Dispelling ESG Investing Risk Misconceptions

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ABSTRACT

This research paper investigates the risks associated with Environmental, Social, and Governance (ESG) funds, aiming to clarify common misconceptions. We conduct an empirical study comparing the Value at Risk (VaR) and Downside-to-Upside Volatility (DUVOL) for ESG and non-ESG funds (the control sample). First, we establish that although VaR and DUVOL are both interpreted as downside risk measures, they exhibit different behaviors because one is an absolute measure and the other captures asymmetric volatility behavior, thus the results differ. Our results show that ESG funds have a higher VaR and ESG scores. However, no statistically significant relationship is found between ESG funds (or ESG risk scores) and DUVOL. This finding is consistent across a range of methods, including adding category and time effects, using instrumental variables, and matching methods. Finally, we investigate the predictability of downside risk using random forests methods. The results suggest that ESG risk scores are relatively more important in predicting downside risk than being an ESG fund. The overall findings are supportive of a link between ESG risk scores and downside risk, challenging the conventional belief that ESG funds inherently carry higher risks. These insights aim to enrich our understanding of the role of ESG investing in modern portfolio management strategies.

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1. Introduction

In recent years, the surge of interest in sustainable investing has brought Environmental, Social, and Governance (ESG) funds into the spotlight. These funds, prioritizing investments based on ESG criteria, are no longer a niche segment but a significant part of the global investment landscape. As the prevalence of ESG funds continues to rise, understanding their risk profile has become a topic of paramount importance for investors, fund managers, and policymakers alike.

However, ESG investing is controversial due to the incorporation of non-pecuniary factors in valuation analysis and security selection. As ESG assessment adds non-financial assessment and screenings, it may limit investment options, as securities that do not meet ESG criteria might be excluded from investment portfolios (Joliet and Titova, 2018). Moreover, it can also cause underinvestment in certain industries or regions, because ESG criteria can inadvertently favour companies in developed countries where standards and reporting on ESG issues are more advanced, or sectors that inherently have lower ESG risks, such as technology or healthcare, and underinvest in sectors like energy, utilities, or manufacturing, which are traditionally viewed as having higher ESG risks. This may result in less diversification and potentially lower returns for investors, thus increasing downside risk. On the other hand, ESG integration brings some advantages as it considers a wider spectrum of risks and opportunities. Investing in companies with strong ESG practices, potentially better positioned to weather environmental, social, and governance risks, may improve security selection, a key ingredient of outperformance. Additionally, it is widely recognized that holding a large number of securities in a fund can be costly. Consequently, portfolio construction often involves using sampling or optimization techniques to mitigate these costs. Furthermore, investors in ESG funds tend to be less reactive to short term performance, resulting in lower rates of redemption. This, in turn, means these funds generally maintain smaller cash positions and can make more long-term bets.

Therefore, the question of the risk of ESG funds[1] is far from having a straightforward answer. While ESG funds may confront challenges in terms of screen criteria and diversification, their strategic focus on firms adept at managing non-financial risks presents a compelling counterpoint, as improved assessment practices can be more beneficial for investors. For instance, Humphrey and Lee (2011) use a sample of 157 Australian SRI funds over the period 2003-2009, find that positive screens reduce fund risk. The study highlights that positive screens make funds invest in larger companies, while negative screens make funds invest in smaller firms.

[1]We will use the terminology "ESG funds" to denominate the spectrum of all funds that apply non-financial selection criteria.

While extensive empirical analyses have examined the performance of ESG funds, there has been a notable gap in assessing the associated risks. Empirically, whether ESG funds present more risk is not clear-cut. This paper aims to address this gap by analysing the downside risk of ESG funds. Moreover, in recent years, ESG (Environmental, Social, and Governance) rating methodologies have developed substantially. Investors now have at their disposal a set of indicators, such as ESG scores and ratings, designed to provide guidance in evaluating ESG performance. The critical question is how effectively these ratings capture downside risk.

In this study, we examine the downside risks of Environmental, Social, and Governance funds. We begin by calculating Value at Risk (VaR) and Downside-Upside Volatility (DUVOL) for ESG and non-ESG funds using daily returns data from 2019 to 2022 from more than 10,000 funds from an international sample. Because the landscape of ESG investing encompasses a range of strategies, we use several classification criteria, including Morningstar's sustainable fund tag, the Low Carbon Designation, and the use of exclusion policies, to identify ESG funds. By examining ESG funds across these different categorizations, we can gain a more comprehensive understanding of the risks within the varied approaches of ESG investing. To ensure the accuracy of our analysis, we contrast these ESG funds with a control group composed of funds that are not designated as Sustainable, Low Carbon, present exclusion policies or get a SFDR classification in 2021. This approach is crucial because many funds often embody two or three of these attributes simultaneously. Thus, by comparing ESG funds against a carefully selected control sample, we can draw more precise and meaningful conclusions. When comparing measures of downside risk, it is important to note that although they aim to capture downside risk, they differ significantly and show low correlation. Value at Risk (VaR) is expressed in terms of returns and captures potential losses. In contrast, DUVOL is a standardized measure, with a reference value of one, that focuses on the relationship between downside and upside volatility, capturing the asymmetric behavior of volatility. As a result, their behaviors differ, leading to distinct conclusions. While ESG risk scores are positively correlated with VaR, they show no association with asymmetric volatility behavior.

The results from the regression analysis indicates that ESG funds are positively associated with Value at Risk. However, when it comes to DUVOL, the analysis reveals no significant statistical relationship. To gain a more detailed understanding, we conducte quantile regressions, particularly focusing on the upper quantiles, that measure greater loss risk. The regression analysis reveals a positive association between ESG funds and Value at Risk. However, the relationship between ESG funds and DUVOL is not statistically significant. To explore these dynamics further, we conducted quantile regressions. Our findings indicate that the relationship between ESG risk scores and Value at Risk strengthens in the upper quantiles. But the coefficient for DUVOL varies across quantiles, being positive in lower quantiles and turning negative in higher ones. This variation explains the lack of a clear relationship in the initial regression analyses.

To enhance the validity of our findings, we performe additional analyses with different approaches. First, we create matched samples that confirme a positive association between ESG scores and Value at Risk, while also establishing no significant relationship with DUVOL. Then we further reinforced these results by using instrumental variables. Our analysis segmented by ESG fund type revealed that i) Sustainable Funds show no notable differences from conventional funds in terms of VaR and DUVOL, except for some instances where higher VaR was identified via instrumental variable analysis; ii) Low Carbon Funds are associated with higher VaR, but the evidence on DUVOL remains inconclusive. Iii) Funds that employ exclusions policy are associated with higher VaR, as consistently indicated by various tests using different VaR specifications. However, these funds tend to show lower DUVOL, a finding supported by our instrumental variable analysis. The use of multiple analytical methods helps to bolster the robustness of our findings.

A pratical question concerns whether the characteristics of funds can predict downside risk effectively. We applied random forest methods to investigate this, and our results indicate that ESG scores serve as more significant predictors of both Value at Risk (VaR) and downside volume (DUVOL) compared to the ESG funds themselves.

Our study makes a significant contribution to the debate on the likelihood of higher losses of ESG funds compared to traditional funds. This analysis is important in understanding ESG adoption and its compatibility with fiduciary duties, a subject that has captured the attention of investors, fund managers, media, and policymakers.[2] Our paper also makes a contribution to the literature that uses signals using machine learning methods in mutual funds (DeMiguel et al., 2023; Kaniel et al., 2023; Li and Rossi, 2020). We further explore whether ESG scores and ESG labels can effectively signal downside risk. Understanding these dynamics is crucial for investors who seek to incorporate ESG considerations into their risk management strategies. This suggest that the measurement by ESG scores are associated with downside risk metrics than the broader classification of funds as "ESG funds."

Moreover, our research indirectly addresses the question of the financial materiality of ESG

[2]The debate on fiduciary duty and ESG investing revolves around whether fiduciaries are legally obligated to consider ESG factors in their investment decisions. Traditionally, fiduciaries are expected to maximize financial returns for their clients. Some argue that incorporating ESG factors might conflict with this duty. However, others contend that ESG factors can significantly impact long-term financial performance, thus necessitating their consideration in investment decisions.

risks. Central to this discussion is whether comprehensive assessment and integration of ESG risks can enhance investment outcomes. By scrutinizing the downside risk of ESG funds, our study offers empirical evidence on the effectiveness of ESG risk management in practice.

2. Data and Variables

2.1. Sample

Our study examines a sample of equity funds spanning from December 2019 to December 2022. This period was specifically chosen due to the recent availability of ESG risk ratings.[3]

The analysis is conducted at the fund level, acknowledging that the holdings are equal at the fund. Data for this study was sourced from Morningstar Direct and Eurofidai. To calculate the downside risk measures, we used daily returns data obtained from Eurofidai and Morningstar, with the latter being the source for US-based funds. This approach enabled us to calculate a comprehensive set of risk measures for over 10,000 funds of an international sample.

However, the availability of certain fund features is more limited. Notably, Morningstar ESG scores are only available for a subset of these funds, reducing the sample size in our empirical analysis.

Consistent with standard practices in similar studies, we applied a series of filters to refine our sample: i) We excluded funds with fewer than 11 assets, as these often contain derivatives. ii) Funds with a total size of less than 1 million dollars were omitted to avoid inception bias. iii) Sharia funds were excluded due to their specific religious focus. iv) Funds of funds were also excluded because they include bond holdings. v) Leveraged funds were also excluded because of the use of derivatives as other type of funds as strategic beta and risk enhance funds.

[3]It is noteworthy that the focus on ESG risks and opportunities by rating agencies has gained prominence in recent years. Our ESG risk data is sourced from Morningstar, which has been evaluating financial risks since November 2019.

2.2. Variables

2.2.1. Financial Risk

Two risk measures are used in this paper, namely Value-at-risk and downside-to-upside volatility (DUVOL). VaR is often used to assess the level of financial risk within a company, portfolio or position over a given period of time, as it indicates the maximum potential loss during a given period for a given confidence level. It is widely accepted as a measure of risk in the banking sector, and has been gaining acceptance in the investment industry. We have calculated the historical VaR for a confidence level of 95%. Its main advantages include: its ease of calculation; the fact that it does not assume a theoretical distribution of returns, which can be beneficial when the actual distribution of returns deviates significantly from the normal distribution, which is often the case for financial returns; the inclusion of actual correlations observed in the past between asset returns, which can be complex and difficult to model using other methods; the wide acceptance by financial industry regulators, which means that companies can use this method to calculate regulatory capital requirements, and the fact that it is not necessary to forecast volatilities and correlations, which can be difficult and unreliable.[4]

DUVOL refers to the ratio of downward volatility (when prices fall) to upward volatility (when prices rise). This ratio can give investors a more comprehensive view of risk by incorporating both downside risk and the level of uncertainty, offering a more robust risk assessment compared to traditional risk measures like VaR (Ameur et al., 2024). DUVOL provides insight into how an investment will perform under different market conditions, especially in falling versus rising markets. The key benefits include: It provides nuanced insights into the asymmetric behaviour of asset price movements and highlights the differences in volatility between rising and falling states, which is critical to understanding risk. [5]

VaR and DUVOL are calculated every six months from June 30, 2019 to December 30, 2022 using about 120 daily observations to calculate them. The summary statistics for these two metrics can be found in Table 1. For easier interpretation, we have adjusted the variables by multiplying them by 100. Additionally, we multiplied the VaR by -1 that corresponds to the VaR of the loss. This standardization ensures that for both variables, a higher value indicates a greater downside risk, making it more intuitive for readers to understand the analysis and

[4]Some papers, among many others, that use historical VaR are Danielsson and De Vries (1997); Boudoukh et al. (1998); Hull and White (1998); Barone-Adesi et al. (1999); Boucher and Maillet (2013); Claußen et al. (2019); Hendricks (2022) and an overview of the methods for calculating VaR can be found in Abad et al. (2014).

[5]Recent papers that use this measure are, for instance, Chang et al. (2017); Jung et al. (2022); Liao et al. (2023); Zhao et al. (2023).

coefficients on the tables.

While DUVOL is essentially about understanding the behaviour of asset volatility in response to different states, VaR provides an estimate of the potential level of loss in a portfolio over a given time period, which is crucial for financial risk assessment and decision making. Nevertheless, we note that DUVOL is standardized and independent of the level of the risk of the fund, while VaR will be dependent on the overall level of risk of the fund. To illustrate this point, we exhibit in Figure 1, where the two downside risk measures are displayed against the standard deviation. In addition, we have fitted a quadratic form to capture the nature of the relationship. In Panel A we see that VaR is increasing with standard deviation, while in panel B, DUVOL displays an almost flat relationship with the standard deviation, coming from the fact that is a standardized measure with 1 being the reference value. This confirms the different nature of measures and that the results might differ.

The mean value of DUVOL is higher than the median, which indicates a right-skewed distribution, i.e. there are extreme values that push the average upwards. The large difference between the mean and the median in combination with a high standard deviation (SD) and a wide range between the minimum and maximum values indicates that the DUVOL distribution is likely to have strong peaks and outliers, indicating periods of significantly higher volatility under certain market conditions. The negative values of DUVOL represent when the downside volatility is lower than the upside, as the ratio is logarithmic, the values of the variable become negative. We see that these values are lower than the 25 percentile. Similarly, the mean of VaR is also higher than the median. The mean VaR is 2.05% for daily values. [6]

In the robustness section, we provide additional analysis using estimations using as downside risk measures: the negative conditional skewness (NCSKEW) provided by Chen et al. (2001) , the VaR computed with other specifications and downside volatility.

2.2.2. Measures of extra financial risk

To assess non-financial risk, we use the Morningstar Historical Corporate Sustainability Score (*ESG risk score*), also known as the ESG risk score for corporates. This score offers a retrospective evaluation of a company's ESG performance over the previous 12 months. It is derived from a weighted average of the company's monthly Portfolio Corporate Sustainability Scores. The score is presented on a scale ranging from 0 to 100, with a higher score indicating a greater level of

[6] We have winsorized VaR and DUVOL at 0.005 because we notice some extremely higher outliers, possibly due to data errors.

ESG risk.In Table 1 we see that both the mean and median values are around 23. The standard deviation is 3 which means that values are quite concentrated around the mean.

2.2.3. ESG funds

ESG investing has undergone significant development. In its early stages, it primarily focused on choosing assets that aligned with moral and ethical standards, often involving the exclusion of "sin stocks". [7] Over time, the investment strategy has progressed. It moved from being simply about Socially Responsible Investing (SRI) to adopting a broader approach known as ESG integration, which encompasses a more comprehensive strategy. This modern paradigm adopts a holistic view, factoring in multiple dimensions of non-financial risks in asset selection. At its core lies the concept of the financial materiality of non-financial risks and their consequential impact on security valuation.[8] We define ESG funds using the classification from Morningstar, which categorizes these funds based on specific ESG attributes. This approach allows us to capture the variety inherent in ESG investing strategies. We focus on three key salient attributes: Morningstar's Sustainable Attributes framework.[9] We utilize a dummy variable to denote whether a fund is labelled as sustainable (*Sustainable*) during our study period. Morningstar also identifies funds with a 'Low Carbon' label, indicating those with minimal overall carbon risk and reduced involvement with fossil fuel companies. A dummy variable (Low Carbon) is used to tag whether a fund is classified as a Low Carbon fund throughout the analysis period. Another aspect of ESG funds is their use of exclusion policies. We rely on Morningstar data to determine whether a fund employs an exclusion policy (*Exclusions*) and create a separate variable to quantify the extent of these exclusions. In Table 1 we see that 30% of funds of our sample are classified as sustainable, 45% as low carbon and 61% have exclusions policy.[10]

The implementation of the Sustainable Finance Disclosure Regulation (SFDR) in March 2021 represented an important development. The SFDR allows funds to be categorized as Article 6, 8, or 9. This classification provides investors with clear information about the sustainability characteristics and objectives of each fund. According to the regulation, asset managers have the option to classify funds into article 8 (pertaining to funds that promote environmental and social

[7]'Sin stocks' generally refer to sectors such as tobacco, gambling, and alcohol, among others.

[8]Financial materiality refers to the impact that non-financial information can have on a company's operational and financial performance.

[9]It was introduced in 2020, superseded the earlier 'Socially Responsible Fund/Socially Conscious' categorization

[10]We observe a significant correlation among these variables, particularly between the sustainable classification and the exclusion policies. However, our tests for multicollinearity do not indicate any substantive issues arising from these correlations.

characteristics but without prioritizing them as the overarching objective) or article 9 (pertaining to funds with sustainable goals as their primary objective), with all other funds falling under article 6. We additionally use this classification to help in the design of our research design and for robustness.

We are interested in analysing ESG funds versus peer funds, so we construct a control sample that includes non ESG funds, which excludes previous classifications of Sustainable, Low Carbon, and funds with exclusions, as well as funds that will be classified as articles 8 and 9. This ensures that the control group strictly consists of conventional funds, devoid of any implicit ESG influence.

We begin by conducting an initial inspection to determine whether there are differences among the subsamples. Panel A of Table 2 shows the average downside risk measures by the subgroups. The control group, conventional funds, exhibits the highest value at risk (VAR = 2.2) and significantly higher asymmetric volatility (DUVOL =20.20), suggesting greater downside risk compared to the other subsamples of ESG funds. However, we note that the basket of conventional funds includes a large variety of investment strategies. Low carbon funds are the ESG fund type with higher VaR and DUVOL. Figure 2 displays the distribution of both downside risk measures by type of funds. The VaR distribution is skewed to the left, and the DUVOL tends to resemble comparatively a more normal distribution.

Panel B of Table 2 shows the distribution of ESG scores by the types of sustainable funds. The bulk of distribution is centered around 20-30 scores for all type of funds. The second fact to point is that knowing that all types of ESG funds have a large frequency on the lower tail of ESG scores (lower scores) than conventional funds. Thus, conventional funds tend to have higher ESG risk scores than ESG funds. Notably, the Low Carbon, Exclusions, and Sustainable subsamples display a more varied distribution in 10-20 risk scores categories. For instance, investments with scores in the 10 range are predominantly found in the Low carbon (20.6%), Exclusions (21.7%), and Sustainable (25.6%) subsamples. The control group, conversely, has higher percentages in the 30 (10%) risk categories than other subsamples, indicating a broader acceptance or occurrence of medium ESG risks.

2.2.4. Control Variables

The selection of control variables is connected to variables that could affect either the dependent variable or the variable of interest, specifically in the context of an ESG fund.

Size of the fund Previous studies indicate that Socially Responsible Investment funds are often newer and have smaller assets compared to conventional funds. To accommodate this difference, our analysis includes a control for fund size. We measure this using the total value of all share classes in millions of U.S. dollars (Total Net Assets). To address the skewed distribution in fund sizes, we use the logarithm of this value (log TNA). Generally, larger funds have the capacity to invest in a more diverse range of securities, potentially increasing diversification. However, they might face challenges in maintaining liquidity, particularly when investing in smaller, less liquid assets. Conversely, smaller funds often have greater flexibility and can adjust their holdings with minimal market impact. Both these factors can influence a fund's risk profile.

Morningstar Star Ratings and Past returns Past returns affect the computation of our risk measures, so we control for that effect. Moreover, research has demonstrated that that investor decision making is often influenced by past performance and that Morningstar star ratings significantly impact the flow of investments into funds (Evans and Sun, 2020; Ben-David et al., 2022).[11] Consequently, funds with poorer past performance may be motivated to undertake higher risks, as successful outcomes could result in increased investment flows. Research has shown that higher -level convexity is positively associated with higher levels of risk taking by fund managers.

In our analysis, we use Morningstar's three-year ratings (*Star ratings*), which assess a fund's historical risk-adjusted returns in comparison to other funds in the same category. These ratings range from one to five stars, with a higher star rating indicating superior past performance, adjusted for risk. To account for the impact of past performance on risk-taking behaviour, our study considers not only the returns from the previous six months but also those from the past three semesters. This approach helps us understand how historically poor performance might incentivize funds to engage in riskier investments. For ease of interpretation, all return values are multiplied by 100.

Concentration of Holdings To measure concentration of holdings, we use a variable that measures the sum of weights of top 10 holdings *(Concentration Top 10)* in Morningstar, thus the larger it is, the larger is concentration. Morningstar defines as *"The aggregate assets, expressed as a percentage, of the fund's top 10 portfolio holdings. This figure is meant to be a measure of portfolio risk. Specifically, the higher the percentage, the more concentrated the fund is in a few companies or issues, and the more the fund is susceptible to the market fluctuations in these few*

[11] Additionally, research has shown that higher -level convexity is positively associated with higher levels of risk taking by fund managers (Chen and Pennacchi, 2009; Ferreira et al., 2012; Fu et al., 2012)

holdings. Cash and cash equivalents are generally not included in this calculation. (An exception is made for money market portfolios.)"

Static Fund Variables In our study, we use several dummy variables to control for fund characteristics that could contribute to higher risk. These variables help us control for specific fund features in our analysis. The key features we consider are as follows:

Index (*Index*) Index Funds are pure passive funds. Table 1 shows that 8% of our sample are index funds.

Non-Diversified Funds (*Non-Diversified*): Identified by Morningstar as non-diversified, these funds do not spread their investments across a wide range of assets, potentially increasing their risk due to higher concentration in specific stocks, sectors, or regions. This binary attribute is obtained from the fund's prospectus language. Table 1 shows that 6% of our sample are non diversified funds.

Institutional Funds (*Institutional*): Funds with share classes designed for institutional investors typically involve more sophisticated investors who may be more inclined to take risks. These funds cater to the needs and expectations of institutional investors, who often have different risk-return profiles compared to retail investors. Table 1 shows that 53% of our sample are funds with an institutional share class.

Investment style Additionally, we use Morningstar equity style box, which determines the investment style of each individual stock in its database. The style attributes of individual stocks are then used to determine the style classification of stock portfolios. We consider investment styles such as size (large-cap (*Large*) vs. small-cap (*Small*)) and value strategy (value (*Value*) vs. growth (*Growth*)). These styles have distinct risk profiles, with small-cap and growth funds generally perceived as higher risk compared to large-cap and value funds, respectively. Table 1 shows that 68% of our sample are large capitalization funds, while 11% small capitalization funds. 22% of our sample are classified as value funds, while 30% are classified as growth funds.

Table 3 presents the correlations among the variables analysed in our study. Correlation between the two risk measures, Value at in the robustness section and Down-Up Volatility (DUVOL), is relatively low at 0.04. This indicates that VaR and DUVOL are influenced by different factors and demonstrate distinct behavioural patterns. This difference may stem from VaR being expressed in absolute returns, while DUVOL is a standardized measure, representing a ratio of the two-state volatility of an asset. This distinction is further evident in the way the ESG risk score correlates with these measures: the correlation in higher with VaR than with DUVOL. Additionally, We observe that sustainable, low carbon and funds that implement exclusion policies show a negative correlation with both DUVOL and VaR.

Regarding fund characteristics, our analysis highlights varied correlations with risk measures based on fund styles. Specifically, small-cap and value styles exhibit positive correlations with ESG risk scores, while the large-cap and growth style shows a negative correlation.We also note a positive correlation between fund concentration with VaR and negative with DUVOL. Moreover, non-diversified funds are positively correlated with concentration, indicating a higher concentration on top holdings.

3. Empirical Results

3.1. Do ESG Funds Have Lower ESG Risk Scores ?

We start by analysing whether ESG funds have higher or lower ESG risk controlling for different fund features. We do the following regression where the dependent variable are ESG risk scores,

$$\text{ESG Risk Score}_{i,t} = \alpha_0 + \beta \times \text{ESG\_Fund}_{it} + \theta X_{i,t-1} + \text{FE} + \varepsilon_{i,t} \tag{1}$$

ESG_Fund are our dummies that indicate whether the fund is Sustainable, Low Carbon or has exclusions and $X\_(i, t-1)$ is a set of fund control variables. β will be our coefficient of interest, if ESG funds have higher (lower) risk, the coefficient β should be positive (negative). We control for fund investment styles using Morningstar categories, and time effects.

Given our objective of comparison of ESG funds with conventional funds. We use a control sample consisting exclusively of funds that are not classified as any "ESG label" as Sustainable, Low Carbon, do not apply Exclusion policies, and are not labelled on SFDR categories. This method ensures that our comparisons focus solely on types of ESG and conventional funds. In Table 4 column (1) compares Sustainable funds with conventional funds. In column (2), we evaluate Low Carbon funds alongside the control sample. Similarly, column (3) compare funds with Exclusions with conventional funds. Analysing all these funds together could potentially confound our analysis, so we carefully separate the comparisons for clearer insights. The results of estimation of Equation 1 displayed in Table 4 show that the coefficients for our three ESG fund proxies are negative and statistically significant. This suggests that ESG funds tend to be linked with lower ESG risk scores, a finding that aligns with correlations on Table 3.

Additionally, we observe trends in ESG risk scores based on the investment style of the funds. Funds that focus on value and small-cap stocks tend to have higher ESG risk scores. In contrast, funds that concentrate on large-cap and growth stocks usually show lower risk scores. These patterns remain consistent across various models in the table. We also note that funds with higher star ratings are associated with lower ESG risk scores. Regarding the explanatory power of our models, indicated by the R^2 value, it is relatively high. This suggests that the model explains well the variation in ESG risk scores.

We have also recomputed this table using Morningstar sustainability globes as dependent variable, or incorporating scores from the environmental, social, and governance pillars. The findings reveal that ESG funds not only achieve higher globe ratings but also exhibit lower risk scores, particularly in the environmental pillar (results available from authors upon request).

3.2. Do ESG risk scores capture downside risk?

The question we tackle in this section is whether ESG risk scores capture downside risk. To investigate this, we first conduct a visual analysis by plotting downside risk measures against ESG scores. We also add a quadratic form to understand better the nature of the relationship. Figure 3 reveals that Value at Risk tends to increase with ESG scores, at an increasing rate, indicating that higher ESG risk scores have a stronger impact on VaR. However, DUVOL does not show any clear relationship with ESG scores, we observe a flat line. To gain more insight, we examine other key variables. The standard deviation increases with ESG scores and shows a similar marginal increasing relationship with ESG scores. Returns exhibit a concave pattern, meaning that funds with both very low and very high ESG scores tend to underperform. Finally, star ratings, which are risk and category adjusted performance metrics, have a declining relationship with ESG scores, suggesting that better-performing funds within each category generally have lower ESG scores.

Overall, this analysis indicates that ESG risk scores are linked to general risk levels, but their relationship with downside risk, as measured by DUVOL, is less clear.

Next, we analyse the relationship between ESG risk scores and downside risk, focusing whether differences exist across subsamples by examining conventional funds, sustainable funds, low-carbon funds, and funds with exclusions. We explore both linear and nonlinear specifications, given that VaR and volatility often have nonlinear relationships with predictors, particularly driven by market events (Mittnik et al., 2015). Nonlinear models more effectively capture asymmetric responses, which are crucial when analysing reactions to market events. This is relevant for DUVOL because it is affected by both rising and falling volatility.

To disentangle the effect of ESG risk, we separate the conventional funds and the types of ESG funds. Table 5 presents the results. To start, we note that much of the observed variability can be attributed to investment style and time effects, as indicated by the R^2 values. In Panel A, the coefficients for the ESG Risk Score are positive across subsamples, but they are higher for ESG funds. This means that higher ESG scores are associated with higher downside risk. The coefficients past 6 months returns and star ratings are negative and significant across the models. This shows that good performance is associated with lower downside risk, as highlighted in the correlation table. The coefficient of concentration of holdings is positive and significantly statistically, which implies that higher concentration of holdings correlates with higher downside risk. The coefficients fund size and non-diversified are not significant. The investment style of large Capitalization is not statitically significant in conventional funds, but is negative on ESG funds. Growth style coefficient is positive indicating impacts of this investment style on VaR.

An intriguing finding emerges on Panel B, when examining the relationship between ESG risk scores and DUVOL within ESG-focused funds. We find no significant relationship for ESG funds, while a negative one appears in the control group. The coefficients past 6-months returns and star rating are positive and significant across the models. This shows that good performance is associated with higher DUVOL. The coefficient of concentration of holdings is negative, which implies that higher concentration of holdings correlates with lower DUVOL. The coefficient of fund size is negative and statistically significant.

Two main results emerge from our analysis: First, that the relationship between ESG risk scores and VaR is positive and nonlinear. Secondly, that the relationship between ESG risk scores and DUVOL seems absent in ESG funds but negative in the control sample. These findings highlight the need to consider different specifications for these variables, as they have distinct underlying drivers. Multicollinearity tests reveal high multicollinearity between ESG scores and their squares. As a result, we continue using the squared term in subsequent specifications. This choice is further justified by the visual inspection of Figure 4, where we see that the relationship between VaR and ESG scores is convex, and DUVOL and ESG scores is concave.

3.3. Do ESG Funds Have More Downside Risk?

In this subsection, we analyse whether ESG funds have more downside risk, and thus investors have more probability of losses. We run the following regression where the dependent variable are downside risk measures VaR and DUVOL,

$$\text{Downside Risk}_{i,t} = \alpha_0 + \beta \times \text{ESG\_Fund}_{i,t} + \gamma \times \text{Risk Score}^2_{i,t} + \theta X_{i,t-1} + \text{FE} + \varepsilon_{i,t} \qquad (2)$$

ESG_Fund are our dummies that indicate if the fund is labeled Sustainable, Low Carbon or applies exclusions and $X\_(i, t-1)$ is a set of fund control variables. β will be our coefficient of interest, if ESG funds have higher risk, the coefficient should be positive. The coefficent γ will control for the effect of ESG risk scores. As shown on Table 5, γ is expected to be positive for VaR and not to be staitically significant for DUVOL. We control for investment style effects using Morningstar categories, and time fixed effects.

We keep the regressions running between the different ESG categories and the control group of conventional funds, to better isolate the *ESG fund* effect. Table 6 presents the results, Panel A for VaR and Panel B for DUVOL. Columns (1), (3) and (5) of Panel A show that ESG funds coefficients are not statistically significant, but when we add the risk score, the coefficients become positive and significant for funds with exclusions policies. This means that sustainable funds and funds with exclusions have higher downside risk compared to non-sustainable funds. The coefficients of star rating and past performance are negative as in Table 5, and the coefficient of concentration of holdings is significantly positive, which implies that higher concentration of holdings correlates with higher downside risk. The coefficient of the Large Cap investment style is negative and statistically in most cases, meaning that this investment style tends to be negatively associated with VaR, while for the Growth investment style funds, we find the opposite effect.

In Panel B of Table 6, the dependent variable is DUVOL, and in all the models the coefficient β is negative. For sustainable funds and funds with exclusions, β is statistically significant suggesting that funds labelled as sustainable are associated with lower DUVOL. For Low Carbon funds, the coefficient is positive but not statistically significant. The coefficient of variable $ESGRiskScore^2$ is negative and statistically significant, mostly driven by non ESG funds as suggested in table Table 5. The other coefficients do not show much difference from Table 5. Concentration of holdings shows negative coefficients. Star Rating and past 6-months returns have positive and significant across all models, suggesting a positive relationship between performance and downside risk. Another point worth to notice is the lower R^2 value, indicating lower explanatory power of the model compared to the VaR one.

The overall analysis of Table 6 confirms again that the factors influencing Value at Risk and Downside to Upside Volatility seem distinct, as already noticed by the low correlation between variables and the evidence of Table 5, pointing to different underlying drivers for these two downside risk measures. We next proceed with different analysis that aim to explore the non-linearities we find and the disentangling of the simultaneous effect of ESG funds and ESG scores.

3.3.1. Quantile regression analysis

We proceed to re-examine whether ESG funds exhibit greater downside risk by employing quantile regression. This method offers a more nuanced perspective, especially regarding the behaviour of ESG funds under conditions of higher losses and increased downside volatility. Our primary focus is on the coefficients corresponding to the upper quantiles, as these represent scenarios with potential losses. In our analysis, we estimate the quantile regression incorporating fund-specific variables and time fixed effects, enabling a more detailed understanding of the risk dynamics in ESG funds.

Table 7 presents the results of our quantile regression analyses. Due to space constraints and the extensive size of tables typically generated by quantile estimations, we only include the results for Sustainable funds in the main document. Results for other ESG fund classifications are available in the supplementary appendix. The overall patterns observed across these classifications are similar.

The inspection of ESG Risk Score^2 on the different quantiles is quite enlightening about the relationship with downside risk measures. There is an increasing trend with both downside risk measures, so its impact is higher at higher quantiles. However, the difference is that in VaR the coefficient is always positive in all quantiles, while in DUVOL in negative in the lower quantiles and positive in the upper quantiles, elucidating the lack of statistical significance observed in Table 5 and in Table 6. This variation across quantiles suggests that the coefficient is not constant. Our dependent variable being a ratio, lower values imply that the denominator (upside volatility) is more significant than the numerator (downside volatility), resulting in a ratio lower than 1, that converted to log becomes negative. For this case, we find a positive coefficient. Conversely, in the upper quantiles, downside volatility outweighs upside volatility, thus the ratio is higher than 1, and the log is positive, and we find a negative coefficient. Overall, it suggests that ESG risk scores are positively related with upside volatility and negatively related with downside volatility. For the variable ESG fund, we consistently observe a negative coefficient β. Increasing in VaR and decreasing with DUVOL, suggesting that ESG funds are less likely to have downside risk, but with changes of intensity over the quantiles.

3.3.2. Matching on ESG scores and other fund features

The close relationship between ESG funds and ESG scores prompted us to conduct additional analysis. To better distinguish the effect of ESG funds from ESG scores, we utilize matching methods that help identify and control for potential confounding variables. The core of this approach involves creating two comparable groups: a 'treated' group, comprising ESG funds, and a 'control' group made up of non-ESG funds.

In a first step, we examine the fund characteristics most closely linked to being labelled as an ESG fund. We employ a logistic regression and assess the significance of the variables using margins and t-statistics. The results indicate that ESG funds are more likely to be categorized under Growth or Large capitalization investment styles but are less likely to be indexed, non-diversified, or value investment style. As expected, they are also associated with lower ESG scores. The variables selected to match samples are the ESG risk score and investment styles, which include Growth, Large, Index, and Non-Diversified. These variables were chosen to ensure comparability between the groups and to prevent confounding effects. [12]

To improve this process, we perform period-by-period matching with replacement and calculate propensity scores. We then exclude the lowest quartile of funds based on their propensity scores to enhance the comparability of the groups, dropping observations with poorer matches. After the matching process, we have two well-defined groups: the 'Treated' group (ESG funds) and the 'Control' group (non-ESG funds). By comparing these groups, we can more accurately assess whether the lower Value at Risk observed in ESG funds is attributable to their ESG attributes or if other confounding factors are affecting the results.

Next, we reestimate Equation 2 using the matched sample. The results are presented in Table 8. Sustainable funds are not statistically significant for VaR in column (1). However, when we add the ESG risk score to the model, the coefficient becomes positive and statistically significant. For DUVOL, the coefficient of Sustainable funds is not statistically significant in any of the specifications. However, the ESG risk score is statistically significant and positive. (Results for other ESG fund classifications available from authors upon request).

[12] Results of the logistic regression are presented in supplementary appendix.

3.3.3. Instrumental Variables

In this section, we continue with alternative methods to analyse the effect of ESG funds and ESG scores on downside risk, now using instrumental variables (IVs) that are a powerful tool for removing unmeasured confounding and endogeny that can bias estimates of causal effects in observational studies (Arellano and Bover, 1995; Honoré and Hu, 2004). IVs can mitigate the effects of unmeasured confounders by influencing treatment choice without directly affecting the outcome, allowing more reliable inferences about causal relationships.[13]

We carefully select two variables as instruments for our analysis. The first is a dummy variable indicating whether a company has signed the Principles for Responsible Investment (PRI)[14]. The second instrument is a dummy variable for growth investment style. Investment companies that adhere to the PRI are more likely to offer sustainable funds, so we identify these companies and create a dummy variable for their affiliation. Our tables show that the growth investment style is highly correlated with ESG funds. While selecting suitable and valid instruments is always challenging due to the difficulty in finding appropriate ones, we aim to clarify the relationships by choosing these distinct instruments.

For reasons of clarity, we only present the results for sustainable funds on Table 9. The results for other ESG fund classifications can be found in the Supplementary Appendix. In Panel A, we find that in all specifications, the coefficient of sustainable funds is positive and statistically significant for VaR. The coefficient γ of the square of the ESG risk score yields consistently statistically significant positive coefficients in all models. In Panel B, the coefficient β is statistically insignificant or negative and statistically significant, depending on the instrument. The other variables are consistent with the previous analysis, and we do not repeat the comments for the sake of brevity.

Overall, the results are consistent with those of Table 6 and the conclusions from the use of matching methods, which underlines the robustness of the results of the different effects depending on the measure.

[13]Recent papers that use this methodology are, for instance, Mertzanis and Tebourbi (2024); Powell (2022); Rakowski and Yamani (2021)

[14]Principles of Responsible Investment (2015) defined the Principles for Responsible Investment (PRI) as an international initiative endorsed by the United Nations in 2006. It is a set of guidelines developed by investors for investors that aim to integrate environmental, social and corporate governance (ESG) factors into investment strategies. The main objectives of the PRI are to promote sustainable financial practices, mitigate investment risks and achieve long-term returns. The effects of PRI compliance can be observed through statistical data reflecting increased investment in sustainable initiatives, reduced financial risks associated with ESG factors and improved corporate governance in companies.

3.4. Do fund features predict Downside risk?

In this section, we investigate the research question through the lens of predictability. Existing evidence supports non-linear relationships between dependent and independent variables, so we employ machine learning methods, such as random forests, to analyse the relationship between our variables of downside risk and ESG funds, and ESG risk scores.

Random forests are a powerful ensemble learning method often used for classification, regression and other prediction tasks. This method builds on the concept of decision trees and combines the predictions of numerous trees to mitigate the problem of overfitting that often occurs with single decision trees. By incorporating randomness in both the selection of split candidates and the bootstrap sampling of data points, random forests improve the prediction accuracy and robustness of the model.

In our research, we use the package `randomForest` in R (Liaw and Wiener, 2023), where we set the parameter `ntree` to 1000 to construct 1000 decision trees to improve the stability and predictive power of the model. Choosing a large number of trees helps to achieve a good balance between bias and variance, effectively capturing complex structures in the data while avoiding overfitting.

An important aspect of using this methodology is the evaluation of the importance of the variables using the IncNodePurity measure. This measure quantifies the increase in the prediction error of the model when the values of a variable are permuted across nodes. In Random Forests, IncNodePurity is calculated by summing the reduction in node impurity (variance in the regression) attributed to each variable across all trees. Variables with a higher IncNodePurity are considered more important as their correct values are crucial to achieve a lower prediction error. This gives a clear indication of which features contribute most to the prediction model. To improve the interpretability of the results, we calculate the sum of the measure of node impurity measure across all variables. Each variable is then weighted so that the total sum of all variable weights equals one.

Given that, we have a panel dataset consisting of observations over time for different funds. To evaluate the prediction performance of our model, we split the data into a training and a testing dataset, where 80% of the funds data are used for training and the remaining 20% for testing.

Our prediction task specifically targets the last semester of the dataset to gain insights into the temporal dynamics and possible future trends in the panel data. To evaluate the predictions of our model, we use different statistical measures. The Mean Absolute Error (MAE) provides a simple interpretation of the average error magnitude without considering the direction. Root Mean Squared Error (RMSE) is a more sensitive measure where errors are squared before averaging, penalizing larger errors more heavily, which is particularly useful for highlighting the impact of outliers. In addition, the coefficient of determination, commonly known as R^2, measures the proportion of variance in the dependent variable that is predictable by the independent variables. It provides a scale-free value that we can use to assess the explanatory power of the model.

Results The use of random forests provides valuable insights into the hierarchical importance of variables that influence downside risk. In these models, the concept of "variable importance" helps to understand how different predictors contribute to the model's predictions.

In the Value-at-Risk model, the analysis shows that past returns, ESG scores and the concentration and size of the funds are the most important variables. These factors strongly influence the model's ability to predict downside risk. On the other hand, the "sustainable fund" designation is less important for predicting short-term financial risk. For the DUVOL model, the results are consistent and show that past returns and fund concentration are the most important indicators besides ESG risks. In addition, fund size is significant, suggesting that larger funds may have higher risk. Similar to the VaR results, the sustainable label of a fund is not an important predictor for the DUVOL model.

Figure 5 provides a basis for discussing the impact of different variables on downside risk measures. In terms of Value-at-Risk, the variable concentration on the top 10 holdings initially has an increasing effect, meaning that as concentration increases, so does the level of downside risk. At higher concentration levels, however, this relationship weakens and the marginal effects decrease. In the case of DUVOL downside risk, the effect of concentration is exactly reversed. Initially, it has a diminishing effect on DUVOL, but after a certain point its influence increases again, which means that a higher concentration ultimately leads to a higher downside risk. The relationship between ESG risk scores and downside risk measures is more complex. For Value-at-Risk, the relationship is initially flat, indicating minimal influence. However, the influence of risk scores then increases and leads to higher VaR values. However, this increasing effect is eventually reversed, and the influence decreases again. With DUVOL, the relationship is flat at lower risk values. However, as the values increase, the relationship increases again. We note that the ESG scores show most of the distribution between 10 and 30 scores, so meaningful conclusions should be drawn from this. The numbers allow us to understand the non-linear relationship between the variables.

Finally, Table 10 shows the out-of-sample performance metrics for the last semester. The results indicate that the predictions of Value-at-Risk are generally more accurate than those of DUVOL downside risk, as evidenced by lower RMSE and MAE values and a comparatively high R^2.

4. Robustness Analysis

4.1. Other Downside risk measures

We have re-analyzed the estimates by using other proxies for downside risk such as the negative conditional skewness (NCSKEW) of Chen et al. (2001) as a measure of financial risk. NCSKEW is a financial metric that describes the asymmetry of return distributions and emphasizes the negative side. It quantifies the likelihood and severity of negative returns, with a higher NCSKEW indicating a greater risk of negative returns due to a longer or thicker left tail. This measure is particularly valuable during financial crises or bear markets when investors are especially concerned about potential losses.[15]

In addition, we have taken downward volatility (DVOL) into account. We have also used other methods to calculate the Value-at-Risk, in particular the modified VaR (VaR-M) and the Gaussian VaR (VaR-Gaussian). These metrics are calculated semi-annually, from June 30, 2018 to December 30, 2022, based on approximately 120 daily observations.

Figure 7 illustrates the relationship between these indicators and the ESG scores. The VaR and volatility measures show a convex relationship with the ESG scores, while the negative skewness shows a concave relationship.

We re-stimate our main Equation 2 with dependent variables, the above variables. Panel A of Table A17 in the supplementary appendix presents results for other VaR measures. The findings for modified VaR are similar, a positive coefficient observed for low carbon and funds with exclusions. Sustainable funds show no significant relationship with VaR. For negative skewness, ESG risk scores appear more influential than Sustainable funds. Exclusion funds have a negative coefficient, while sustainable funds show no significant relationship, and low-carbon funds reveal a significant positive relationship when ESG risk scores are added. Regarding downside volatility, low-carbon funds have a positive coefficient. However, the coefficients for

[15] A recent application of this measure is in Jung et al. (2022), which employs various crash risk measures, including NCSKEW, to investigate firm-specific factors contributing to crash risk.

sustainable and exclusion funds are not statistically significant.

5. Conclusion

In recent years, the interest in sustainable investing has notably increased, bringing Environmental, Social, and Governance funds into prominence. These funds, which prioritize investments based on ESG criteria, have become a significant component of the global investment landscape.

ESG investing, integrating non-financial factors in valuation and security selection, remains controversial. The inclusion of ESG criteria might limit investment options and lead to under-investment in certain industries or regions, potentially reducing diversification and increasing downside risk. However, investing in companies with strong ESG practices could lead to better risk management and potentially enhance performance.

The study seeks to fill the gap in understanding the downside risks associated with ESG funds, focusing on two key metrics: Value at Risk (VaR) and Downside-to-Upside Volatility (DUVOL) computed using data from 2019 to 2022 for a large sample of international funds.

The regression analysis reveals that ESG funds are positively associated with VaR, suggesting lower likelihood of losses. However, there is no significant statistical relationship with DUVOL. Quantile regressions, particularly on upper quantiles which indicate higher loss risk, show that the negative correlation with ESG funds is more pronounced in these riskier scenarios. The coefficients for DUVOL vary across quantiles, being positive in lower ones and negative in upper ones, which explains the absence of a clear relationship in initial analyses. Thus, the detailed inspection of quantiles shows evidence supportive of the association between ESG funds and lower downside risk.

The study reveals that the behaviours of the two proxies for downside risk – Value at Risk (VaR) and Downside-Upside Volatility (DUVOL) – do not always align. This discrepancy is largely due to the differences on the focus of these measures. However, they are still valuable as they provide complementary perspectives on risk.

ESG risk scores seem to subsume ESG funds importance, and seem to be an indicator of downside risk. The machine learning evidence seem to confirm that they are important signals.

We acknowledge several limitations in our study. The chief one is related to data constraints. Our analysis is based on more recent periods, where data quality is comparatively higher. We also recognize that our study might not encompass the full spectrum of ESG strategies, and it is noteworthy that conventional funds encompass a wide range of strategies. To counter this, we have included various style and category fixed effects in our analysis.

The research also indirectly addresses the financial materiality of ESG risks. It provides empirical evidence on the effectiveness of ESG risk management, scrutinizing the financial losses and risk-return profiles of ESG funds. This is central to discussions about whether comprehensive assessment and integration of ESG risks can enhance investment outcomes, thus offering insights into the practical application of ESG risk management in investment decisions.

Our findings are particularly relevant for regulators. In Europe, for instance, the EU's Sustainable Finance Disclosure Regulation (SFDR) mandates financial market participants to disclose their integration of ESG factors in investment decision-making, aiming to enhance transparency and encourage the consideration of ESG factors. In the US, the stance on ESG investing is more divided. The US Department of Labour, in 2020, issued guidance permitting ESG investing as part of fiduciary investment strategies, provided it focuses on economic benefits and does not compromise investment returns or increase risk. However, this guidance was subsequently retracted in 2021. The evolving regulatory landscape underscores the importance of our work in informing policy and regulatory decisions.

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6. Figures

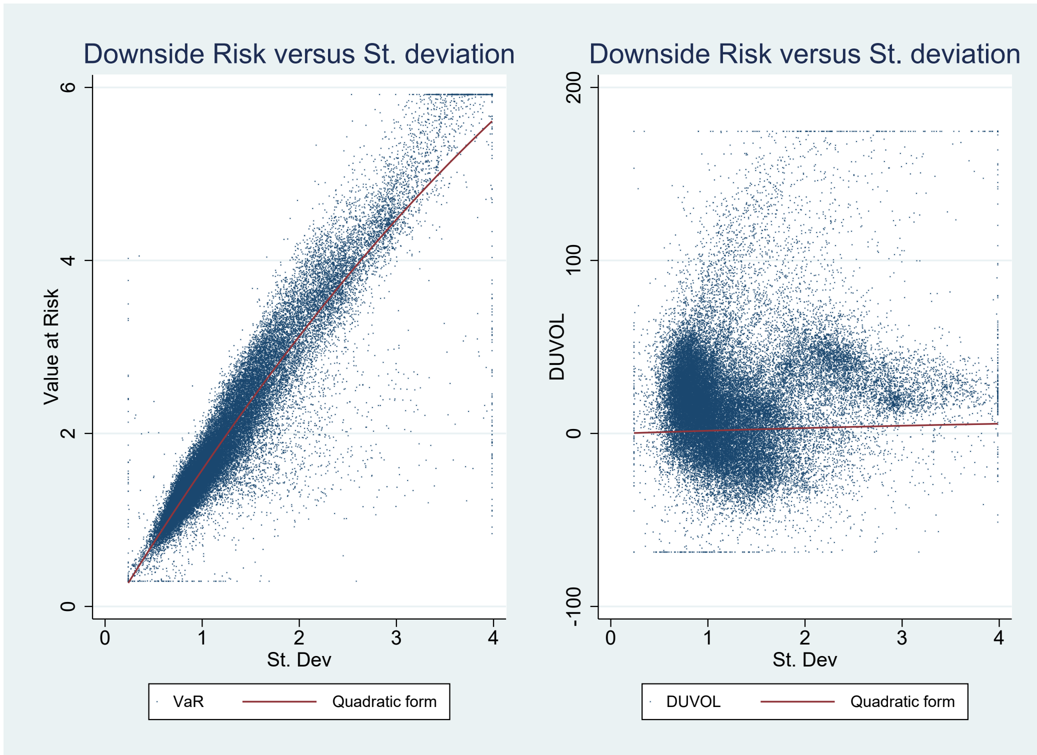

Figure 1. Downside Risk versus Standard Deviation. Panel A displays Value at Risk (VaR), Panel B displays Downside to Upside Volatility (DUVOL). A quadratic form is fitted to data.

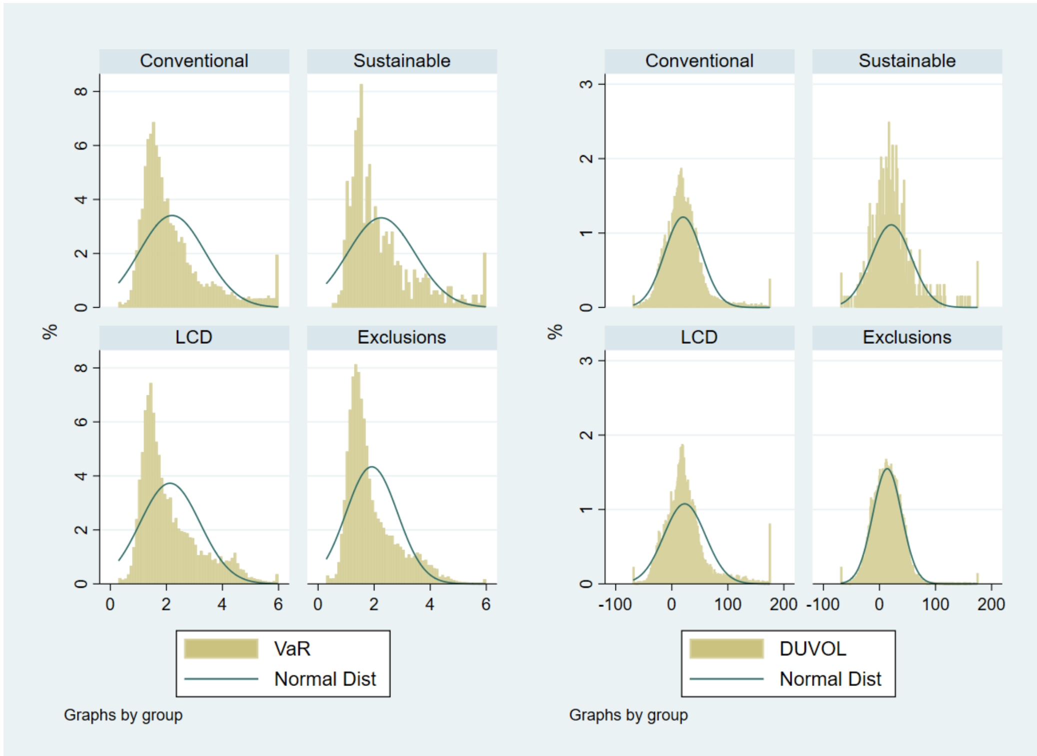

Figure 2. Histogram of Downside risk measures by subsamples. Panel A displays Value at Risk, Panel B displays Downside-to-upside Volatility. A normal distribution is fitted to the graph.

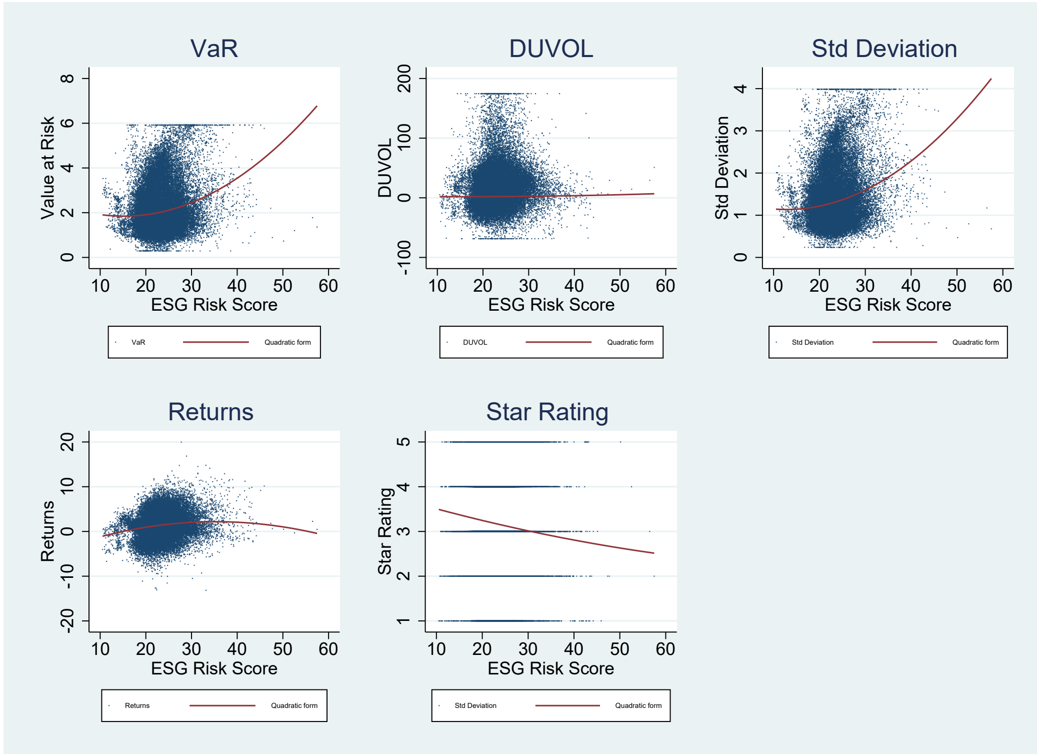

Figure 3. Downside risk measures versus ESG risk scores. Panel A displays Value at Risk, Panel B displays Downside-to-upside Volatility. Panel C displays Standard Deviation. Panel D displays 6 months returns. Panel E displays fund star ratings.

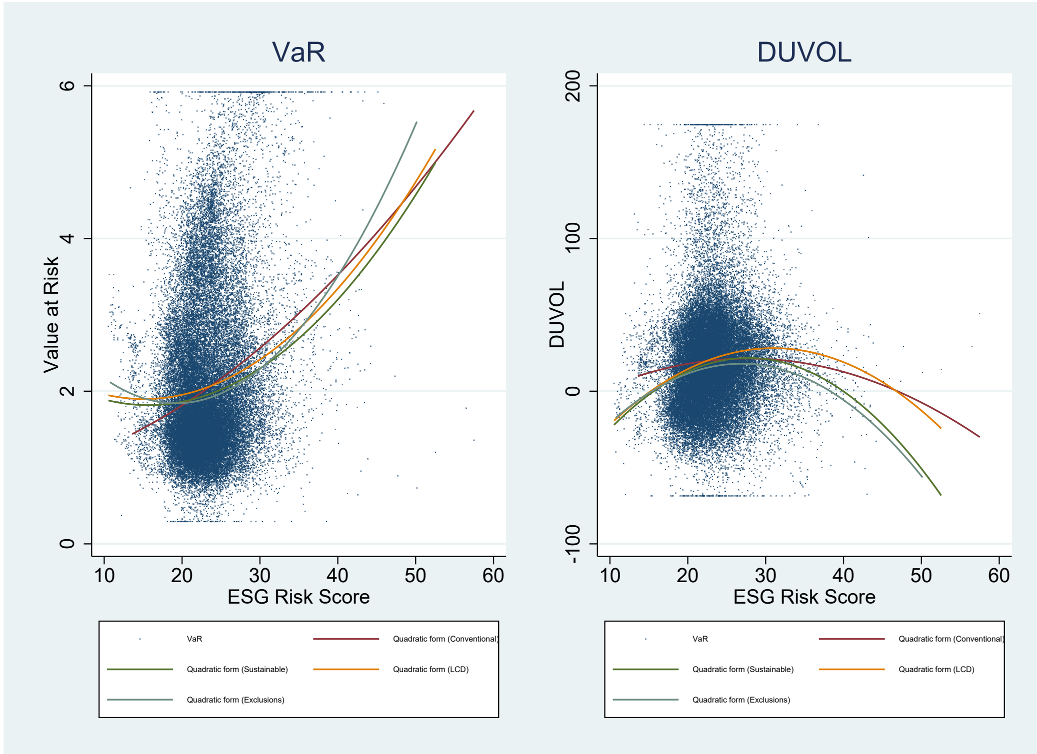

Figure 4. Downside risk measures versus ESG risk scores. Panel A displays Value at Risk, Panel B displays Downside-to-upside Volatility.

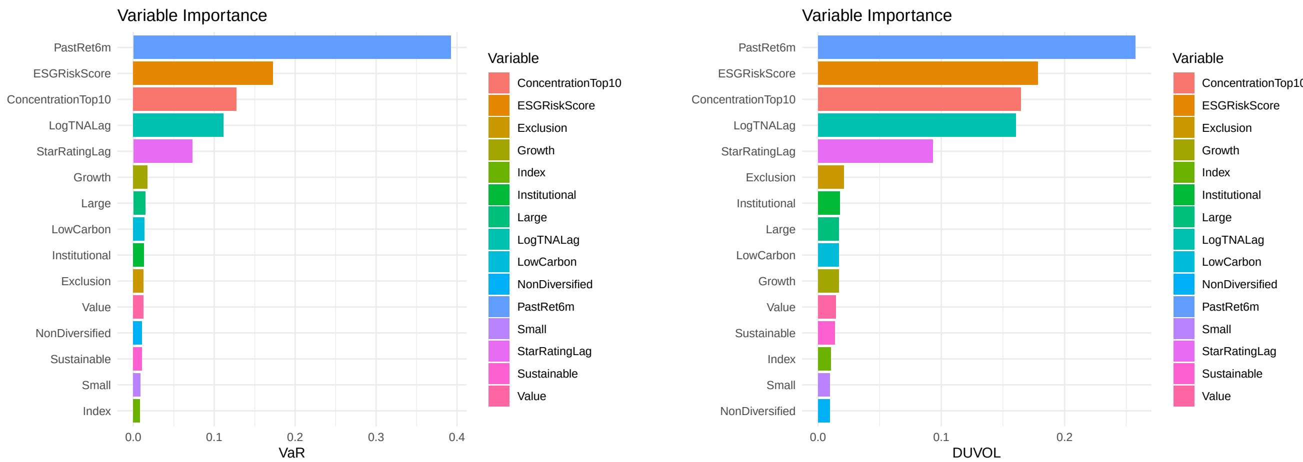

Figure 5. Machine Learning: Random Forests procedure. Left panel displays Value at Risk, right panel displays Downside-to-upside Volatility. The figure presents the variable's importance in the training dataset for explaining the Value at Risk or the Downside-to-upside Volatility.

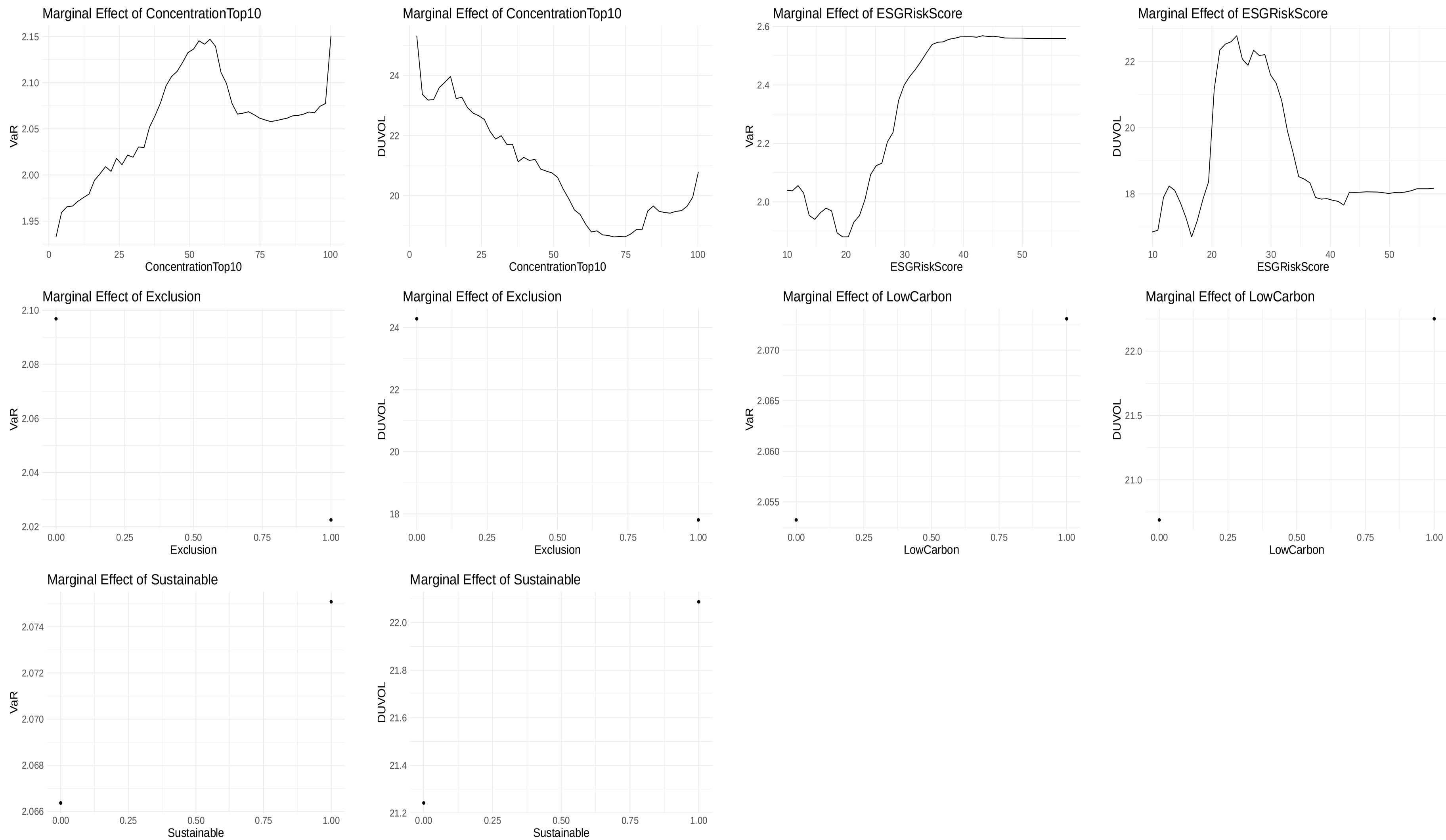

Figure 6: Machine Learning: Random Forests procedure. The left panel displays the marginal effects of several variables on Value at Risk. The right panel displays the marginal effects of several variables on Downside-to-upside Volatility.

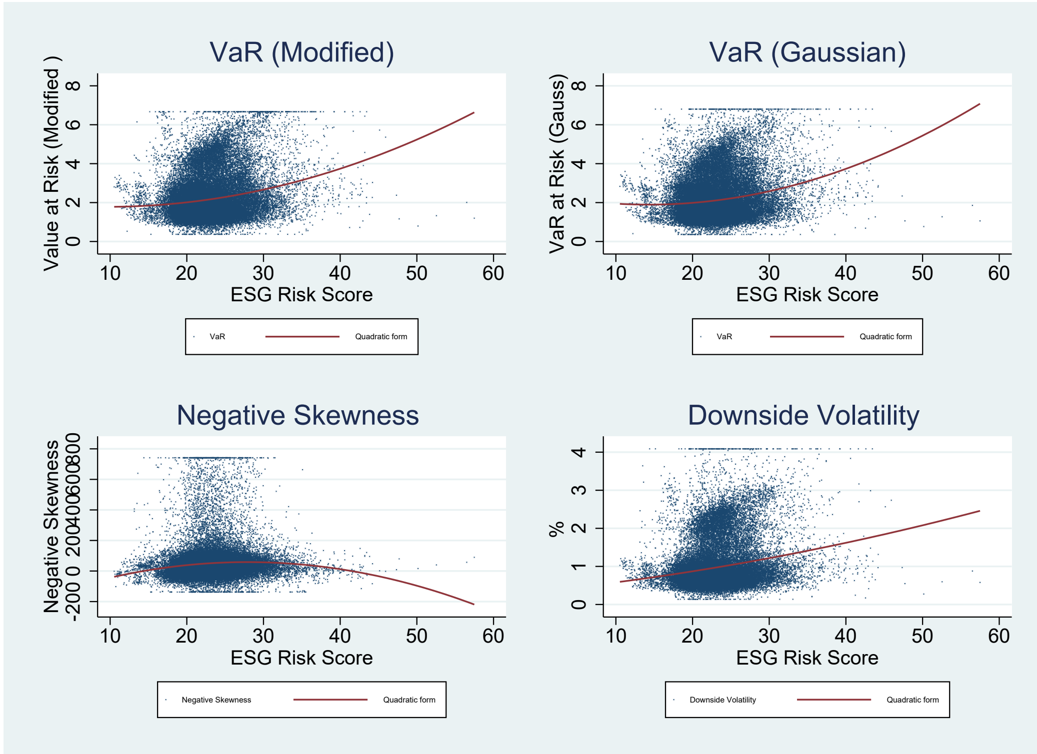

Figure 7. Downside risk measures versus ESG risk scores. Panel A displays Value at Risk, Panel B displays Downside-to-upside Volatility. Panel C displays Standard Deviation. Panel D displays 6 months returns. Panel E displays fund star ratings.

7. Tables

Table 1: Summary Statistics

	Mean	SD	Min	p10	p25	Median	p75	p90	Max	N
VaR (Loss)	2.05	1.04	0.29	1.09	1.33	1.70	2.50	3.61	5.92	44,328
DUVOL	18.13	31.49	-68.57	-17.01	-1.59	16.16	33.41	50.33	174.62	44,328
ESG Risk score	23.11	3.47	10.53	19.34	20.88	22.73	24.91	27.43	57.50	43,428
Sustainable	0.30	0.46	0.00	0.00	0.00	0.00	1.00	1.00	1.00	44,328
Exclusion	0.45	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00	44,328
Low Carbon	0.61	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00	44,328
Past Ret 6m	1.34	2.64	-13.15	-2.17	0.05	1.32	2.72	4.69	19.97	44,328
Total Net Assets (millions)	2,559.18	36,108.27	1.02	23.73	67.79	242.48	836.59	2,542.22	2,826,813.30	44,328
Concentration Top 10 Holdings	35.60	14.62	2.56	17.70	25.07	34.90	45.21	54.51	100.19	44,328
Star Rating	3.17	1.08	1.00	1.83	2.33	3.00	4.00	4.83	5.00	44,328
Index	0.08	0.27	0.00	0.00	0.00	0.00	0.00	0.00	1.00	44,328
Non Diversified	0.06	0.23	0.00	0.00	0.00	0.00	0.00	0.00	1.00	44,328
Institutional	0.53	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00	44,328
Large	0.68	0.47	0.00	0.00	0.00	1.00	1.00	1.00	1.00	44,328
Small	0.11	0.31	0.00	0.00	0.00	0.00	0.00	1.00	1.00	44,328
Value	0.22	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00	44,328
Growth	0.30	0.46	0.00	0.00	0.00	0.00	1.00	1.00	1.00	44,328

This table presents summary statistics of the variables analysed as characteristics of funds. The 'Mean' represents the average value of each variable, while 'N' denotes the total number of observations in the dataset. 'SD' stands for the standard deviation, indicating the variability of the variable's values. 'Min' signifies the lowest value observed, whereas 'Max' represents the highest value. Additionally, 'p10', 'p25', 'Median', 'p75', and 'p90' correspond to specific percentiles within the variable's distribution. VaR (Loss) is in absolute returns and DUVOL is a standardized measure, a ratio of the two-state volatility of the asset. ESG risk score is a scale ranging from 0 to 100. The variables 'Sustainable', 'Exclusion', and 'Low Carbon' are binary indicators, taking a value of 1 if the fund is categorized as such, and 0 otherwise. 'Past return 6m' reflects the fund's performance over the previous six months. 'Total Net Assets' are denominated in million USD. The "Concentration Top 10 Holdings" is quantified based on Morningstar's defined variable, representing the total assets, expressed as a percentage, of the top 10 holdings within the fund's portfolio. 'Start Rating' is computed using the Morningstar three-semester ratings multiplied by 100. Furthermore, 'Enhanced', 'Index', 'Strategic Beta', and 'Non-Diversified' are dummy variables indicating the fund's investment strategies. 'Institutional' is a binary variable identifying institutional funds, while 'Large', 'Small', 'Value', and 'Growth' are dummy variables representing different investment styles of the fund taking the value 1 is the fund follows a large, small, value or growth style of investment respectively and 0 otherwise.

Table 2
Analysis of Downside Risk Measures and ESG Scores

	Panel A		Panel B: frequency Risk Score				
Subsamples	**VaR**	**DUVOL**	**10-20**	**20-30**	**30-40**	**40-50**	**50-60**
Conventional	2.20	20.20	5.5	84.3	9.8	0.4	0.0
Sustainable	1.93	15.39	25.6	72.6	1.8	0.0	0.0
Low Carbon	2.02	18.24	20.6	78.8	0.6	0.0	0.0
Exclusions	1.92	13.89	21.7	76.1	2.2	0.0	0.0

This table displays in Panel A, the average of VaR and DUVOL for different subsamples. We divide the sample into conventional funds (Control group) and ESG Funds type (classified by dummies variables, as 'Sustainable', 'Exclusion', 'Low Carbon'. Panel B displays the percentages of ESG Risk scores across different ranges for each subsamples from 0-60.

Table 3: Correlations among variables

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**
(1) VaR (Loss)	1.00																
(2) DUVOL	0.04	1.00															
(3) ESG Risk score	0.18	0.09	1.00														
(4) Sustainable	-0.08	-0.06	-0.22	1.00													
(5) Exclusion	-0.12	-0.12	-0.20	0.54	1.00												
(6) Low Carbon	-0.03	0.00	-0.40	0.20	0.14	1.00											
(7) Past Ret 6m	-0.01	0.10	0.15	-0.02	-0.05	-0.02	1.00										
(8) Total Net Assets (millions)	0.00	0.01	-0.01	-0.01	0.00	0.02	0.02	1.00									
(9) Concentration Top 10 Holdings	0.07	-0.06	-0.06	0.00	0.00	0.12	-0.01	-0.02	1.00								
(10) Star Rating	-0.03	0.02	-0.08	0.10	0.12	0.11	0.04	0.03	0.02	1.00							
(11) Index	-0.01	-0.03	-0.05	-0.03	0.01	-0.06	0.00	0.05	-0.09	0.09	1.00						
(12) Non Diversified	0.12	0.05	0.05	-0.11	-0.21	0.01	0.03	0.00	0.28	0.01	0.01	1.00					
(13) Institutional	0.06	0.07	0.08	-0.06	-0.07	-0.05	0.00	0.04	-0.13	0.07	0.00	0.07	1.00				
(14) Large	-0.13	-0.04	-0.26	0.05	0.10	0.19	-0.05	0.03	0.07	0.05	0.07	-0.03	-0.04	1.00			
(15) Small	0.12	0.03	0.32	-0.08	-0.11	-0.19	0.05	-0.01	-0.20	-0.03	-0.02	-0.05	0.05	-0.50	1.00		
(16) Value	-0.02	-0.01	0.19	-0.13	-0.09	-0.34	0.01	-0.02	-0.01	-0.19	-0.10	0.00	0.01	-0.04	0.00	1.00	
(17) Growth	0.11	0.03	-0.12	0.10	0.04	0.33	0.01	0.02	0.14	0.17	-0.14	0.10	0.03	-0.04	0.04	-0.34	1.00

This table displays the correlation coefficients matrix for the 17 variables analysed. Every value on the lower triangle of the matrix shows the estimated correlation. Variables related to risk are located in columns (1) VaR, (2) DUVOL and (3) ESG risk score, both horizontally and vertically. VaR (Loss) is in absolute returns and DUVOL is a standardized measure, a ratio of the two-state volatility of the asset. ESG risk score is a scale ranging from 0 to 100. The remaining variables were defined in Table 1.

Table 4
ESG Risk and ESG funds

	Sustainable vs. **Conventional** **(1)**	**Low carbon** vs. **Conventional** **(2)**	**Exclusions** vs. **Conventional** **(3)**
Sustainable	-1.465***		
	(0.076)		
Low Carbon		-1.551***	
		(0.064)	
Exclusion			-1.155***
			(0.074)
Past Ret 6m	0.003	-0.017**	-0.006
	(0.011)	(0.007)	(0.009)
Log TNA t-1	-0.001*	-0.014***	-0.007**
	(0.016)	(0.012)	(0.015)
Concentration Top 10	0.000	-0.005**	-0.002
	(0.003)	(0.002)	(0.003)
Star Rating t-1	-0.097***	-0.092***	-0.108***
	(0.024)	(0.017)	(0.022)
Index	-0.192***	-0.144***	-0.057***
	(0.083)	(0.062)	(0.069)
Non Diversified	-0.210	-0.134	-0.279
	(0.227)	(0.125)	(0.259)
Institutional	0.072	-0.041	0.061
	(0.057)	(0.041)	(0.049)
Large	-1.014***	-0.972***	-1.097***
	(0.141)	(0.110)	(0.140)
Small	1.619***	1.437***	1.504***
	(0.213)	(0.161)	(0.200)
Value	0.746***	0.449***	0.757***
	(0.087)	(0.071)	(0.074)
Growth	-0.390***	-0.279***	-0.546***
	(0.085)	(0.060)	(0.082)
Constant	24.874***	25.208***	25.0492***
	(0.179)	(0.143)	(0.167)
Observations	22,473	35,946	29,170
R-squared	0.797	0.768	0.781
Category & Time FE	YES	YES	YES

This table reports the results from fixed effects regressions of semester ESG risk scores and fund control characteristics defined in Equation 1. ESG risk score is computed on scaled ranging from 0 to 100. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable', 'Low Carbon', and 'Exclusion' are dummy variables taking a value of 1 if the fund is categorized as such, and 0 otherwise. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. The remaining variables are dummies. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Downside Risk and ESG Risk Scores

	Conventional	Conventional	Sustainable	Sustainable	Low Carbon	Low Carbon	Exclusions	Exclusions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: VaR (Loss)								
ESG Risk Score	0.017***		0.032***		0.036***		0.035***	
	(0.006)		(0.006)		(0.004)		(0.005)	
ESG Risk Score^2		0.000***		0.001***		0.001***		0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
Past Ret 6m	-0.024***	-0.024***	-0.055***	-0.056***	-0.062***	-0.062***	-0.060***	-0.060***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Log TNA t-1	0.006	0.006	0.005	0.005	0.009***	0.009***	0.008***	0.008***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Concentration Top 10	0.002***	0.002***	0.005***	0.005***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Star Rating t-1	-0.061***	-0.061***	-0.008	-0.008	-0.012***	-0.012***	-0.014***	-0.013***
	(0.008)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Index	0.145***	0.145***	0.052***	0.051***	0.003	0.003	0.044***	0.044***
	(0.030)	(0.030)	(0.015)	(0.015)	(0.013)	(0.013)	(0.012)	(0.012)
Non Diversified	0.001	0.001	0.073	0.076	0.049	0.049	0.191**	0.195***
	(0.036)	(0.036)	(0.085)	(0.085)	(0.032)	(0.032)	(0.077)	(0.077)
Institutional	-0.006	-0.006	0.045***	0.045***	0.034***	0.034***	0.035***	0.035***
	(0.014)	(0.014)	(0.012)	(0.012)	(0.009)	(0.009)	(0.010)	(0.010)
Large	-0.043	-0.045	-0.132***	-0.132***	-0.137***	-0.137***	-0.120***	-0.116***
	(0.037)	(0.037)	(0.026)	(0.026)	(0.024)	(0.024)	(0.023)	(0.022)
Small	0.025	0.024	-0.049	-0.051	-0.100***	-0.103***	-0.067	-0.073*
	(0.038)	(0.038)	(0.055)	(0.054)	(0.038)	(0.037)	(0.043)	(0.042)
Value	-0.013	-0.012	-0.052***	-0.051***	-0.009	-0.008	-0.027*	-0.027*
	(0.020)	(0.020)	(0.018)	(0.018)	(0.018)	(0.018)	(0.015)	(0.015)
Growth	0.114**	0.113**	0.114***	0.113***	0.147***	0.146***	0.124***	0.124***
	(0.048)	(0.048)	(0.014)	(0.014)	(0.011)	(0.011)	(0.012)	(0.012)
Constant	1.879***	2.123***	1.170***	1.545***	1.176***	1.595***	1.102***	1.492***
	(0.159)	(0.086)	(0.139)	(0.079)	(0.090)	(0.054)	(0.116)	(0.066)
Observations	9480	9480	12987	12987	26459	26459	19683	19683
R-squared	0.850	0.850	0.804	0.804	0.795	0.795	0.789	0.790
Category & Time FE	YES	YES	YES	YES	YES	YES	YES	YES

This table reports the results from fixed effects regression of Downside Risk between conventional funds and the types of ESG funds ('Sustainable', 'Low Carbon', and 'Exclusion'). Panel A shows the results of downside risk measure for VaR. We control for style effects using Morningstar categories, and time fixed effects. We include ESG risk score and ESG risk score squared. The first is scaled ranging from 0 to 100, and the second is scaled from 0 to 10000. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. The remaining variables are dummies taking a value of 1 if the fund is categorized as such, and 0 otherwise. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 (continuation)

	Conventional	Conventional	Sustainable	Sustainable	Low Carbon	Low Carbon	Exclusions	Exclusions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: DUVOL								
ESG Risk Score	-0.258*		0.034		0.156		0.078	
	(0.148)		(0.130)		(0.118)		(0.102)	
ESG Risk Score^2		-0.006**		-0.002		0.001		-0.001
		(0.003)		(0.003)		(0.003)		(0.002)
Past Ret 6m	0.733***	0.737***	0.783***	0.7830***	0.770***	0.766***	0.709***	0.708***
	(0.183)	(0.183)	(0.141)	(0.141)	(0.106)	(0.106)	(0.111)	(0.111)
Log TNA t-1	-0.400**	-0.396**	-0.175	-0.178	-0.391***	-0.394***	-0.359***	-0.362***
	(0.184)	(0.184)	(0.137)	(0.137)	(0.106)	(0.106)	(0.099)	(0.099)
Concentration Top 10	-0.095***	-0.093**	-0.111***	-0.112***	-0.181***	-0.183***	-0.103***	-0.104***
	(0.028)	(0.028)	(0.021)	(0.021)	(0.018)	(0.018)	(0.017)	(0.017)
Star Rating t-1	1.381***	1.378***	0.435**	0.423**	0.646***	0.638***	0.947***	0.934***
	(0.324)	(0.325)	(0.212)	(0.212)	(0.165)	(0.165)	(0.158)	(0.158)
Index	-5.063***	-5.087***	-2.529***	-2.540***	-4.755***	-4.762***	-1.501***	-1.491***
	(1.054)	(1.055)	(0.748)	(0.748)	(0.733)	(0.733)	(0.563)	(0.563)
Non Diversified	-0.691	-0.742	-2.909	-2.901	-1.015	-1.012	0.577	0.548
	(1.722)	(1.723)	(2.618)	(2.623)	(1.443)	(1.442)	(4.034)	(4.042)
Institutional	1.039	1.040	-0.376	-0.353	0.497	0.492	-0.008	0.005
	(0.671)	(0.672)	(0.421)	(0.421)	(0.349)	(0.349)	(0.310)	(0.310)
Large	-0.637	-0.687	0.591	0.452	1.489*	1.393*	1.272**	1.126*
	(1.097)	(1.096)	(0.746)	(0.741)	(0.728)	(0.727)	(0.589)	(0.587)
Small	1.241	1.376	-1.237	-0.967	1.140	1.274	-0.677	-0.468
	(1.874)	(1.878)	(1.394)	(1.367)	(1.153)	(1.148)	(0.956)	(0.950)
Value	1.829**	1.847**	0.651	0.773	-1.180*	-1.148	0.514	0.622
	(0.910)	(0.911)	(0.683)	(0.681)	(0.688)	(0.687)	(0.482)	(0.481)
Growth	0.340	0.346	-1.274**	-1.307**	-0.617	-0.640	-1.180**	-1.242***
	(1.579)	(1.581)	(0.544)	(0.544)	(0.418)	(0.418)	(0.417)	(0.416)
Observations	9480	9480	12987	12987	26459	26459	19683	19683
R-squared	0.326	0.326	0.383	0.383	0.376	0.376	0.372	0.372
Category & Time FE	YES	YES	YES	YES	YES	YES	YES	YES

This table reports the results from fixed effects regression of Downside Risk between conventional funds and the types of ESG funds ('Sustainable', 'Low Carbon', and 'Exclusion'). Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. We include ESG risk score and ESG risk score squared. The first is scaled ranging from 0 to 100, and the second is scaled from 0 to 10000. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. The remaining variables are dummies taking a value of 1 if the fund is categorized as such, and 0 otherwise. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Downside Risk and ESG Funds

	VaR (Loss)			2 Stage Least Square		
	(1)	(2)	(3)	(4)	(5)	(6)
Sustainable	0.021			0.035***		
	(0.013)			(0.013)		
Low Carbon		0.013			0.035***	
		(0.012)			(0.011)	
Exclusions			0.031***			0.041***
			(0.012)			(0.012)
ESG Risk Score^2	0.000***	0.001***	0.001***	0.028***	0.033***	0.030***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)	(0.004)
Past Ret 6m	-0.040***	-0.055***	-0.045***	-0.040***	-0.055***	-0.045***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Log TNA t-1	0.006**	0.008***	0.007***	0.003	0.004*	0.004
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Concentration Top 10	0.004***	0.004***	0.003***	0.004***	0.004***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Star Rating t-1	-0.032***	-0.029***	-0.032***	-0.025***	-0.022***	-0.027***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Index	0.099***	0.054***	0.081***			
	(0.016)	(0.013)	(0.013)			
Non Diversified	0.023	0.039	0.044			
	(0.036)	(0.025)	(0.035)			
Institutional	0.022**	0.025***	0.022***			
	(0.009)	(0.008)	(0.008)			
Large	-0.096***	-0.115***	-0.095***			
	(0.022)	(0.020)	(0.020)			
Small	0.002	-0.032	-0.016			
	(0.030)	(0.027)	(0.028)			
Value	-0.029**	-0.019	-0.023*			
	(0.014)	(0.013)	(0.012)			
Growth	0.127***	0.154***	0.129***			
	(0.015)	(0.011)	(0.013)			
Constant	1.787***	1.763***	1.712***	2.166***	2.213***	2.145***
	(0.060)	(0.050)	(0.057)	(0.033)	(0.027)	(0.030)
Observations	22,473	35,946	29,170	22,473	35,946	29,170
R-squared	0.817	0.802	0.805	0.814	0.799	0.802
Category & Time FE	YES	YES	YES	YES	YES	YES

This table reports the results from regression of Downside Risk defined in Equation 2. Panel A shows the results of downside risk measure for VaR. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable', 'Low Carbon', and 'Exclusion' are dummy variables taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. The remaining variables are dummies taking a value of 1 if the fund is categorized as such, and 0 otherwise. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 (continuation)

	DUVOL			2 Stage Least Square		
	(1)	(2)	(3)	(4)	(5)	(6)
Sustainable	-1.255**			-1.098**		
	(0.524)			(0.506)		
Low Carbon		-0.037			0.324	
		(0.502)			(0.477)	
Exclusions			-1.472***			-1.371***
			(0.450)			(0.443)
ESG Risk Score^2	-0.004**	-0.002	-0.003*	-0.131	-0.014	-0.073
	(0.002)	(0.002)	(0.002)	(0.096)	(0.088)	(0.081)
Past Ret 6m	0.532***	0.684***	0.477***	0.538***	0.684***	0.480***
	(0.112)	(0.091)	(0.095)	(0.111)	(0.091)	(0.094)
Log TNA t-1	-0.255**	-0.403***	-0.353***	-0.317***	-0.494***	-0.398***
	(0.111)	(0.090)	(0.093)	(0.110)	(0.090)	(0.092)
Concentration Top 10	-0.113***	-0.159***	-0.101***	-0.112***	-0.154***	-0.099***
	(0.017)	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)
Star Rating t-1	0.891***	0.961***	1.137***	0.717***	0.863***	1.002***
	(0.185)	(0.148)	(0.150)	(0.173)	(0.143)	(0.141)
Index	-3.666***	-4.748***	-2.718***	19.949***	22.992***	18.245***
	(0.623)	(0.581)	(0.512)	(1.059)	(0.936)	(0.908)
Non Diversified	-1.437	-0.979	-0.968			
	(1.383)	(1.122)	(1.472)			
Institutional	0.144	0.524*	0.268			
	(0.370)	(0.308)	(0.289)			
Large	0.172	0.951	0.586			
	(0.602)	(0.594)	(0.515)			
Small	0.664	1.311	0.422			
	(1.172)	(0.971)	(0.980)			
Value	1.390**	0.210	1.101**			
	(0.576)	(0.532)	(0.466)			
Growth	-1.257**	-0.795**	-1.135***			
	(0.519)	(0.401)	(0.415)			
Constant	22.293***	23.343***	19.379***			
	(1.560)	(1.462)	(1.362)			
Observations	22,473	35,946	29,170	22,473	35,946	29,170
R-squared	0.338	0.349	0.334	0.336	0.348	0.333
Category & Time FE	YES	YES	YES	YES	YES	YES

This table reports the results from regression of Downside Risk defined in Equation 2. Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable', 'Low Carbon', and 'Exclusion' are dummy variables taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. The remaining variables are dummies taking a value of 1 if the fund is categorized as such, and 0 otherwise. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Downside Risk and ESG Funds: Quantile Regression

	VaR (Loss)					DUVOL				
	Q10	**Q25**	**Q50**	**Q75**	**Q90**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Sustainable	-0.092***	-0.081***	-0.079***	-0.072***	-0.060***	-3.094***	-2.641***	-2.842***	-3.685***	-6.446***
	(0.011)	(0.009)	(0.008)	(0.011)	(0.016)	(0.466)	(0.379)	(0.342)	(0.424)	(0.901)
ESG Risk Score^2	0.000***	0.001***	0.001***	0.001***	0.002***	-0.019***	-0.017***	-0.013***	-0.002**	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Past Ret 6m	0.003	0.001	0.001	-0.012***	-0.030***	0.382***	0.620***	0.949***	1.297***	1.472***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.138)	(0.112)	(0.101)	(0.125)	(0.266)
Log TNA t-1	0.027***	0.024***	0.018***	0.009***	0.009**	0.096	-0.007	-0.131	-0.171	0.172
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.117)	(0.095)	(0.086)	(0.107)	(0.227)
Concentration Top 10	0.001***	0.001***	0.002***	0.004***	0.006***	-0.099***	-0.064***	-0.077***	-0.050***	-0.106***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.011)	(0.010)	(0.013)	(0.027)
Star Rating t-1	-0.005	-0.008**	-0.008**	-0.008*	0.000	0.665***	0.693***	0.418***	0.209	0.259
	(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.197)	(0.161)	(0.145)	(0.180)	(0.382)
Constant	0.600***	0.620***	0.573***	0.545***	0.464***	21.347***	30.916***	43.025***	49.538***	58.581***
	(0.032)	(0.028)	(0.025)	(0.033)	(0.047)	(1.407)	(1.144)	(1.034)	(1.281)	(2.722)
Observations	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522

This table reports the results from fixed effects regression of Downside Risk and ESG Funds by quantiles measure by VaR and DUVOL. The categories 'Sustainable', is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD. Concentration Top 10 is considered as the percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Downside Risk and ESG Funds: Matched sample

	Panel A: VaR		Panel B: DUVOL	
	(1)	(2)	(3)	(4)
Sustainable	-0.001	0.026*	-0.809	-0.456
	(0.013)	(0.014)	(0.598)	(0.626)
ESG Risk Score^2		0.001***		0.007**
		(0.000)		(0.003)
Past Ret 6m	-0.055***	-0.055***	0.691***	0.698***
	(0.004)	(0.004)	(0.138)	(0.138)
Log TNA t-1	0.005*	0.005*	-0.147	-0.149
	(0.003)	(0.003)	(0.123)	(0.124)
Concentration Top 10	0.003***	0.004***	-0.122***	-0.118***
	(0.001)	(0.001)	(0.020)	(0.020)
Star Rating t-1	-0.019***	-0.017***	0.480**	0.503**
	(0.004)	(0.004)	(0.195)	(0.196)
Index	0.062***	0.065***	-2.728***	-2.685***
	(0.013)	(0.013)	(0.647)	(0.646)
Non Diversified	0.079	0.096	-4.621**	-4.410**
	(0.078)	(0.076)	(2.022)	(2.017)
Institutional	0.037***	0.036***	0.062	0.039
	(0.010)	(0.010)	(0.385)	(0.385)
Large	-0.095***	-0.085***	-0.028	0.101
	(0.023)	(0.023)	(0.672)	(0.674)
Small	-0.063*	-0.088**	-0.046	-0.363
	(0.035)	(0.035)	(1.269)	(1.258)
Value	0.007	-0.005	0.769	0.605
	(0.015)	(0.015)	(0.595)	(0.601)
Growth	0.105***	0.103***	-0.940*	-0.970*
	(0.013)	(0.013)	(0.527)	(0.527)
Constant	1.940***	1.645***	21.146***	17.352***
	(0.033)	(0.060)	(1.180)	(2.102)
Observations	16,783	16,783	16,783	16,783
R-squared	0.815	0.816	0.373	0.373
Category & Time FE	YES	YES	YES	YES

This table reports the results from regression of the matching analysis. Panel A informs the results of downside risk measure for VaR. Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable'is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Downside Risk and ESG Funds: Instrumental Variables

	Panel A: VaR		Panel B: DUVOL	
	PRI	**Growth**	**PRI**	**Growth**
	(1)	**(2)**	**(3)**	**(4)**
Sustainable	0.468***	1.026***	1.256	-9.929**
	(0.141)	(0.091)	(7.196)	(3.958)
ESG Risk Score^2	0.001***	0.001***	-0.001	-0.011***
	(0.000)	(0.000)	(0.007)	(0.004)
Past Ret 6m	-0.038***	-0.036***	0.550***	0.503***
	(0.002)	(0.003)	(0.118)	(0.116)
Log TNA t-1	0.004*	-0.001	-0.364***	-0.257**
	(0.002)	(0.002)	(0.122)	(0.108)
Concentration Top 10	0.004***	0.004***	-0.114***	-0.111***
	(0.000)	(0.000)	(0.015)	(0.015)
Star Rating t-1	-0.040***	-0.063***	0.598*	1.051***
	(0.007)	(0.005)	(0.333)	(0.228)
Constant	1.345***	0.864***	8.993	18.624**
	(0.201)	(0.205)	(10.291)	(8.947)
Observations	22,476	22,476	22,476	22,476
R-squared	0.794	0.713	0.336	0.327
Category & Time FE	YES	YES	YES	YES

This table reports the results from regression of the Sustainable Funds using instrumental variables: The Principle of Responsible Investment (PRI) and Growth Style for Funds. Panel A informs the results of downside risk measure for VaR. Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable' is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Out-of-sample prediction

Measures	RMSE	R^2	MAE
VaR	0.270	0.830	0.207
DUVOL	20.09	0.832	17.38

This table presents the performance's criteria when predicting the VaR and DUVOL out-of-sample for the last semester.

8. Appendix

Table A11
Description of Variables

Variables	Description	Source
Value at Risk: VaR (Loss)	The potential loss for a period obtained with the historical VaR for a confidence level of 95%. We calculated every 6 months using about 120 daily observations. We multiplied the data by -100. We use the variable winsorized at 0.05	Authors
Down-to-up volatility (DUVOL)	Ratio that gives information to understand the behaviour of asset volatility in response to different states. We calculated every 6 months using 120 daily observations. We multiply the data by 100	Authors
ESG risk Score	Scale of the evolution of the company's ESG performance over the previous 12 months	Morningstar
Sustainable	A dummy variable that indicates if the fund is labelled as sustainable in the period of the study	Morningstar
Exclusion	A dummy variable that indicates if the fund employs an exclusion policy in the period of the study	Morningstar
Low Carbon	A dummy variable that indicates if the fund shows a low carbon level in the period of the study	Morningstar
PRI	A dummy variable that indicates if the fund is classified as a signatory of the PRI (Principles for Responsible Investment) in the period of the study. These principles encompass integrating environmental, social, and governance (ESG) factors into investment decisions and practices, thereby demonstrating a dedication to sustainable and responsible investment strategies	unpri.org
Article 8	A dummy variable that indicates if the fund is classified as Article 8 zero otherwise. Article 8 funds promote environmental and social characteristics but without prioritizing them as the overarching objective	Morningstar
Article 9	A dummy variable that indicates if the fund is classified as Article 9 zero otherwise. Article 9 funds define sustainable goals as their primary objective characteristics but without prioritizing them as the overarching objective	Morningstar
Past Ret 6m	Fund return over the period 6 months (measured in USD)	Morningstar
Total Net Assets (millions)	Aggregate Net Asset Value (measured in million USD)	Morningstar
Holdings	Number of holdings that compose the portfolio of the fund at the end of each semester	Morningstar
Concentration Top 10 Holdings	The percentage of the aggregate assets of the fund's top 10 portfolio holdings	Morningstar
Star Rating	The fund's historical risk-adjusted returns compared to other funds in the same category. These ratings range from one to five stars, with a higher star rating indicating superior past performance, adjusted for risk	Morningstar
Enhanced	A dummy variable that indicates if the fund outperforms the benchmark index in the period of the study	Morningstar
Index	A dummy variable that indicates if the fund is pure passive fund in the period of the study	Morningstar
Strategic Beta	A dummy variable that indicates if the fund aims to outperform market-cap-weighted indexes combining passive and active investment strategies in the period of the study	Morningstar
Non Diversified	A dummy variable that indicates if the fund does not spread its investment across a wide range of assets in the period of the study	Morningstar
Institutional	A dummy variable that indicates if the fund is identified as institutional funds in the period of the study	Morningstar
Large	A dummy variable that indicates if the fund is classified as a large-cap fund by size in the period of the study	Morningstar
Small	A dummy variable that indicates if the fund is classified as a small-cap fund by size in the period of the study	Morningstar
Value	A dummy variable that indicates if the fund follows an investment value strategy in the period of the study	Morningstar
Growth	A dummy variable that indicates if the fund follows an investment growth strategy in the period of the study	Morningstar

Table A12: Downside Risk and ESG Funds: Quantile Regression for Low Carbon Funds

	VaR (Loss)					DUVOL				
	Q10	**Q25**	**Q50**	**Q75**	**Q90**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Low Carbon	-0.068***	-0.058***	-0.026***	-0.003	0.002	-2.367***	-1.575***	-1.613***	-2.002***	-1.423
	(0.009)	(0.008)	(0.008)	(0.010)	(0.016)	(0.489)	(0.340)	(0.317)	(0.410)	(0.960)
ESG Risk Score^2	0.000***	0.000***	0.001***	0.001***	0.002***	-0.016***	-0.014***	-0.010***	0.002	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Past Ret 6m	0.005*	0.000	-0.006***	-0.024***	-0.053***	0.818***	0.896***	1.169***	1.558***	1.921***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.127)	(0.088)	(0.082)	(0.106)	(0.249)
Log TNA t-1	0.027***	0.027***	0.028***	0.030***	0.033***	0.196*	0.139*	0.077	0.117	0.355*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.103)	(0.071)	(0.067)	(0.086)	(0.202)
Concentration Top 10	0.001***	0.002***	0.004***	0.007***	0.011***	-0.099***	-0.074***	-0.088***	-0.074***	-0.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.009)	(0.008)	(0.011)	(0.026)
Star Rating t-1	-0.012***	-0.016***	-0.016***	-0.011***	-0.010	0.685***	0.691***	0.390***	-0.048	-0.226
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.180)	(0.125)	(0.117)	(0.151)	(0.353)
Constant	0.679***	0.698***	0.498***	0.300***	0.175***	18.822***	29.537***	42.835***	50.581***	69.807***
	(0.027)	(0.024)	(0.024)	(0.028)	(0.046)	(1.417)	(0.984)	(0.918)	(1.188)	(2.780)
Observations	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522	22,522

This table reports the results from fixed effects regression of Downside Risk and ESG Funds by quantiles measure by VaR and DUVOL. The categories 'Low Carbon', is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD. Concentration Top 10 is considered as the percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A13: Downside Risk and ESG Funds: Quantile Regression for Exclusion Funds

	VaR (Loss)					DUVOL				
	Q10	**Q25**	**Q50**	**Q75**	**Q90**	**Q10**	**Q25**	**Q50**	**Q75**	**Q90**
Exclusions	-0.103***	-0.107***	-0.112***	-0.126***	-0.155***	-3.824***	-3.198***	-3.205***	-3.857***	-8.983***
	(0.010)	(0.008)	(0.008)	(0.010)	(0.015)	(0.436)	(0.358)	(0.313)	(0.361)	(0.711)
ESG Risk Score^2	0.000***	0.000***	0.001***	0.001***	0.001***	-0.018***	-0.016***	-0.013***	-0.003***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Past Ret 6m	-0.012***	-0.013***	-0.012***	-0.020***	-0.037***	0.464***	0.534***	0.897***	1.248***	1.267***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.127)	(0.104)	(0.091)	(0.105)	(0.208)
Log TNA t-1	0.024***	0.021***	0.017***	0.012***	0.016***	-0.106	-0.184**	-0.292***	-0.313***	-0.234
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.109)	(0.089)	(0.078)	(0.090)	(0.178)
Concentration Top 10	0.002***	0.002***	0.003***	0.005***	0.007***	-0.109***	-0.055***	-0.060***	-0.045***	-0.101***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.011)	(0.009)	(0.011)	(0.021)
Star Rating t-1	-0.007*	-0.007*	-0.007**	-0.007*	-0.000	1.037***	1.045***	0.532***	0.458***	0.513*
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.181)	(0.148)	(0.130)	(0.150)	(0.295)
Constant	0.662***	0.704***	0.668***	0.603***	0.563***	19.108***	28.025***	41.000***	47.195***	57.891***
	(0.030)	(0.026)	(0.023)	(0.030)	(0.045)	(1.323)	(1.084)	(0.951)	(1.095)	(2.158)
Observations	29,269	29,269	29,269	29,269	29,269	29,269	29,269	29,269	29,269	29,269

This table reports the results from fixed effects regression of Downside Risk and ESG Funds by quantiles measure by VaR and DUVOL. The categories 'Exclusion', is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD. Concentration Top 10 is considered as the percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A14
Logit regressions

	Sustainable (1)	**Low Carbon** (2)	**Exclusion** (3)
ESG Risk Score^2	-0.350***	-0.231***	-0.337***
	(0.011)	(0.009)	(0.011)
Past Ret 6m	0.034***	0.024***	0.025***
	(0.010)	(0.008)	(0.009)
TNA t-1	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Concentration Top 10	0.004**	0.009***	0.006***
	(0.002)	(0.002)	(0.002)
Star Rating t-1	0.282***	0.148***	0.307***
	(0.023)	(0.019)	(0.022)
Index	-1.141***	-0.625***	-0.863***
	(0.085)	(0.065)	(0.076)
Non Diversified	-2.289***	-0.633***	-3.995***
	(0.135)	(0.089)	(0.184)
Institutional	-0.315***	-0.178***	-0.277***
	(0.046)	(0.038)	(0.043)
Large	0.772***	0.813***	0.716***
	(0.064)	(0.055)	(0.062)
Small	-0.258**	-0.063	-0.104
	(0.119)	(0.098)	(0.110)
Value	-1.471***	-1.377***	-1.389***
	(0.060)	(0.046)	(0.054)
Growth	1.573***	1.417***	1.496***
	(0.068)	(0.057)	(0.064)
Constant	7.091***	5.499***	7.049***
	(0.252)	(0.214)	(0.242)
Observations	13,178	27,906	16,406

This table presents the logistic regression results, where the dependent variable is the likelihood of being labelled as an ESG fund. Column (1) shows the results of the independent variables for 'Sustainable' funds. Column (2) and Column (3) show the results for 'Exclusion', and 'Low Carbon' funds respectively. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A15
Downside Risk and ESG Funds: Instrumental Variables for Low Carbon Funds

	Panel A: VaR		Panel B: DUVOL	
	PRI	Growth	PRI	Growth
	(1)	(2)	(3)	(4)
Low Carbon	1.079***	1.471***	22.120	-3.952
	(0.307)	(0.092)	(14.513)	(3.701)
ESG Risk Score^2	0.002***	0.002***	0.022	-0.006
	(0.000)	(0.000)	(0.015)	(0.004)
Past Ret 6m	-0.050***	-0.048***	0.792***	0.664***
	(0.003)	(0.002)	(0.122)	(0.097)
Log TNA t-1	0.008***	0.007***	-0.545***	-0.489***
	(0.002)	(0.002)	(0.089)	(0.081)
Concentration Top 10	0.001	0.000	-0.214***	-0.143***
	(0.001)	(0.000)	(0.041)	(0.016)
Star Rating t-1	-0.052***	-0.064***	0.167	0.983***
	(0.010)	(0.004)	(0.475)	(0.177)
Constant	0.625*	0.242	2.349	27.873***
	(0.347)	(0.217)	(16.415)	(8.749)
Observations	35,947	35,947	35,947	35,947
R-squared	0.703	0.617	0.303	0.346
Category & Time FE	YES	YES	YES	YES

This table reports the results from regression of the Low Carbon Funds using instrumental variables: The Principle of Responsible Investment (PRI) and Growth Style for Funds. Panel A informs the results of downside risk measure for VaR. Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Low Carbon'is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A16
Downside Risk and ESG Funds: Instrumental Variables for Exclusion Funds

	Panel A: VaR		**Panel B: DUVOL**	
	PRI	**Growth**	**PRI**	**Growth**
	(1)	**(2)**	**(3)**	**(4)**
Exclusions	0.507***	1.597***	-6.353	-14.270***
	(0.117)	(0.146)	(5.673)	(5.123)
ESG Risk Score^2	0.001***	0.002***	-0.005	-0.011***
	(0.000)	(0.000)	(0.004)	(0.004)
Past Ret 6m	-0.044***	-0.041***	0.466***	0.442***
	(0.002)	(0.003)	(0.098)	(0.099)
Log TNA t-1	0.002	-0.016***	-0.332***	-0.204*
	(0.003)	(0.003)	(0.125)	(0.119)
Concentration Top 10	0.004***	0.004***	-0.101***	-0.102***
	(0.000)	(0.000)	(0.013)	(0.013)
Star Rating t-1	-0.036***	-0.068***	1.127***	1.354***
	(0.004)	(0.006)	(0.211)	(0.201)
Constant	1.520***	1.207***	-12.628	-10.355
	(0.241)	(0.338)	(11.752)	(11.881)
Observations	29,172	29,172	29,172	29,172
R-squared	0.781	0.568	0.330	0.312
Category & Time FE	YES	YES	YES	YES

This table reports the results from regression of the Exclusion Funds using instrumental variables: The Principle of Responsible Investment (PRI) and Growth Style for Funds. Panel A informs the results of downside risk measure for VaR. Panel B shows the results of downside risk measure for DUVOL. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Exclusion' is a dummy variable taking a value of 1 if the fund is categorized as such, and 0 otherwise. ESG risk score is included as squared of the original ESG risk score. Past return is measured by previous 6-month return. Size is measured as the Logarithm of TNA in USD and Concentration Top 10 Holdings shows aggregate assets, expressed as a percentage of the fund's top 10 portfolio holdings. Star Rating is defined as a lagged variable from the past three semesters. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A17: Downside Risk and ESG Funds: Robustness section

	Panel A: VaR Modified (Loss)						Panel B: VaR Gauss (Loss)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sustainable	-0.022	0.018					-0.011	0.026*				
	(0.014)	(0.015)					(0.015)	(0.015)				
Low Carbon			-0.030**	0.023*					-0.011	0.039***		
			(0.013)	(0.013)					(0.013)	(0.014)		
Exclusions					-0.011	0.022*					0.002	0.033**
					(0.013)	(0.013)					(0.013)	(0.013)
ESG Risk Score		0.015		0.035***		0.003		-0.001		0.021		-0.013
		(0.014)		(0.013)		(0.014)		(0.014)		(0.015)		(0.016)
ESG Risk Score^2		0.000		-0.000		0.001*		0.001**		0.000		0.001**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Observations	23,036	22,473	36,634	35,946	29,826	29,170	23,036	22,473	36,634	35,946	29,826	29,170
R-squared	0.819	0.825	0.799	0.804	0.814	0.819	0.780	0.786	0.751	0.755	0.775	0.780
Category & Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table reports the results from regression of Downside Risk defined in Equation 2. Panel A shows the results of downside risk VaR Modified (Loss). Panel B shows the results of downside risk measure for VaR Gauss (Loss). We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable', 'Low Carbon', and 'Exclusion' are dummy variables taking a value of 1 if the fund is categorized as such, and 0 otherwise. We include ESG risk score and ESG risk score squared. The first is scaled ranging from 0 to 100, and the second is scaled from 0 to 10000. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A17 (continuation)

	Panel C: Negative skewness						Panel D: Downside Volatility					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sustainable	-1.532	-0.240					-0.008	0.009				
	(1.748)	(1.897)					(0.008)	(0.008)				
Low Carbon			2.821	3.550*					-0.005	0.017**		
			(1.830)	(1.953)					(0.007)	(0.008)		
Exclusions					-3.076**	-2.478*				-0.006	0.008	
					(1.370)	(1.430)				(0.007)	(0.007)	
ESG Risk Score		9.981***		10.531***		9.480***		0.011*		0.022***		0.007
		(1.706)		(1.682)		(1.459)		(0.006)		(0.006)		(0.006)
ESG Risk Score^2		-0.191***		-0.206***		-0.184***		-0.000		-0.000		0.000
		(0.033)		(0.034)		(0.029)		(0.000)		(0.000)		(0.000)
Observations	23,036	22,473	36,634	35,946	29,826	29,170	23,036	22,473	36,634	35,946	29,826	29,170
R-squared	0.226	0.231	0.238	0.242	0.225	0.230	0.716	0.721	0.664	0.667	0.730	0.734
Category & Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table reports the results from regression of Downside Risk defined in Equation 2. Panel C shows the results of downside risk for Negative Skewness. Panel D shows the results of downside risk measure for Downside Volatility. We control for style effects using Morningstar categories, and time fixed effects. The categories 'Sustainable', 'Low Carbon', and 'Exclusion' are dummy variables taking a value of 1 if the fund is categorized as such, and 0 otherwise. We include ESG risk score and ESG risk score squared. The first is scaled ranging from 0 to 100, and the second is scaled from 0 to 10000. Robust standard errors in parentheses, clustered at the fund level. ***, **, and *, denote statistical significance at the 1%, 5%, and 10% levels, respectively.