Analyzing the Volatility of Sustainable Finance: an Investigation of Volatility, Risk Measures, and ESG Reputational Impact (A.V.S.F.)

Team composition: Francesca Battaglia[1], Maria Grazia Starita[1], Giorgia Rivieccio[1], Giovanni De Luca[1], Gabriele Sampagnaro[1], Andrea Regoli[1], Salvatore Scognamiglio[1], Gian Paolo Stella[1], Daniele Previtali[1]

[1] University of Napoli Parthenope

Finanziato dall'Unione europea NextGenerationEU

Ministero dell'Università e della Ricerca

Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA

Partenariato Esteso Finanziato dal PNRR - Missione 4, Componente 2, Investimento 1.3

MOTIVATION

- Retail and institutional investors consider the potential long-term environmental impact of their financial decisions

- Buying stocks associated with the Environmental, Social and Governance (ESG) aspects of financial markets also has the potential to yield greater returns than standard financial investments. If this asset class demonstrates the benefits of diversification or has safe-haven qualities, this will further encourage investors worldwide to include it in their portfolios

- We are interested in analyzing sustainable asset allocation decisions: to achieve this goal, a deeper understanding of volatility dynamics and dependence structure of sustainable asset returns is needed

MOTIVATION

- For this purpose, the application of parametric and non-parametric models to describe the volatility of sustainable asset time series and the evaluation of their goodness of fit is of great interest for:

  - ✓ market participants (e.g. retail and institutional investors)in order to provide them with accurate forecasts of future volatility

  - ✓ asset managers in order to measure the contribution of an individual asset to the systemic risk within the broader ESG framework

Project objectives

- ***WP1 – WP2***: to analyze the volatility of sustainable assets in order to predict their expected patterns with parametric (WP1 of our project) and non-parametric (WP2 of our project) models. We believe that developing different deep learning methods for volatility models could provide additional insights into the volatility dynamics of sustainable assets

- ***WP3***: *to* quantify the risk associated with extreme events by analyzing the distribution of their returns in the tails. Assuming that the CoVaR is a proper systemic risk measure, this WP compares different models in computing CoVaR using backtests

- ***WP4***: to identify novel determinants of volatility patterns, by analyzing if the reputational risk associated with the ESG dimensions of listed companies (both in terms of the potential occurrence of reputational damage and its impact on yield distributions) could be a key driver of volatility in sustainable asset classes

What have we done so far?

WP1
COMPLETED
Assessing volatility dynamics of sustainable indexes with parametric models

WP2
STARTED
Assessing volatility dynamics of ESG indexes with deep learning models

WP3
TO START
Backtesting models for Conditional Value-at-Risk measures

WP4
TO START
ESG Reputational Risk

The Dataset

- We built a unique dataset of EU Climate Benchmark indexes, i.e. Climate Transition Benchmarks (CTBs) and Paris Aligned Benchmarks (PABs) as outlined in Regulation (EU) 2019/2089, and their parents. We collected daily data from November 2017 to June 2024 (final sample: 122 time series)

- Our dataset is based on Hoepener and Zdanceviciute (2024). It is collected via keyword search on Bloomberg and the relevant index providers' websites.

- The issuers of the EU Climate Benchmark indexes that we take into account are (in alphabetical order): 1) Euronext for FTSE and STOXX indices; 2) Goldman Sachs; 3) MSCI; 4) RAFI; 5) S&P. The indices provided by Morgan Stanley are the largest group

The Analysis: the GARCH family models

- To capture the volatility dynamics in the return time series, we rely on GARCH family models

- The inability to account for asymmetric performance is the main drawback of the standard GARCH models. Consequently, the APARCH, GJR-GARCH and E-GARCH models are used

- We run 96 models for each time series: we estimate all models (GARCH, APARCH, GJR-GARCH, and E-GARCH) with orders (1,1) and (2,1) using different error term distributions, including normal, student-t, GED, skew-normal, skew-student and skew-GED. When appropriate, we consider the inclusion of a first-order autoregressive (AR(1)) component

The Analysis: the Identification of the Best Fitting Models

- To assess the goodness of fit of the estimated models, we considered the adjusted Pearson Goodness-of-Fit Test (Palm, 1996) beyond the Information criterions AIC and BIC

- We select models with the lowest AIC and BIC values among those with the highest p-values (p-values higher than 5%) of GoF

RESULTS: There are fourteen cases where this condition does not apply to the MSCI indices (out of ninety cases). For FTSE provider, this condition does not apply in two out of twelve cases

- The R package rugarch is used to perform the estimations. We develop a comprehensive code to estimate all possible models in the GARCH family and select the best fitting model, based on standard goodness-of-fit tests and model selection criteria

The Analysis: the Persistence

- Long-memory (persistence) volatility features are a key factor of most financial time series

- Several findings (Baillie, 1996; Baillie, Bollerslev, and Mikkelsen, 1996; Andersen, Bollerslev, Diebold, and Labys, 2001; Andersen, Bollerslev, Diebold, and Ebens, 2001) show that both realized and conditional volatilities have long memories

- Since volatility and persistence affect the accuracy of modelling, valuation, and forecasting, and since the volatility of climate benchmark indexes is considerably different from that of their parents, an analysis of their persistence is required

Issuer: Euronext

Group	Asset	Model	AIC	BIC	p-values of GOF
Gruppo 1	EURO STOXX Total Market Net Return EUR	"eGARCH-sstd-0-2"	2,588	2,618	0,851
	EURO iSTOXX Ambition Climat **PAB** EUR (Net Return)	"eGARCH-sstd-0-2"	2,584	2,614	0,998
Gruppo 2	FTSE EPRA Nareit Developed **Europe** ex UK Index	eGARCH-std-0-2	3,070	3,097	0,001
	FTSE EPRA Nareit Developed Europe ex UK Green EU **CTB** Net Tax Index	"apARCH-sstd-1-1"	3,124	3,150	0,000
Gruppo 3	FTSE EPRA Nareit Developed Index	"apARCH-sstd-1-1"	2,474	2,503	0,411
	FTSE EPRA Nareit Developed Green EU **CTB** Net Tax Index	"apARCH-sstd-1-1"	2,390	0,242	0,438
Gruppo 4	Euronext **Europe** 500 NR	"apARCH-sstd-1-1"	2,399	2,428	0,557
	Euronext Low Carbon 100 **Europe PAB** Net Total Return Index	"apARCH-sstd-0-1"	2,397	2,423	0,503
Gruppo 5	Euronext **Eurozone** 300 NR	"apARCH-sstd-0-1"	2,552	2,578	0,645
	Euronext Low Carbon 100 Eurozone **PAB** NR	"apARCH-sstd-0-1"	2,576	2,602	0,833
Gruppo 6	STOXX **Europe** 600 (Net Return) EUR	"eGARCH-sstd-0-2"	2,405	2,435	0,622
	STOXX **Europe** 600 Paris-Aligned Benchmark Net Return EUR	"eGARCH-sstd-0-2"	2,402	2,433	0,908

Notes: «Asset» column: the first asset of each group is the parent index; «Model» column: the first number is 0 if AR(0), 1 if AR(1); the second number is 1 or 2 if respectively it's a GARCH (1,1) or GARCH (2,1)

RESULTS: There are only fourteen cases where this condition does not apply to the MSCI indices (out of ninety cases). For FTSE provider, this condition does not apply in two out of twelve cases

Issuer: Euronext

	Higher_Persistence	Higher_Mean	Higher_SD	Higher_SMean	Higher_SSD
Gruppo 1	PARENT	PARENT	PARENT	NO PARENT	PARENT
Gruppo 2	NO PARENT	NO PARENT	NO PARENT	PARENT	NO PARENT
Gruppo3	NO PARENT	NO PARENT	PARENT	NO PARENT	PARENT
Gruppo4	PARENT	NO PARENT	PARENT	NO PARENT	PARENT
Gruppo5	NO PARENT	PARENT	PARENT	NO PARENT	PARENT
Gruppo6	NO PARENT	NO PARENT	PARENT	NO PARENT	PARENT

Notes: This table compares the parent index and the corresponding EU Climate Benchmarks, in terms of higher persistence, higher mean, higher standard deviation, higher semi-mean (SMean), and higher semi-standard deviation (SSD). The term "NO PARENT" refers to the corresponding EU Climate Benchmark

The Analysis: the Identification of the Best Performing Models

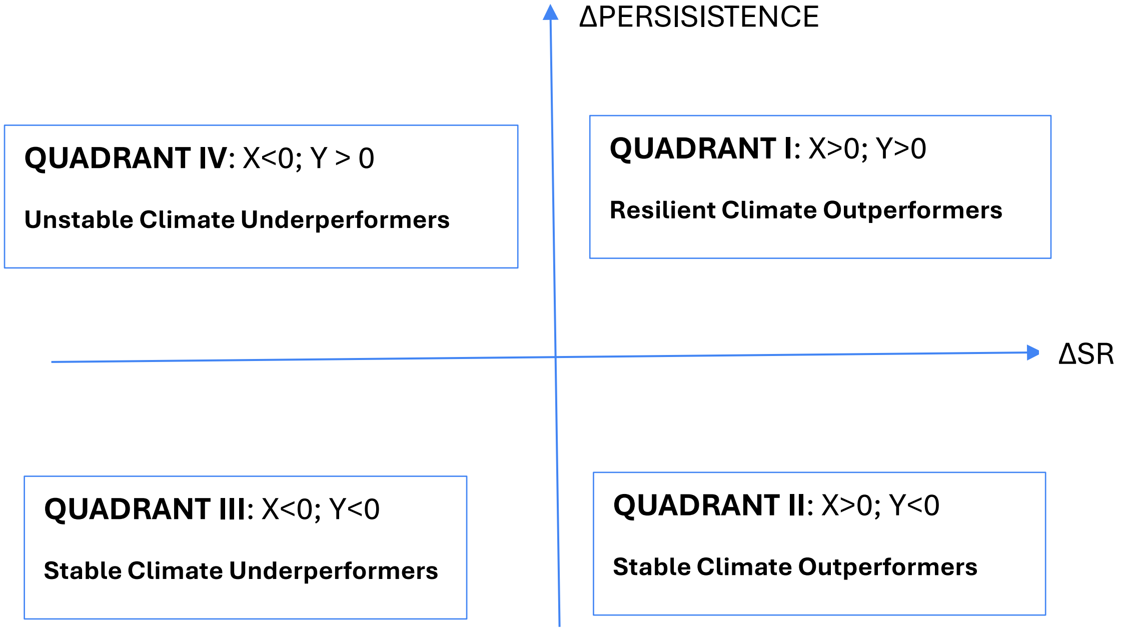
- estimation of the ***differential Persistence*** (ΔPersistence) between each Climate Benchmark and the corresponding parent

- estimation of a risk-adjusted performance measure (i.e. the Sharpe Ratio, SR) and ***differential SR*** (**ΔSR**) between each Climate Benchmark and the corresponding parent

- to represent the different behaviour of each parent and its climate benchmark indices in terms of performance and riskiness, we built some maps based on the differential Sharpe Ratio (ΔSR on X-axis) and differential Persistence (ΔPersistence on Y-axis)

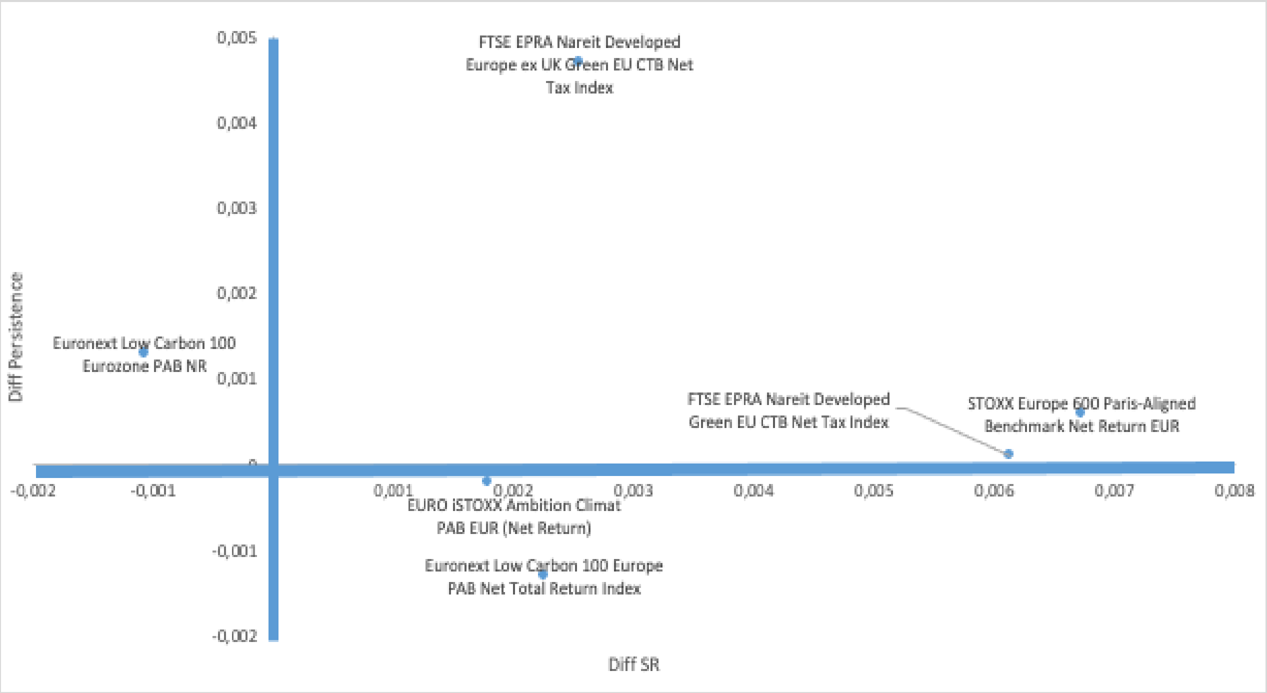
The Analysis: the Identification of the Best Performing Model

Four quadrants arise:



The Analysis: the identification of the best performing model

Scatter-plot of relative differences in Sharpe Ratio (ΔSR on X-axis) and Persistence (ΔPersistence on Y-axis) of Euronext Climate Benchmark indices compared to their parents



What are we doing?

- The results of the previous analyses show that parametric models are not the best fitting models for all of our time series. Specifically, there are fourteen cases where this condition does not hold for the MSCI indices (out of ninety cases) and two cases (out of twelve cases) for the FTSE providers

- We are exploring the application of deep learning models to capture the volatility dynamics of climate benchmarks. These models offer flexibility and could provide more insights into the behaviour of assets with complex, non-linear patterns than traditional parametric models

What are we doing?

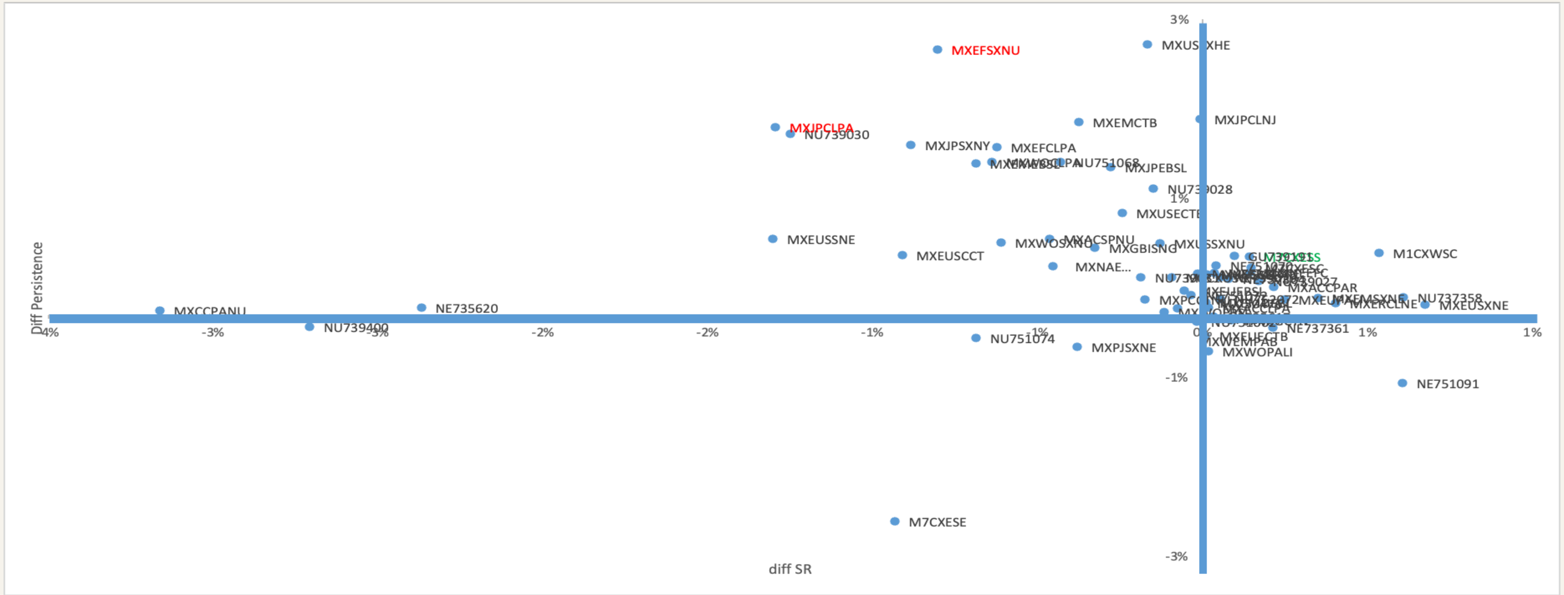
We plan to leverage recurrent neural networks (RNNs), such as Long Short-Term Memory (LSTM) networks designed for processing sequential data like time series

We aim to incorporate external variables, such as market sentiment measures, which may enhance our ability to describe volatility behaviour more comprehensively

We intend to consider a multivariate approach by investigating deep learning models that can jointly model the volatility dynamics of multiple assets

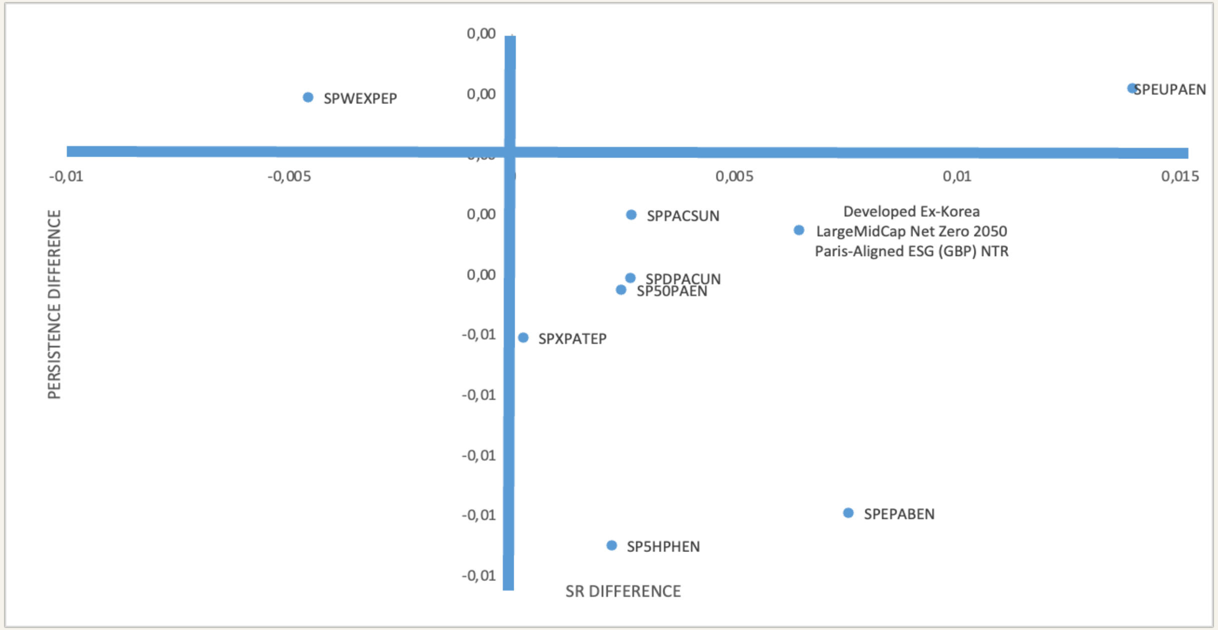
APPENDIX A

Figure 1 - Scatter-plot of relative differences in Sharpe Ratio (ΔSR on X-axis) and Persistence (ΔPersistence on Y-axis) of MSCI Climate Benchmark indices compared to their parents



APPENDIX A

Figure 2 Scatter-plot of relative differences in Sharpe Ratio (ΔSR on X-axis) and Persistence (ΔPersistence on Y-axis) of S&P Climate Benchmark indices compared to their parents.



THANK YOU!