Machine learning applied to active fixed income portfolio management: a Lasso logit approach[1]

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Abstract

The use of quantitative methods constitutes a standard component of the institutional investor's portfolio management toolkit. In the last decade, several empirical studies have used probabilistic or classification models to predict stock market excess returns, to model bond ratings and default probabilities, or for yield curve forecasting. To the authors' knowledge, there is little previous research on 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 investment strategy (buy and hold) in the construction of a duration management model for high-grade bond portfolios, specifically focusing on US Treasuries. Additionally, we propose a two-step procedure, together with a simple ensemble averaging aimed at minimising the potential overfitting of traditional machine learning algorithms. We also introduce a method to select thresholds that translate probabilities into signals based on conditional probability distributions. A large set of financial and economic variables serves as an input to obtain a signal for active duration management relative to a passive benchmark portfolio. As a first result, the model selects variables related to financial flows and economic fundamentals, but the parameters appear to be unstable over time, suggesting that the variable relevance may be dependent on the timing. Backtesting of the model, conducted on a sovereign bond portfolio denominated in US dollars, yields a small but statistically significant outperformance over the benchmark index in the out-of-sample data set while controlling for overfitting. These results support the case for incorporating quantitative tools in the active portfolio management process for institutional investors while paying special attention to potential overfitting and unstable parameters. Quantitative tools should be considered as a complementary input to the qualitative and fundamental analysis, in conjunction with the portfolio manager's expertise, to facilitate better informed investment decisions.

JEL classifications(s): C45, C51, C53, E37, G11.

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1. Introduction and literature review

In the last decade, a vast empirical econometric literature has been devoted 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.

Kara et al (2011) apply two models based on ML techniques (artificial neural networks – ANNs – and support vector machines – SVMs) 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 those generated by Kumar and Thenmozhi (2006), who try to predict the direction of the S&P CNX NIFTY market index using several ML tools, resulting in a superior performance of SVMs compared to random forest, ANNs and other traditional discriminant analysis and logit models. Rapach et al (2013) apply the least absolute shrinkage and selection operator (Lasso) method 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&P 500 index.

Other authors use hybrid approaches to combine the strengths of parametric (logistic regressions) and non-parametric models or tree-based models (such as classification and regression trees – CART). This is the case in Zhu et al (2011), which applies these models 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 stock market trends in Saudi Arabia. Additionally, some researchers apply ML 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&P 500 index with successful risk-adjusted overperformance. Another application can be found in Roy et al (2015), where a Lasso method based on a linear regression model is proposed as a method to predict stock market behaviour. Finally, Gu et al (2020) perform a comparative analysis of ML methods for measuring 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 ML methods, mainly neural networks, for forecasting and trading the EUR/USD exchange rate, finding significant outperformance evidence.

With regard to the application of ML 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. Nunes et al (2018) apply several ANN models for forecasting the main benchmarks of the European yield curve, concluding that, in general, neural network models tend to improve results and comparing favourably to Dunis and Morrison's results, in spite of the different data set used.

Another example of yield curve forecasting with neural network models can be found in Rosadi et al (2011), where no outperformance is observed for neural network models in the prediction accuracy of the yield curve compared to more traditional methods, such as Nelson-Siegel or vector auto-regression (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 empirical analysis using classification-based qualitative models, it has predominantly been devoted to modelling 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 (2006), 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 et al (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 ML 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 ML 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). López De Prado (2018) concludes that these mixed results are mainly due to the fact that financial data sets violate standard assumptions of ML applications, including stationarity, independence, data labelling and sampling. In this study, we have carefully considered these factors and accounted for the unique statistical properties of the series when selecting the variable groups, as detailed in Section 2.2.

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[5] (let $y_t^* = 1$ if we observe a positive total return, ie if $I_t - I_{t-1} > 0$ where I_t is the index value at time t; $y_t^* = 0$, otherwise). The logistic Lasso approach is applied to handle the high number of predictors.[6] 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 penalised 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 et al (2009) found that autoregressive integrated moving average (ARIMA) models outperformed neural networks for short-term wind speed forecasting in terms of lower root mean square errors (RMSE), while Rahman et al (2022) found that an ARIMA model performed better than an XGBoost model for predicting Covid-19 in Bangladesh. However, different results were achieved in the Fang et al (2022) study for the United States.

2.1. Hyperparameter, lambda or regularisation parameter

The penalising 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[7] λ such that the final log-likelihood is given by equation (2):

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

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 (ie 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*),[8] Pereira et al (2016) suggest that other regularisation techniques are more appropriate (eg ridge regressions, elastic net, etc).

[5] Portfolio is used interchangeably to refer to the benchmark index used in this paper: the Bloomberg-Barclays fixed income index for US bonds, which contains US domestic government debt with maturities higher than one year (Section 3).

[6] We opted for Lasso over ridge and stepwise regression primarily due to our data set's high multicollinearity. Lasso handles this more effectively, selecting and regularising variables simultaneously. In contrast, stepwise regression's sequential approach may lead to suboptimal results depending on the order of incorporation.

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

[8] This is not the case in this data set; there are 201 variables and 275 observations.

To deal with potential overfitting, which can be more severe in more complex ML algorithms such as XGBoost due to the subjectivity associated with the selection of hyperparameters, the Lasso hyperparameter λ[9] 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 minimise the cross-validation deviance[10] defined in the algorithm as minus twice the log-likelihood on the left-out data.

The estimation exercise is performed by dividing the database into 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[11] and leaves the 2012 for testing (out-of-sample).

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 the Lasso logit algorithm consists of a two-step procedure. In the first step, a Lasso logit model is estimated with a long time span (ie 10 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.

[9] Only one hyperparameter in the simple Lasso approach compares to more complex models that have more than one hyperparameter to choose from.

[10] Cross-validation deviance is a statistical technique commonly used in model evaluation to assess the predictive performance of a statistical or ML model. It is particularly useful when working with complex models that may have a high risk of overfitting or poor generalisation to new data. Cross-validation deviance involves dividing the available data set 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 generalise to unseen data, enabling them to make informed decisions regarding model selection and refinement.

[11] The two-step procedure, as explained in Section 2.2, involves the division of the trained set into two subsamples. The first subsample contains no more than 10 years of data, while the second encompasses a period of four 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 subsample comprising four years of data with the one-year test data, this approximation is achieved.

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 et al (2018). However, in the present study, a simpler approach is adopted, where three distinct models are estimated so as to tackle non-stationarity of the variables. Each model pertains 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

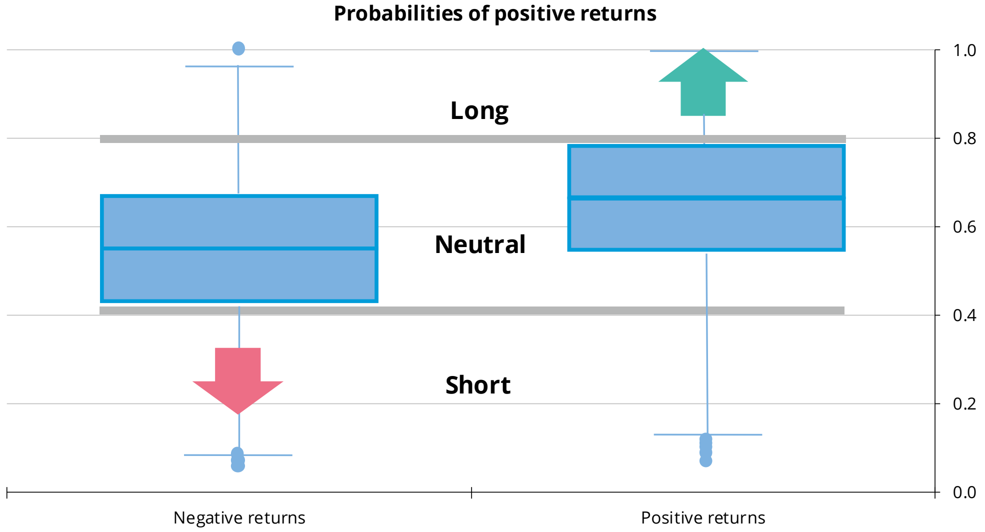
We propose an algorithm to translate probabilities into three portfolio duration signals (short, neutral and long). The algorithm checks the distribution of probabilities given by the model in the in-sample period conditioned on the observed direction of the portfolio market value (ie if it had positive or negative returns). We derive short signals from probabilities lower than the 25th percentile of the distribution when the index was down and long signals when probabilities are higher than the 75th percentile, but in this case, conditioned on cases where the index was up (Graph 1). We assign neutral signals to probabilities between those two previously defined thresholds (ie 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" (probability up to 33% short position, 33%–66% neutral and more than 66% long).

It is assumed that a short position means reducing the investment by 10%, neutral implies maintaining the previous invested amount and a long position derives in increasing the investment by 10%.[12] For instance, assuming that in $t = 0$ we invest I_0 and the return of the portfolio is r_1 in $t = 1$, then we would have $I_1 = (1 + r_1)I_0$. Assuming that in $t = 0$ the model gives a "long signal", then we invest an additional 10%, $I_{long,0} = (1 + 0.1)I_0$ and in $t = 1$ we would have $I_{long,1} = (1 + r_1)I_{long,0}$. But this equation is equivalent to $I_{long,1} = (1 + r_1)(1 + 0.1)I_0$, so that every month, we would scale the returns of the portfolio to obtain the returns of the model depending on the signal:

Long → 1.1 * $(1 + r_t)$
Neutral → $(1 + r_t)$
Short → 0.9 * $(1 + r_t)$

[12] The percentage of investment withdrawal or increase is selected to be 10% to match standard constraints in active portfolio management, but is proposed to be a topic for further research.

Thresholds based on conditional probability distributions | Graph 1



Source: Authors' elaboration.

2.4. Model-based strategies compared to passive investment

We compare five models to a passive investment:

1. **LassoDefault**: A Lasso logit that selects the hyperparameter applying cross-validation as defined in Section 2.1.
2. **LassoDefaultTwoStep**: A Lasso logit that uses the two-step procedure defined in Section 2.2.
3. **LassoSimpleEnsemble**: A Lasso logit for every group of variables as defined in Section 2.2 (we estimate three models according to different data features: a first one in levels, a second using first differences, and a third using monthly growth stationary variables).
4. **LassoSimpleEnsembleTwoStep**: The same as in the LassoSimpleEnsemble model (3) but applying the two-step procedure defined in Section 2.2.
5. **Always long strategy**: A strategy that always invests 10% more than the passive investment.

These models are compared to a passive investment algorithm. The passive investment is the trading strategy that invests in the benchmark or tries to replicate its total return while minimising the tracking error. In this study passive investment will be referred to as being neutral or investing in the same constituents and same weights as the benchmark.

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 A1). The selection of these indicators was driven by a focus on maximising 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% financial data and 9% fixed income market variables (Table A2). In addition, these indicators include mixed frequencies, 107 of which are updated on a monthly basis, 85 daily and 24 quarterly (Table A3).

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 Great Financial Crisis (GFC). Only 201 out of 250 analysed variables fulfil the requirement imposed by this study.[13]

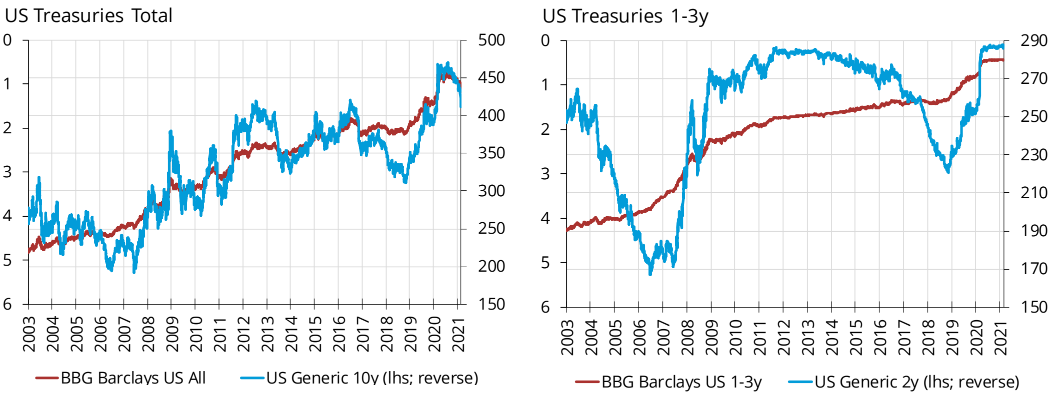
As regards the missing values, an imputation method is applied, in which the last non-missing observed value is used to assign a particular missing value. This approach allows us to maintain the temporal structure of the data and minimise any potential biases introduced by imputation. For daily and weekly 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 excluding missing values entirely, and found that the results remain unchanged. Additionally, the variables are standardised in order to ease the comparison of scores measured on different scales. It is important to note that only the in-sample values are standardised, 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, the Bloomberg Barclays USD Treasuries Total Return Index is used, which includes all domestic government debt with maturities higher than one year. This total return index has been selected for two reasons. First, it represents the whole yield curve and has a higher correlation with the 10-year US Generic Government Bond than with the two-year (see Graph left- and right-hand panels). Second, it is transparent in its constituents and their weights.

13 From a theoretical standpoint, we anticipate that the state of the macroeconomy can impact interest rates and inflation pressures. When the macroeconomy performs well, inflation pressures may arise, potentially leading to an increase in interest rates. Additionally, financial variables such as interest rates in other countries, like Japan or the euro zone, may influence the flow of capital and impact the US interest rate. If interest rates increase in Japan, for instance, capital may flow to Japan, exerting upward pressure on US interest rates to prevent outflows. These theoretical expectations underpin our inclusion of certain indicators and provide a framework for interpreting the results in the context of market dynamics and interdependencies.

Benchmark indices and generic Treasury bonds — Graph 2



Source: Authors' 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 in 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 analysed. 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.

Correlation of explanatory variables (month-over-month (MoM) vis-à-vis the benchmark) — Table 1.a

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

Correlation of explanatory variables by categories (month-over-month (MoM) vis-à-vis the benchmark) — Table 1.b

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

Source: Authors' elaboration.

4. Results

First, we compare the naive 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 (2012–21). The signals given by this approach are too small (one 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.

Confusion matrix

Table 2

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: Authors' elaboration.

Second, we carry out performance analysis for the LassoDefault model. This model has a hit ratio[14] of 58% in the in-sample period (2004–11), but only because it correctly predicts the direction of returns when they are positive (74%). It is not able to identify the negative returns, and correctly predicts a bearish move only 43% of the time. It is very active in the in-sample period, where it gives a long/short signal 42% of the time (Table 3; first panel). 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 in 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 3; second panel). The two-step procedure is not able to increase the performance of the model in the out-of-sample period (Table 3; third panel).

14 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.

Model performance

Table 3

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: Authors' elaboration.

The "poor" out-of-sample performance of the LassoDefault model could be explained by possible overfitting when choosing the lambda's value in the cross-validation exercise. To try to overcome this possible 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 4, first panel). The simple ensemble model also behaves well in the out-of-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 4, second panel). In this case, the two-step procedure is able to increase the performance slightly to achieve a hit ratio of 62%, with correct short signals 71% of the time, and correct long signals 57% of the time (Table 4, third panel).

Model performance Table 4

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: Authors' elaboration.

Previously it has been shown that the Lasso regression with default options is worse than the model with the simple ensemble. However, it is possible that a model with a low hit ratio may outperform one with a high hit ratio if the former produces signals whenever there are significant movements in returns. This could happen if the LassoDefault model 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 5, both models (with the two-step procedure applied to each) are compared to the passive investment strategy. As illustrated there, the LassoDefault model is not able to beat the passive investment strategy in the out-of-sample period either in absolute returns or in Sharpe ratio terms. The passive investment strategy also has better risk ratios than the LassoDefault model. The LassoDefault model suffers the worst drawdown across the models analysed. The two-step procedure (LassoDefaultTwo-Step) does not 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 (+4 bp).

The simple ensemble model outperforms passive investment strategy on almost all indicators except for maximum drawdown, where it slightly underperforms (–7.75% versus –7.72%). However, the simple ensemble has the lowest CVaR95 and the highest excess return. When a two-step procedure is applied to the simple ensemble (LassoSimpleEnsembleTwoStep), the model's risk ratios improve, and it achieves the highest Sharpe ratio and information ratio and the lowest drawdown. Although the outperformance of the simple ensemble begins from 2011, the two-step procedure only shows significantly better performance since 2019, as indicated by Graph 4. The always long strategy has almost the same information ratio as the Lasso Simple Ensemble (Two-Step), but it has the worst Sharpe ratio and risk ratios.

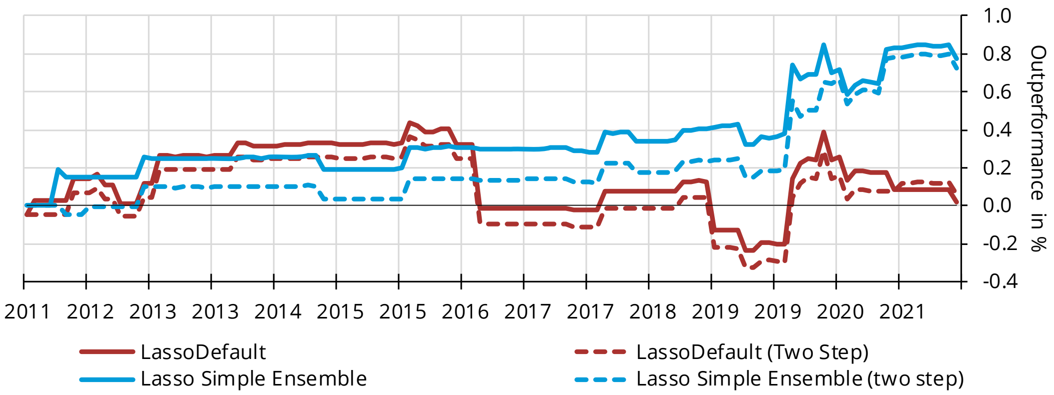
Performance and risk ratios — Table 5

	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	2.18	0.57	23.49	0.02	0.02	3.83	0.19	-7.94	-15.83	-23.67
Lasso Default (Two step)	2.19	0.57	23.53	0.06	0.04	3.83	0.19	-7.93	-15.83	-23.67
Lasso Simple Ensemble*	2.25	0.59	24.25	0.78	0.42	3.82	0.15	-7.75	-16.44	-22.97
Lasso Simple Ensemble (Two Step)*	2.24	0.59	24.20	0.73	0.44	3.81	0.14	-7.60	-16.44	-22.97
Always Long	2.60	0.56	26.00	2.53	0.44	4.67	0.96	-8.69	-19.53	-28.89

SE = statistical error, MaxDD = maximum drawdown, VaR = value-at-risk and CVaR = conditional value-at-risk. Note: * p < 0.1. Period 2012-2021. [1] Excess returns compared to Passive Investment's cumul. returns.

Source: Authors' elaboration.

Outperformance — Graph 4



Source: Authors' elaboration.

The alpha generated by the best model (Lasso Simple Ensemble Two-Step) is statistically significant at 10%, but the most interesting result is that most of the alpha generated comes from correctly identifying "extreme" movements (return movements higher than 1.3 standard deviations; Table 6).

Performance and risk, Lasso Simple Ensemble Two-Step: alpha — Table 6

	alpha (%)[1]	p-value	n
Whole sample	0.06	0.09	120
returns > 1.28σ	**0.42**	**0.05**	**18**
returns > 1.64σ	0.31	0.17	11
returns > 1.96σ	0.86	0.20	4

alpha (%)[1]	coefficient	Std. Err.	p-value
percentile 80 (> 1.28σ)	0.42	0.37	0.002
constant	0.00	0.01	0.979

[1] Annualised figures.

Source: Authors' elaboration.

Table 7 shows the set of variables that the ML 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 to financial flows (Japanese two-year government bond). US capacity utilisation appears nine out of 10 years, jointly with the seven-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-of-sample period, US capacity utilisation is losing forecasting power compared to US 1y1y inflation forward rate.

Set of variables selected by year — Table 7

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: Authors' elaboration.

This result is in line with the increase in inflation uncertainty observed in 2021 when Covid-19 measures started to be loosened and demand began to lift out.

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 (ML) algorithm, "the Lasso logit regression", with a passive investment strategy 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 performs better. That is, choosing as the higher threshold (long signals) the 75th percentile of the distribution of probabilities given that the benchmark has positive returns, and as the lower threshold (short signals) the 25th percentile of the distribution of probabilities given that the index has negative returns, using only the in-sample data set. The probabilities between the higher and lower thresholds are assigned as "neutral".

The ML 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 increased. The algorithm that seems to work well is the simple ensemble alternative, which achieves the best risk and return ratios. This algorithm splits the data set 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 and information ratio and the lowest maximum drawdown.

The variables selected by the ML algorithm behave as expected a priori. For the evolution of our monthly fixed income portfolio, economic variables and financial flows are the most relevant. For most of the years the following variables are selected: US capacity utilisation, 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, inflation expectations increased their forecasting power in 2021 compared to US capacity utilisation, something that one should expect because of the increasing inflation uncertainty post Covid-19 in 2021.

The alpha generated by the Lasso Simple Ensemble model 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, ML algorithms should be applied 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 that are widely used in investment decisions, like Bollinger Bands, relative strength index (RSI), moving average oscillator, or Ichimoku, among others. It could also be interesting to test other types of ML algorithms like XGBoost, among others, to investigate if they are less prone to overfitting issues.

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ANNEX

Data description (final indicators **in bold**) Table A1

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**

The data are available from Bloomberg, except the Geopolitical Risk Index, which is available from Matteo Iacoviello's website (www.matteoiacoviello.com/gpr.htm#data).

Source: Authors' elaboration.

Data classification

Table A2

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

Source: Authors' elaboration.

Data periodicity

Table A3

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

Source: Authors' elaboration.