PREDICTING STOCK MARKET DRAWDOWNS

USING POLYMODELS

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From the book

Artificial Intelligence for Financial Markets: the Polymodel Approach

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Foreword by

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POLYMODELS - DEFINITION

In finance, a common problem for artificial intelligence methods is to model a label, Y, as a function of a set of n features X_1 , X_2 , ... , X_n , such as:

$$Y = f(X_1, X_2, \dots, X_n) + \varepsilon$$

The proposal of polymodels is to decompose the problem by modeling the label by a collection of univariate, non-linear models. These small models, called "elementary models" are alternative representations of the label, all simultaneously valid and complementary.

$$\begin{cases} Y = f_1(X_1) + \varepsilon_1 \\ Y = f_2(X_2) + \varepsilon_2 \\ \dots \\ Y = f_n(X_n) + \varepsilon_n \end{cases}$$

POLYMODELS - MOTIVATION

Polymodels provide clear advantages, compared to traditional multivariate alternatives:

- **Reducing overfitting**, which is a recurrent problem when modelling in high dimension
- **Increasing precision**, by allowing more accurate representations of non-linearities
- **Increasing robustness**, as it avoids the undesirable effects of multicollinearity

But these advantages come with some challenges to tackle:

- A **rigorous estimation procedure** is needed for non-linear elementary model estimation, as it can bring back overfitting
- An **aggregation method** is required for some applications to merge the results of the collection of models. Especially, it is important to consider the correlation of the features in this stage

POLYMODELS - ESTIMATION

Polymodels can be estimated using the Linear-Non-Linear-Mixed (LNLM) model, defined as follows:

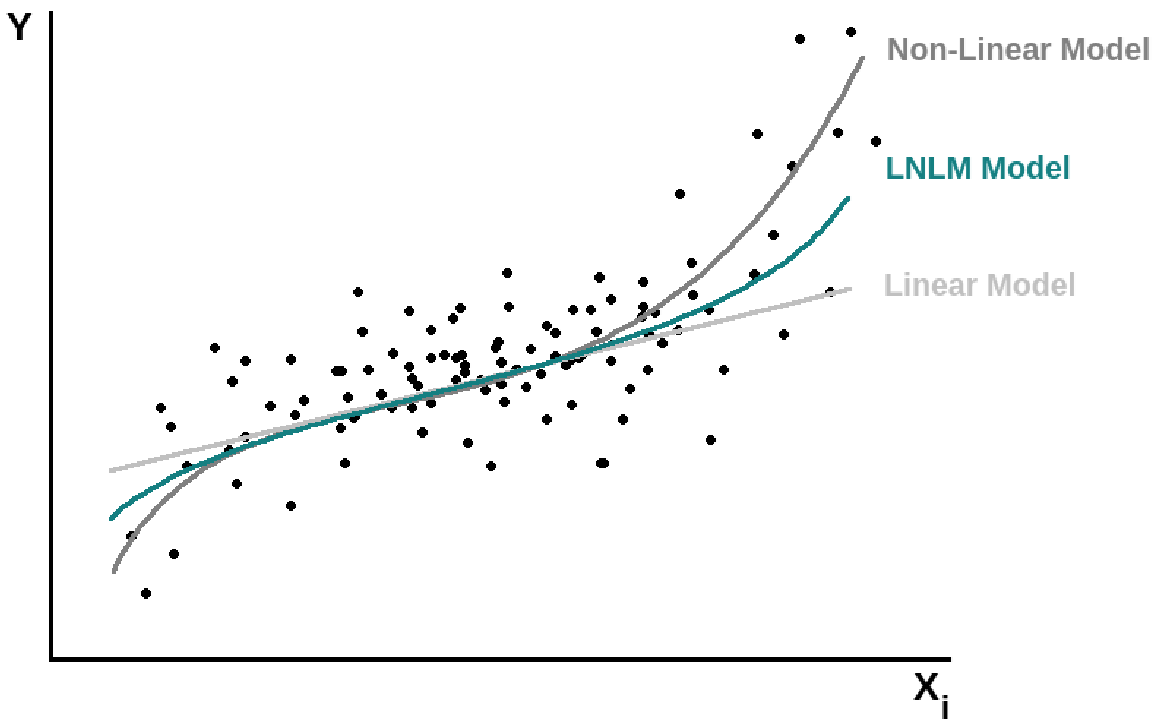
$$\boldsymbol{LNLM(X)} \stackrel{\text{def}}{=} \overline{\boldsymbol{y}} + \boldsymbol{\mu} \sum_{h=1}^{u} \widehat{\boldsymbol{\beta}}_h^{NonLin} \boldsymbol{H_h(X)} + (\mathbf{1} - \boldsymbol{\mu}) \widehat{\boldsymbol{\beta}}^{Lin} \boldsymbol{X} + \boldsymbol{\varepsilon}.$$

LNLM is simply a weighted combination of a linear model (usually underfitted) and a non-linear model (usually overfitted). The different elements of the equation can be detailed as follows:

- The target variable is centered before parameters estimation, thus the constant $\overline{\boldsymbol{y}}$ is finally reintegrated.
- The linear model $\widehat{\boldsymbol{\beta}}^{Lin} \boldsymbol{X}$ is fitted using OLS.
- The non-linear model $\sum_{h=1}^{u} \widehat{\boldsymbol{\beta}}_h^{NonLin} \boldsymbol{H_h(X)}$ is a weighted combination of polynomials of X, also fitted with OLS
- The parameter $\boldsymbol{\mu}$, which controls from the balance between the two models, is defined between 0 and 1, and is called the *non-linearity propensity*. It is obtained by cross-validation.

POLYMODELS - ESTIMATION

The following stylized representation of an LNLM fit allows to better understand how the model works:



POLYMODELS - ESTIMATION

The LNLM model is thus used to obtained the fit of each of the elementary models in the polymodel:

$$\begin{cases} Y = LNLM_1(X_1) + \varepsilon_1 \\ Y = LNLM_2(X_2) + \varepsilon_2 \\ \qquad \dots \\ Y = LNLM_n(X_n) + \varepsilon_n \end{cases}$$

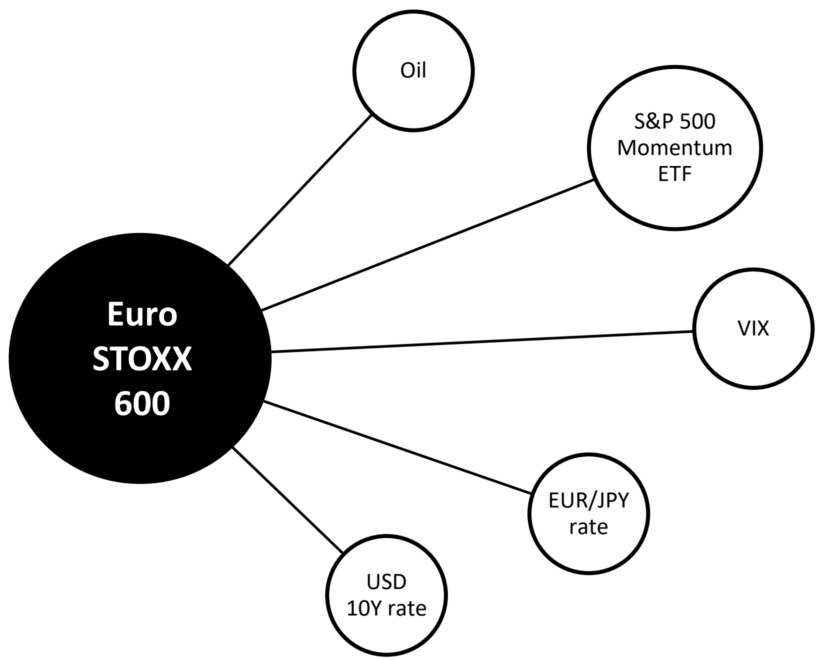
A more detailed explanation of the LNLM model, as well as a set of simulations demonstrating the robustness and the ability of the model to identify patterns in noisy data can be found in:

Barrau, Thomas, and Raphael Douady. "Estimation Method: The Linear Non-Linear Mixed Model." *Artificial Intelligence for Financial Markets: The Polymodel Approach*. Cham: Springer International Publishing, 2022. 35-57.

TIMING THE MARKET

Thereafter, we propose to time the market drawdowns of the Euro STOXX 600.

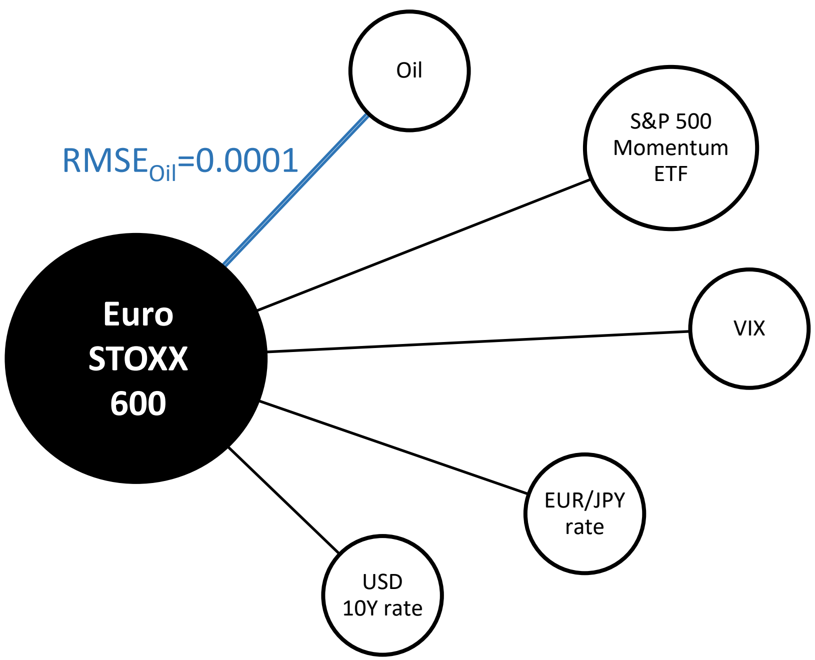
To do so, we estimate dynamically a polymodel, in which **the market is the target variable**, and **the predictors are 1200 variables representing the economic environment** of the market (equity indices, volatility, currencies, commodities, rates, real estate, smart beta factors, etc).



TIMING THE MARKET

The polymodel is re-estimated every month, using a 5 years rolling window.

For each of the fitted elementary models, we compute the Root Mean Square Error, which measures **the strength of the link** between the market and the variable considered:



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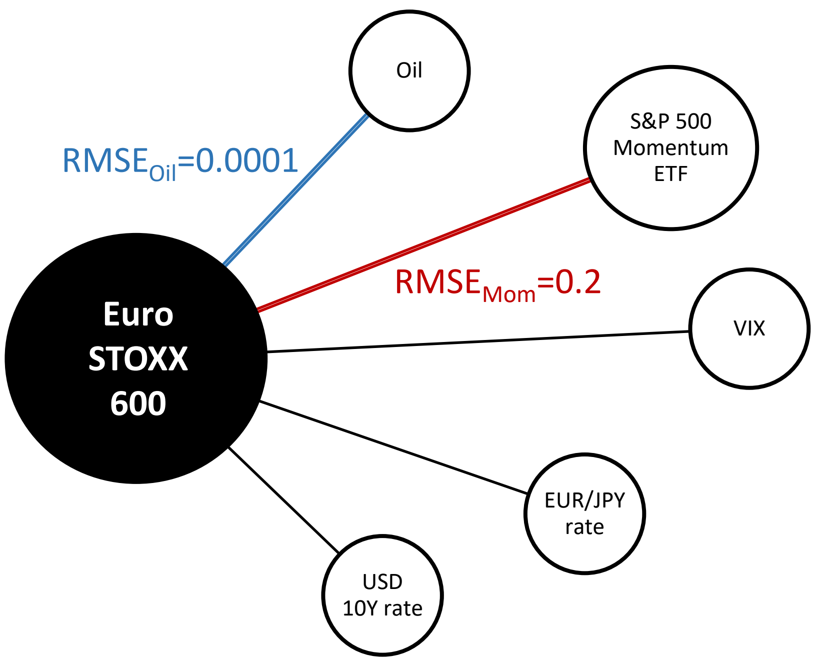

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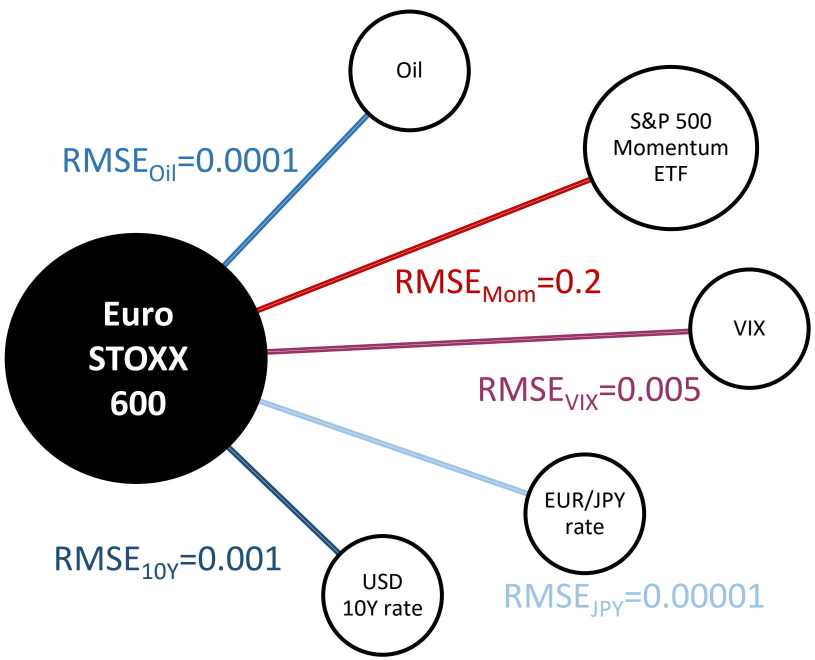


TIMING THE MARKET

Once all the RMSE are computed, we can assemble them on the form of a **distribution**.

The distribution of the RMSE capture, at an aggregate level, the strength that the market maintains with its whole economic environment.

This distribution, available at each date, is then averaged on a rolling basis, using two methods:

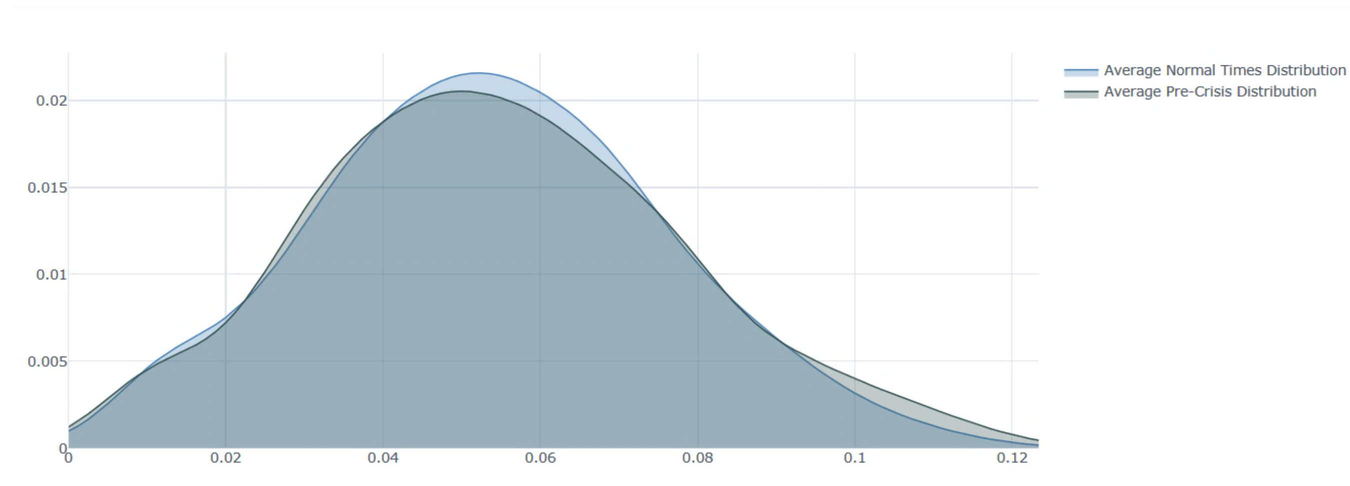
- By averaging all the past distributions, which produced a **"normal times" average distribution**

- By averaging only the past distributions which precedes a drawdown, weighted by the intensity of the following drawdown, which produces a **"pre-crisis" average distribution**

TIMING THE MARKET

The “normal times” and “pre-crisis” distributions are themselves dynamic representations, which varies over time and are available at each rebalancing dates.

In order to understand general differences between these 2 representations, we can average them over the full period, which lead to the two aggregated representations:

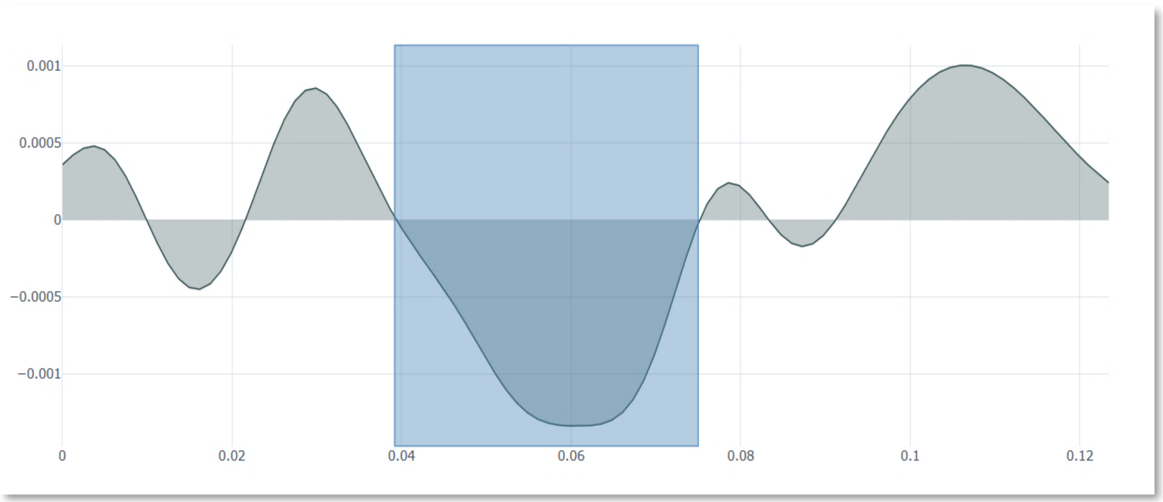


TIMING THE MARKET

The pre-crisis distribution tends to have fatter tails, which means that:

- Some variables see the strength of their link with the market increasing before a crisis
- Some other variables see the strength of their link decreasing before a crisis

Below, we differentiate the two distributions averaged over time:



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TIMING THE MARKET

The mechanism that we suspect to appear here is as follows:

- For some reason, the exposures of the market to the various factors composing its environment becomes more extreme, with some factors being more correlated, and some of them being less
- The results of such a change in the exposures is that the volatility of the market will increase
- The following increase of volatility decrease the confidence of investors in the market and generates the drawdowns

TIMING THE MARKET

Our Systemic Risk Indicator (SRI) is defined as:

$$SRI_t \stackrel{\text{def}}{=} \begin{cases} 1 \;\; if \;\; \mathcal{H}\left(\mathcal{R}_t^{Current}, \mathcal{R}_t^{Pre-Crisis}\right) < \mathcal{H}\left(\mathcal{R}_{t-1}^{Current}, \mathcal{R}_{t-1}^{Pre-Crisis}\right) \\ 0 \;\; if \;\; \mathcal{H}\left(\mathcal{R}_t^{Current}, \mathcal{R}_t^{Pre-Crisis}\right) \geq \mathcal{H}\left(\mathcal{R}_{t-1}^{Current}, \mathcal{R}_{t-1}^{Pre-Crisis}\right) \end{cases}$$

Here, "$\mathcal{R}_t^{Current}$" is the distribution of the RMSE at the current date "t",

"$\mathcal{R}_t^{Pre-Crisis}$" is the last representation of the pre-crisis distribution of the RMSE available at date "t"

and "$\mathcal{H}(\,)$" is the Hellinger distance

TIMING THE MARKET

The Hellinger distance is defined in our discrete framework as:

$$\mathcal{H}\left(\mathcal{R}_t^{Current}, \mathcal{R}_t^{Pre-Crisis}\right) \stackrel{\text{def}}{=} \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{n} \left(\sqrt{\mathcal{R}_{i,t}^{Current}} - \sqrt{\mathcal{R}_{i,t}^{Pre-Crisis}}\right)^2}$$

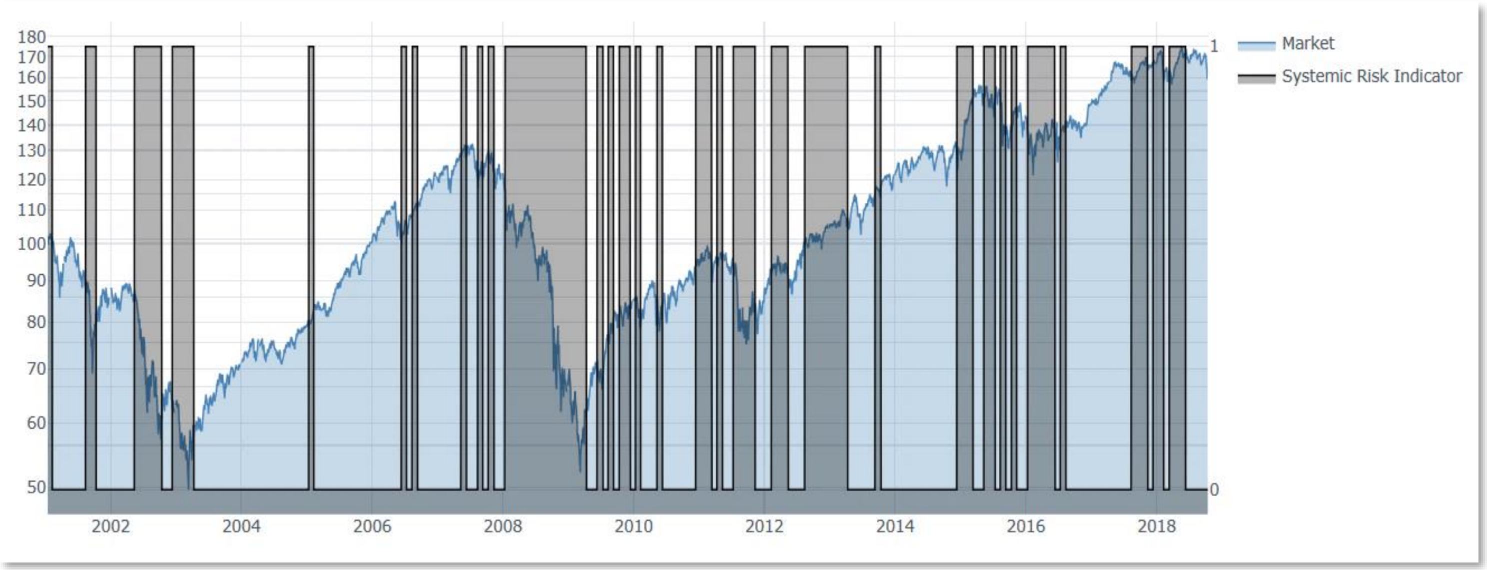
“$\mathcal{R}_{i,t}^{Current}$” is the value of the RMSE at the current date “t” for a given factor “i"

and ”$\mathcal{R}_{i,t}^{Pre-Crisis}$” is the value of the RMSE for the factor “i” drawn from the last representation of the pre-crisis distribution of the RMSE available at date “t”.

TIMING THE MARKET

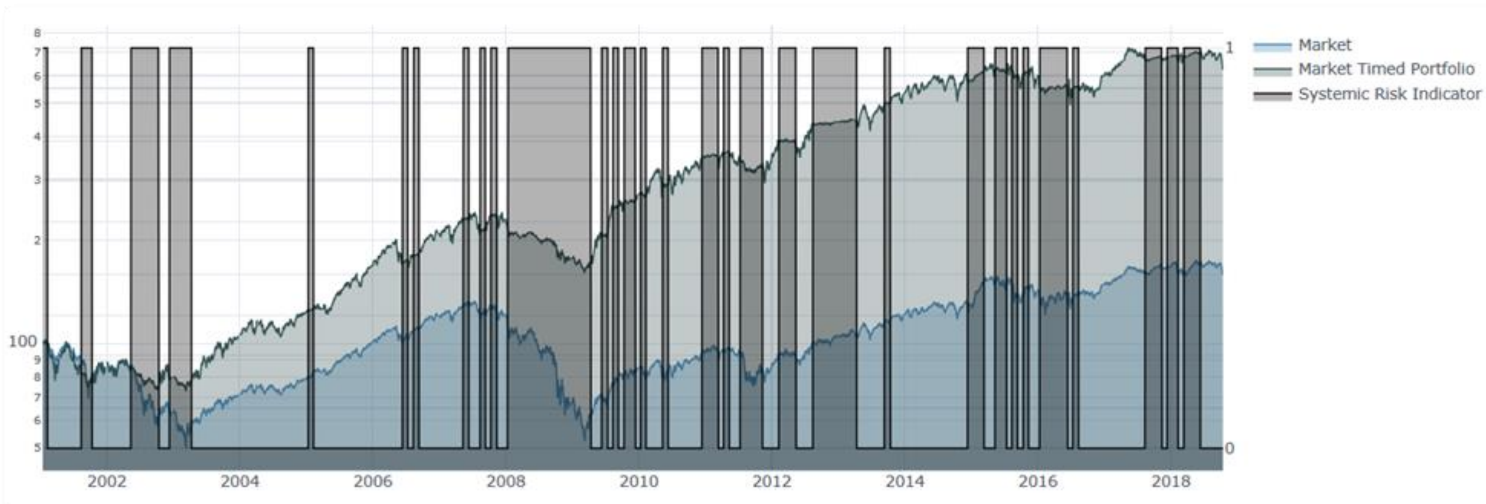
In simple words, the indicator is equal to 1 when the current distribution gets closer to the pre-crisis distribution, 0 otherwise.

Here is what it gives for the Euro STOXX 600 over an 18 years period:



TIMING THE MARKET

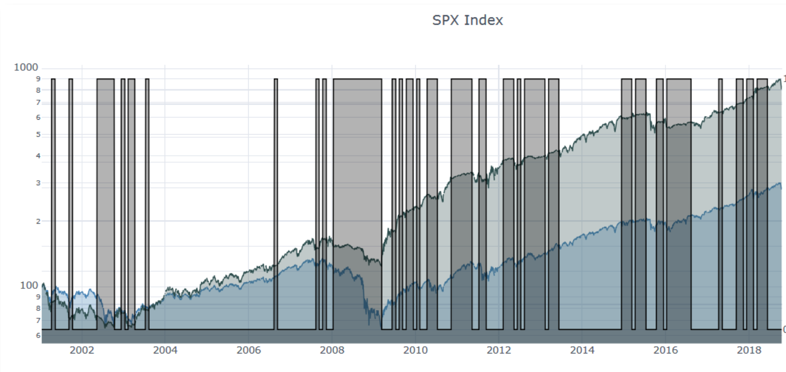
It looks promising, but to rather assess the predictive power of the indicator, we build a trading strategy based on it. With a monthly rebalancing, we will go long the market with a **leverage of 2 if the SRI is equal to 0**, and a **leverage of 0.5 if the SRI is equal to 1**. This dynamic leverage strategy strongly outperforms the market:

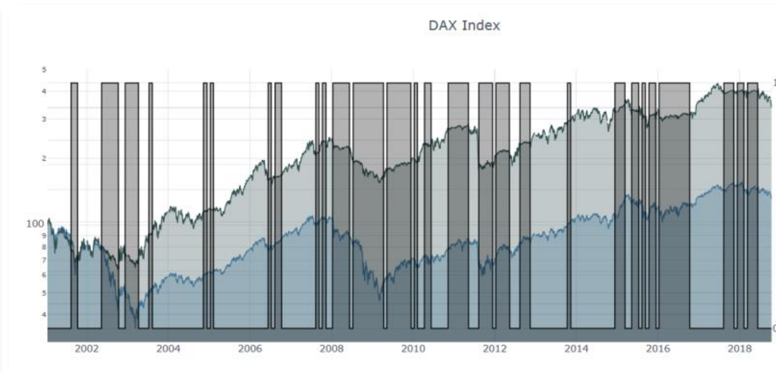


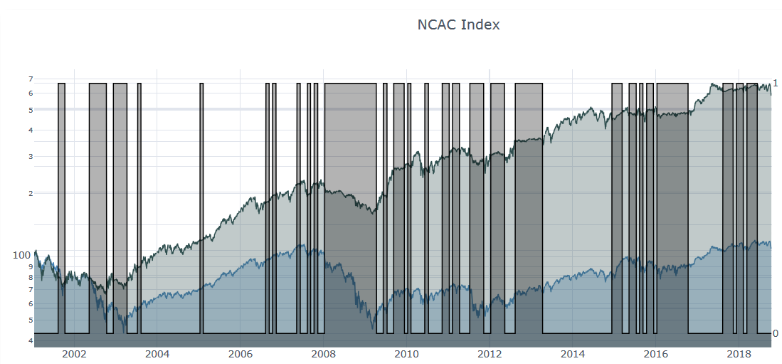
The Sharpe ratio of our timed strategy is of 0.53, versus 0.17 for the market, which is an improvement of 211% of the performance.

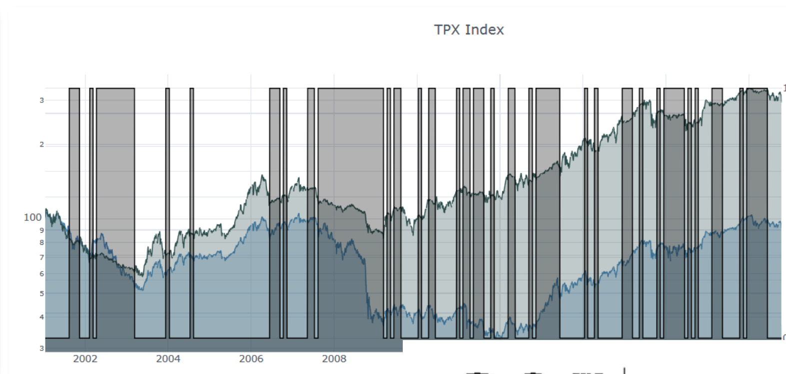
TIMING THE MARKET

These results have been replicated over 12 different markets, and the benchmark is outperformed in each of them:









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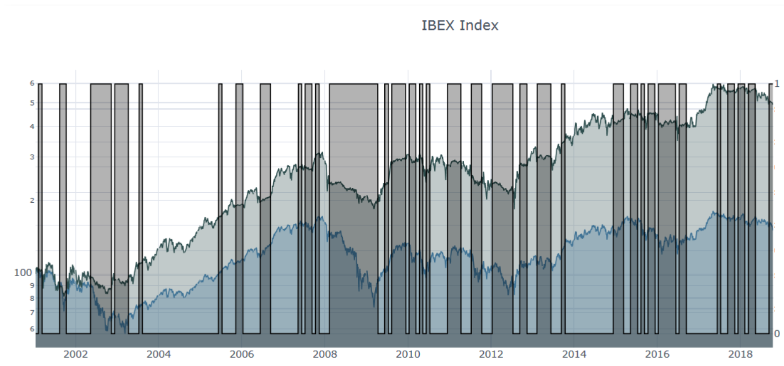

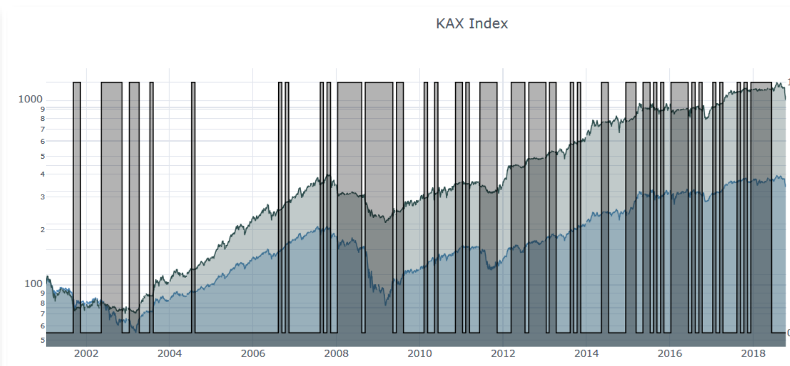

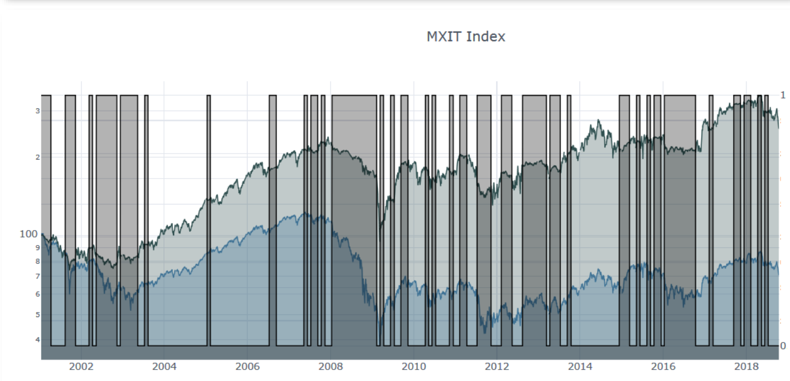

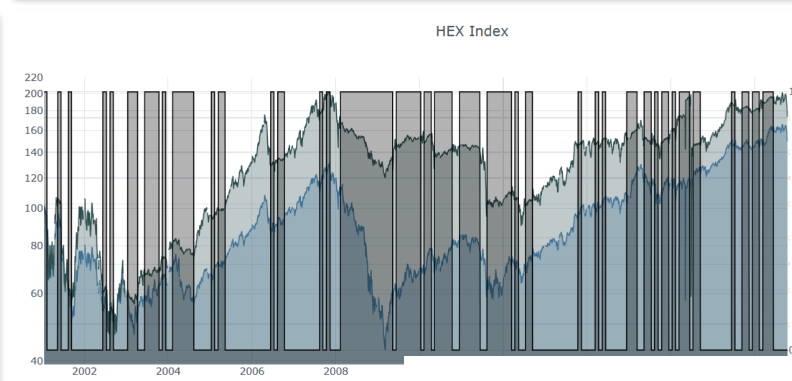

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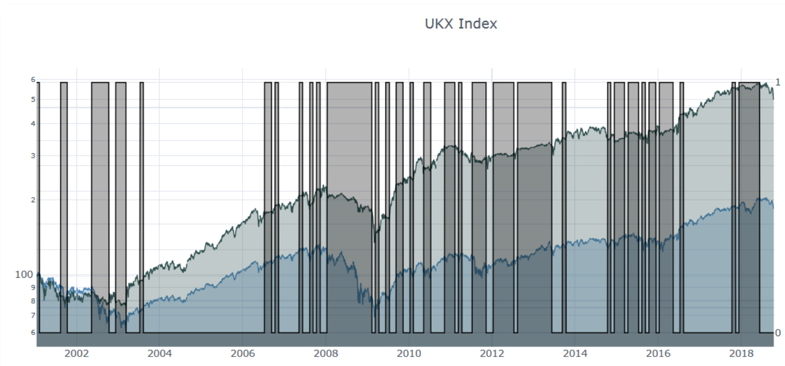

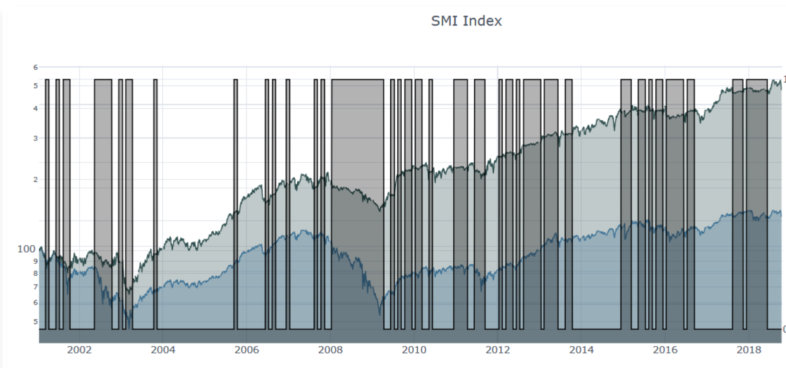

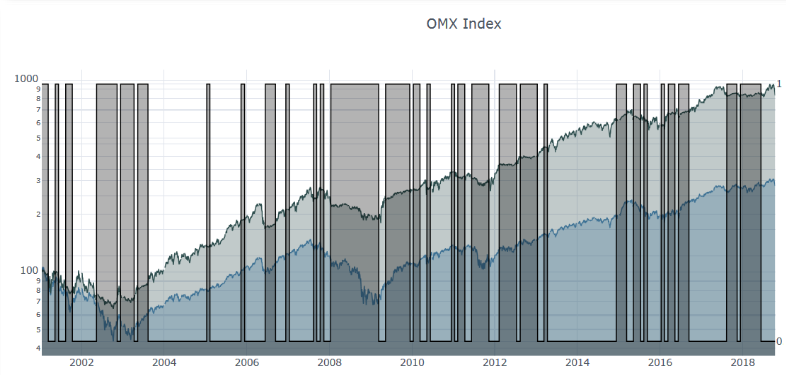

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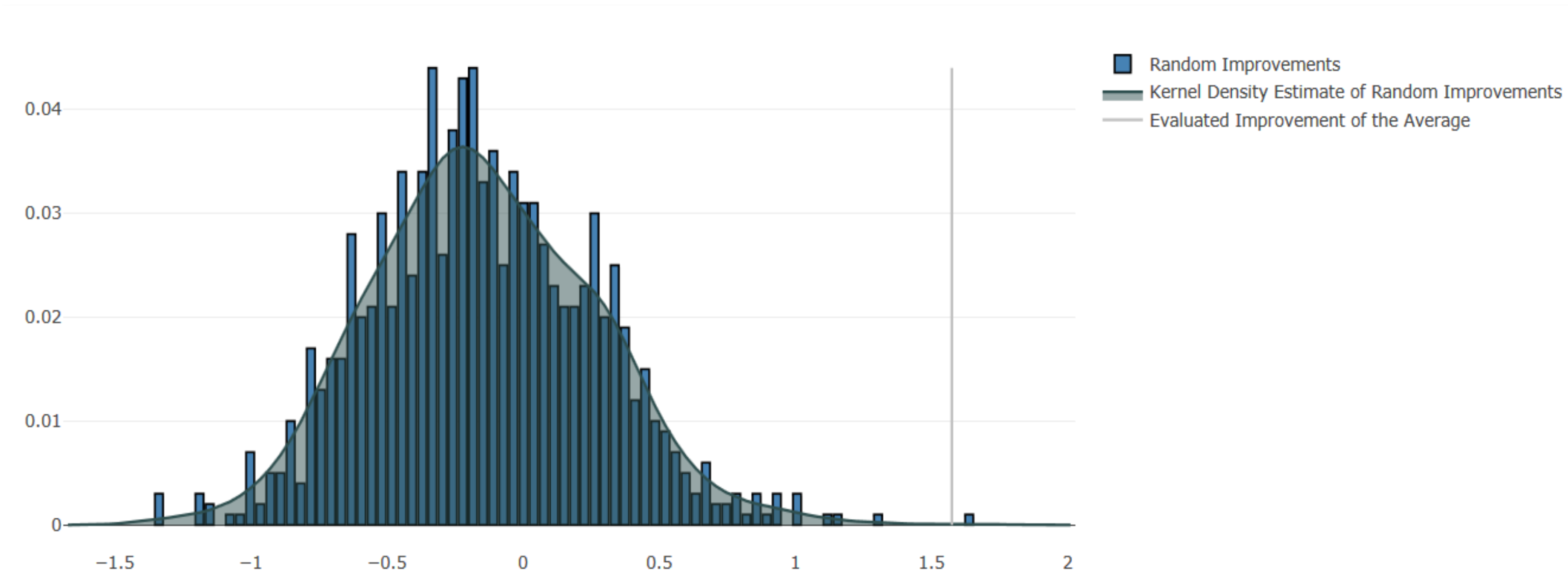
TIMING THE MARKET

Of course, one may argue that such an indicator can be obtained by random chance.

To test for this point, we produced 1000 shuffled versions of the SRI for each of the markets.

These versions are all going high and low leverage in the same proportions that our SRI, but just at different, random points in time. The only difference among them and the SRI is thus **the timing of the SRI.** For each of these versions we compute the improvement of the average Sharpe Ratio among the different markets.

TIMING THE MARKET



Out of 1000 random shuffles, only 1 improves more the Sharpe Ratio than the SRI on average, which corresponds to a p-value of 0.1%, strongly statistically significant.

LIMITS AND FURTHER RESEARCH

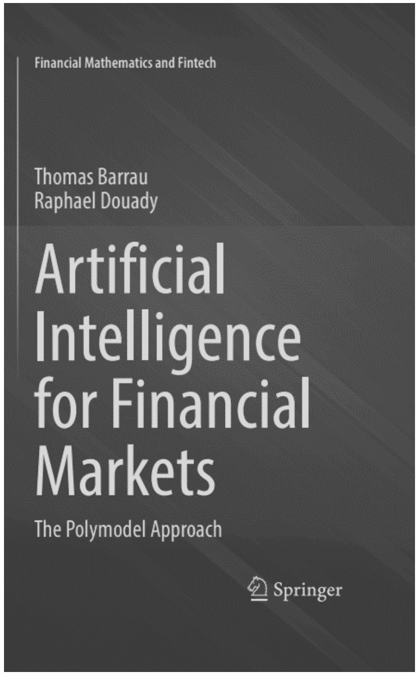
The robustness of the SRI is supported by a large number of tests which can be found in:

Barrau, Thomas, and Raphael Douady. "Predictions of market returns." *Artificial Intelligence for Financial Markets: The Polymodel Approach*. Cham: Springer International Publishing, 2022. 59-81.

However, a few other points will be addressed in further research:

- The **sample should be extended to a more recent period**, so that the out-of-sample performance of the SRI can be observed on more recent events, including the COVID crisis and the current bear market.
- The indicator lacks **more solid economic foundations**: it seems to work, but why?
- The indicator should be tested **on other asset classes**, as well as **on a higher frequency** than monthly.

GOING FURTHER



The Systemic Risk Indicator is presented more in depth in our book. Other quantitative strategies are presented, as well as a proposal of a portfolio construction method, which combines several signals together in an optimal manner, considering transaction costs. Finally, the Polymodels theory is presented in depth, and the LNLM estimation technique is discussed in details.

Obtaining the book:

https://link.springer.com/book/9783030973186

https://www.amazon.com/Artificial-Intelligence-Financial-Markets-Mathematics/dp/3030973182

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