Low Turbulence ®

– Methodology Document[1] –

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Introduction

The research field of asset allocation has been evolving over the past 50 years from traditional asset allocation methods involving the estimation of a covariance matrix to the use of artificial intelligence methods in a supervised or unsupervised manner. Machine learning algorithms have indeed proven successful to model complex data by learning useful data representations.

This approach explores an interpretable low-dimensional representation framework of financial time series combining signal processing, deep neural networks along with bayesian statistics. This representation framework exhibits particularly good clustering properties, which enables us to define two market regimes: The High and the Low

[1] A Methodology protected by Patent FR2013868 @INPI in France on 12-25-2020

Turbulence regimes. By modeling their dynamics, we are able to forecast the market regime over the next period of time. Hence, we enrich the paradigm of asset management by reducing investable periods for any risky asset to their low turbulence periods and alternatively invest in safe assets (typically cash or treasuries) during high turbulence periods.

By doing so, we not only enable investors to enjoy smoother "investment journeys", but we also aim at generating reasonable returns by considerably reducing the volatility and the drawdowns along the way.

There are three different steps involved in the Low Turbulence Method:

- Step (a) : Decomposition of the daily return windows into **spectral vectors**[2].
- Step (b) : Dimensionality reduction of the above vectors.
- Step (c) : Forecasting the **Turbulence state** associated with the low-dimensional representations of the spectral vectors over the next period.

Let us now dive into the model.

The Low Turbulence Approach

I. Extracting the information from the asset returns themselves

When musicians play together, their instruments' sounds superimpose and form a single complex sound mixture. In the same way, the price signal is the aggregate of a large number of players / investors who get vocal and express their own view.

The traditional music information retrieval is based on the decomposition of the audio signal into different elementary components which describe the harmonic structure of the music. Similarly, we fit the **harmonic structure** of the daily returns signal using this decomposition paradigm, i.e., by introducing a set of elementary

[2] Terms in bold are defined in the glossary on the last page.

waveforms well localized in time, which we correlate with the signal in order to capture the harmonic information over a short period of time.

As mentioned in the introduction, step (a) consists in extracting the harmonic content of the signal for a window of 60 days. From the 60 daily returns, we extract the harmonic content using a decomposition in 128 elementary dimensions[3]. We group all these dimensions using standard aggregate filters and end up with a vector of 26 dimensions, where each dimension encodes part of the harmonic information.

The complexity of the resulting structure can be summarized by the intensity within each dimension and the correlations between these dimensions.

Along time, the entire signal can then be decomposed into a series of T vectors of dimension 26 called the **spectral vectors** as shown in Figure 1. (where T refers to the number of windows in the entire signal)

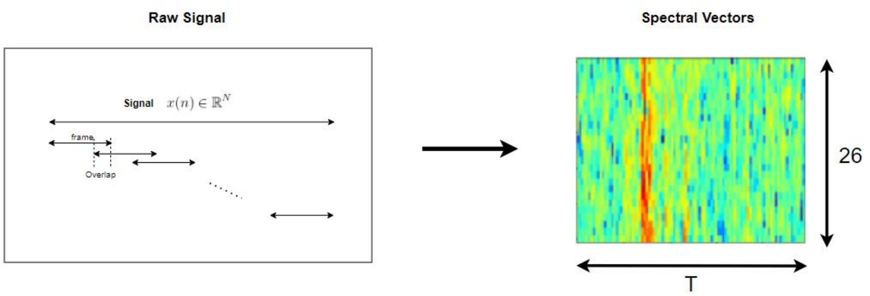

Figure 1. Information Retrieval from the daily returns of an asset

[3] Using a Fast Fourier Transform.

II. Reducing the dimensionality using autoencoding architectures

The harmonic structure of the signal is now transformed into a series of spectral vectors. In order for a prediction model to make sense of it, we need to reduce the complexity of the data even further.

Describing complex features in a few dimensions is a well-known challenge in the computer vision community. Let us take the example of a face image. The overly complex structure of the face results from the intensity of each pixel composing the image, as well as from the correlations between the pixels.

By using **autoencoder neural networks**, we are able to map the whole picture into a low-dimensional representation called the **bottleneck vector.**

We can think of each dimension of the bottleneck vector as a parsimonious description of the main facial features. The model is trained to reconstruct the face image based on the few descriptions provided by this bottleneck vector.

Table 1 summarizes the evolution of the data shape after each transformation.

Initial signal	Decomposition in overlapped[4] windows of 60 samples	Extracting the harmonics	Grouping using the triangular filters	Extracting the bottleneck vectors
(N,)	(T, 60)	(T, 128)	(T, 26)	(T, 2)

Table 1. The different data shapes after each transformation

[4] We use an overlap of 20 days between two successive windows

We need a sufficiently large number[5] of data samples to train this autoencoder. Therefore, for a specific index, we extract the harmonic information of all the single stocks composing the index in order to train the autoencoder.

Once the model loss has converged, we consider the sector sub-indices (using the GICS classification) related to the targeted index, say the MSCI World, and apply the trained encoder to map the spectral vectors extracted from these series into their bottleneck vectors as shown in Figure 2.

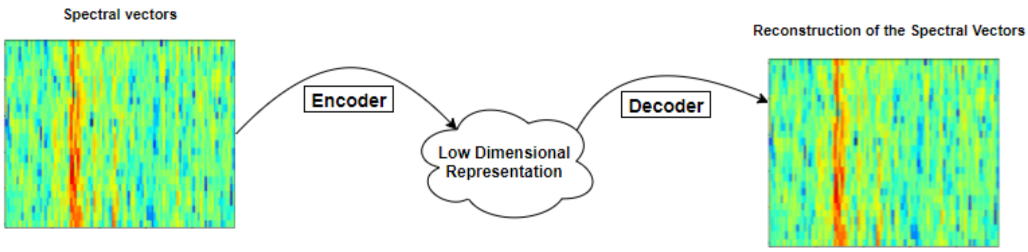

Figure 2. Creating the low dimensional representation of the spectral vectors, which encapsulates all the information needed to reconstruct the spectral vectors

We end up with a series of vectors of dimension two associated with each sector sub-index.

III. Forecasting the Market Turbulence States

Let us go back to our previous example of the face image. We have interpreted the bottleneck vector dimensions as the most synthetic descriptions of the facial features. The face emotion can directly be derived from these descriptions instead of looking at the whole image.

[5] In 2020 in the US geography, we have used 89658 spectral vectors of 26 dimensions to train the autoencoder

The same principle holds true for our bottleneck vectors. For each series of bottleneck vectors associated with a sub-index, we are able to capture two market emotions / states at each time step: the **Low Turbulence** state and the **High Turbulence** state. These states are characterized by clearly differentiated Sharpe ratios, as well as a specific level of skewness and kurtosis.

Each bottleneck vector is associated with a hidden Turbulence State. It is worth noticing that these turbulence states are idiosyncratic, i.e each sub-index has its own Turbulence States. The main finding at this stage is that in almost all cases, for single stocks or indices, the Market Turbulence States tend to be very **stable**[6] over time, which suggests the possibility of forecasting the Market Turbulence state over the next period of time.

This legitimates the usage of a graphical model[7] to learn the dynamics of the hidden Turbulence States. For each sub-index, the model outputs the probability of being in the Low Turbulence State over the next period.

At this stage, instead of applying the approach directly on a geographical index such as the MSCI World, we use an intermediary step, which is to apply the methodology to all MSCI sectors sub-indices in order to measure the probability of being in a Low Turbulence state at a sector level.

By aggregating these probabilities through equal weighting among sectors, we get a final prediction value, which encapsulates the global market condition over the next period, taking into account the idiosyncratic behavior among homogeneous industries.

[6] This stability within each of the Turbulence States is in the range of 80% on average from one period to the next.
[7] The graphical model used is a Hidden Markov Model.

Such an equal weighting approach among sectors is relevant from two angles: It is naïve and therefore robust. It is not momentum prone as it does not emphasize the “winners” of the current time.

IV. Risk Control to build the Low Turbulence Indices

Volatility control is a key point of the Low Turbulence approach. A first step we use to reduce volatility is to multiply the probability value from the previous section by 0.7 in order to determine the allocation of the underlying index. Why do we do this ?

Let us remember that the Low Turbulence approach is looking to blend equities and bonds. Long term sovereign bonds are meant to provide convexity at a time when coupons are not yielding much anymore. If we were starting from a high equity allocation before the implementation of the risk control cap overlay at a low level such as 7%, we would really not benefit as much from the convexity effect of bonds, as the bulk of the deleveraging would be through cash. We want to benefit from as much convexity as possible to have a distribution of returns as Gaussian as possible.

We then define a threshold called the **volatility target**[8], which is in fact a volatility cap, above which we consider ourselves in a high volatility environment. The risk control framework aims at reducing the volatility by allocating between the underlying raw strategy and cash. In periods of high volatility, we reduce the weight allocated to the underlying strategy, while in periods of low volatility, all the weight is allocated to the index.

The mechanism for computing the level of volatility of the raw strategy is called EWMA (Exponentially Weighted Moving Average), i.e, a moving average with a rapid memory decay factor[9].

At the end of this structuring step, we obtain a family of Low Turbulence Indices.

[8] In our implementation, we have chosen a volatility target of 7%

[9] In our implementation, the decay factor is equal to 0.5.

Results at the Low Turbulence Index level

I. Maximum Drawdowns

Figure 3 and 4 present the downside protection offered by the Low Turbulence approach for different underlying reference indices during the period 2003-2020.

In order to look at a fair comparison , we take the reference equity index which we submit to the same volatility control of 7% with a decay factor of 0.5.

Both the volatility and the maximum drawdown are drastically reduced using the Low Turbulence approach, across all geographies, in comparison with the underlying index and the 70/30 benchmark with or without volatility control.

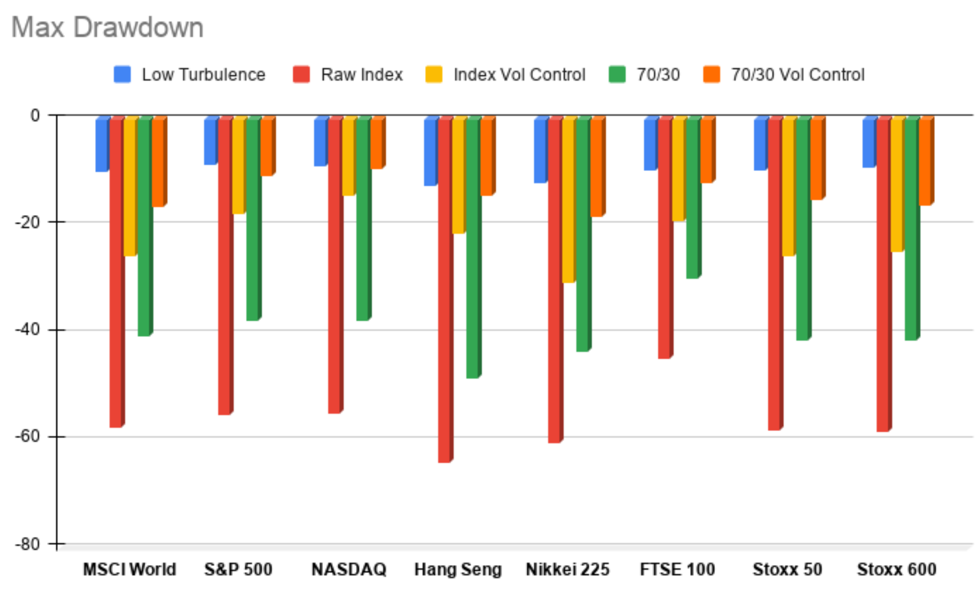

Figure 3. The Low Turbulence indices Max Drawdowns, compared to the underlying indices and the 70/30 benchmark with and without volatility control.

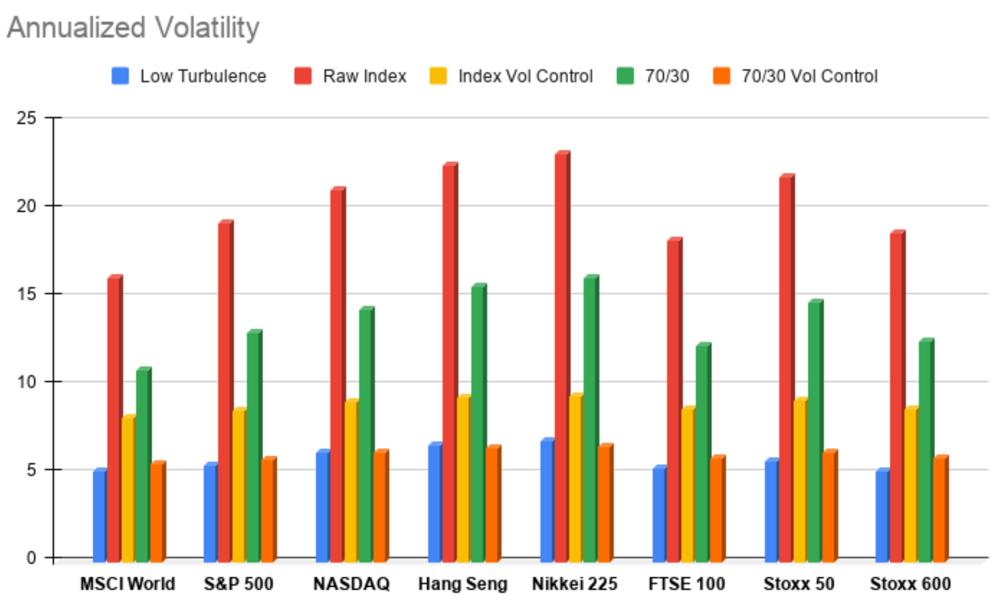

Figure 4. The Low Turbulence indices Annualized Volatility, compared to the underlying indices and the 70/30 benchmark with and without volatility control.

II. Return/Risk characteristics

Figure 5 presents the Sharpe ratios of the Low Turbulence approach, compared to the underlying index and the 70/30 benchmark, with or without the volatility control during the period 2003-2020.

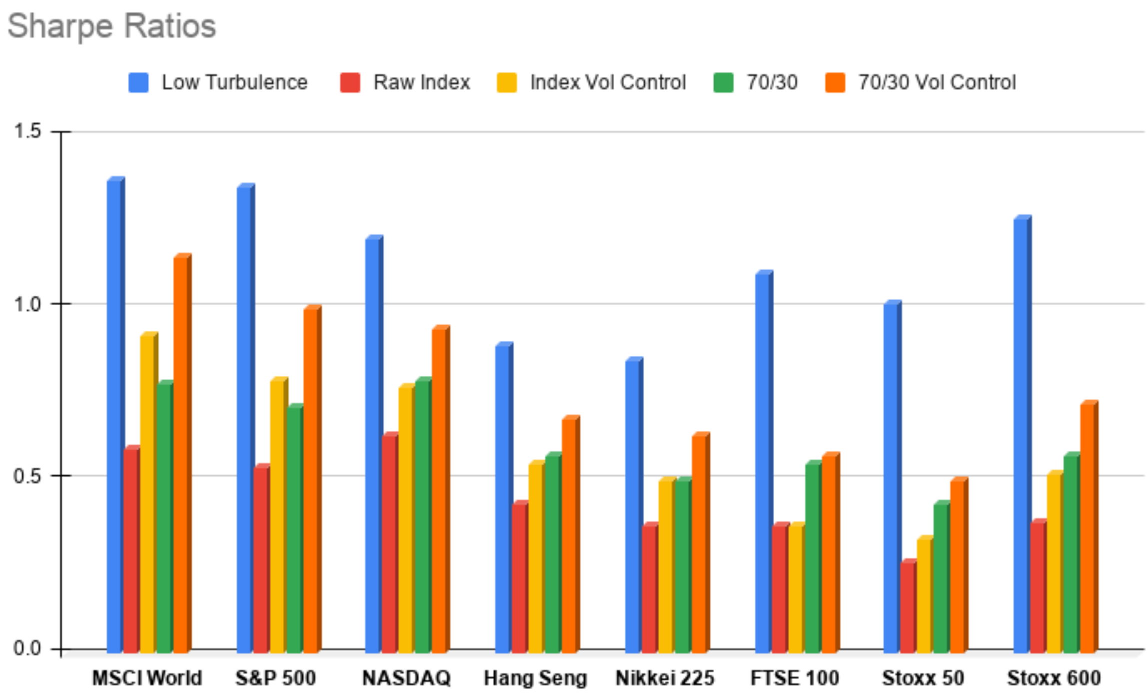

Figure 5. The Low Turbulence indices Sharpe ratios, compared to the underlying indices and the 70/30 benchmark with and without volatility control.

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Conclusion

The Low Turbulence methodology is a disruptive approach based on several intuitions coming from a wide range of Artificial Intelligence applications and algorithms. The resulting indices rebalance dynamically between equity and fixed income according to the Low Turbulence forecast. The approach offers a strong downside protection by drastically reducing the volatility and the maximum drawdown and shows higher Sharpe ratios across all geographies.

Glossary

Harmonic structure	The intensity of each harmonic present in the signal (single stocks or sub-indices daily returns) and the correlations between the different harmonics.
Spectral vectors	Vectors of dimension 26 where each dimension encapsulates part of the harmonic structure.
Autoencoder	The unsupervised Neural Network composed of an encoder and a decoder aiming at mapping the spectral vectors to their low dimensional representation, i.e, the bottleneck vectors.
Bottleneck vectors	The representation of the spectral vectors in an optimal two dimensional space.
Turbulence states	Binary discrete states describing the idiosyncratic emotion / state of a sub-index in a window of 60 days.