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Financial analysis in energy Sector, A comparative study between Mean-GINI and Mean-Variance model.

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Abstract

This paper presents a comparative study between the mean-Gini and the mean-variance models in financial analysis of the energy sector. It aims to see how efficient both approaches are in optimizing investment portfolios related to renewable and fossil energies. This will be done by optimizing representative stocks from the two sectors using the Gini index and the standard deviation as a measure of risk, and then comparing two models. Then, GARCH and Value at risk are applied in order to compare volatility and the efficiency of both models. The energy sector has been marked by high volatility in the last decade, which provides a good opportunity to find out which models best capture tail risk. The results show that the mean-Gini model leads to a portfolio with a higher average return than the mean-variance model. Additionally, the Gini portfolio has better-managed volatility and has lower extreme loss based on VaR. After validating the model, we made a comparison of the performance of investments in renewable energies and fossil energies, which revealed contrasting results. Even if the fossil fuel portfolio presents a less negative expected loss in the medium term according to the Capital Market Line approach, the performance ratios indicate a preference for investments in renewable energies in the long term. The renewable energy portfolio thus presents better measures of risk-adjusted return. This study highlights the interest of the mean-Gini model for portfolio optimization in the energy sector and highlights the complex dynamics between investments in renewable and fossil energies.

Keywords: Mean Gini, Mean variance, financial risk, Portfolio Optimization, Energy sector

Abbreviations :

MG : Mean Gini; MV: Mean Variance, RE: renewable energies; FE: fossil energies.

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Introduction:

Within the realm of financial analysis in the energy sector, this study explores the application of the Gini index, a statistical indicator traditionally used to measure social inequalities. Initially introduced by the Italian statistician Corrado Gini (in 'Variability and Mutability', 1912), this index has been referenced in financial analysis by (Shalit and Yitzhaki 1984). This paper investigates its novel use as a metric for assessing financial risk, exploring its innovative application in this context. The subject of this research focuses on a comparative study of the Mean-Gini and Mean-Variance models in financial risk measurement and portfolio optimization, with particular emphasis on renewable and fossil energy investments. The primary objective of this study is to demonstrate how the Gini index can be used to evaluate financial risk and construct optimal portfolios, and to study the responsiveness and resilience of renewable energy stocks that have shown certain resilience during critical periods, such as crisis (Nautiyal et al. 2024). We also explore the limitations of the traditional risk measurement method variance showing its inadequacy when used with non-normal probability distributions (Leland 2005). In this context, we propose the Gini index as a robust alternative that does not require a specific probability distribution.

From an epistemological perspective, this research adopts a positivist approach, as it is based on the observation, measurement, and statistical analysis of financial market data. This positioning allows us to examine the relationships between financial returns and risk through objective quantitative indicators and empirical testing. The study therefore seeks to assess the validity and efficiency of the Mean-Gini model by comparing its results with those of the traditional Mean-Variance model. Regarding the research approach, this study follows a hypothetical-deductive reasoning process. It starts from existing financial theories and previous research on portfolio optimization and risk measurement, from which we formulate the hypothesis that the Mean-Gini model provides a more efficient alternative to the Mean-Variance model, particularly when financial returns do not follow a normal distribution. This hypothesis is then examined empirically through portfolio optimization, performance ratio calculations, GARCH modeling, and VaR and CVaR analysis. The first question we seek to address is: how can the Gini index be used to evaluate financial risk? In response, we introduce the Mean-Gini model as an alternative to the Mean-Variance model, essentially proposing that financial risk, which is often measured by variability (variance), could instead be measured by dispersion (the Gini index). This measure of dispersion will be applied to the returns of financial assets in the energy sector, which is well known for its variability. The more dispersed the returns, the riskier the asset is considered. This method is particularly advantageous as it is

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adaptable to various probability distributions (Kashif et al., 2016). The second question we address is: how can this model be used in the construction of optimal portfolios? In order to answer this question, we will show how the Mean-Gini model overcomes the restrictions of the traditional Mean-Variance model in constructing an optimized portfolio in terms of the risk-return combination by using the stochastic dominance rule for a more robust evaluation of systematic risk (Barucke Marcondes and al., 2017), particularly in highly volatile areas such as the energy sector (Song et al. 2019). The idea of optimization, therefore, is to maximize returns while minimizing dispersion. We conclude by explaining how the traditional performance ratios -Sharpe, Treynor, and Jensen- can be perfected using the Gini Index as a measure of risk. The purpose of the present study is to throw new light on financial risk assessment and also to propose innovative methodologies for constructing optimal portfolios.

To achieve these objectives, the paper is organized as follows. The first section presents the theoretical foundations of the Gini index and the Mean-Gini model, as well as the performance ratios adapted to this approach. The second section focuses on the empirical analysis and validation of the Mean-Gini model through a comparison with the traditional Mean-Variance model, using portfolio optimization and risk measurement tools, including GARCH models and Value-at-Risk (VaR). The third section examines the performance of renewable and fossil energy portfolios using the Mean-Gini approach, with particular attention to their risk-return characteristics. Finally, the conclusion summarizes the main findings and presents the contributions and perspectives for future research.

I. The Gini Index

1. Definition:

The Gini index is a measure of dispersion primarily used to assess inequalities, functioning as a concentration coefficient to evaluate how equitable or inequitable a distribution is. It is normalized between 0 and 1, making it a common tool for analyzing income inequality. A Gini value of zero represents perfect income equality, where everyone has the same income, while a value of one signifies complete income inequality, where one individual holds all the income and others have none. In this paper, we examine the Gini index as a means of measuring risk. By calculating pairwise deviations in the returns of a security, this index enables us to rank securities based on their relative volatility within the overall portfolio. Unlike traditional risk measurement methods that typically rely on variance and face challenges with non-normal probability distributions, we propose using the Gini index as a stochastic dominance risk indicator instead of variance (or standard deviation). This approach is advantageous because it

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does not depend on a specific probability distribution, but instead utilizes the probability density function F(R) (Denuit, Sznajder, and Trufin 2019).

2. Calculation

The Gini index is defined as twice the area between the line of equality (the 45-degree line) and the Lorenz curve (Denuit et al. 2019). This relationship can also be represented mathematically in the following way:

$$\Gamma_p = 2\text{cov}\,[\text{Rp}, \text{F(Rp)}]$$

Where:

cov: Covariance

Rp: represents the return of asset p

F(Rp): represents the cumulative distribution function

Alternatively, it can be written as:

$$\Gamma_p = 2\sum_{1}^{N} \text{cov}\,[R_p, \text{F}(R_p)]$$

The risk of the portfolio can be broken down into the sum of the products of the weights and the covariance between the variable Rp and the cumulative distribution of the portfolio p. This covariance illustrates the area between the Lorenz curve and the 45-degree line, which represents equality. To make this expression clearer, we recognize that the area of a unit square is 1, indicating that the area of the triangle formed by the 45-degree line is 1/2. Consequently, the Gini index is defined as twice the area between the Lorenz curve and the 45-degree line, divided by 1/2. This can be expressed as follows: $\Gamma_p = \frac{\text{cov}\,[\text{Rp,F(Rp)}]}{\frac{1}{2}}$

By inverting the denominator, we determine that the Gini index equals twice the area between the Lorenz curve and the 45-degree line. Thus:

$$\Gamma_p = 2\text{cov}\,[\text{Rp}, \text{F(Rp)}]$$

(Kolb and Okunev 1992) utilize rank as a cumulative distribution function F(Rp), which is based on arranging returns in ascending order. This results in : $F(Rp) = RANK\ (Rp)$ Therefore :

$$\Gamma_p = 2 \times \frac{\text{cov}\,[\text{Rp}\,, RANK\ (Rp)]}{N}$$

3. The Mean-Gini Model

For risk evaluation and optimal portfolio construction, instead of the with standard deviation or variance which are not universal for non-normal distributions that traditional risk measures require, MG model is more flexible in its form and can accommodate various probability

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distributions (Furman, Wang, and Zitikis 2017). It combines the simplicity of a mean-variance analysis with characteristics of stochastic dominance which overcomes traditional limitations in applying conventional models. Given the concentration relationship, through which asset returns are ranked in accordance with their volatility or dispersion ,hence it is more useful risk-measuring model as the MG (Psarrakos and Sordo 2019) , by taking these properties can create optimal portfolios according to stochastic dominance principle and this will provide a system that possesses its systematic risk better assessment.

In the MG model, beta is calculated as follows (Shalit and Yitzhaki 1984):

$$\beta_{GINI} = \Theta_i(\Gamma_i/\Gamma_m)$$

Where $$\Theta_i = \frac{cov[R_i, F_m(R_m)]}{cov[R_i, F_i(R_i)]}$$

Then: $$\beta_{GINI} = \frac{cov[R_i, F_m(R_m)]}{cov[R_i, F_i(R_i)]}(\Gamma_i/\Gamma_m)$$

The beta indicates how sensitive a security is to market fluctuations, while Θ_ir represents the overall risk involved. It's important to draw a comparison between the beta in the MG model and that in the MV model. In the MG model, beta relates to the effectiveness of stochastic dominance as determined by the Gini index, whereas in the MV model, beta is found by dividing the covariance of the asset with the market by the market's variance. This metric depends on the mean and standard deviation, suggesting that its effectiveness is contingent upon having a normally distributed dataset.

4. Performance Ratios Using the Gini Index

- **The Sharpe ratio**

The Sharpe ratio, introduced in 1966 by William Forsyth Sharpe, is a measure that evaluates the profitability of a portfolio in relation to its risk. According to this ratio, average returns alone are not sufficient to accurately measure performance. The Sharpe ratio is defined as the ratio of the average excess return of a portfolio (Kircher and Rösch 2021), calculated as the difference between the portfolio's average return and the risk-free rate, to the standard deviation of the portfolio's return:

$$S_p = \frac{R_p - R_f}{6_p}$$

Where :

R_p: profitability of Portfolio p

R_f :Risk-free rate

6_p : Standard deviation of the portfolio

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As the standard deviation of a portfolio's returns tends to decrease with the number of securities composing the fund, a more diversified portfolio will generate a higher Sharpe ratio compared to a less diversified fund. By dividing the excess return by the total risk of the portfolio, the Sharpe ratio thus adjusts the performance not only for risk but also for the level of diversification of the portfolio. The Sharpe ratio analyzes two different dimensions of performance. It is indeed harder to achieve superior performance on a single asset than on a set of assets. This reduction in the denominator with the increase in the number of securities composing the fund does not apply to the Treynor ratio because the Treynor ratio uses the marginal risk of the portfolio instead of the total risk, and the beta of a fund is not a decreasing function of the number of securities.

- **Sharpe Ratio by Mean-Gini:**

The Sharpe ratio according to the MG method works in the same way as the Sharpe ratio according to the MV model. In this methodology, we utilize the Gini index as a comprehensive measure of risk. Substituting standard deviation by Gini index. The Sharpe ratio is calculated using the following formula:

$$S_p = \frac{R_p - R_f}{\Gamma p}$$

Where:

R_p: profitability of Portfolio p

R_f :Risk-free rate

Γ_p **:**Portfolio Gini index

- **The TREYNOR ratio**

I. This ratio, introduced by economist Jack TREYNOR in 1965, akin to the Sharpe and Jensen ratios, evaluates the profitability of a portfolio relative to its risk.

II. The TREYNOR ratio is calculated using the following formula:

$$RT_p = \frac{R_p - R_f}{\beta_p}$$

Where :

R_p: profitability of Portfolio p

R_f : Risk-free rate

β_p : the beta of portfolio p

- **TREYNOR Ratio by Mean-Gini**

The TREYNOR ratio analyzes the relative volatility of the portfolio compared to the benchmark index, rather than solely focusing on the portfolio's volatility. Therefore, we will adopt a beta

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calculated using the Gini method here. Thus, the TREYNOR ratio is well-suited for a well-diversified portfolio relative to its reference market.

$$RT_p = \frac{R_p - R_f}{\beta_{p\ GINI}}$$

We remind in section 3 that:

$$\beta_{GINI} = \frac{cov[R_i, F_m(R_m)]}{cov[R_i, F_i(R_i)]} \times (\Gamma i/\Gamma m)$$

- **Alpha de JENSEN**

Jensen's Alpha or Jensen's coefficient directly leverages the objectives of the Capital Asset Pricing Model (CAPM). Jensen's Alpha evaluates the performance of a fund or portfolio of financial assets and is defined by the following expression (Jensen,1968):

$$\alpha_p = \overline{R_p} - [R_f + \beta_p(\overline{R_m} - R_f)]$$

With :

$\overline{R_p}$: Expected return of the portfolio

R_f: Risk-free rate

β_p : Portfolio beta

$\overline{R_m}$: Expected market return

Jensen's Alpha measures the outperformance (or underperformance) of a portfolio compared to its theoretical performance predicted by the Capital Asset Pricing Model (CAPM). It thus measures the excess return - positive or negative - beyond what the CAPM predicts based on systematic risk realized on a given portfolio compared to what its risk would have justified if we refer to the expected return calculated according to the CAPM or the MG model. A positive value of alpha indicates a realized performance superior to normal, and vice versa.

Alpha de Jensen Mean-Gini:

Jensen's alpha calculated by the Gini method serves the same purpose as the MV method. We will replace the beta with the beta calculated according to the Mean-Gini method, which gives:

$\alpha_p = \overline{R_p} - [R_f + \beta_{Gini}(\overline{R_m} - R_f)]$

So :

$$\alpha_p = \bar{R}_p - \left[R_f + \left(\frac{cov[R_i, F_m(R_m)]}{cov[R_i, F_i(R_i)]}\left(\frac{\Gamma i}{\Gamma m}\right)\right)(\bar{R}_m - R_f)\right]$$

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I. Analysis of assets in the energy sector

1. Validation of the model

- **Data collection**

To carry out this comparative study of the MG and MV models using the example of the portfolio of stocks from the renewable and fossil energy sectors, a careful selection of stocks was made. Thus, the selection of stocks was guided by two main criteria: the comparability of the two sectors, ensuring that chosen stocks are comparable in terms of market capitalization, trading volume, and the availability of enough historical data for precise statistical analysis. For the renewable energy portfolio, we selected three companies that represent key segments of the sector. Enphase Energy (ENPH) Produces solar microinverter systems for residential and commercial photovoltaic systems. First Solar (FSLR) is an American manufacturer of thin-film solar cells and photovoltaic module. Plug Power Inc (PLUG) Focuses on developing hydrogen fuel cell systems, represents renewable energy stocks in the domain of hydrogen and energy storages. For the fossil energy portfolio, the following stocks were selected. Exxon Mobil Corporation (XOM) is one of the world's leading oil and gas companies. Chevron Corporation (CVX) is another major international oil and gas corporation engaged in exploration, production and oil refining. And Occidental Petroleum Corporation (OXY) which is a large player in the oil and gas sector, involved in exploration, production, and marketing of oil and gas.

Reliable price data was collected over a period of ten years beginning in May 2014 until May 2024 from reputable and well-known financial sources. This data will be used to calculate returns and risks using the MG and MV models for both sectors to determine their performance in a risk-adjusted environment and the portfolio diversification.

2. Performance Ratio Optimization

In a detailed comparison between the Mean-Gini and Mean-Variance models, we propose an optimization strategy based on the performance ratios: Sharpe ratio, Treynor ratio, and Jensen alpha. A more in-depth analysis of the portfolio construction is performed in this section. We started with a portfolio optimized by maximizing the Sharpe ratio calculated by the standard method (Farinelli et al. 2008), then we constructed another portfolio by maximizing the Sharpe ratio of the Mean-Gini model. We then compare the two portfolios that are constructed, based on the (VaR) in order to determine the least risky portfolio. Finally, we extend this optimization procedure by maximizing the Treynor ratio and Jensen alpha. We evaluate the performance and risks of these portfolios under the two models by exploring various optimizations (Chakrabarti 2021), presenting a comprehensive comparison for two custom methods – Mean-Gini versus conventional framework -Mean-Variance model.

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Maximization of the Sharpe ratio $(\frac{R_p - R_f}{\Gamma p})$ *compared with the maximization of* $(\frac{R_p - R_f}{\beta_P})$

Maximization of the Treynor ratio $\left(\frac{R_p - R_f}{\beta_p}\right)$ *compared with the maximization* $(\frac{R_p - R_f}{\beta_{GINI}})$

Maximization of the Jensen Alpha

$$\alpha_p = \bar{R}_p - \left[R_f + \beta_{GINI}(\bar{R}_m - R_f)\right] \textit{compared with the maximization} \alpha_p$$
$$= R_p - [R_f + \beta_p(R_m - R_f)]$$

with :

$$\begin{cases} \mathrm{E(Rp)} \geq \mu \\ \sum_i^n Xi = 1 \\ \mathrm{Xi} \geq 0 \end{cases} \quad \text{and} \quad 1 \geq \mathrm{i} \geq \mathrm{n}$$

	Sharpe-based weight			VAR	Treynor-based weight			VAR	Jensen's alpha-based weight			VAR
	ENPHASE ENERGY	FIRST SOLAR	PLUG POWER		ENPHASE ENERGY	FIRST SOLAR	PLUG POWER		ENPHASE ENERGY	FIRST SOLAR	PLUG POWER	
GINI	100%	0%	0%	-0,06928	100%	0%	0%	-0,06928	100%	0%	0%	-0,06928
VARIANCE	100%	0%	0%	-0,06928	100%	0%	0%	-0,06928	100%	0%	0%	-0,06928

TABLE1 : Results of Weighting and Var for Renewable Energy Portfolios

We evaluated our strategy using the following stocks: Enphase Energy, FIRST SOLAR, and Plug Power. By implementing both methods (Mean-Gini and Mean-Variance) and optimizing based on three performance ratios (Sharpe ratio, Treynor ratio, and Jensen's alpha), we discovered that the assigned weights were the same (table1). The Value-at-Risk (VaR) calculated for this specific portfolio is -0.06928, suggesting a maximum potential loss of 6.92809% in a typical scenario. These findings indicate that none of the models significantly distinguished the performance, as the resulting portfolios were identical. This points to a limitation in our initial approach, which did not allow us to clearly identify the most effective model for risk management and optimization. To address this limitation, we propose a new methodology that focuses on minimizing the Gini index and comparing the outcomes with those achieved by minimizing the variance. This strategy aims to create distinct portfolios in terms of asset allocation, potentially offering a clearer understanding of the performance differences between the two models. By minimizing the Gini index, we seek to lessen the dispersion of returns, while minimizing the variance focuses on reducing variability. This comparative

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approach should yield valuable insights for investors looking to select more robust and less risky portfolios.

3. Mean Gini optimization

Portfolio management employs a range of methods utilized by professionals and economists, spanning from theoretical frameworks to various management styles, along with risk and performance assessments. The MV model, is recognized as one of the most prominent approaches in optimal portfolio analysis. In this analysis, we will explore optimal portfolio analysis using the MG model. The main idea is to select a portfolio with maximum returns while minimizing risk, meaning it minimizes the Gini index (Nisani 2018).

- **Optimal portfolio (using the Gini model)**

As previously mentioned, the selection of a portfolio using the Gini index is based on one that presents maximum returns while minimizing risk. We know that the Gini index (Γp) represents risk, so we seek a portfolio that minimizes the Gini index(Γp). We rely on the risk calculated by the Gini index to make a comparison with the MV model. Utilizing the Excel software, we can apply the solver to the energy sector data. We aim to minimize the Gini index of the portfolio while maximizing expected returns, subject to the following constraints: the sum of weights must equal 1, and the weights are greater than or equal to 0. Formally, the optimization problem can expressed as:

$$\text{Min } \Gamma_p = \text{Min } \{2\text{cov}\left[R_p, \text{F}\left(R_p\right)\right]\}$$

Subject to:

$$\begin{cases} \text{E}(R_p) \geq \mu \\ \sum_i^n X_i = 1 \\ \text{Xi} \geq 0 \end{cases} \qquad \text{for } i=1,\ldots.n$$

Where:

R_p :is the portfolio return

$\text{F}\left(R_p\right)$:is the cumulative distribution function of

Γ_p :is the portfolio Gini index

X_i is the weight of asset i

μ :is the minimum expected return

n: is the number of assets in portfolio

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- **Optimization results:**

Assests	ENPHASE ENERGY	FIRST SOLAR	PLUG POWER	TOTAL
Weight by mean-GINI	3,7466955%	86,1737506%	10,0795539%	100%
Weight by mean-VARIANCE	0%	100%	0%	100%

TABLE 2 : Optimization results for Renewable Energy Portfolios

	GINI Method	Variance Method
MEAN	0,00095972	0,00088031
STD DEV	0,02865214	0,02961032
GINI index	0,01513686	*
Beta	0,60229182	0,5308293
Jensen's alpha	-0,0193784	-0,0229772
Sharpe's ratio	-3,239792	-1,6588707
Treynor's ratio	-0,0814228	-0,0925339

Table 3: summary table of results

3.1.Efficiency of risk measurement

- **Stationarity**

Unit root tests highlight the stationary or non-stationary nature of a time series. Stationarity is a key concept for the validity of regression on time series data. The Dickey and Fuller test has the particularity of detecting both the presence or absence of a unit root, synonymous with non-stationarity, and the determination of a deterministic or stochastic trend, thus also determining the nature of non-stationarity.

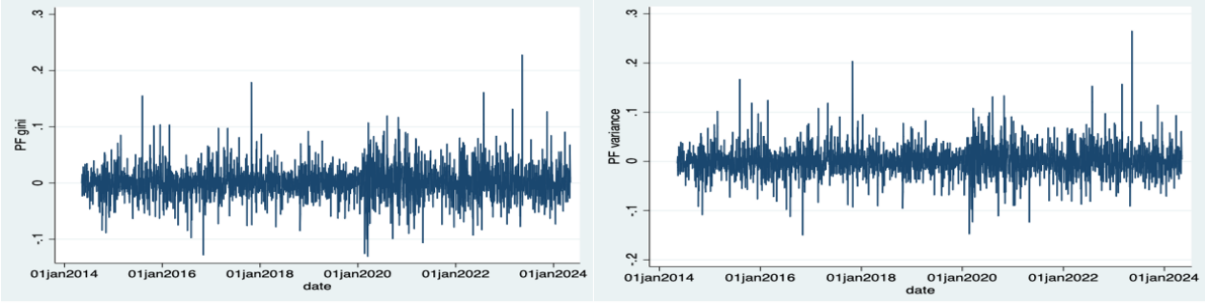


Figure 1 : results of Stationarity Analysis for Renewable Energy Portfolios

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Tests	GINI-Portfolio	Variance-Portfolio
ADF	-43.704	-43.183
Probability	0.00	0.00
Stationnarity	Stationary	Stationary

Table 4 : stationarity test

- **Normality**

Test / Pf	GINI-Portfolio			Variance-Portfolio		
	W	Prob>z	N Obs	W	Prob>z	N Obs
Shapiro wilk	0.95507	0.00000	2,514	0.94020	0.00000	2,514
Normality	Non-normal			Non-normal		

Table 5 : Normality test

3.2.The ARCH models

The ARCH (Autoregressive Conditional Heteroskedasticity) models were introduced by Engle in 1982, and their extension, GARCH (Generalized ARCH), was developed by Bollerslev in 1986. Their characterization relies on the concept of conditional variance. This specification proves to be very fruitful because it allows for a comprehensive study of solution properties while remaining sufficiently general. According to (Philip Igeland et al. 2024) GARCH models -specially Garch(1-1)- are indeed capable of capturing the characteristic properties of certain series.

	GINI-portfolio			Variance-portfolio		
	Coef.	Std. Err.	P>|z|	Coef.	Std. Err.	P>|z|
_cons	0.0007885	0.0005866	0.179	0.0006684	0.0006031	0.268
arch | L1.	0.0858598	0.0197528	0.000	0.0860126	0.0208374	0.000
Garch | L1.	0.5457772	0.161994	0.001	0.2738844	0.1734458	0.114

Table 6 : Results of GARCH Model for Renewable Energy Portfolio

From the GARCH models, we observe that there is not much of a difference when comparing both portfolios with two probabilities equal to zero for the ARCH model (table6). for GARCH model of the Gini-portfolio, the coefficient of 0.5457772 with a p-value of 0.001 suggests that

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past volatility shocks significantly influence the current volatility of the Gini-portfolio. The statistical significance of this coefficient means that there is a persistence of volatility, which may indicate a greater responsiveness of the portfolio to market fluctuations, without directly concluding that it is riskier. The second portfolio (Variance-portfolio) has the coefficient of 0.2738844, with a p-value of 0.114 (table6) indicates a weaker influence of past volatility shocks on the current volatility of this portfolio. This lack of significance suggests that past fluctuations have a less pronounced effect on current volatility, which may imply a lower responsiveness to shocks, but this does not necessarily mean that the portfolio is less risky. The Gini-portfolio appears to be more responsive to volatility shocks due to the higher significance and magnitude of its GARCH coefficient. However, this increased responsiveness does not mean that it is riskier in absolute terms, but rather that it is more sensitive to recent market fluctuations. To compare the overall risk between these two portfolios, it would be relevant to complement the analysis with other measures. One way to tackle this problem is by using a metric, the Value at Risk (VaR) which represents the maximum potential loss for a portfolio. Essentially though what VaR does is measure how much the absolute most you could potentially lose would be if that happened with some level of confidence over a given time period. Note that this metric is useful for contrasting the model performance between Mean-Gini and Mean-Variance models, it picks up the tail risks in distribution where GARCH models may not.

3.3.Backtesting

To evaluate the effectiveness of the two models, we need to conduct backtesting, a series of statistical procedures designed to confirm that the actual losses observed align with the expected losses. This process involves a systematic comparison of the historical forecasts generated by the method with the actual returns of the portfolio. In this section, we will analyze the two approaches, Markowitz and Gini, by applying value-at-risk (VaR and CVaR) to identify the least risky portfolio that maximizes returns.

- **VaR**

Value-at-Risk indicates the highest possible loss an investor might face on an asset or a portfolio of financial assets, which should only occur with a certain probability over a specified time frame (Rockafellar and Uryasev 2002). In other words, VaR is the expected worst loss over a given time horizon for a certain confidence level. VaR can be considered as a quantile of the loss and profit distribution associated with holding an asset or a portfolio of assets. If considering a coverage rate of a percentage (often 95% or 99%).

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- **Historical VAR**

	GINI-Portfolio	Variance-Portfolio
var (95%)	-0,042603971*	-0,043158075
var (99%)	-0,074562732*	-0,080080754

Table 7: Results of Historical VaR for Renewable and Fossil Energy Portfolios

- **Conditional VAR**

	GINI-Portfolio	Variance-Portfolio
Cvar (95%)	-0,061434567*	-0,063717442
Cvar (99%)	-0,089755889*	-0,098242126

Table 8 : Results of Conditional VaR for Renewable and Fossil Energy Portfolios

« * » The less risky portfolio between the two portfolios

Interpretations:

The purpose of this section is to validate the Mean-Gini methodology and recommend it for optimal portfolio selection. Different portfolios were selected (table2)based on both the MG and MV models. The MG model has a higher average return than MV model (Mean-Gini Return is 0.00095972 vs 0.000880314 for Mean-Variance Model) that we see in the (table3). To optimize the returns and at the same time maintain them test for risk specific to portfolios. For this purpose, we carried out some extra tests to study the risk better within each strategy. Support as imposed by the stationarity and non-normality test in (table 4, table 5 and figure 1), the Gini portfolio appears to be better modeled by a GARCH process, which could indicate more effective management of volatility risk compared to the Variance portfolio (table6). In addition, historical VaR (table7) and conditional VaR (table8) both confirm that the MG model portfolio risk is smaller than that of MV model portfolio. In summary, we can say that the Gini model ensures more efficient optimization in terms of return/risk than the MV model, which will allow us to continue our analysis based only on the MG method to compare the reactivity and resistance of investments in renewable energy and fossil energy.

4. Comparison Between Renewable Energy and Fossil Energy

In a context where energy transition and environmental sustainability are at the forefront of global concerns, investment in renewable and fossil energy sources is drawing increasing attention. While renewable energy emerges as a promising and environmentally friendly alternative, fossil energy remains a major pillar of the global energy supply, despite its environmental implications and associated financial risks (Igeland et al. 2024).

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This part of the article elaborates on a comparative study between investments in renewable energy and fossil energy through MG model. Having demonstrated their utility in evaluating financial risks, we next compare the performance of various econometric approaches to evaluate how effectively they can predict between investments in RE and FE. Investors and decision-makers will gain an in-depth view of these dynamics via this research. More specifically, we will dissect the existing return differentials in addition to defining what constitutes current standardized volatility and risk profiles for pure renewables companies versus those still with exposed to fossil energy.

This contrast will provide insight into the opportunities and threats these two sectors of the energy market pose, creating a roadmap for decision-making in an inherently fluid financial landscape against the backdrop of global environmental challenges.

4.1.Analysis and Discussion

To compare investment opportunities in renewable and fossil energy sectors, we apply the Mean-Gini model to construct two optimal portfolios. The objective is to identify the optimal asset allocation within each sector while minimizing portfolio risk. The following table presents the resulting portfolio weights.

renewable energy				**Total**
	ENPHASE ENERGY	**FIRST SOLAR**	**PLUG POWER**	
Weights by GINI	0,037466955	0,861737506	0,100795539	1
fossil energy				**Total**
	EXXON MOBIL	**CHEVRON**	**OCCIDENTAL PETROLEUM**	
Weights by GINI	0,548722665	0,451277335	0	1

Table 9 : Results of Mean Gini Optimization for Renewable and Fossil Energy Portfolios

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	Market	RE	EF
MEAN	0,000751692	0,00095972	0,00023819
STD DEV	0,014928142	0,02865214	0,01723347
GINI index	0,007620127	0,01513686	0,00873278
Beta by GINI	1	0,60229182	0,36426352
Jensen's alpha by GINI	-7,91468E-18	-0,0193784 *	-0,0318224
Sharpe's ratio by GINI	-3,299024553	-3,239792 *	-5,698281
Treynor's ratio by Gini	-0,049248308	-0,0814228 *	-0,1366094

Table 10 : summary table of results

* Prefered portfolio

4.2.Capital market line

The capital market line (CML) represents the risk-return trade-off efficient portfolios that combine a risk-free asset with the market portfolio. It shows the expected return of a portfolio as a function of its total risk (standard deviation) . In the traditional Mean-variance framework, the slope of the CML is determined by the market risk premium divided by market standard deviation. When applying the Mean-Gini model, the standard deviation is replaced by the Gini index, allowing the CML to capture the impact of inequality in the distribution of portfolio returns.

$$E(r) = Rf + \frac{E(Rm) - Rf}{6_m} 6_i$$

Therefore, the equation for the CML when applying the Mean-Gini model is:

$$E(r) = Rf + \frac{E(Rm) - Rf}{\Gamma_m} \Gamma_i$$

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The following table summarizes the expected returns calculated using the Capital Market line based on the Mean-Gini model for renewable and fossil energy portfolios.

Sector	Applied (Mean-Gini)	$E(r)$
Renewable energy	$5\% + \frac{0,000751692 - 5\%}{0,007620127} * 0,01513686$	**-0,0478284**
Fossil Energy	$5\% + \frac{0,000751692 - 5\%}{0,007620127} * 0,00873278$	**-0,0064393**

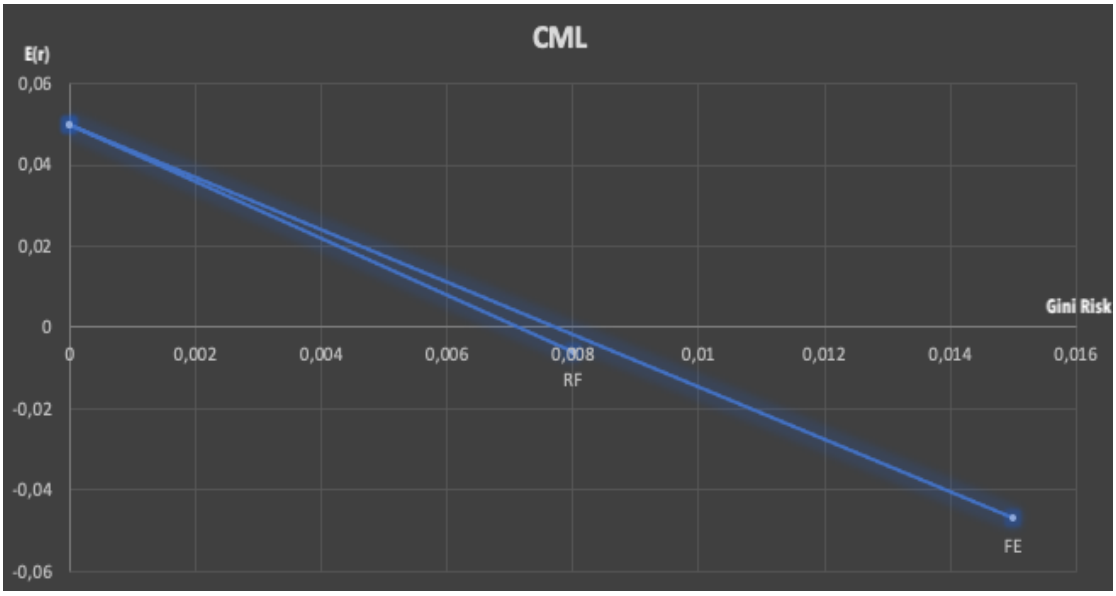


Figure 2: the capital market line by Gini method

Interpretation

To analyze the performance of renewable energy and fossil energy portfolios using performance ratios and the Capital Market Line (CML), At first glance we look at the different weights given to the two portfolios (table9) So, to determine the riskiest portfolio we need to look at the performance indicators: Jensen's Alpha, the Sharpe Ratio, and the Treynor Ratio. The renewable energy portfolio shows a Jensen's Alpha of -0.0193784 (table10), which suggests that it has underperformed relative to expectations set by the Capital Asset Pricing Model (CAPM) (figure2). This means that the returns from the renewable energy portfolio are lower than what would be expected given its level of systematic risk. Compared with the fossil energy portfolio, Jensen's Alpha is -0.0318224 (table10) . This more negative alpha than that of the renewable energy portfolio indicates even greater underperformance relative to the expected return according to the CAPM (figure2). Furthermore, the Sharpe Ratio for the renewable

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energy portfolio stands at -3.239792 (table10). This ratio measures the excess return per unit of total risk (standard deviation in the standard case and the Gini index in our case), and a negative ratio indicates that the portfolio offers a lower return than the risk-free rate after adjustment for total risk. This means that the renewable energy portfolio exhibits poor performance in terms of risk-adjusted return. Although the sharp ratio is negative for renewable energies, but the sharp ratio for fossil energies which is even more negative than that of the renewable energy portfolio, with a ratio sharp of -5.698281, This indicates even worse performance in terms of risk-adjusted return. Thus, the fossil energy portfolio exhibits very poor performance on a total risk basis. Regarding the Treynor Ratio, which measures excess return per unit of systematic risk (Gini beta), the renewable energy portfolio displays a ratio of -0.0814228. A negative ratio here means that the portfolio has a lower return than the risk-free rate after adjustment for systematic risk, showing unfavorable performance. Compared to the fossil energy portfolio, which is also more negative than the renewable energy portfolio, with a Treynor Ratio of -0.1366094. This shows even less favorable performance after adjustment for systematic risk. Although the expected returns of both portfolios are negative, the fossil energy portfolio has a less negative expected return than the renewable energy portfolio. However, based on performance ratios, the renewable energy portfolio is overall more favorable. It exhibits less underperformance and better measures of risk-adjusted return compared to the fossil energy portfolio. The fossil energy portfolio presents a less negative expected return according to the CML, with a predicted loss of 0.64393%, compared to a loss of 4.78284% for the renewable energy portfolio (figure2). This means that, from the CML perspective, the fossil energy portfolio is preferred because it is expected to lose less value.

Performance ratios, such as the Treynor Ratio or the Sharpe Ratio, measure risk-adjusted profitability, but they are usually based on historical volatility (in the case of Sharpe) or systematic risk (in the case of Treynor). However, the renewable energy portfolio could be considered less risky in terms of volatility (or dispersion in our case), especially if the companies in the sector are perceived as innovative or aligned with sustainable market trends (Damodaran, 2002). This would explain why these ratios prefer renewables, as investors could expect continued growth and stable returns, even in a volatile environment.

The Capital Market Line, on the other hand, is based on the concept of efficient market portfolio according to Markowitz's modern portfolio theory. Fossil energy, although more volatile, may be associated with higher expected returns, due to their cyclical nature and strong global demand. According to (Philip Igeland et al.2024) Portfolios of fossil energy are often sensitive to economic and political fluctuations (oil prices, industrial demands, etc.) and the economic

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policy uncertainty positively impacts the returns of renewable stocks, attributing to an increased engagement towards a renewable transition, which can create opportunities for quick returns depending on supply and demand.

So, in the medium term, The CML would indicate that the fossil energy can offer a more attractive return because their high volatility, but it is riskier. But, In the long term, the renewable energy portfolio is preferred in terms of sustainable growth and resilience to environmental and societal risks. Because they are aligned with environmental, social and governance (ESG) criteria (Tlaty M., El Idrissi E.M et al, 2024), which are increasingly valued by institutional investors. These assets are therefore less exposed to energy transition risks and offer a safer and more ethical option for portfolios over a 10-20 year horizon. (Gencer et al 2024) highlights that policymakers should carefully consider the choice of intermediate objectives that impact paths toward greener energy in terms of trade-offs between governmental subsidies and market forces.and they have to determine roadmaps to achieve their long-term renewable energy objectives.

These contradictions reveal a tension between an approach based on short-term stability and an approach favoring better risk management. Renewable energies, although more volatile in the short term, offer better long-term growth prospects, aligned with global trends toward sustainable energy transition. In contrast, fossil energies are currently more stable in short term but face a growing regulatory landscape and potential downturn in demand. Therefore, if the priority is minimizing short-term losses and one has a low risk tolerance, then the fossil energy portfolio would be preferable because it has less of an expected return penalty. In contrast, if the investor can tolerate moderate short-term volatility in exchange for higher expected long term returns then they are directed to the renewable energy portfolio. The latter, -which not only better manages risk- but is also well positioned to benefit from the global transition to more sustainable energy sources.

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Conclusion

This study highlights that the Mean-Gini model, based on the Gini index, can be useful and versatile as a financial evaluation tool for the energy sector. Measuring dispersion using the Gini index improves on traditional risk measures such as variance that do not perform well for non-normal probability distributions. It allows us to construct optimal portfolios more efficiently than the traditional Mean-Variance model, adopting a superior framework for risk-return optimization. This is particularly relevant in the energy sector, given that renewable energy and fossil fuel markets are highly volatile sectors with aberrant reactivity. We concluded that fossil fuel returns would be less negative in the short term, but our analysis suggests that renewable energy portfolios better manage risks in the long term and will benefit from a broader transformation towards climate solutions. Furthermore, the Gini index as a risk measure improves traditional performance ratios and sets new directions for financial analysis and portfolio management. Given this, we recommend further studying the Mean-Gini model across sectors and developing new performance ratios linked to the Gini index. This study complements the ongoing discussion and research on financial risk measurement and portfolio optimization. It seeks to offer a new perspective to analysts and investors in this energy sector.

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