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MORE SUSTAINABLE, LESS VOLATILE? HOW ESG CHARACTERISTICS AFFECT STOCK RETURN VOLATILITY

Prof. Dominik DAMAST
RELATORE

Prof. Marco MORELLI
CORRELATORE

Matr. Giacomo MONTICCO
CANDIDATO

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Abstract

The study examines the relationship between Environmental, Social, and Governance (ESG) scores and stock return volatility, a commonly used proxy for market risk. Using a panel dataset of 1,012 publicly listed companies over the period 2016–2024, the analysis shows that higher sustainability metrics are on average associated with lower stock market volatility, both in aggregate and in asymmetric terms (upside/downside). Specifically, the overall stabilising effect is conditional on microstructural characteristics captured through econometric interactions between green ratings, trading volumes and liquidity, thus representing the main channels through which sustainable information is absorbed by the market. Furthermore, the inclusion of year-specific dummy interactions highlights the time-varying nature of the ESG-volatility relationship, with a progressive reduction in the negative impact. Therefore, this suggests a weakening of a generalised reputational role in favour of a stabilising premium increasingly tied to the economic and financial soundness of companies. These findings underline the efficacy of ESG measures as a mitigating instrument for financial risk and support their strategic integration into the construction of resilient portfolios.

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Keywords: ESG, Volatility, Stock Markets, Risk Management, Portfolio Optimisation

Introduction

In recent years, the integration of Environmental, Social, and Governance (ESG) factors within investors' decision-making processes has taken on a prominent role in international financial markets. In particular, their inclusion in portfolio optimisation theory has progressively become a widespread practice among asset managers, as well as institutional and retail investors. This deep change reflects a growing sensitivity towards different but related topics such as sustainability, corporate social responsibility and managerial transparency, which nowadays represent important elements in the asset valuation in the risk-return profile.

The general attention concerning ESG metrics was additionally hastened by systemic global events – the COVID-19 pandemic and increasing regulatory focus – that led markets and investors to reconsider firms' resilience in the long run. However, although there has been large-scale adoption of these factors within the processes of both screening and capital allocation, their concrete effect on the volatility of financial markets continues to raise concerns and questions remain regarding their reliability and interpretability. Indeed, the academic literature has widely analysed the relationship between ESG factors and financial performance, while empirically overlooking the potential links between sustainability and risk – especially volatility. Uncertainties still persist regarding their capacity to act as "stabilisers" within financial markets, as well as their methodological and interpretative coherence given by the main data providers. These ambiguities are still fuelling an open debate on the real efficacy of sustainable investments as mitigating instruments of both systemic and idiosyncratic risks.

Therefore, the research adopts a progressive empirical approach structured into three complementary phases. First, it assesses the existence and strength of the relationship between ESG scores and stock price volatility. Second, it investigates the potential transmission channels of this relationship through firm-level interactions, particularly with corporate liquidity and trading volume. Finally, the analysis explores its evolution over time by integrating year-specific dummy variables, in order to capture structural shifts in market perception and behaviour toward ESG signals. In other words, the stepwise methodology aims to move beyond correlation, thus providing a deeper understanding of the dynamics at play.

Empirically, the study examines how ESG scores affect stock price volatility, using a panel dataset of 1,012 publicly listed companies from the United States, Europe and the People's Republic of China, spanning the period from 2016 to 2024 (sourced from LSEG Workspace). This broad dataset provides an extensive basis for exploring geographical heterogeneity and normative divergences in both market behaviours and sustainable practices.

Furthermore, the analysis delves into the underlying mechanisms of this relationship, through a focus on both key econometric interactions and its yearly evolution. Firstly, the integration of econometric interactions between ESG metrics and firms' financial and corporate variables offers an in-depth comprehension of the channels through which sustainable characteristics affect market dynamics. These interactions help to reveal subtle models and conditional effects that would have been lost in simple linear correlations, thus providing a broader vision of the complex relationship between green performance and financial risk. Secondly, the temporal dimension allows to identify potential structural changes in ESG factors on volatility across time.

The study is conducted through a multivariate panel regression with multiple fixed effects (FE), which allows to control for unobservable heterogeneity among companies (Entity FE) and across time (Time FE), hence improving the robustness of the estimates. Among the independent variables, a set of financial and corporate control parameters is included in order to both accurately ensure the estimation of the coefficients and isolate the specific effect of ESG scores on stock volatility. For instance, these controls include market capitalisation, financial leverage and the pre-tax Return On Assets (ROA), which can simultaneously influence perceived sustainability and market risks.

The empirical findings suggest that higher ESG scores are generally associated with lower market volatility, as well as upside and downside volatilities. In particular, the risk-reducing effect mainly depends on two firm-level variables interacting with the sustainable metric: trading volumes and liquidity. The influence of these two factors appears to be determinant through which ESG-related risk information is transmitted and absorbed by financial markets, thus enhancing overall informative and allocative efficiency in the markets. This result points out how ESG efficacy in mitigating stock return volatility also depends both on the microstructural environment, within which companies operate, and on the market capability of efficiently integrating such signals.

In addition, year-specific dummy interactions are included in the study, with the aim of confirming the time-varying nature of the ESG-volatility relationship, hence highlighting correlated dynamics between trading volumes, liquidity and green ratings. The estimated ESG coefficients show a progressive reduction of the negative effect on volatility, until becoming statistically insignificant in the last years. This outcome suggests a weakening of the ESG stabilising role in the post-pandemic trend, with a shift from a generalised reputational effect to a fundamentals-based ESG one. In other words, the green capacity to reduce volatility seems actually to focus only on corporations that are both sustainable and financially robust. Therefore, it emphasises a more sophisticated attitude of the markets in valuing ESG informational essence, which is translated into a less "automatic" stabilising efficacy in favour of a growing coherence between sustainability and economic-financial strength.

From a sustainable finance perspective, the study offers valuable insights for the design of risk management policies, particularly for risk-averse investors. In a context in which macroeconomic uncertainty and the growing complexity of financial markets raise new challenges to portfolio stability, it is of paramount importance to identify instruments capable of reducing volatility without limiting the investable subset of firms. Indeed, the integration of ESG factors serves as a potential tool to improve portfolio stability and enhance efficient capital allocation. Accordingly, sustainability does not only represent an ethical vehicle, but it assumes a strategic role within resilient portfolio construction, thus supporting a more conscious management of risk and optimal allocation of financial resources.

Literature Review

In the contemporary financial landscape, academic literature has been progressively broadening its interest in the analysis of Environmental, Social, and Governance factors as a response to both emerging paradigms in sustainable finance and growing socio-normative pressures (Bolton and Kacperczyk, 2021; Heeb et al., 2023). The majority of studies initially focused on the relationship between ESG performance and expected returns, often finding that firms' greenness[1] is positively priced in the cross-section of stock returns (Alves et al., 2024; Aswani et al., 2024; Bauer et al., 2022; Pastor et al., 2022). However, the effects of ESG factors on equity-linked volatility were at first neglected, with volatility usually treated as an additional variable[2]. Only more recently, increasing systemic uncertainty and the widespread diffusion of responsible investing have shifted attention toward the potential contribution of ESG metrics to risk mitigation. A new strand of research has emerged, aimed at assessing the role of these factors as "stabilising" mechanisms in financial markets.

Within this challenging context, Albuquerque et al. (2020) highlight that including companies involved in corporate social responsibility (CSR) activities reduces the overall riskiness of the portfolio. Similarly, improved performances are reported during the 2008 global financial crisis for companies with a broader CSR attitude as shown by Lins et al. (2017). Hoepner et al. (2019) additionally provide empirical evidence, revealing that active engagement with ESG topics lowers downside risk, while Ilhan et al. (2019) confirm higher levels of tail risk associated with firms with larger carbon emissions.

However, the heterogeneity of ESG impact on volatility is often linked to sectoral, geographical and temporal differences. Eccles et al. (2014) differentiate companies integrating sustainability within corporate strategies from those that exploit it as a reputational tool. This distinction is of paramount importance because it determines whether ESG scores are mitigating risks through financial fundamentals or, instead, are driven by marketing signals. Sabbaghi (2022) confirms this complexity by showing on a global scale how the efficacy of sustainable practices significantly depends on the region and type of asset class considered. Moreover, their efficacy also depends on the consistency among ratings provided by data providers, which can affect investors' interpretation of sustainable metrics (Berg et al., 2022; Capelle-Blancard and Petit, 2019).

Confirming the topic's intricacy, additional contributions have explored the temporal and dynamic roles of the ESG-risk relationship. Ferriani and Natoli (2021) analyse the im-

[1]It reflects the share of firms' sustainable activities. In practice, total emissions, changes in emissions, or emissions intensity are often used as proxies in cross-sectional regressions.

[2]The effective portfolio performance is affected by systematic and idiosyncratic risks, which might bias the measurement of the "pure" ESG return (Friede et al., 2015).

pact of economic uncertainty and ESG sentiment in fixed-income markets, observing a decreasing effect on risk only in circumstances characterised by high financial volatility. Paridhi et al. (2021) assess how green initiatives contribute to the financial stability of healthcare companies in emerging markets throughout the COVID-19 pandemic, showing evidence of improved resilience in the context of systemic shocks. Furthermore, Broadstock et al. (2021)'s equity research on Chinese stock markets during the COVID-19 period links higher ESG ratings to lower volatility. Likewise, Liu et al. (2022) examine green performance and stock idiosyncratic volatility, finding a negative relationship especially in emerging markets.

In other words, academic literature suggests that ESG factors not only reduce market volatility and risks, but are progressively evolving from simple reputational instruments into indicators of corporate resilience. Indeed, in this regard, Verheyden et al. (2016) empirically demonstrate how the inclusion of ESG filters in investment selection processes – for instance, positive screening – can improve portfolio performance, delivering higher returns and lower tail risks without sacrificing diversification.

Hypothesis Development

The sustainable financial industry has experienced unprecedented growth over the last decades, assuming a central role in the global financial landscape. According to the Global Sustainable Investment Review, assets under management (AUM) related to ESG criteria amount to more than USD 30 trillion in 2022, representing approximately 25% of the overall industry. Moreover, compared to 2012, when the total was about USD 13 trillion, the threefold increase in market size within just a decade confirms the structural nature of this phenomenon.

The growth has been driven by multiple factors:

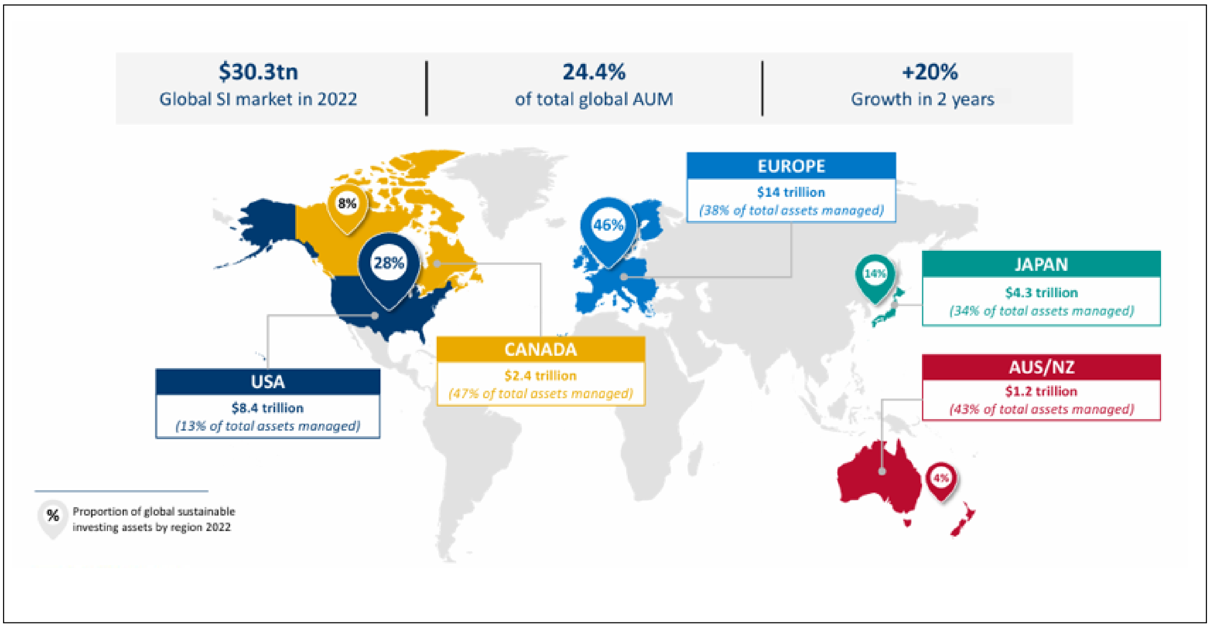
- Regulatory factors, with the diffusion of frameworks like the Sustainable Finance Disclosure Regulation (SFDR) in Europe and the SEC's guidelines in the United States.

- Institutional factors, thanks to the pivotal role of pension funds, Sovereign Wealth Funds (SWFs), and the largest asset managers, which are progressively integrating sustainability within investment decision-making processes.

- Socio-cultural factors, as retail investors and younger savers increasingly attribute importance to ESG objectives in addition to returns.

Figure 1
The Global Sustainable Financial Industry

This figure illustrates the sustainable financial sector. It includes data on the total AUM, its share relative to the overall financial industry, its growth rate[3], and the market share of each geographic region involved in the sector.



Source: Professor Morelli, LUISS University – lecture 8, 2024.

The fast expansion of the ESG industry, as described by both the preceding data and the global growth of green financial instruments, offers a starting point for the development of hypotheses on the research topic. Indeed, the growth of the sustainable financial sector is expected to translate into higher demand and trading volumes, with positive consequences on prices and returns of these assets[4]. Furthermore, the spread of dedicated financial instruments and strategies – such as green bonds, CAT bonds, ESG funds, and impact

[3] 2022 growth rate excludes US data due to the change in methodology and to allow consistent comparison across regions.

[4] According to Görgen et al. (2020), Zhang (2023) and Huij et al. (2024) green stocks have outperformed brown ones.

investing – should increase investors' appetite and consequently attract a broader investor base, thus consolidating this phenomenon. At the same time, the nature of these large investors – typically long-only or SWFs oriented toward stability rather than speculative activities – could contribute to further reducing stock market volatility.

In this context, it is possible to expect that the institutionalisation of ESG capital is not expected to represent a transitory phase, but rather a structural dynamic capable of affecting market risk. Therefore, as stated in Hypothesis 1, companies with higher ESG ratings should exhibit less volatile performance – particularly in terms of downside risk – as reflected in lower beta estimates compared to brown investments. Moreover, the idea is that the ESG effect may be primarily driven by financial characteristics, while corporate features are expected to differentiate its intensity (Hypothesis 2). Finally, as described in Hypothesis 3, the ESG-volatility relationship is expected to evolve over time, strengthening with the growing maturity of the sustainable finance industry.

Hypothesis 1. *Firms with higher ESG scores are expected to exhibit lower stock return volatility, especially on the downside.*

Hypothesis 2. *The ESG–volatility relationship is influenced by firm-specific characteristics, both financial and corporate.*

Hypothesis 3. *The stabilising role of ESG is expected to strengthen over time, in line with the growing maturity of the sustainable finance industry.*

In other words, this global evolution has led to a progressive capital shift towards sustainable financial instruments, thereby widening product offering as well as boosting expectations regarding ESG effects in terms of risk-return trade-off and financial market stability. Therefore, the growing relevance of sustainable financing on a global scale makes it crucial to verify whether higher ESG ratings could be interpreted not only as reputational indicators, but also as evidence of structural resilience of businesses. Indeed, the research hypothesis takes shape from this idea: green investments can contribute to mitigating volatility in stock markets, offering a stabilising role within portfolios.

Empirical Strategy

The empirical structure of the research relies on the application of a panel regression, a particularly suitable choice with respect to the objectives pursued. Indeed, panel data models enable the combination of the transversal dimension (cross-section) with the temporal one (time-series), hence allowing the simultaneous analysis of a wide number of companies over many years. Compared to a classical cross-section regression, which only focuses on statistical differences among units, or a time-series regression that studies the aggregate time evolution, the panel regression provides a dynamic and multidimensional perspective. Therefore, it can incorporate the heterogeneity between firms as well as variations revealed along the time horizon considered.

Furthermore, another crucial advantage of panel data models is the possibility to control for unobserved heterogeneity. Every corporation has intrinsic and relatively time-stable characteristics – for instance, its historic reputation, the organisational structure or the governance model – which can be difficult to measure in a precise way, but that can affect both the volatility of stock returns and its relationship with the ESG scores. Therefore, through the introduction of fixed effects, the model is capable of neutralising these specific and unobserved factors, avoiding potential distortion in the estimates. Analogously, the inclusion of temporal effects enables accounting for common shocks among companies in a given year, such as macroeconomic changes (inflation expectations), normative variation (SFDR in Europe) or global crisis (COVID-19 pandemic).

Moreover, from a methodological point of view, panel regressions provide greater statistical efficiency, because the combination of cross-sectional and longitudinal observations increases the sample size and mitigates multicollinearity among explanatory variables. As a result, it generates more robust and trustworthy estimates, especially in a complex setting such as sustainable financing, where multiple factors may interact in a non-linear manner.

From an operational perspective, the baseline model can be formalised as follows:

$$Log\ Volatility_{i,t} = \alpha + \beta \cdot ESG_{i,t} + \varepsilon_{i,t} \tag{1}$$

where the dependent variable represents the annual volatility of excess returns of firm i in year t, which is log-transformed to improve the statistical distribution. The coefficient β measures the average effect of ESG ratings on volatility, whilst $\varepsilon_{i,t}$ represents the idiosyncratic error term.

Furthermore, Equation 2 presents the first specification in order to enable a clean and coherent estimation of the ESG-volatility relationship, reducing the risk of omitted variable bias.

$$Log\ Volatility_{i,t} = \alpha + \beta \cdot ESG_{i,t} + \sum_{k=1}^{12} \theta_k \cdot Control_{k,i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

where the term $\sum_{k=1}^{12} \theta_k \cdot Control_{k,i,t}$ captures the role of financial and corporate factors in isolating the specific contribution of sustainability, while γ_i and δ_t fixed effects allow accounting for, respectively, heterogeneity across firms and common yearly shocks.

In addition to these general advantages, the use of the panel model assumes a particular value within the context of this study. Indeed, the threefold structure of the research requires a flexible tool, not only able to test a direct hypothesis but also to allow more detailed ancillary analyses. Firstly, as highlighted in Equation 3, the model is enriched with interaction terms in order to explore the transmission channels of the phenomenon. In particular, the aim is to understand which firm-specific indicators and in what way they influence the ESG effect on volatility. Secondly, by interacting ESG scores with time dummy variables, as described in Equation 4, the model allows tracing the evolution of the relationship over the years, making it possible to assess whether the stabilising role of ESG criteria remains steady or varies across time.

$$\begin{aligned} Log\ Volatility_{i,t} = \alpha + \beta \cdot ESG_{i,t} &+ \sum_{k=1}^{12} \theta_k \cdot Control_{k,i,t} \\ &+ \sum_{k=1}^{12} \phi_k \cdot (ESG_{i,t} \times Control_{k,i,t}) + \gamma_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} Log\ Volatility_{i,t} = \alpha &+ \sum_{j=1}^{9} \beta_j \cdot (ESG_{i,t} \times Time\ Dummy_{j,t}) \\ &+ \sum_{k=1}^{12} \theta_k \cdot Control_{k,i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

In other words, panel regression should be viewed not only as a technical approach to enhance estimation accuracy, but as a methodological framework that is fully consistent with the purposes of the analysis. In fact, it allows moving from a general layout to a specific one, up to a dynamic one, always guaranteeing a wide and complete picture. The capacity of the model to combine statistical robustness, analytical flexibility and interpretative depth makes this econometric tool particularly suitable for investigating the complex relationship between sustainability and volatility.

Data

The dataset is built starting from all publicly listed corporations within US, European and Chinese stock exchanges (more than 16,000 entities) available on LSEG Workspace. To guarantee an adequate temporal analysis, only firms with at least nine consecutive years of ESG scores are selected. Thereafter, companies without complete data on control variables since 2016 are excluded from the study. Furthermore, an additional filter is applied, retaining only organisations with more than 150 trading days per year. As a result, after applying all these criteria, the final sample consists of 9,108 observations from 1,012 different listed businesses. It covers three main geographic areas – United States 52%, Europe 42%, and China 6% – which provide a useful behavioural and normative heterogeneity to assess the effect of ESG scores on stock market volatility. Overall, the sample includes corporations from 25 countries and 11 sectors – as classified by LSEG Workspace – thus sufficiently covering a wide and diversified share of the markets.
The dependent variables considered are three measures of stock market volatility:

- Log Volatility, computed on the basis of daily excess returns with respect to the risk-free rate in every specific year;
- Downside Log Volatility, focusing on the negative component of excess returns;
- Upside Log Volatility, focusing on the positive component of excess returns.

The main explanatory variable is the annual ESG rating, which is calculated as a composite index accounting for self-reported information on environmental, social and governance pillars. Moreover, to correctly isolate the ESG–volatility relationship and improve the explanatory power (R^2), twelve control variables are included: on one hand pre-tax ROA, leverage, Capital Expenditure, liquidity, Cost Of Goods Sold for business characteristics; on the other hand, market beta, company market capitalisation, trading volume, Fama-French risk-free rate, inflation-adjusted risk-free rate, Sharpe ratio, and Sortino ratio for financial features. All these variables allow the model to focus on both firm-specific and market-level circumstances potentially affecting stock returns.

It is of paramount importance to highlight that some variables are manually computed starting from daily stock prices, whereas others are obtained from consolidated financial data providers – LSEG Workspace and the Kenneth R. French Data Library. In addition, some of them are log-transformed in order to improve statistical distribution. Finally, thanks to the screening of incomplete observations, the dataset does not contain missing values (see Table D.1 which reports the detailed definitions as well as the respective sources).

To provide an initial representation of the dataset, three statistical tools for graphical visualisation are employed. Scatter plots, box plots and correlation heatmaps intuitively display the main characteristics of the sample as well as the relationships between variables. Firstly, the scatter plots illustrate the temporal dynamics and the distribution of observations across years, thus allowing the detection of potential outliers. Secondly, the box plots summarise the distribution of the data, highlighting median, interquartile ranges and extreme values. Thirdly, the correlation heatmap exhibits the linear associations among regressors, hence excluding potential multicollinearity issues. Overall, the aim of these graphical instruments is to preliminarily support the specification of the regression model and the subsequent quantitative analysis.

It should be emphasised that many variables – for instance, volatilities, pre-tax ROA, COGS, trading volume – exhibit both extreme observations and substantial heterogeneity across variables (see Figure A.1). Therefore, a symmetric winsorisation at the 1% level is applied to all continuous variables: the values below the 1^{st} percentile are set equal to the 1^{st} percentile and the values above the 99^{th} percentile are set equal to the 99^{th} percentile. The ESG score, being a categorical variable, is not winsorised, preserving its original distribution. Consequently, as described in Figure A.2, the overall shape of the distributions remains coherent, whilst the influence of outliers is significantly reduced. This technical procedure limits the impact of extreme observations, thereby enhancing the robustness of the econometric analysis without altering the underlying traits of the sample.

Moreover, the analysis of the correlation matrix shows the absence of relevant multicollinearity problems (see Figure A.3), as most of the coefficients are close to zero. However, some exceptions should be underlined: the –0.40 correlation between Cost of Goods Sold and Capital Expenditure, the 0.84 correlation between the risk-free rate and its inflation-adjusted version, and the 0.99 correlation between the performance indexes Sharpe and Sortino. These results are consistent with the nature of the considered control variables and confirm the dataset's robustness for implementing the econometric analysis.

Results

ESG & Log Volatility. The first step of the analysis consists of exploring the "raw" relationship between firms' ESG scores and their stock return volatility. Table 1 reports the results of the estimated parameters of the baseline panel regression without including any controls or fixed effects.

Table 1
ESG Scores and Log Volatility

This table reports estimated coefficients for Equation 1. The dependent variable is the annual log volatility of firms, computed using daily log excess returns from stock prices over the calendar year. The explanatory variable is the annual ESG rating. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). To limit the influence of extreme outliers, the dependent variable is winsorised at the 1^{st} and 99^{th} percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations.

	Dependent variable: *Log Volatility*			
	Estimate	Std. Error	T-stat	P-value
Alpha	-0.3993	0.0054	74.458	<0.01
ESG	-0.1216	0.0083	-14.575	<0.01
$R^2 = 0.0243$				

The beta coefficient associated with sustainability is negative and statistically significant, thus confirming that greener companies tend to show lower volatility of stock returns. This result provides preliminary evidence in support of Hypothesis 1. Indeed, a negative association could be interpreted as a signal that investors perceive sustainable firms as less risky. A possible reason lies in the nature of investors attracted by this sector, who usually are institutional with long investment horizons. Despite the high growth rate of the industry (larger trading volumes), their trading behaviour tends to soften price fluctuation, hence contributing to return stabilisation.

ESG & Asymmetric Volatilities. To better understand the phenomenon, the research is then extended by regressing ESG ratings on two complementary constituents of volatility: downside volatility (related to losses) and upside volatility (linked to gains). This distinction allows to verify whether the original negative effect is symmetric or more concentrated in one of the two directions.

Table C.1's results exhibit a negative and statistically significant coefficient for downside log volatility, as well as for upside volatility. Furthermore, both estimates show a lower magnitude compared with the one from Table 1, suggesting that each component partially contributes to reducing volatility overall. Moreover, their comparison indicates that the green effect is slightly more pronounced toward the upside component, which highlights how ESG information not only mitigates the risk of losses, but also helps to diminish the width of positive unstable returns. This result is coherent with the intrinsic features of the sustainable finance sector, which has been a dynamic and constantly growing market over time, with wide development margins and favourable future perspectives. In other words, stock markets acknowledge the value of sustainable characteristics both as a risk-protection factor and as a stabilising element of stock prices.

Therefore, Table C.1 confirms and strengthens the preliminary evidence from the aggregated log volatility regression, providing additional arguments in support of the main Hypothesis 1. The adoption of ESG criteria seems to be associated with a wiser management of risk perceived by investors, fostering portfolio resilience in both positive and negative market conditions. Finally, their symmetric effect on volatility reduces concerns about a potential market bias in absorbing green information only in negative contexts.

ESG & Trading Volume. The twofold observed reduction in both volatility's components suggests that the mechanisms through which ESG affects returns' stability are not entirely linked to idiosyncratic factors, but may also reflect broader market dynamics. In particular, a crucial focus concerns trading volumes, because liquidity and intensity of transactions can amplify or mitigate stock return volatility. Therefore, an ancillary analysis between the independent variable and trading volumes is conducted (see Equation B.1).

As shown in Table C.2, the results of the panel regression exhibit a positive and statistically significant beta estimate, thereby underlining that sustainable corporations tend to record on average larger trading volumes. These empirical findings support the interpretation that companies' sustainable characteristics favour broader market liquidity and exchange intensity. Consequently, increases in trading volume could partially explain the stabilising factor observed in stock return volatility: more liquid markets are generally subject to fewer extreme price fluctuations. In other words, ESG scores do not only act as firm-specific risk controllers, but also affect aggregate market dynamics through microstructural channels. As a result, the trading volume variable is also used as a control variable and interaction term in the main subsequent regressions in order to specifically assess how it impacts the ESG-volatility relationship.

ESG & Extended Specifications. The study has also been extended through several specifications to both guarantee the robustness of previous results and explain the underlying mechanisms behind them. In detail, the objective is to verify whether the observed effect in the ESG-volatility model maintains significance and consistency after controlling for financial and corporate features, as well as whether it is modulated by specific exogenous variables.

The columns of Table 2 show how the main ESG β maintains a negative sign and remains statistically significant despite the introduction of Time, Sector and Geography fixed effects, together with a full set of financial and corporate control variables. It is of paramount importance to note that the integration of controls considerably improves R^2 (from 0.0437 to 0.4848), thus explaining a large portion of stock return volatility.

Table 2

ESG Scores and Log Volatility including Specifications

This table reports estimated coefficients for four specifications based on Equation 1. The dependent variable is the annual log volatility of firm, computed using daily log excess returns from stock prices over the calendar year. The main explanatory variable is the annual ESG rating. Column (1) reports the baseline model without fixed effects, control variables or interactions. Column (2) includes Time, Sector, and Geography fixed effects. Column (3) adds the full set of 12 control variables. Column (4) additionally includes interaction terms between ESG ratings and control variables. Column (5) replaces the fixed effects in column (4) with time and entity fixed effects to better isolate firm-specific variation over time. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). Four different fixed effects are used: Time (9), Entity (1,012), Geography (3), and Sector (11). The model includes 12 control variables: *Pretax ROA*, *Leverage*, *CapEx*, *Liquidity*, *COGS*, *MKT beta*, *Company market capitalisation*, *Trading volume*, *Fama-French risk-free rate*, *Inflation adjusted with the risk-free rate*, *Sharpe ratio*, and *Sortino ratio.* To mitigate asymmetries in the distribution of residuals, some control variables are transformed into their logarithmic form, which improves the R^2. To limit the influence of extreme outliers, continuous variables are winsorised at the 1st and 99th percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent variable: *Log Volatility*				
	(1)	(2)	(3)	(4)	(5)
ESG	-0.1216***	-0.1435***	-0.0202***	-0.9466***	-0.2735
ESG×Liquidity				-0.0142**	0.0030
ESG×Trading volume				$-2.1e^{-9}$***	$-3.2e^{-9}$***
ESG×FF risk-free rate				-5.9418***	-3.5441***
Controls			Yes	Yes	Yes
Interactions				Yes	Yes
T-S-G FEs		Yes	Yes	Yes	
T-E FEs					Yes
No. of obs.	9,108	9,108	9,108	9,108	9,108
R^2	0.0243	0.0437	0.4848	0.5004	0.3549

The inclusion of interaction terms between ESG and some exogenous variables – corporate liquidity, trading volume and the Fama-French risk-free rate – makes it possible to identify the transmission channels through which sustainable characteristics modulate total volatility. Indeed, the ESG $\times$ Trading Volume estimate is highly significant, validating that the ESG mitigating effect is amplified within more liquid contexts. Moreover, the coefficient's negativity fully reflects previous findings from Table 1 and Table C.2: the green score reduces volatility (negative estimate) and boosts trading volumes (positive estimate); therefore, the product of these two relationships generates the negative effect observed, confirming that sustainability and price stability are connected through market activity. In addition, although the estimates of the last specification are less statistically significant[5], this interpretation is further supported by the most complex specification (column 5), which enhances the overall consistency of results.

A second relevant channel is corporate liquidity. Its interaction shows how greener companies are able to benefit from a solid financial structure, with larger liquid assets that soften stock price fluctuations. In other words, corporate liquidity represents a multiplier of the ESG stabilising role, enabling corporations to better absorb market shocks as well as investors to predict stock returns. Hence, these results also strengthen the assumption related to Hypothesis 2 – green factors do not operate separately, but rather interact with firm-specific characteristics to modulate market volatility.

From Table C.3 and Table C.4 in the appendix, both downside and upside log volatilities provide similar findings. The only difference lies in the values of the parameters estimated, which show smaller magnitudes, thus confirming the important contribution of each volatility component to the overall phenomenon. In other words, the total reduction is explained by the combination of effects on negative and positive stock returns, each one shaped by interactions with trading volume, liquidity and macro-financial circumstances (for instance, the risk-free rate).

ESG & Temporal Dynamics. The research also focuses on the temporal dimension of the ESG–volatility relationship in order to deepen its understanding from a completely

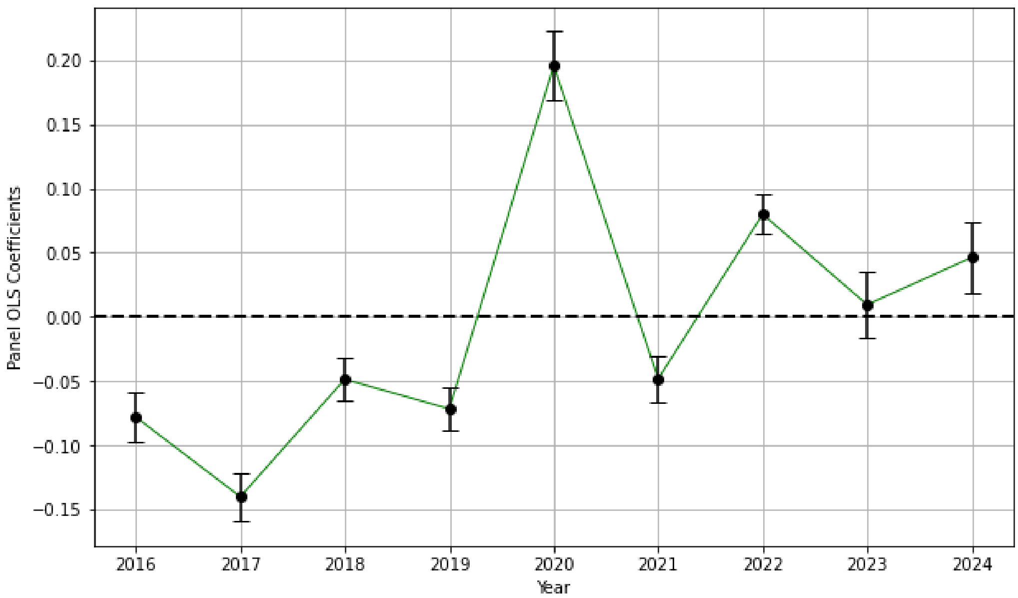
[5] Parameters exhibit higher associated p-values, reflecting a loss of statistical power probably due to the structure of the dataset and the narrower fixed effects included.

different perspective than the previous analyses. Indeed, the efficacy of sustainable criteria in mitigating risks could not remain constant over time, but may reflect structural changes in investors' behaviours and macro-financial conditions. Therefore, the inclusion of yearly dummy variables interacting with ESG scores allows for the study of the time-varying evolution of the phenomenon (see Equation 4).

Figure 2

ESG yearly effect on log volatility (Sector-Geography FE)

This figure presents the estimated yearly effects of ESG scores on log volatility, derived from the panel OLS regression described in Equation 4, where ESG scores are interacted with year dummies. The specification includes sector and geography fixed effects to account for unobserved heterogeneity across industries and regions. Each black dot represents the estimated coefficient of the interaction term for a given year, capturing the isolated effect of ESG ratings on volatility in that year. The green line connects the yearly point estimates, while vertical black lines indicate 95% confidence intervals computed as $\hat{\beta} \pm 1.96 \cdot \mathrm{SE}$. A bold dashed horizontal black line is plotted at zero to visually separate positive from negative coefficients.



The dynamic analysis of the annual estimates depicted in Figure 2 shows that the relationship is not static, but reflects evolving market conditions and structural channels through which sustainable information is absorbed into stock prices:

- During the first years of observation (2016–2019), the green coefficient is negative and statistically significant, highlighting how sustainable characteristics are perceived as a stability factor mitigating stock market fluctuations. This result is coherent with a context where trading volumes and corporate liquidity are relatively contained, thus making ESG information a differentiating and informative element (see Figure A.4 and Figure A.5).

- However, the year 2020 marks an evident discontinuity. The ESG beta becomes positive, reflecting a generalised spike in volatility linked to the COVID-19 pandemic. The increase in trading volumes, without a respective increment in liquidity, amplified global market instability. Furthermore, unprecedented uncertainty about circumstances and the global financial shock of the pandemic reduced the stabilising capability of ESG ratings, because these exogenous and systemic drivers temporarily prevailed over companies' structural features.

- In 2021, the ESG effect returns negative thanks to expansionary fiscal and monetary policies, which provided immediate liquidity support to businesses. In fact, larger availability of liquid resources reduces the perceived risk of default, making firms more resilient to market shocks. Therefore, corporate liquidity acts as a multiplier of the ESG stabilising role, allowing investors to interpret sustainable corporations as both more responsible and financially solid. On the contrary, when the boost concerns only trading volumes, the overall effect can even translate into higher volatility – as in 2020.

- In the following years (2022–2024), the green coefficients seem to fluctuate near zero, signalling a steady weakening of the effect. This result may be interpreted as a sign that, after the pandemic, ESG information appears to be progressively internalised within standard valuation processes, indicating a shift from an ESG reputational premium to a more fundamental-based premium.

In line with the previous analyses, the breakdown between downside and upside volatility shows very similar trends, despite their different magnitudes (see Figure A.6 and Figure A.7). Therefore, the stabilising phenomenon associated with ESG scores symmetrically acts as protection against both losses and volatile positive returns. Moreover, the regression is also replicated using specifications with Time-Entity fixed effects, as described in Figure A.8 in the appendix. However, the confidence intervals are notably wider, and the estimated coefficients do not consistently follow the previously observed trend, revealing greater uncertainty due to the limited temporal dimension of the dataset. This evidence reflects a loss of statistical power linked to the data structure, without, however, questioning the overall robustness of the findings.

Conclusion

The research shows how the sustainable characteristics of companies, measured through ESG scores, can play a relevant role in reducing stock return volatility. In detail, the results suggest that investing in greener corporations not only softens the risk of losses but also contributes to stabilising positive returns. Furthermore, the empirical evidence shows that the stabilising effect of ESG factors depends on market environments: circumstances such as high liquidity and exchange intensity shape the mitigating potential of ESG ratings. The ESG–volatility relationship is not static over time, but reflects the evolution of market conditions and investor behaviour, with varying efficacy of green criteria depending on macroeconomic and microstructural contexts. Indeed, sustainable information acts at the firm-specific level while interacting with multiple corporate and financial dynamics, thereby representing a useful tool for market participants whose interests focus on overall financial market stability.

Despite these intriguing results, the analysis has some limitations. It focuses on a confined number of companies and geographic areas, and the temporal dimension of the dataset is relatively narrow, thus reducing the statistical power of some specifications. In addition, the use of ESG scores as the sole sustainability indicator can affect the final outcomes due to existing differences among various data providers and computational methodologies. These limitations provide insights for future studies, such as extending the analysis to new markets and longer timespans, exploring alternative green measures, or evaluating sector-specific channels through which ESG features impact volatility.

In conclusion, these findings confirm that sustainable characteristics are nowadays both a strategic framework for ethical objectives and a practical element of financial stabilisation. They can be integrated into portfolio risk assessment to improve resilience and foster more informed investment decisions and risk management policies.

References

Albuquerque, R., Koskinen, Y., and Zhang, C. (2020). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 66(10):4451–4469.

Alves, R., Krueger, P., and van Dijk, M. A. (2024). Drawing up the bill: Is esg related to stock returns around the world? Working Paper.

Aswani, J., Raghunandan, A., and Rajgopal, S. (2024). Are carbon emissions associated with stock returns? *Review of Finance*, 28(1):75–106.

Bauer, M. D., Huber, D., Rudebusch, G. D., and Wilms, O. (2022). Where is the carbon premium? global performance of green and brown stocks. *Journal of Climate Finance*, 1:100006.

Berg, F., Kölbel, J. F., and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings. *Review of Finance*, 26(6):1315–1344.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*.

Broadstock, D. C., Chan, K., Cheng, L. T. W., and Wang, X. (2021). The role of esg performance during times of financial crisis: Evidence from covid-19 in china. *Finance Research Letters*, 38:101716.

Capelle-Blancard, G. and Petit, A. (2019). Every little helps? esg news and stock market reaction. *Journal of Business Ethics*, 157(2):543–565.

Eccles, R. G., Ioannou, I., and Serafeim, G. (2014). The impact of a corporate culture of sustainability on corporate behavior and performance. *Management Science*, 60(11):2835–2857.

Ferriani, F. and Natoli, F. (2021). Esg risks in times of covid-19. Technical Report 1302, Bank of Italy Working Papers.

Friede, G., Busch, T., and Bassen, A. (2015). Esg and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, 5(4):210–233.

Global Sustainable Investment Alliance (2013). Global sustainable investment review 2012.

Global Sustainable Investment Alliance (2023). Global sustainable investment review 2022.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). Carbon risk. Working paper.

Heeb, F., Kölbel, J. F., Paetzold, F., and Zeisberger, S. (2023). Do investors care about impact? *Review of Financial Studies*, 36(5):1737–1787.

Hoepner, A. G. F., Oikonomou, I., Scholtens, B., and Schröder, M. (2019). Esg performance and downside risk. *Journal of Banking & Finance*, 104:106–122.

Huij, J., Laurs, D., Stork, P. A., and Zwinkels, R. C. (2024). Carbon beta: A market-based measure of climate risk. Working paper.

Ilhan, E., Sautner, Z., and Vilkov, G. (2019). Carbon tail risk. *The Review of Financial Studies*, 34(4):1540–1571.

Lins, K. V., Servaes, H., and Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824.

Liu, D., Gu, K., and Hu, W. (2022). Esg performance and stock idiosyncratic volatility. *Finance Research Letters*, 47:102667.

Morelli, M., De Spirito, L., and Fantasia, P. (2024). Lecture 8 - overview of responsible investing. University lecture slides, LUISS.

Paridhi, P., Ritika, and Kumar, R. (2021). Esg practices and financial stability in emerging market healthcare companies: Insights amidst the covid-19 pandemic. *International Journal of Management Studies and Research*, 9(5):1–10.

Pastor, L., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424.

Sabbaghi, O. (2022). Esg and volatility risk: International evidence. *Journal of Sustainable Finance & Investment*, 12(3):674–691.

Verheyden, T., Eccles, R. G., and Feiner, A. (2016). Esg for all? the impact of esg screening on return, risk, and diversification. *Journal of Applied Corporate Finance*, 28(2):47–55.

Zhang, S. (2023). Carbon returns across the globe. Working paper.

Online Appendix

A Additional Figures

Figure A.1
Distribution of Panel Variables Before Winsorisation

This figure presents the distribution of the 16 panel variables before winsorisation. On the left of each subplot, scatter plots display individual observations per year with jittering applied to the x-axis to avoid overlap, while the right side features a box plot summarising the overall distribution of each variable. Black lines with circular markers indicate the mean value of each variable per year. This layout allows for a visual comparison of both temporal trends and cross-sectional dispersion across variables.

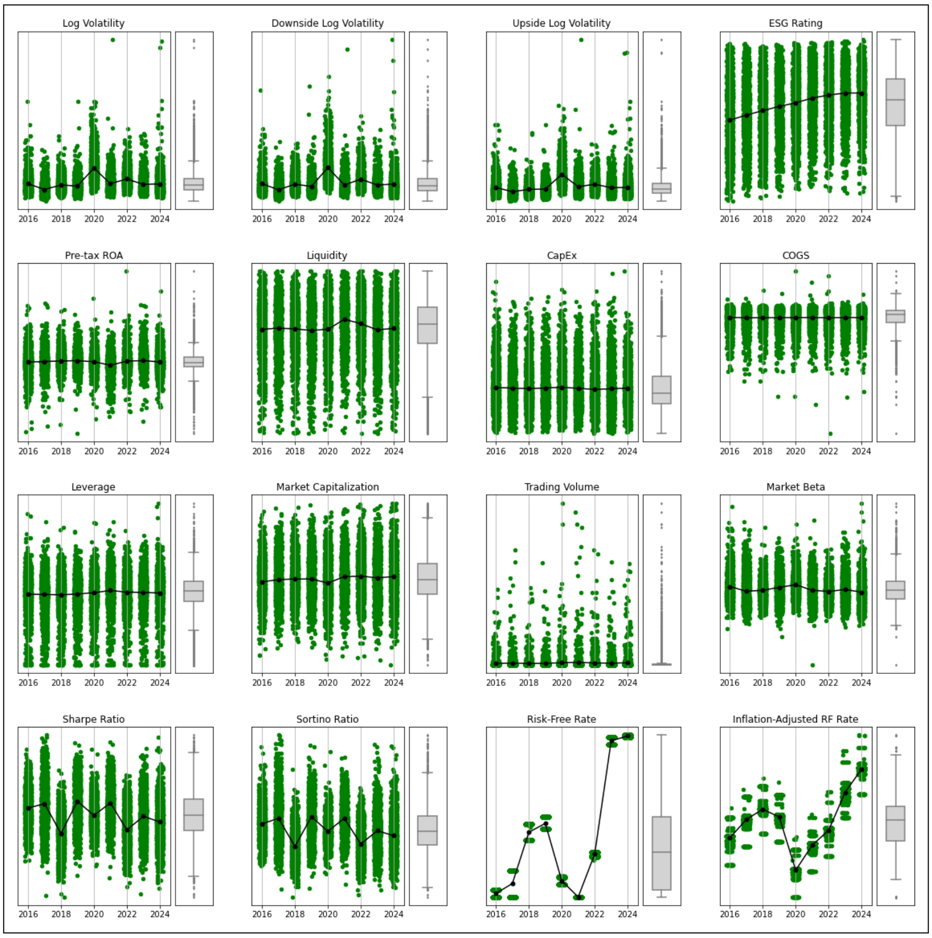


Figure A.2
Distribution of Panel Variables After Winsorisation

This figure illustrates the distribution of the 16 panel variables after winsorisation. Scatter plots are displayed on the left of each subplot with jittering applied to the x-axis to avoid overlapping points, while box plots summarise the overall distribution on the right side. Black lines with circular markers indicate the mean value of each variable per year. Notably, the ESG Rating variable (shown with dark green triangles) was not winsorised, since it is categorical, which allows visual comparison with the winsorised continuous variables.

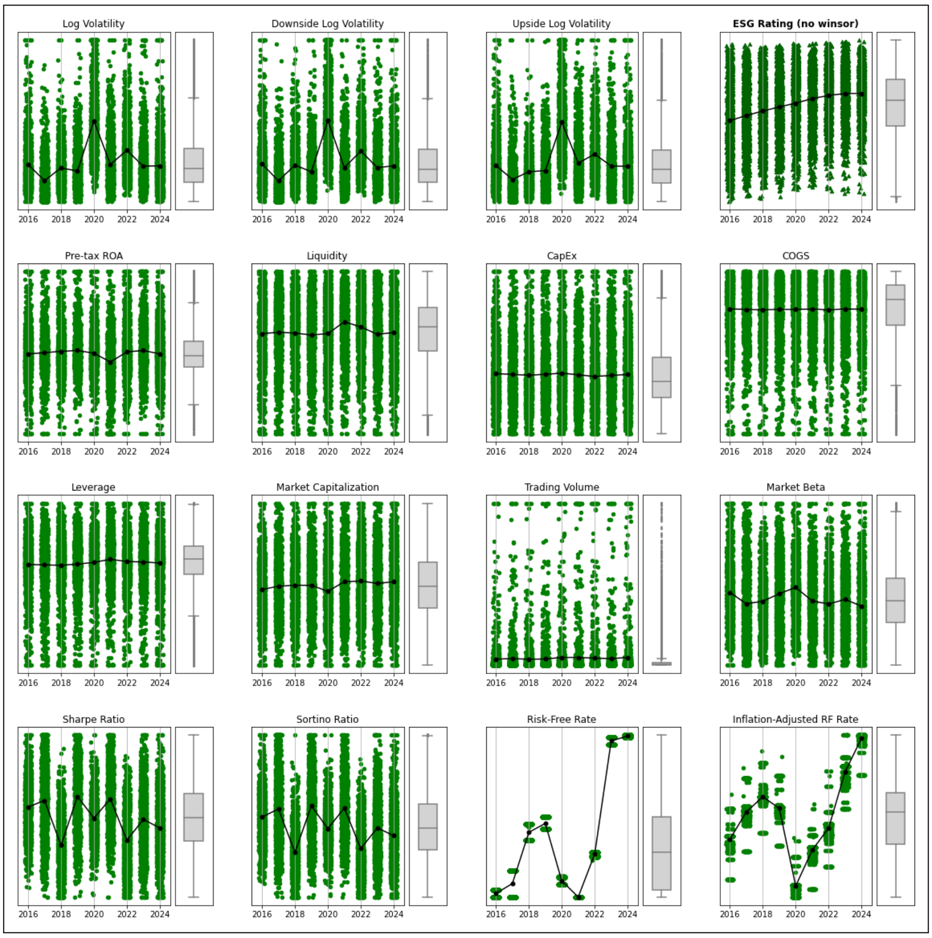


Figure A.3
Correlation Heatmap of Panel Variables

This figure illustrates the pairwise correlations among the 13 explanatory panel variables. Each cell in the heatmap represents the correlation coefficient between two variables, with colors indicating the strength and direction of the relationship. High positive correlations are shown in darker shades, while negative correlations appear in lighter shades. This visual representation allows for a quick assessment of potential multicollinearity and interdependencies across variables after applying any transformations or winsorisation.

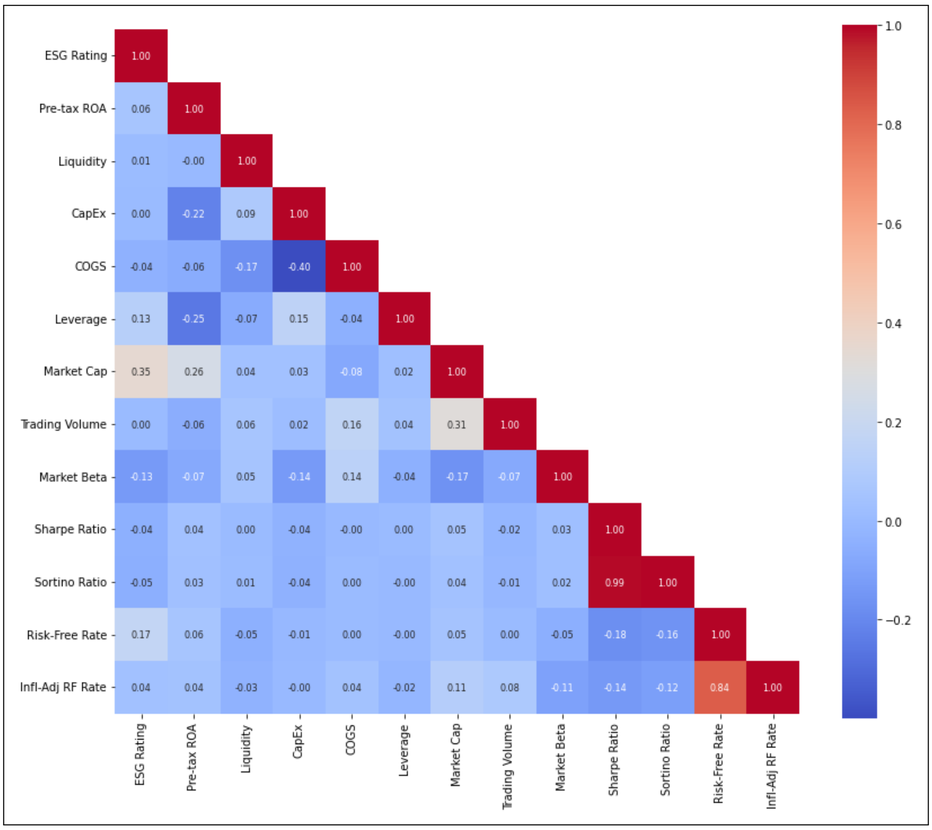


Figure A.4
Mean Annual Trading Volume (aggregated)

This figure plots the average annual trading volume across all firms, computed as the mean of each firm's annual trading volume for each calendar year. This aggregate measure provides an overview of market activity trends over time, highlighting periods of increased or decreased trading intensity.

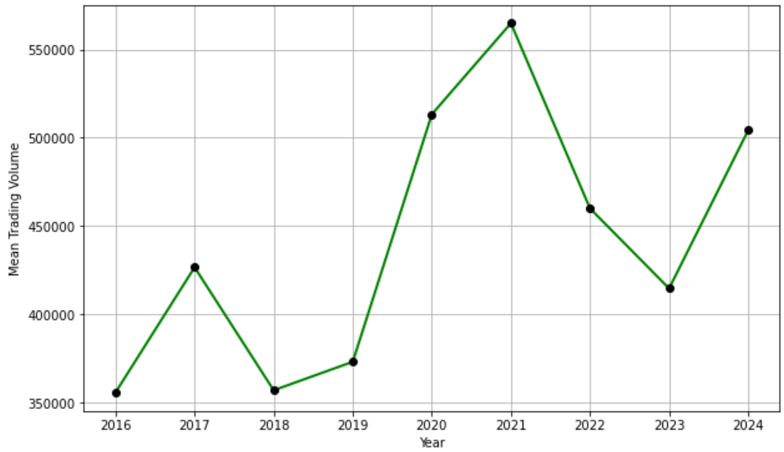


Figure A.5
Mean Annual Corporate Liquidity (aggregated)

This figure plots the average annual corporate liquidity (in logarithmic scale) across all firms, computed as the mean of the log-transformed annual liquidity measure for each calendar year. Taking the logarithm allows for a wider range of values and better discrimination, since the original liquidity values were initially very similar. This aggregate measure provides insight into firms' liquidity trends over time, highlighting periods of tightening or easing liquidity conditions in the market.

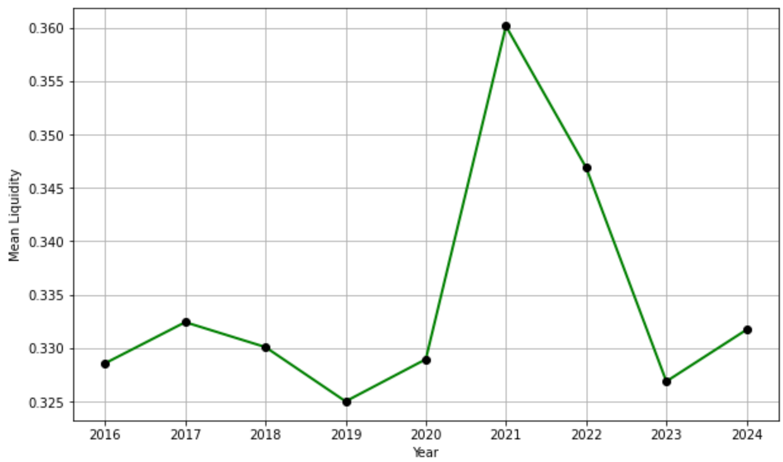


Figure A.6

ESG Yearly Effect on Downside Log Volatility (Sector-Geography FE)

This figure presents the estimated yearly effects of ESG scores on downside log volatility, derived from the panel OLS regression described in Equation 4. The specification includes sector and geography fixed effects to account for unobserved heterogeneity across industries and regions. Each black dot represents the estimated coefficient of the interaction term for a given year, capturing the isolated effect of ESG ratings on downside volatility in that year. The green line connects the yearly point estimates, while vertical black lines indicate 95% confidence intervals computed as $\hat{\beta} \pm 1.96 \cdot \mathrm{SE}$. A bold dashed horizontal black line is plotted at zero to visually separate positive from negative coefficients.

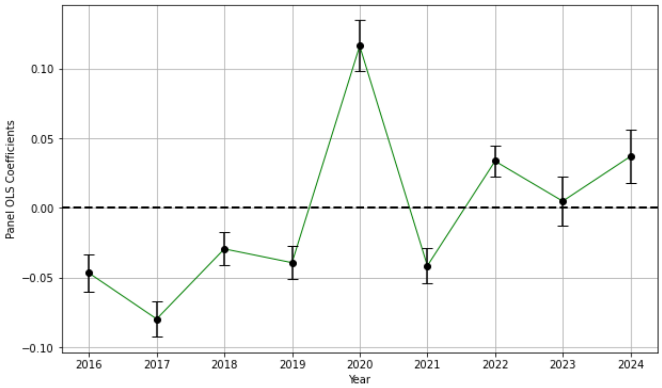


Figure A.7

ESG Yearly Effect on Upside Log Volatility (Sector-Geography FE)

This figure presents the estimated yearly effects of ESG scores on upside log volatility, derived from the panel OLS regression described in Equation 4. The specification includes sector and geography fixed effects to account for unobserved heterogeneity across industries and regions. Each black dot represents the estimated coefficient of the interaction term for a given year, capturing the isolated effect of ESG ratings on upside volatility in that year. The green line connects the yearly point estimates, while vertical black lines indicate 95% confidence intervals computed as $\hat{\beta} \pm 1.96 \cdot \mathrm{SE}$. A bold dashed horizontal black line is plotted at zero to visually separate positive from negative coefficients.

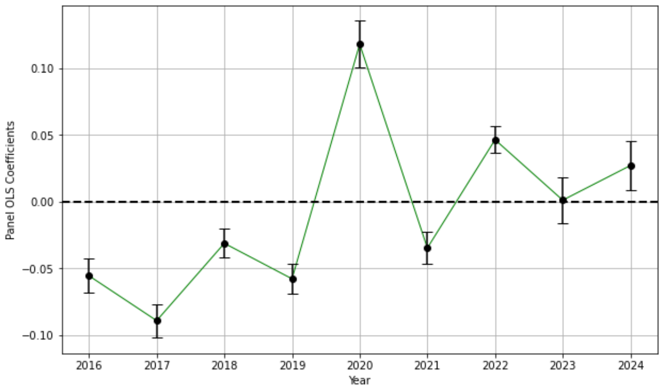
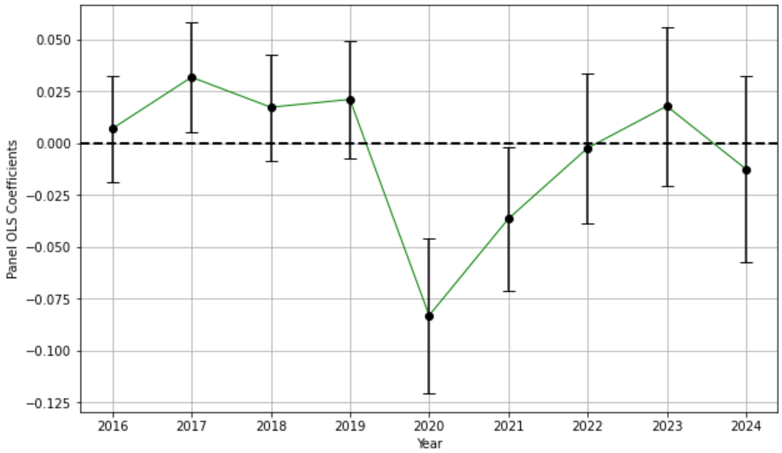


Figure A.8
ESG Yearly Effect on Log Volatility (Time-Entity FE)

This figure presents the estimated yearly effects of ESG scores on log volatility, derived from the panel OLS regression described in Equation 4, where ESG scores are interacted with year dummies. The specification includes time and entity fixed effects to control for unobserved temporal shocks and firm-specific heterogeneity. Each black dot represents the estimated coefficient of the interaction term for a given year, capturing the isolated effect of ESG ratings on volatility in that year. The green line connects the yearly point estimates, while vertical black lines indicate 95% confidence intervals computed as $\hat{\beta} \pm 1.96 \cdot \mathrm{SE}$. A bold dashed horizontal black line is plotted at zero to visually separate positive from negative coefficients.



B Additional Equations

Ancillary regression used to assess the importance of trading volumes in the context of this research. Three fixed effects are included in order to isolate the ESG effect: sector (γ_s), time (δ_t) and geography (ζ_g).

$$\mathit{Trading\ Volume}_{i,t} = \alpha + \beta \cdot \mathit{ESG}_{i,t} + \gamma_s + \delta_t + \zeta_g + \varepsilon_{i,t} \tag{B.1}$$

C Additional Tables

Table C.1
ESG Scores on Downside & Upside Log Volatility

This table reports estimated coefficients for Equation 1. The dependent variables are respectively the annual downside log volatility and the annual upside log volatility of firms. The explanatory variable is the annual ESG rating. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). To limit the influence of extreme outliers, the dependent variables are winsorised at the 1st and 99th percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations.

	Dependent variable: *Downside Log Volatility*			
	Estimate	Std. Error	T-stat	P-value
Alpha	0.2455	0.0035	69.956	<0.01
ESG	-0.0713	0.0055	-13.020	<0.01
$R^2 = 0.0193$				

	Dependent variable: *Upside Log Volatility*			
	Estimate	Std. Error	T-stat	P-value
Alpha	0.2416	0.0033	72.466	<0.01
ESG	-0.0798	0.0052	-15.434	<0.01
$R^2 = 0.0275$				

Table C.2

ESG Scores and Trading Volume

This table reports estimated coefficients for Equation B.1 (it includes Time, Sector, and Geography fixed effects). The dependent variable is the annual trading volume of firms, while the explanatory variable is their annual ESG rating. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). To limit the influence of extreme outliers, the dependent variable is winsorised at the 1^{st} and 99^{th} percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations.

	Dependent variable: *Trading Volume*			
	Estimate	Std. Error	T-stat	P-value
Alpha	-3.267e+05	2.341e+05	-1.3956	0.1629
ESG	6.437e+06	4.399e+05	14.632	<0.01
$R^2 = 0.0214$				

Table C.3
ESG Scores and Downside Log Volatility

This table reports estimated coefficients for four specifications based on Equation 1. The dependent variable is the annual downside log volatility of firms, computed using only negative daily log excess returns from stock prices over the calendar year. The main explanatory variable is the annual ESG rating. Column (1) reports the baseline model without fixed effects, control variables or interactions. Column (2) includes Time, Sector, and Geography fixed effects. Column (3) adds the full set of 12 control variables. Column (4) additionally includes interaction terms between ESG ratings and control variables. Column (5) replaces the fixed effects in column (4) with time and entity fixed effects to better isolate firm-specific variation over time. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). Four different fixed effects are used: Time (9), Entity (1,012), Geography (3), and Sector (11). The model includes 12 control variables: *Pretax ROA*, *Leverage*, *CapEx*, *Liquidity*, *COGS*, *MKT beta*, *Company market capitalisation*, *Trading volume*, *Fama-French risk-free rate*, *Inflation adjusted with the risk-free rate*, *Sharpe ratio*, and *Sortino ratio*. To mitigate asymmetries in the distribution of residuals, some control variables are transformed into their logarithmic form, which improves the R^2. To limit the influence of extreme outliers, continuous variables are winsorised at the 1st and 99th percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent variable: *Downside Log Volatility*				
	(1)	(2)	(3)	(4)	(5)
ESG	-0.0713***	-0.0841***	-0.0108**	-0.5634***	-0.2164*
ESG×Liquidity				-0.0100**	0.0012
ESG×Trading volume				$-1.4e^{-9}$***	$-2.3e^{-9}$***
ESG×FF risk-free rate				-3.2104***	-1.8099**
Controls			Yes	Yes	Yes
Interactions				Yes	Yes
T-S-G FEs		Yes	Yes	Yes	
T-E FEs					Yes
No. of obs.	9,108	9,108	9,108	9,108	9,108
R^2	0.0193	0.0339	0.4428	0.4544	0.3193

Table C.4

ESG Scores and Upside Log Volatility

This table reports estimated coefficients for four specifications based on Equation 1. The dependent variable is the annual log volatility of firms, computed using only positive daily log excess returns from stock prices over the calendar year. The main explanatory variable is the annual ESG rating. Column (1) reports the baseline model without fixed effects, control variables or interactions. Column (2) includes Time, Sector, and Geography fixed effects. Column (3) adds the full set of 12 control variables. Column (4) additionally includes interaction terms between ESG ratings and control variables. Column (5) replaces the fixed effects in column (4) with time and entity fixed effects to better isolate firm-specific variation over time. The dataset contains observations from 1,012 companies over 9 years (US: 52%, EU: 42%, CH: 6%). Four different fixed effects are used: Time (9), Entity (1,012), Geography (3), and Sector (11). The model includes 12 control variables: *Pretax ROA*, *Leverage*, *CapEx*, *Liquidity*, *COGS*, *MKT beta*, *Company market capitalisation*, *Trading volume*, *Fama-French risk-free rate*, *Inflation adjusted with the risk-free rate*, *Sharpe ratio*, and *Sortino ratio*. To mitigate asymmetries in the distribution of residuals, some control variables are transformed into their logarithmic form, which improves the R^2. To limit the influence of extreme outliers, continuous variables are winsorised at the 1st and 99th percentiles. After computing the Breusch-Pagan test, the robust residuals' variance-covariance matrix is used to address heteroskedasticity, capturing non-constant residual variance across observations. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent variable: *Upside Log Volatility*				
	(1)	(2)	(3)	(4)	(5)
ESG	-0.0798***	-0.0927***	-0.0144***	-0.6018***	-0.1533
ESG×Liquidity				-0.0086**	0.0019
ESG×Trading volume				$-1.3e^{-9}$***	$-1.9e^{-9}$***
ESG×FF risk-free rate				-3.9318***	-2.3641***
Controls			Yes	Yes	Yes
Interactions				Yes	Yes
T-S-G FEs		Yes	Yes	Yes	
T-E FEs					Yes
No. of obs.	9,108	9,108	9,108	9,108	9,108
R^2	0.0275	0.0462	0.4746	0.4927	0.3768

D Data

Table D.1
Variable Definitions and Data Sources

This table contains the first part of variable definitions and data sources.

Variable	Definition
	Dependent variables
Log volatility	Annualised volatility manually computed using daily log excess returns derived from stock prices over the calendar year. *Source: LSEG Workspace.*
Downside log volatility	Annualised downside volatility manually computed using negative daily log excess returns derived from stock prices over the calendar year. *Source: LSEG Workspace.*
Upside log volatility	Annualised upside volatility manually computed using positive daily log excess returns derived from stock prices over the calendar year. *Source: LSEG Workspace.*
	Main independent variable
ESG rating	Overall company score based on the self-reported information in the environmental, social and corporate governance pillars. *Source: LSEG Workspace.*
	Corporate control variables
Pre-tax ROA	Computed as income before tax divided by the average total assets. *Source: LSEG Workspace.*
Liquidity	Calculated as the sum of all high-quality liquid assets. *Source: LSEG Workspace.*
CapEx	Capital expenditures represent the sum of purchases of fixed assets, acquisitions of intangibles and software development costs. *Source: LSEG Workspace.*
COGS	Cost of goods sold represents total operating expenses directly related to the goods sold and services provided. *Source: LSEG Workspace.*

Leverage	Calculated as total debt divided by the value of total shareholders' equity – including minority interest and hybrid debt. *Source: LSEG Workspace.*
	Financial control variables
Market capitalisation	Calculated as the sum of market values for all relevant instrument level share types. *Source: LSEG Workspace.*
Trading volume	Aggregate quantity of a security exchanged between buyers and sellers over the course of the year. *Source: LSEG Workspace.*
Market beta	Manually estimated for each firm-year by running a time-series regression of daily firm-level log excess returns on daily market log excess returns. *Sources: Kenneth R. French Data Library.*
Sharpe ratio	Manually computed as the annualised mean of daily excess returns divided by the annualised standard deviation of daily excess returns. *Source: LSEG Workspace.*
Sortino ratio	Manually computed as the annualised mean of daily excess returns divided by the annualised downside deviation of daily excess returns. *Source: LSEG Workspace.*
Fama-French risk-free rate	Daily one-month Treasury bill returns for the US, Europe, and Asia Pacific regions. *Source: Kenneth R. French Data Library.*
Inflation-adjusted risk-free rate	Calculated as the US 10-year Treasury yield plus the difference between the 10-year forecasted inflation rate of the given country and that of the US. *Source: LSEG Workspace.*