186,0	Price
USD Trsyies 7-10Y Tot	Fixed Income	1999	Daily	313,5	93,5	191,7	Price
US Generic Govt 10 Yr	Fixed Income	1999	Intraday	6,8	0,5	3,4	Rate
US Generic Govt 2 Yr	Fixed Income	1999	Intraday	6,9	0,1	2,1	Rate
US Generic Govt 3 Yr	Fixed Income	1999	Intraday	6,9	0,1	2,3	Rate
US Generic Govt 5 Yr	Fixed Income	1999	Intraday	6,8	0,2	2,8	Rate
US Generic Govt 7 Yr	Fixed Income	2009	Intraday				Rate
TREASURY BILL	Monetary	2001	Daily	5,3	-0,1	1,2	Rate
US Treasury 3 Month Bill Money	Monetary	1999	Daily	6,3	0,0	1,7	Rate
Federal Funds Target Rate Mid	Monetary	1999	Intraday	6,5	0,1	1,8	Price
US Federal Funds Effective Rat	Monetary	1999	Intraday	7,0	0,0	1,8	Rate
US Generic Govt 3 Mth	Monetary	1999	Intraday	6,4	-0,1	1,7	Rate
Federal Reserve Balance Sheet	Monetary	1999	Monthly	35,2	5,5	14,5	Balance
BofA Securities GF	Other	2000	Daily	3,0	-0,7	0,1	Index (state)
GeoQuant Italy Extent of Political Risk	Other	2016	Daily				Index
GeoQuant Italy Political Risk Score	Other	2016	Daily				Index
GeoQuant Italy Political Risk Score Forecast	Other	2018	Daily				Index
GeoQuant United States Politic	Other	2016	Daily				Index
Bloomberg Country Risk Politic	Other	2009	Quarterly				Index
ECB Survey of Professional Forecasters HICP 1y Ahead	Survey	1999	Quarterly	2,4	0,8	1,6	Rate
ECB Survey of Professional Forecasters HICP 5y Ahead	Survey	1999	Quarterly	2,0	1,6	1,9	Rate
Survey of Prof Forecasters Moody's BAA Corporate Bond	Survey	2010	Quarterly	6,4	3,4	4,9	Rate
Survey of Prof Forecasters Moody's AAA Corporate Bond	Survey	1999	Quarterly	7,8	2,5	5,3	Rate
Survey of Professional Forecasters 5y CPI Inflation Rate	Survey	2005	Quarterly	2,8	1,9	2,2	Rate
Survey of Professional Forecasters 10y Treasury Bill Current Q	Survey	1999	Quarterly	6,6	0,6	3,4	Rate
Survey of Professional Forecasters Anxious Index Current Q +4	Survey	1968	Quarterly	-	-	-	Rate
Survey of Professional Forecasters Anxious Index Current Q +1	Survey	1999	Quarterly	74,8	4,3	16,3	Rate
Survey of Professional Forecasters 10y Treasury Bill Rate Prior Q	Survey	1999	Quarterly	6,5	0,6	3,4	Rate
Survey of Professional Forecasters 10y Treasury Bill Current Q+4	Survey	1999	Quarterly	6,5	0,9	3,9	Rate
U.S. JP Morgan Treasury Investor Sentiment All Client Long	Survey	2003	Weekly on Monday	50,0	0,0	17,1	Rate
U.S. JP Morgan Treasury Investor Sentiment Active Client Long	Survey	2003	Weekly on Monday	60,0	0,0	12,1	Confidence/survey
U.S. JP Morgan Treasury Investor Sentiment All Client Neutral	Survey	2003	Weekly on Monday	85,0	26,0	58,1	Confidence/survey
U.S. JP Morgan Treasury Investor Sentiment Active Client Short	Survey	2003	Weekly on Monday	70,0	0,0	16,4	Confidence/survey
U.S. JP Morgan Treasury Investor Sentiment Active Client Neutral	Survey	2003	Weekly on Monday	100,0	3,0	37,1	Confidence/survey
U.S. JP Morgan Treasury Investor Sentiment All Client Short	Survey	2003	Weekly on Monday	66,0	0,0	24,8	Confidence/survey
Cboe Volatility Index	Uncertainty	1999	Daily	82,7	9,1	20,1	Index
Índice de Volatilidad Global	Uncertainty	2000	Daily	7,0	-1,3	0,0	Rate
MOVE	Uncertainty	1999	Daily	264,6	36,6	87,5	Index
Geopolitical Risk Index	Uncertainty	1985	Monthly				Index
US Economic Policy Uncertainty	Uncertainty	1999	Monthly	350,5	57,2	119,9	Index
US Treasury Yield Curve Rate T	Yield Curve	2001	Daily	5,3	0,0	1,2	Rate
Market Matrix US Sell 10 Year	Yield Curve	1999	Intraday	159,8	-42,9	62,6	Rate
Market Matrix US Sell 2 Year &	Yield Curve	1999	Intraday	291,0	-56,0	123,9	Rate
Market Matrix US Sell 5 Year &	Yield Curve	1999	Intraday	149,2	-42,2	62,0	Rate

Source: Own elaboration.

Notes: The data are available from Bloomberg, except the Geopolitical Risk Index that is available from Matteo Iacoviello's Web site (https://www.matteoiacoviello.com/gpr.htm#data).

Table 13. Data classification.

Classification	Number of indicators
Butterfly	3
Commodity	5
Currency	11
Economics	123
Equity	3
Financial	45
Fixed Income	22
Monetary	6
Other	6
Survey	17
Uncertainty	5
Yield Curve	4

Source: Own elaboration.

Table 14. Data periodicity.

Periodicity	Number of indicators
Daily	85
Intraday	17
Monthly	107
Quarterly	24
Weekly	17

Source: Own elaboration.

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