High idiosyncratic risk and low expected returns: The role of ESG engagement

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Dissertation submitted in partial fulfilment of requirements for the MSc in Finance, at the Universidade Católica Portuguesa, 06.01.2025.

Abstract

Scholars have established a positive relation between risk and return, particularly with the introduction of the CAPM. However, evidence on whether this relationship extends to idiosyncratic risk and returns remains inconclusive. While Ang et al. (2006, 2009) identified a negative relation between lagged idiosyncratic volatility and expected returns, Fu (2009) reported a positive relation between expected idiosyncratic volatility and expected returns. This thesis revisits this debate, while controlling for ESG engagement. The findings reveal (1) a negative relation between lagged, realized, and expected idiosyncratic risk with expected stock returns, (2) controlling for ESG Scores does not significantly impact this relationship, and (3) high ESG stocks were, on average, less exposed to idiosyncratic risk and its variability compared to low ESG stocks. These results challenge conventional risk-based explanations of expected stock returns and highlight the importance of ESG engagement in effectively mitigating risk.

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Keywords: Idiosyncratic risk, expected idiosyncratic risk, ESG, cross-sectional returns, EGARCH

Resumo

Os académicos estabeleceram uma relação positiva entre risco e retorno, particularmente com a introdução do CAPM. No entanto, as evidências sobre se esta relação se estende ao risco idiossincrático e aos retornos permanecem inconclusivas. Enquanto Ang et al. (2006, 2009) identificaram uma relação negativa entre a volatilidade idiossincrática defasada e os retornos esperados, Fu (2009) relatou uma relação positiva entre a volatilidade idiossincrática esperada e os retornos esperados. Esta tese revisita este debate, controlando pelo envolvimento em ESG. Os resultados revelam (1) uma relação negativa entre o risco idiossincrático defasado, realizado e esperado com os retornos esperados das ações, (2) controlar pelos Scores ESG não afeta significativamente esta relação, e (3) as ações com alta classificação ESG estavam, em média, menos expostas ao risco idiossincrático e à sua variabilidade em comparação com as ações de baixa classificação ESG. Estes resultados desafiam as explicações convencionais baseadas em risco dos retornos esperados das ações e destacam a importância do envolvimento em ESG na mitigação efetiva do risco.

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Título: Risco idiossincrático elevado e retornos esperados baixos: O papel do compromisso ESG

Palavras-chave: Risco idiossincrático, risco idiossincrático esperado, ESG, retornos transversais, EGARCH

List of contents

List of figures

List of tables

List of appendices

List of abbreviations

Abbreviation	Description
ARCH	Autoregressive conditional heteroskedasticity
billion	bn
Carhart	Fama-French three factor model augmented by the momentum factor
CAPM	Capital asset pricing model
CSR	Corporate Social Responsibility
E(IVOL)	Expected idiosyncratic volatility
EGARCH	Exponential generalized autoregressive conditional heteroskedasticity
ESG	Environmental, Social, and Governance
FF3	Fama-French three factor model
GARCH	Generalised autoregressive conditional heteroskedasticity
IVOL	Idiosyncratic volatility
LNASCOMP	NASDAQ Composite
LNYSEALL	NYSE Composite
million	mn
MV	Market Value (Capital)
RI	Total Return Index
TRESGS	ESG Score
U.S.	United States
VO	Turnover by Volume

1 Introduction

The relationship between idiosyncratic risk and stock returns has been the subject of considerable academic debate. Modern portfolio theory suggests that idiosyncratic risk is diversifiable and does not influence expected returns. Hence, only systematic risk, also called market risk, is considered to drive returns. This theory is captured in the capital asset pricing model (CAPM), discovered by Sharpe (1964), Lintner (1965) and Mossin (1966), which builds on Markowitz's (1952) mean-variance portfolio optimization. These models assume all investors hold the same optimal risky portfolio, which is the same as the market portfolio.

However, empirical evidence suggests that not all investors follow this theoretical model. In reality, investors often employ distinct strategies that deviate from holding the market portfolio. Institutional investors, for instance, frequently seek positive alphas by investing in non-market portfolios. Retail investors seem to be under-diversified due to factors such as limited financial literacy, home bias, or preference for employer stocks (Reinholtz et al., 2021) or due to the numerous other biases that further inhibit the formation of market portfolios (Zahera & Bansal, 2018). Additionally, some individual investors may restrict their investments to specific sectors or pursue impact investments, limiting their ability to diversify effectively. Furthermore, the number of stocks needed to archive a well-diversified portfolio has increased over the past years. In particular, the number of equities required in the developed financial markets is higher than in the emerging markets (Zaimovic et al., 2021).

The above-mentioned imperfections, which may lead to under-diversification, suggest that investors want to be compensated for their increased risk. Consequently, many studies have examined the relationship between idiosyncratic risk and expected stock returns, yet findings remain mixed. Some studies report a positive relationship (Bergbrant & Kassa, 2021; Chua et al., 2010; Fu, 2009; Goyal & Santa-Clara, 2003; Guo & Savickas, 2006, 2008; X. Jiang & Lee, 2006; Levy, 1978; Merton, 1987; Spiegel & Wang, 2005; Xu & Malkiel, 2004) , while others indicate a negative relationship (Ang et al., 2006, 2009; Babenko et al., 2016; Brockman et al., 2022; G. J. Jiang et al., 2009; Stambaugh et al., 2015) or no relationship at all (Bali & Cakici, 2008).

Furthermore, recent research highlights a relationship between ESG (Environmental, Social, and Governance) practices and CSR (Corporate Social Responsibility) activities with idiosyncratic risk. Studies indicate that companies disclosing ESG information or engaging in strong CSR activities generally experience reduced idiosyncratic risk, as seen in findings from

He et al. (2022) and Chen et al. (2018). These effects are particularly evident during periods of economic instability, where Zhou and Zhou (2022) found that Chinese firms with better ESG performance faced less volatility. Additionally, Reber et al. (2022) demonstrate that U.S. companies with robust ESG disclosures benefit from lower firm-specific volatility and downside tail risk, suggesting that both ESG and CSR activities contribute to stabilising stock performance and mitigating risk.

Building on Fu (2009)'s methodology, this thesis seeks to extend the understanding of the relationship between idiosyncratic risk and stock returns in the U.S. market over the period from January 1, 2003, to June 30, 2024, which hasn't been studied yet. Additionally, given the unique idiosyncratic risk profiles of ESG-focused stocks and their tendency to exhibit reduced risk during market downturns, this research will examine the potential influence of ESG factors on the idiosyncratic risk-return relationship. It will also analyse this relationship specifically during periods of market crisis, offering practical insights for investors interested in impact-oriented strategies.

Utilising methodologies such as cross-sectional correlations, Fama-MacBeth regressions and portfolio analyses, a predominantly negative relationship between lagged, realized and expected idiosyncratic risk and expected returns is identified. No significant differences are observed between high and low ESG stocks, except in periods of crisis where high ESG stocks appear to exhibit a positive relation. Additionally, high ESG stocks demonstrate, on average, reduced idiosyncratic volatility and greater stability, even during times of crisis. These findings challenge traditional views on risk and return, illustrating that investing in ESG can be an effective strategy for companies looking to minimize risk.

The thesis is structured as follows: Firstly, Chapter 2 presents a comprehensive literature review. Subsequently, Chapter 3 describes the data under consideration, including the data cleaning process. Chapter 4 introduces the calculation of idiosyncratic volatility and expected idiosyncratic volatility, alongside some associated statistical tests and their results. Following this, Chapter 5 details the cross-sectional methodologies and their outcomes for measures of idiosyncratic risk, with a focus on periodic cross-sectional correlation, Fama-MacBeth regression, and portfolio formation. Chapter 6 discusses the limitations of the analysis and suggests directions for future research. Finally, the thesis ends with the Conclusion.

2 Literature review

This section provides a comprehensive review of the literature on the relationship between idiosyncratic risk and stock returns, as well as the impact of ESG factors on idiosyncratic risk. Chapter 2.1 discusses the evolving perspectives on idiosyncratic risk and expected returns, showcasing conflicting findings from studies like those by Ang et al. (2006, 2009) and Fu (2009) on whether a positive or negative relationship exists. Chapter 2.2 shifts the focus to the role of ESG factors in managing risk, discussing how ESG disclosures and strong CSR practices have been shown to reduce firm-specific risk and stabilise returns during periods of market downturn. This chapter ultimately highlights the complexity and ongoing debate surrounding the influence of idiosyncratic risk.

2.1 Relationship between idiosyncratic volatility and expected returns

Levy (1978) was one of the first to challenge the key assumptions of the CAPM, as most investors are not fully diversified, nor do they hold the market portfolio. In the paper, the author demonstrates that when the estimated CAPM beta and the variance of the residual value from the CAPM are regressed on excess returns in a time-series regression, the coefficient of the residual variance is significantly positive. This indicates that idiosyncratic risk, as the variance of the CAPM residual, is positively related to stock returns. This positive relationship has also been indicated by the findings of Merton (1987).

Xu & Malkiel (2004) also emphasise the imperfect assumptions of the CAPM that every investor holds the same market portfolio or is even well diversified. The authors use the variance of the residual value of the CAPM and Fama-French three-factor (FF3) model (also referred to as idiosyncratic volatility or IVOL) as a proxy for idiosyncratic risk. Including this proxy in the Fama-MacBeth cross-sectional regression analysis, they find that IVOL is better at explaining the cross-section of returns than beta or size measures in the U.S. and Japanese stock markets. Their results further indicate a positive significant relationship between IVOL and stock returns.

Spiegel & Wang (2005) investigated the relationship between liquidity and idiosyncratic risk, measured as the square root of a scaled sum of squared residuals from the FF3, and predicted it by an exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, where the FF3 is the mean equation. The authors used monthly U.S. data and found that an increase in expected idiosyncratic risk leads to higher stock returns and vice versa for liquidity. The authors also note that while both factors are relevant for determining returns, IVOL is more pronounced and often eliminates the effect of liquidity.

Fu (2009) challenges previous findings from Ang et al. (2006) on the negative relationship between idiosyncratic risk and expected stock returns, demonstrating that when accounting for time-varying IVOL through EGARCH models, there is a significant positive relationship between expected IVOL (E(IVOL)) and expected stock returns. Fu (2009) suggests that the negative relationship observed in earlier studies can be attributed primarily to return reversals among small, high-volatility stocks rather than a generalisable pattern across all stocks. Similar results have been found for global data employing Fu's methodology (Brockman et al., 2022).

Goyal & Santa-Clara (2003) applied a different approach to capture idiosyncratic risk, where they take the cross-sectional average of all stocks traded in a month and then run a predictive regression with the market returns as dependent and stock variance measure as independent variable. They find a significant positive relationship between average stock variance, which is largely idiosyncratic risk, and market return. Further, they highlight that idiosyncratic risk measures are a big component of total risk and explain most of the time variation in average risk.

Bégin et al. (2020) developed a GARCH-jump model and utilised option data, thereby demonstrating that "… idiosyncratic risk explains 28% of the variation in the risk premium on a stock". Moreover, it has been established by the authors that the contribution of idiosyncratic risk to the equity risk premium exclusively derives from jump risk, while emphasising the pivotal role of tail risk in the pricing of idiosyncratic risk.

Additional evidence supporting a positive relationship between idiosyncratic risk has been published (Bergbrant & Kassa, 2021; Cao & Han, 2016; Chua et al., 2010; Guo et al., 2014; Guo & Savickas, 2006, 2008; X. Jiang & Lee, 2006).

In contrast, Ang et al. (2006, 2009) investigate the relationship between idiosyncratic risk and expected stock returns, finding that stocks with high IVOL tend to exhibit significantly lower future returns. This effect persists globally across 23 developed markets and is robust to controls for size, value, and market factors. To capture IVOL the monthly variance of the daily residual value of the FF3 model was calculated.

Jiang et al. (2009) find that IVOL is inversely related to future stock returns applying the same methodology as Ang et al. (2006, 2009). They suggest this predictive power stems from the information IVOL carries about future earnings shocks. Their analysis indicates that this relationship is not simply a reflection of other known market anomalies but could be related to selective corporate disclosure and is more pronounced for stocks with a less sophisticated investor base.

Babenko et al. (2016) also found a negative relationship between expected returns and IVOL, measured as a time-series regression of returns on systematic profitability shocks. It is further highlighted that “a positive idiosyncratic shock decreases the sensitivity of firm value to priced risk factors and simultaneously increases firm size and idiosyncratic risk”, which can explain the negative relationship.

Stambaugh et al. (2015) argue that for many equity investors, purchasing stocks is simpler than short selling. This tendency, along with the arbitrage risk indicated by IVOL, explains the negative relationship observed between IVOL and average returns.

Finally, several studies provide evidence suggesting the absence of a robust relationship between IVOL and expected stock returns. Bali & Cakici (2008) investigate the link between IVOL and expected stock returns, where IVOL is estimated using a FF3 model with monthly and daily data. Their findings reveal that various factors significantly influence this relationship, including data frequency, weighting methods, and sorting breakpoints. Concluding that there is no robustly significant relationship between IVOL and expected returns.

Huang et al. (2010) find that idiosyncratic volatility estimated on daily data is not related to expected returns due to negative serial correlation in monthly stock returns, indicating short-term return reversals. However, when controlling for returns reversal the positive relation between monthly IVOL and expected stock returns is still significant.

Additionally, Guo et al. (2014) argue that using an EGARCH model to estimate IVOL often results in a look-ahead bias. If this is considered, the relationship between the expected idiosyncratic risk and the expected return becomes negligible.

The existing literature mostly employs the standard deviation of the residual value of the FF3 model to identify IVOL, with some scholars proposing that this proxy of IVOL might be a consequence of omitted variables. To elucidate this issue, the present study will employ the Fama-French five-factor (FF5) model to estimate IVOL, incorporating additional explanatory variables. The FF5 will also be used as a mean equation in the EGARCH model. The findings regarding the relationship between expected IVOL and expected stock returns are inconclusive.

The primary driver appears to be data frequency, with daily data resulting in a negative relationship and monthly data resulting in a positive relationship. As outlined above, several explanations for this phenomenon have been proposed; however, these will not be further explored in this thesis. The relationship during crises remains to be studied, a topic that will be addressed in this thesis.

2.2 Idiosyncratic risk and ESG factors

In recent years, ESG factors have garnered significant attention due to mounting environmental challenges like global warming, as well as pressing governance and social issues such as supply chain integrity and labour practices. This heightened focus has led to a substantial increase in capital allocated to ESG investments of $30 trillion in 2022 and is projected to exceed 25% of total assets under management by 2030 according to Bloomberg (2024). The discussion about the impact of companies' engagement with ESG and CSR topics on corporate financial performance is quite extensive. However, research regarding idiosyncratic risk associated with ESG-focused stocks is scarce, although this area has recently attracted an increasing amount of attention.

Reber et al. (2022) show that, based on U.S. data and the standard deviation of the residual of the CAPM and FF3 to estimate IVOL, ESG disclosures help decrease IVOL and downside tail risk. They also find that companies with higher ESG ratings have lower IVOL and downside tail risk in the first year after their initial public offering. Applying a similar methodology He et al. (2022) also finds that firms disclosing ESG information exhibit lower IVOL exposure in China, with non-disclosing firms facing higher levels of this risk.

Zhou & Zhou (2022) found that Chinese companies with strong ESG performance experience lower stock price volatility, particularly during the COVID-19 pandemic. Their analysis shows that while COVID-19 generally heightened stock price volatility, companies with high ESG ratings saw relatively smaller volatility increases than those with lower ESG ratings.

Chen et al. (2018) found that strong CSR practices mitigate idiosyncratic risk across various market states, while companies with weaker CSR performance face higher idiosyncratic risk. To identify IVOL, the standard deviation of the residual value of the CAPM, FF3 and FF3 augmented by the momentum factor (Carhart) were applied to stocks listed at the Taiwan and Taipei stock exchanges.

Jo & Na (2012) examined the influence of corporate social responsibility (CSR) on firm risk, focusing specifically on controversial industries in the U.S. Their findings reveal that CSR initiatives significantly mitigate firm risk in these sectors, with the risk-reduction effect being notably stronger in controversial industries compared to their non-controversial counterparts. Mishra & Modi (2013) also found that positive CSR reduces IVOL and negative CSR increases IVOL among different industries in the U.S.. IVOL here was calculated as the variance of the residual value of the Carhart model.

Research on ESG and CSR engagement and risk has consistently shown a reduction in idiosyncratic risk when companies disclose ESG and CSR information, which is amplified when they have a high ESG rating or a positive SCR. Moreover, evidence from China suggests that high ESG companies have lower IVOL during recessions. However, this phenomenon has not yet been examined in studies of U.S. stocks, which is why this paper addresses it. Furthermore, this paper will address the unexplored cross-sectional relationship between IVOL and expected stock returns while controlling for ESG performance.

3 Data

This chapter outlines the data used in this study. Chapter 3.1 provides an overview of the datasets, including the sources, variables, and sample period. Chapter 3.2 describes the data preparation process, including data cleaning, return calculations, and excess return calculations. Finally, Chapter 3.3 discusses techniques for managing extreme values in financial time series, such as Winsorization and log transformation.

3.1 Dataset overview

Data for the analysis was sourced from Workspace Datastream for all stocks listed on the NYSE Composite (LNYSEALL) and NASDAQ Composite (LNASCOMP) to perform the following analyses. This is intended to represent the U.S. market. The period of research begins in January 2002 and ends in June 2024. Specifically, the dataset includes the monthly Total Return Index (RI), Turnover by Volume (VO), and Market Value (Capital) (MV), as well as the annual ESG Score (TRESGS). Additionally, daily and monthly data for the Fama-French 5-Factor model was obtained from the Kenneth R. French data library (Fama & French, 2015).[1]

[1] Kenneth French's data library is found at:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The ESG scores assess the ESG performance of companies based on publicly reported data in the areas of environmental, social and corporate governance, as well as ten different ESG topics. Since the ESG score represents a company's ESG performance over a one-year period, they were shifted forward by one year to reflect the delayed availability of this information to investors. An ESG score exceeding 75 signifies exemplary relative ESG performance and a high degree of transparency in the reporting of material ESG data to the public. In the following, the term "high ESG" is defined as companies with an ESG score above 75, and "low ESG" is defined as companies with a score equal to or below 75.[2]

Finally, quarterly dummy variables were downloaded from the Federal Reserve Bank of St. Louis, indicating U.S. recessions as inferred by the GDP-based recession indicator.[3] The dummy variables assigned a value of one for recessions and zero for no recessions. The quarterly data was converted into monthly data, with each month assigned the same dummy variable as the corresponding quarter.

3.2 Data preparation

To ensure the models utilise clean data, stocks with any missing data points in any month for the downloaded variables were excluded from the dataset. Companies with less than 30 months of data were also excluded to ensure proper fitting of the models introduced in the next chapter. The impact of the cleaning process is detailed in Appendix A. For the companies remaining after this filtering process, daily RI data for the same period was downloaded.

Subsequently, the continuous monthly returns were calculated as follows:

$$R_{i,t} = \ln\left(\frac{RI_{i,t}}{RI_{i,t-1}}\right), \tag{1}$$

where $i = 1, 2, \dots, N_t$ represents each stock in the sample at the month $t = 1, 2, \dots, T$. Here, N_t denotes the total number of stocks at time t, and T represents the total number of time periods. Similarly, continuous daily returns are defined by:

[2] More details can be found at:
https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores
[3] More details can be found at:
https://fred.stlouisfed.org/series/JHDUSRGDPBR#0

$$R_{i,\tau} = \ln\left(\frac{RI_{i,\tau}}{RI_{i,\tau-1}}\right), \tag{2}$$

where $i = 1, 2, \ldots, N_\tau$ and $\tau \in t$, indicating daily returns for stock i on day τ. Continuous returns R_t and R_τ offer an advantage over discrete returns as they are additive over time, which allows for easier aggregation in the statistical models used in this analysis.

Using the risk-free rate R_f provided by the Kenneth R. French dataset, excess returns were calculated as follows for monthly data:

$$r_{i,t} = R_{i,t} - R_{f,t}, \tag{3}$$

and as follows for daily data:

$$r_{i,\tau} = R_{i,\tau} - R_{f,\tau}. \tag{4}$$

3.3 Techniques for managing extreme values in financial time-series

Financial data often show extreme values in time-series, which can distort the results of analyses. To minimise these effects, the Winsorization method can be used. In this approach, extreme values above or below certain threshold value (so-called cut-off point) are limited to this threshold value. The cut-off point is usually defined by the lth percentile

$$Pctl_l(X). \tag{5}$$

It is determined in advance whether extreme values above or below the cut-off point are considered. This approach limits the impact on the results while still utilising extreme values (Bali et al., 2016).

In instances where the variable X exhibits significant variation between its values (e.g., a wide range of magnitudes) and/or is heavily skewed, the natural logarithm is applied to all values of variable X. This transformation reduces skewness and rescales the values closer together, making the data more suitable for analysis, especially when applying statistical models (Fu, 2009).

4 Idiosyncratic risk measures

This chapter presents the methodology to estimate IVOL and E(IVOL) and examines their properties for companies with different levels of ESG engagement. Chapter 4.1 defines IVOL and describes its calculation using the Fama-French 5-Factor model. The Chapter also presents descriptive statistics and time-series properties of IVOL. Chapter 4.2 examines the stationarity properties of IVOL. Finally, Chapter 4.3 introduces the concept of E(IVOL) and discusses the use of the EGARCH model to estimate it. This section further includes a detailed explanation of the EGARCH model, its parameter estimation, and diagnostic tests for model adequacy.

4.1 Idiosyncratic volatility

The overall objective of this thesis is to determine differences in the idiosyncratic risk profiles of companies depending on their ESG engagement and further investigate the risk-return dynamic, specifically between idiosyncratic risk and stock returns. Idiosyncratic risk, also known as firm-specific risk, refers to the risk that is unique to a particular company. Accordingly, idiosyncratic risk is not influenced by market movements. However, it cannot be directly observed, which is why IVOL is employed as a proxy (Fu, 2009).

To capture IVOL, the methodology proposed by Ang et al. (2006) and Fu (2009) is followed. They employ the Fama-French 3-factor model to explain cross-sectional stock returns. However, I apply the Fama-French 5-factor model instead of the FF3 model, as the former more accurately capture average stock returns (Fama & French, 1993, 2015). Using the FF5 model also weakens the argument that IVOL is only observable due to omitted variables.

The estimation of IVOL is conducted in the following manner: For each firm i in each month t, daily excess returns $r_{i,\tau}$ are regressed on the daily Fama-French 5 factors:

$$r_{i,\tau} = \alpha_i + \beta_{i,MKT} MKT_\tau + \beta_{i,SMB}\, SMB_\tau + \beta_{i,HML}\, HML_\tau + \beta_{i,RMW}\, RMW_\tau + \beta_{i,CMA} CMA_\tau + \varepsilon_{i,\tau}, \tag{6}$$

where MKT_τ is the market excess return $R_{m,\tau} - R_{f,\tau}$, SMB (Small Minus Big) is the average return on nine small stock portfolios minus the average return on nine big stock portfolios, HML (High Minus Low) is the average return on two value portfolios minus the average return on two growth portfolios, RMW (Robust Minus Weak) is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios, CMA (Conservative Minus Aggressive) is the average return on two conservative investment portfolios minus the average return on the two aggressive investment portfolios.[4]

[4] A more detailed explanation of the portfolio formation process can be found in the papers of Fama & French (1993, 2015) as well as on the Kenneth French's data library website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

This regression model and all subsequent regression models presented in this thesis are estimated using Ordinary Least Squares (OLS) method.

To mitigate the potential distortions from infrequent trading, a minimum threshold of 15 trading days is required to estimate IVOL. Monthly IVOL is then calculated as the standard deviation of the regression residuals from equation (6) multiplied by the square root of the number of trading days $d_{i,t}$ in the month:

$$IVOL_t = \sqrt{var(\varepsilon_{i,\tau})}\,\sqrt{d_{i,t}}. \tag{7}$$

Table 1: Time-series properties of idiosyncratic volatility

This table presents descriptive statistics for the variable of IVOL and the log-change of IVOL ($\ln\frac{IVOL_t}{IVOL_{t-1}}$) for the full sample, as well as for the two sub-samples high ESG and low ESG starting from January 2003 until June 2024. The time-series statistics, namely the number of companies (N), mean, standard deviation (SD), coefficient of variation (CV), skewness, and autocorrelation for different lags, were initially calculated for all firms within each sample. Subsequently, the cross-sectional mean of all time-series statistics were calculated and presented.

Group	Variable	N	Mean (%)	SD (%)	CV	Skew	Autocorrelation					
							1	2	3	6	9	12
Full sample	$IVOL$	2,595	8.85	4.90	0.54	2.33	0.23	0.17	0.20	0.13	0.09	0.08
	$\ln\frac{IVOL_t}{IVOL_{t-1}}$	2,595	-0.19	52.63	49.06	0.18	-0.45	-0.05	0.09	0.08	0.08	0.15
High ESG	$IVOL$	380	5.91	2.56	0.43	1.56	0.15	0.11	0.14	0.10	0.05	0.05
	$\ln\frac{IVOL_t}{IVOL_{t-1}}$	380	-0.21	47.30	57.87	0.10	-0.44	-0.05	0.07	0.08	0.06	0.13
Low ESG	$IVOL$	2,591	8.86	4.90	0.54	2.29	0.23	0.17	0.19	0.12	0.09	0.07
	$\ln\frac{IVOL_t}{IVOL_{t-1}}$	2,591	-0.19	52.54	57.58	0.18	-0.45	-0.05	0.09	0.08	0.08	0.14

The mean IVOL is 8.85%, with a standard deviation of 4.90%. This leads to a coefficient of variation of 0.54, suggesting that IVOL exhibits considerable variation over time relative to its mean. Furthermore, IVOL is markedly right skewed, exhibiting a longer right tail, which suggests that extreme high IVOL values are more frequent. The short-term autocorrelation (lag 1-3) is observed to move around 0.20 and to converge closer to zero over the mid- and long-term. This suggests that volatility clustering is a probable phenomenon during the sample period. The log-change of IVOL ($\ln\frac{IVOL_t}{IVOL_{t-1}}$) indicates a slight mean decline in IVOL of -0.19%

over time. The first lag of autocorrelation, with a value of -0.45, suggests that IVOL may be following a first order moving average process.

A comparison of high and low ESG firms reveals that the vast majority of firms were classified as low ESG at least once during the sample period, with only four exceptions. The most notable finding is that the cross-sectional mean for high ESG firms (5.91%) is lower than that of low ESG firms (8.86%), indicating that good ESG performance is associated with lower idiosyncratic risk. Additionally, the variation in IVOL is also lower for high ESG stocks, with a CV of 0.43, further highlighting their relative stability.

4.2 Stationarity of idiosyncratic volatility

Ang et al. (2006) made the implicit assumption that IVOL follows a random walk. This assumption can be tested using a stationarity test. Stationarity is divided into strong and weak stationarity. Since the properties of strong stationarity are hard to test empirically, only weak stationarity is presented in the following. A weakly stationary process can be defined as a stochastic process that satisfies the following conditions:

$$E(p_t) = \mu, \tag{8}$$
$$Cov(p_t, p_{t-\ell}) = \gamma_\ell, \tag{9}$$

where $\{p_t\}$ is a times series, μ is a constant and γ_ℓ depends on ℓ, which is an arbitrary integer. Hence, when applied, weak stationarity allows conclusions to be drawn about future observations, such as making predictions.

However, in a random walk process, predictability diminishes. A time-series $\{p_t\}$ follows a random walk process if it is defined as

$$p_t = p_{t-1} + \varepsilon_t, \tag{10}$$

where $\{\varepsilon_t\}$ represents a series of white noise terms. In a random walk process, the first-order autocorrelation is expected to be one, while the first differences behave as white noise, resulting in zero autocorrelation across all lags.[5] This is also expressed by saying that the process has a unit-root and therefore is not stationary (Tsay, 2010).

[5] Autocorrelation will be defined in the equation (20).

To test whether a random walk process can accurately describe idiosyncratic volatility, I conduct the following time-series regression for IVOL

$$IVOL_{i,t+1} - IVOL_{i,t} = \phi_{0,i} + \phi_{1,i}\, IVOL_{i,t} + \eta_i \tag{11}$$

and the same time-series regression log $IVOL$

$$\ln IVOL_{i,t+1} - \ln IVOL_{i,t} = \phi_{0,i} + \phi_{1,i} \ln IVOL_{i,t} + \eta_i \tag{12}$$

for each stock in the sample, which is a standard unit-root test. H_0: $IVOL_{i,t}$ follows a random walk if $\phi_{1,i}$ is indistinguishable from zero. The t-statistics of the coefficient $\phi_{1,i}$ are compared to the Dickey-Fuller critical values for the unit-root test (Table 2) (Fu, 2009).

Table 2: Critical values for Dickey-Fuller stationarity test

Sample size	Critical t-statistics at a 1% significance level
25	-3.75
50	-3.59
100	-3.50
250	-3.45
500	-3.44

Table 3: Stationarity test of idiosyncratic volatility

This table presents the statistical results of the unit-root tests presented in equation (10) and (11), which are hereinafter referred to, as the regression model $IVOL$ and ln $IVOL$ for the sample period starting from January 2003 until June 2024. The objective of this test is to assess whether the time-series IVOL follows a random walk. The cross-sectional mean, first quartile (Q1), median, and second quartile (Q2) of the coefficient estimate $\phi_1$and its t-statistics are presented for examination. The t-statistics are compared to the Dickey-Fuller critical values from Table 2, and the last column shows the rejection rate of H_0 at the 1% significance level. To apply the test, a minimum of 30 observations are required.

Regression model	Parameter Estimate	Mean	Q1	Median	Q3	Total firms	Random walk rejected (%)
$IVOL$	ϕ_1	-0.77	-0.92	-0.78	-0.62	2,563	98.87
	$t(\phi_1)$	-7.81	-9.20	-7.54	-6.16		
ln $IVOL$	ϕ_1	-0.74	-0.89	-0.74	-0.59	2,563	98.83
	$t(\phi_1)$	-7.58	-8.99	-7.33	-5.87		

The results of the stationarity test are presented in Table 3 Similar to the findings of Fu (2009) the null hypothesis that IVOL follows a random walk is rejected for 99% of firms at the 1%

significance level. Therefore, a random walk cannot be assumed and the relationship between IVOL and expected returns does not hold. This confirms the results of Table 1, which indicated that a first order moving average could approximate IVOL.

4.3 Expected idiosyncratic volatility

As demonstrated in Chapter 4.1, IVOL undergoes considerable variation over time. Furthermore, chapter 4.2 highlights that IVOL does not follow a random walk, and thus the relationship between IVOL and expected stock returns should not be assumed. Instead, a more accurate representation is proposed by establishing a relationship between expected IVOL (E(IVOL)) and expected stock returns. Accordingly, a reliable estimation of conditional idiosyncratic volatility is essential.[6]

Autoregressive conditional heteroskedasticity (ARCH) type models are generally used to model and forecast volatility. These types of models are also called conditional heteroskedastic models. Heteroskedasticity means that the volatility of a financial time-series is not constant over time. Introduced by Engle (1982), the ARCH model is a statistical tool for analysing and predicting time-series data where the variance of errors varies over time, making it particularly effective for capturing volatility clustering. The generalised autoregressive conditional heteroskedasticity (GARCH) model presented by Bollerslev (1986) is a natural generalisation of the ARCH model by including past conditional variances in the equation.

Many more conditional heteroskedastic models have been introduced over the past years. However, in the following the EGARCH model, discovered by Nelson (1991), will be employed. This model has the advantage of considering the leverage effect, which captures the negative relation between returns and volatility, whereby negative returns are often accompanied by increased volatility and vice versa. Moreover, unlike other ARCH-type models, no parameter restrictions are needed. It was also found that models which include the leverage effect outperform a GARCH(1,1) model (Hansen & Lunde, 2005).

[6] Conditional idiosyncratic volatility reflects time-varying changes due to new information or conditions, while unconditional idiosyncratic volatility represents a static average over time.

4.3.1 The EGARCH model

The first step in applying an EGARCH model is to define the mean equation. In the case of this thesis, the FF5 with monthly data,

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB}\, SMB_t + \beta_{i,HML}\, HML_t \\ + \beta_{i,RMW}\, RMW_t + \beta_{i,CMA} CMA_t + \varepsilon_{i,t}, \end{aligned} \tag{13}$$

is calculated. Taking the residual term $\varepsilon_{i,t}$ from the Equation (13), an EGARCH(1,1) process[7] is defined as

$$\begin{cases} \varepsilon_{i,t} = \sigma_{i,t}\, z_{i,t} \\ \ln \sigma_{i,t}^2 = \omega_i + \delta_i \ln \sigma_{i,t-1}^2 + \varphi_i z_{i,t-1} + \vartheta_i |z_{i,t-1}| \end{cases}, \tag{14}$$

where $z_{i,t}$, also called innovation or shock, is assumed to be independent and identically distributed, follows a standardised Student's t-distribution with a zero mean $E(z_{i,t}) = 0$, conditional variance $Var(z_{i,t}) = 1$, and v degrees of freedom. This is denoted as:

$$z_{i,t} \sim t(0,1,\, v). \tag{15}$$

Baillie and DeGennaro (1990) have found that using a student t density outperforms the use of a normal distribution.

$\ln \sigma_{i,t}^2$ is the natural logarithm of the conditional variance $\sigma_{i,t}^2$, which allows the parameters to be negative and the conditional variance still to be positive. Therefore, unlike other GARCH models, no restrictions need to be implemented that the coefficients must be non-negative.

The model's structure includes volatility clusters, as significant past squared shock $z_{i,t-1}$, or logarithmic conditional variance $\ln \sigma_{i,t-1}^2$ likely lead to a higher natural logarithm of the conditional variance $\ln \sigma_{i,t}^2$.

The asymmetry that captures the leverage effect comes from the parameter φ_i as significant negative shocks (i.e. $\vartheta_i - \varphi_i$) have a greater impact than significant positive shock (i.e. $\vartheta_i +$

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[7] While an EGARCH(1,1) model is used here due to computational limitations, it is important to note that models with additional lags (e.g., EGARCH$(p,\ q)$) may be considered. Selection of the optimal lag structure can be guided by criteria such as Akaike information criterion (AIC) and Bayesian information criterion (BIC) to achieve the best fit. However, the choice of EGARCH(1,1) avoids potential overfitting and parameter estimation noise due to a higher number of factors.

φ_i) if $\varphi_i < 0$. If $\varphi_i < 0$ then the asymmetry would be reversed, and if $\varphi_i = 0$ there would be a symmetrical volatility behaviour (Francq & Zakoian, 2019).

The forecasted volatility $\sigma_{i,t}^2$ is calculated by substituting the estimated coefficients (whose estimation is described in the next chapter) into the equation (14). This calculation also incorporates $\sigma_{i,t-1}^2$ and $z_{i,t-1}$. The initial value of $\sigma_{i,t}^2$ is set to the standard deviation of the series $\{\varepsilon_{i,t}\}$. The EGARCH models are applied using an expanding window approach, requiring a minimum of 30 observations. This ensures that the analysis avoids a lookahead bias.

Figure 1: Historical cross-sectional average of IVOL and E(IVOL)

This figure presents the cross-sectional average of IVOL and E(IVOL) during each month of the sample period starting from January 2003 until June 2024 for the full sample, as well as for the sub-samples designated as high ESG and low ESG. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of all variables used have been winsorized at the 1st and 99th percentile. Group Variable check

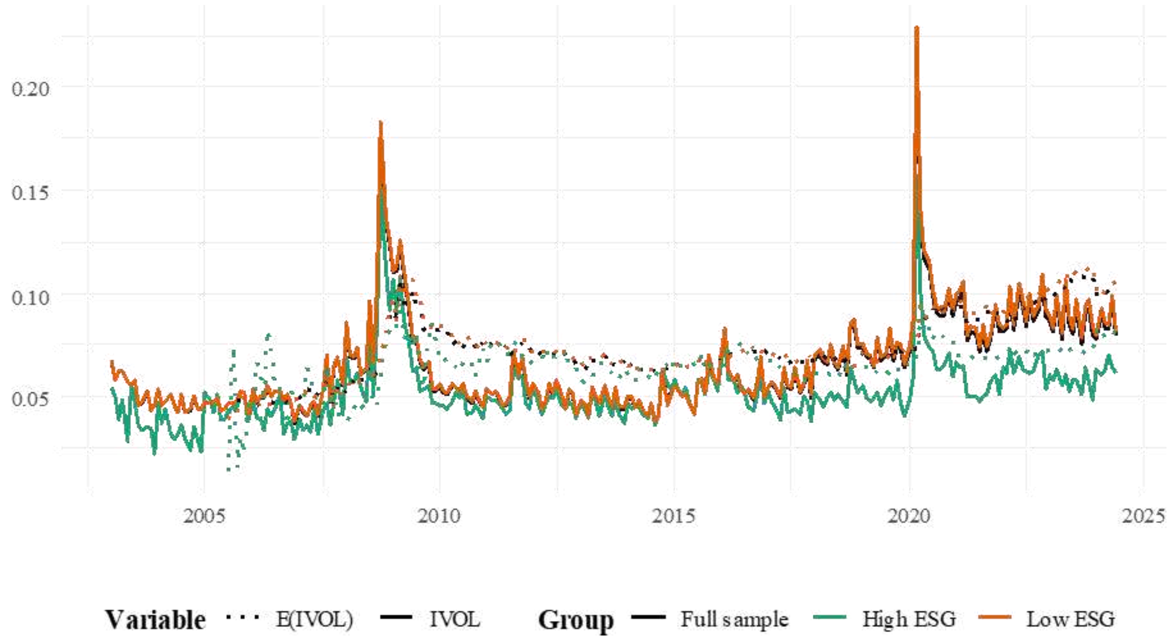

Figure 1 illustrates the development of IVOL and E(IVOL) over time. During the period under consideration, two major crises were observed: the global financial crisis and the COVID-19 pandemic. These crises are clearly evident through the spikes in IVOL and E(IVOL) during these time periods. Following the crisis, E(IVOL) remains at an elevated level, which can be attributed to the incorporation of increased conditional volatility in the EGARCH calculation. The cross-sectional average IVOL and E(IVOL) is consistently the highest for low ESG stocks. However, the difference in IVOL and E(IVOL) for stocks with a high and low ESG rating will only become consistently greater from 2017 onwards, which may indicate a trend of more impact investing starting from that period.

4.3.2 Estimation of EGARCH parameters

When applying the EGARCH model the parameters need to be estimated. Let θ_i be a parameter vector, which holds all EGARCH parameters from the equation (14)

$$\theta_i = (\omega_i, \delta_i, \varphi_i, \vartheta_i, v_i)'. \tag{16}$$

The true values of θ_i are unknown. As mentioned above, the series $z_{i,t}$ is assumed to follow a standardised Student-t distribution, with the probability density function of $z_{i,t}$ being

$$f(z_{i,t}|v_i) = \frac{\Gamma[(v_i + 1)/2]}{\Gamma(v_i/2)\sqrt{(v_i - 2)\pi}} \left(1 + \frac{z_{i,t}^2}{v_i - 2}\right)^{-(v_i+1)/2}, \qquad v_i > 2, \tag{17}$$

where $\Gamma(x)$ is the usual gamma function $\Gamma(x) = \int_0^\infty y^{x-1}e^{-y}dy$. To estimate the coefficients, the value of the conditional likelihood function

$$f(\theta_i) = T\left\{\ln\left[\Gamma\left(\frac{v_i + 1}{2}\right)\right] - \ln\left[\Gamma\left(\frac{v_i}{2}\right)\right] - 0.5\ln[(v_i - 2)\pi]\right\} - \sum_{t=1}^{T}\left[\frac{v_i + 1}{2}\ln\left(1 + \frac{\varepsilon_{i,t}^2}{(v - 2)\sigma_{i,t}^2}\right) + \frac{1}{2}\ln(\sigma_{i,t}^2)\right] \tag{18}$$

is maximised by changing the parameter. This process is also referred to as the conditional maximum-likelihood estimates under t distribution.[8]

4.3.3 Normality of standardised residuals

To verify the distribution properties of the time-series $\{\varepsilon_{i,t}\}$, which was extracted from Equation (13), is not following a normal distribution, the Jarque-Bera test is applied. The Jarque-Bera (JB) (1987) test statistic is defined as

$$JB_i = \frac{S^2(\varepsilon_{i,t})}{6/T} + \frac{[K(\varepsilon_{i,t}) - 3]^2}{24/T}, \tag{19}$$

[8] A "hybrid" strategy is employed to solve the maximization process of Equation (18). This approach begins with the "solnp" solver. If it fails to converge, the process sequentially attempts the "nlminb," "gosolnp," and finally the "nloptr" solvers in R.

where $S(\varepsilon_{i,t}) = \frac{1}{(T-1)\hat{\sigma}_x^3} \sum_{t=1}^{T} (x_t - \hat{\mu}_x)^3$ is the sample skewness and $K(\varepsilon_{i,t}) = \frac{1}{(T-1)\hat{\sigma}_x^4} \sum_{t=1}^{T} (x_t - \hat{\mu}_x)^4$ is the sample kurtosis. The JB statistic follows an asymptotic chi-squared distribution with 2 degrees of freedom, which is used to assess the normality of $\{\varepsilon_{i,t}\}$. To determine whether the data deviates from normality, the null hypothesis H_0 of normality is rejected if the p-value associated with the JB statistic is less than the specified significance level (Tsay, 2010).

The test results for JB statistics, presented in Table 4, demonstrate that the normality assumption was rejected in 50.21 percent of cases at the 5 percent significance level. In conjunction with the findings of Baillie and DeGennaro (1990), which indicate that the t distribution is superior to the normal distribution, the standardized students-t distribution is considered more suitable for estimating the EGARCH model. Additionally, the EGARCH model frequently failed to converge to a coefficient estimate when using a normal distribution, further supporting the preference for the standardized students-t distribution.

Table 4: Jarque-Bera test for normality of standardized residuals

This table presents the statistical results of the Jarque-Bera tests presented in equation (19) for the sample period starting from January 2003 until June 2024. The objective of this test is to assess normality of the residual value of regression presented in Equation (13). The cross-sectional mean, first quartile (Q1), median, and second quartile (Q2) of JB test statistic, along with its p-value (presented in brackets), are provided for examination. The last column displays the rejection rate of H_0 at the 5% significance level.

Statistic	Mean	Q1	Median	Q3	Total firms	Normality rejected (%)
JB	118.15	1.56	6.05	28.13	2,595	50.21
	(0.24)	(0.00)	(0.05)	(0.46		

4.3.4 Testing for heteroskedasticity

Before applying an EGARCH model, it is common to check whether the residuals of the mean equation are heteroskedastic. This is also called the ARCH effect and can be checked with the Ljung-Box-Q and ARCH-LM test. These tests check whether volatility exhibits a positive autocorrelation, which means that periods of high volatility are often followed by further periods of high volatility and vice versa. In the following sections, these tests are defined (Tsay, 2010).

Ljung-Box-Q test

The Ljung-Box-Q test is applied to assess autocorrelation in the time-series $\{\varepsilon^2_{i,t}\}$, where $\varepsilon_{i,t}$ was first calculated in Equation (13). The autocorrelation of $\{\varepsilon^2_{i,t}\}$ can be calculated as

$$\rho_{i,\ell} = \frac{Cov(\varepsilon^2_{i,t}, \varepsilon^2_{i,t-\ell})}{Var(\varepsilon^2_{i,t})}, \tag{20}$$

where $\rho_{i,\ell}$ is the autocorrelation coefficient, which measures the linear dependence between $\varepsilon^2_{i,t}$ and $\varepsilon^2_{i,t-\ell}$ of lag-ℓ. $\{\varepsilon^2_{i,t}\}$ is free from serial correlation if $\rho_\ell = 0$ for all $\ell > 0$. To test whether various autocorrelations of $\{\varepsilon^2_{i,t}\}$ are zero the Portmanteau statistic was introduced by Box and Pierce (1970). To improve accuracy in a finite sample, Ljung and Box (1978) modified the statistic to

$$Q(m) = T(T+0)\sum_{\ell=1}^{m} \frac{\hat{\rho}^2_{i,\ell}}{T-\ell}, \tag{21}$$

where $\hat{\rho}$ is the sample autocorrelation and T is the sample size. H_0: $Q(m) > \chi^2_\alpha$, where χ^2_α denotes the upper $100(1-\alpha)$th percentile of a chi-squared distribution with m degrees of freedom. The decision rule is to reject H_0 if the p-value is less than or equal to the significance level, α (Tsay, 2010).

Table 5: Ljung-Box-Q test for serial correlation in squared residuals

This table presents the statistical results of the Ljung-Box tests presented in Equation (19) for the sample period starting from January 2003 until June 2024. The objective of this test is to determine whether the residuals of the mean equation (Equation (13)) exhibits autocorrelation. The cross-sectional mean, first quartile (Q1), median, and second quartile (Q3) of $Q(m)$ test statistic for different lags, along with its p-value (presented in brackets), are provided for examination. The last column displays the rejection rate of H_0 at the 5% level.

Statistic	Mean	Q1	Median	Q3	Total firms	Serial correlation rejected (%)
$Q(4)$	7.26	1.72	3.46	7.36	2,595	18.65
	(0.47)	(0.12)	(0.48)	(0.79)		
$Q(8)$	12.33	4.25	7.40	12.97	2,595	19.88
	(0.48)	(0.11)	(0.49)	(0.83)		
$Q(12)$	16.42	7.20	11.13	18.25	2,595	19.65
	(0.49)	(0.11)	(0.52)	(0.84)		

ARCH-LM test

The time-series $\{\varepsilon^2_{i,t}\}$ from equation (13) is subsequently used for Engle's (1982) Lagrange multiplier (ARCH-LM) test, which is comparable to using the conventional F-statistic to test $\alpha_i = 0$ $(i = 1, \dots, m)$ in a linear regression model

$$\varepsilon^{2}_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^{2}_{i,t-1} + \cdots + \alpha_{i,m}\alpha^{2}_{i,t-m} + e_{i,t}, \tag{22}$$

where $t = m + 1, \dots, T$, m denotes as a prespecified positive integer, T is the sample size and $e_{i,t}$ is the error term. The null hypothesis H_0 that the parameters $\alpha_1, \alpha_2, \dots, \alpha_m$ are all zero, tests whether there are no ARCH effects in the time series. To test this hypothesis, we define two key quantities: $\mathrm{SSR}_0 = \sum_{t=m+1}^{T}(\varepsilon^2_t - \bar{\omega})^2$, where $\bar{\omega} = 1/T\sum_{t=1}^{T}\varepsilon^2_{(i,t)}$ denotes as the sample average and $\mathrm{SSR}_1 = \sum_{t=m+1}^{T} \hat{e}^2_{i,t}$, where $\hat{e}_{i,t}$ the least-squares residuals of regression (22). The F-Statistic can now be calculated $(m) = \frac{\mathrm{SSR}_0 - \mathrm{SSR}_1/m}{\mathrm{SSR}_1/(T-2m-1)}$, which is asymptotically distributed as a chi-squared distribution with m degrees of freedom. H_0 is rejected if $F > \chi^2_\alpha$, where χ^2_α denotes the upper $100(1 - \alpha)$th percentile of a chi-squared distribution with m degrees of freedom (Tsay, 2010).

Table 6: ARCH-LM test for heteroskedasticity

This table presents the statistical results of the ARCH-LM tests presented in equation (22) for the sample period starting from January 2003 until June 2024. The objective of this test is to determine whether the residuals of the mean equation (Equation (13)) exhibits autocorrelation. The cross-sectional mean, first quartile (Q1), median, and second quartile (Q3) of $F(m)$ test statistic for different lags, along with its p-value (presented in brackets), are provided for examination. The last column displays the rejection rate of H_0 at the 5% level.

Statistic	Mean	Q1	Median	Q3	Total firms	Serial correlation rejected (%)
$F(4)$	63.65	16.27	32.62	76.11	2,595	89.87
	(0.03)	(0.00)	(0.00)	(0.00)		
$F(8)$	24.24	5.29	11.86	30.32	2,595	44.86
	(0.31)	(0.00)	(0.11)	(0.62)		
$F(12)$	12.85	2.10	5.51	16.41	2,595	20.35
	(0.64)	(0.13)	(0.90)	(1.00)		

Table 5 presents the $Q(m)$ statistic of the Ljung-Box test. The rejection rates for different lags are relatively consistent, indicating that approximately 19% of the data exhibit heteroskedasticity. The ARCH-LM test (Table 6) reaches a comparable conclusion at 12 lags.

However, reducing the lags, significantly increases the detected heteroskedasticity to a level of 89.87% at four lags. Overall, the evidence for heteroskedasticity is inconclusive. Due to the strong presence in fewer lags in the ARCH-LM test and to maintain comparability with previous papers, the EGARCH model was applied. However, the application of a simpler model may be more appropriate and could be explored in future research.

5 Cross-sectional properties of idiosyncratic risk measures

This chapter presents cross-sectional research methods and empirical analyses of the relationship between idiosyncratic risk and stock returns, while focusing on the role of ESG. Chapter 5.1 provides summary statistics of key variables, highlighting differences across ESG groups. Chapter 5.2 examines the cross-sectional correlation between different variables. Chapter 5.3 employs the Fama-MacBeth regression to assess the impact of IVOL and E(IVOL) on expected stock returns. Chapter 5.4 investigates the relationship between lagged IVOL, IVOL, and E(IVOL) with stock returns through portfolio analysis, forming portfolios sorted based on different measures of idiosyncratic risk. Finally, Chapter 5.5 analyses the performance of these portfolios during recession periods.

Most of the tables in this chapter show the results for a shorter sample period, from January 2009 to June 2024. This is because, until the end of 2008, the subsample containing high ESG stocks had less than 50 firms per month, so the results would not be reliable. For the full sample, the full period is presented in the Appendices, starting from January 2003.

5.1 Summary statistics for cross-sectional analysis

It is important to gain an in-depth understanding of the data employed. Thus, summary statistics are calculated. This process involves two steps. Initially, the statistics arithmetic mean ($Mean_t$), sample standard deviation (SD_t), sample skewness ($Skew_t$), first quartile ($Q1_t$), median ($Median_t$), third quartile ($Q3_t$), and the total number of observation (N) are calculated for each period t. Subsequently, the time-series average of these statistics is determined over all t, resulting in the average cross-sectional summary statistics. These are then presented without the subscript t (Bali et al., 2016).

In evaluating the summary statistics presented in Table 7, it is important to note that the number of firms included in the sample has increased significantly over the course of the study period. This is due to an increase in the number of firms reporting ESG scores, which have consequently been included in the sample. In January 2003, the sample comprised 250 firms. By December 2023, this had increased to 2,484 firms.

Table 7: Summary statistics of key variables

This table presents summary statistics for the full sample and the subsamples high and low ESG for the sample period starting from January 2003 until June 2024. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile. The table presents the monthly time-series means of cross-sectional statistics mean, standard deviation, skew, Q1, median, Q3, and N as described in Chapter 5.1. These statistics were computed for the variables MV, TRESGS, RET, ExRET, IVOL, and E(IVOL). For the FF5 variables Mkt-RF, SMB, HML, RMW, CMA, and RF, the statistics were only calculated using the time-series means, as only one observation was available per period and variable. Consequently, since the values remain consistent across the sub-samples, they are presented exclusively under full sample.

Group	Variable	Mean	SD	Skew	Q1	Median	Q3	N
Full sample	TRESGS	42.31	19.90	0.40	26.49	39.31	57.19	1,137
	IVOL (%)	6.51	4.33	3.45	3.89	5.37	7.78	1,117
	E(IVOL) (%)	7.35	6.76	3.33	3.73	5.50	8.52	827
	MV ($ mn)	22,204	53,434	8.14	3,023	7,056	19,200	1,137
	RET (%)	0.56	9.42	-0.27	-4.03	0.74	5.37	1,137
	ExRET (%)	0.44	9.42	-0.27	-4.15	0.62	5.26	1,137
	Mkt-RF (%)	0.87	4.39	-0.53	-1.70	1.35	3.38	
	SMB (%)	0.07	2.61	0.17	-1.76	0.06	1.73	
	HML (%)	-0.05	3.11	0.00	-1.72	-0.20	1.44	
	RMW (%)	0.29	1.97	0.16	-0.96	0.40	1.32	
	CMA (%)	0.04	1.91	0.32	-1.11	-0.06	1.16	
	RF (%)	0.12	0.15	1.08	0.00	0.06	0.19	
High ESG	TRESGS	81.37	4.49	0.48	78.12	80.77	84.21	104
	IVOL (%)	5.21	2.66	1.64	3.57	4.63	6.13	102
	E(IVOL) (%)	6.51	4.44	2.37	4.01	5.36	7.56	100
	MV ($ mn)	77,802	108,313	3.19	29,536	50,966	93,512	104
	RET (%)	0.52	6.99	-0.14	-3.14	0.64	4.27	104
	ExRET (%)	0.40	6.99	-0.14	-3.26	0.52	4.15	104
Low ESG	TRESGS	38.83	17.05	0.27	25.36	36.90	51.70	1,033
	IVOL (%)	6.63	4.43	3.42	3.94	5.47	7.93	1,015
	E(IVOL) (%)	7.46	6.98	3.25	3.69	5.53	8.68	727
	MV ($ mn)	17,527	38,409	8.05	2,865	6,257	15,936	1,033
	RET (%)	0.56	9.57	-0.27	-4.09	0.75	5.43	1,033
	ExRET (%)	0.44	9.57	-0.27	-4.21	0.63	5.31	1,033

As anticipated, the market capitalisation is markedly right skewed, with a coefficient of 8.1 indicating the presence of numerous smaller firms and a relatively small number of firms with disproportionately high market capitalisation. This effect is observed to decreases to 3.2 when the high ESG sample is considered. The higher average MV of $78 bn for high ESG stocks compared to $18 bn for low ESG stocks, highlights that capitalisation seems to be a pivotal factor influencing a company's ESG performance. This could be attributed to more available resources, increased regulatory scrutiny, or public pressure.

RET and ExRET display comparable statistics across all samples. In particular, all of the series exhibit slight negative skewness, which is typical for financial time series. This highlights the leverage effect and the appropriateness of using an EGARCH model. The average IVOL and E(IVOL) for the companies in the full sample are 6.51% and 7.35%, respectively. The highest levels are observed during crises, namely the financial and the Covid-19 crises (Figure 1). In accordance with the existing literature, it can be observed that high ESG stocks bear, on average, less idiosyncratic risk than low ESG stocks. Furthermore, skewness is significantly higher in low ESG stocks than in high ESG stocks, highlighting that some stocks exhibit significantly more IVOL or E(IVOL).

5.2 Cross-sectional correlations

To better understand the linear relationship of IVOL, E(IVOL) and other variables, periodic cross-sectional correlations are calculated. The periodic cross-sectional correlation between two variables X and Y, denoted as $\rho_t(X, Y)$ and given by:

$$\rho_t(X,Y) = \frac{\sum_{i=1}^{nt}(X_{i,t} - \bar{X}_t)(Y_{i,t} - \bar{Y}_t)}{\sqrt{\sum_{i=1}^{nt}(X_{i,t} - \bar{X}_t)}\sqrt{\sum_{i=1}^{nt}(Y_{i,t} - \bar{Y}_t)}}. \tag{23}$$

$\rho_t(X, Y)$ quantifies the strength of the linear relationship between X and Y and it satisfies the properties $-1 < \rho_t(X,Y) < 1$ and $\rho_t(X,Y) = \rho_t(Y,X)$. X and Y are uncorrelated when $\rho_t(X,Y) = 1$, positively correlated when $\rho_t(X,Y) > 0$, and negatively correlated when $\rho_t(X, Y) < 0$. $\bar{X}_t$ and $\bar{Y}_t$ are the sample means of $X_{i,t}$ and $Y_{i,t}$ which are taken over the same set of firms i. n_t represents the number of companies for which there are valid values for both X and Y. Step two is to calculate the time-series average of $\rho_t(X, Y)$ by

$$\rho(X,Y) = \frac{\sum_{t=1}^{T}\rho_t(X,Y)}{T}. \tag{24}$$

where $\rho(X,Y)$ is the average cross-sectional correlation (Bali et al., 2016; Tsay, 2010).

The cross-sectional correlation between the different variables is presented in Table 8.The correlation factor for IVOL and ExRET is -0.06. Using the lagged IVOL, the correlation shrinks to -0.02, both of which are significant at 10%. This indicates a negative relationship between idiosyncratic risk and ExRET, which becomes slightly less pronounced when using the lagged value. In contrast, the correlation between E(IVOL) and ExRET is indistinguishable from zero, indicating that the data does not provide evidence of a relationship.

Notably, a negative correlation is observed between TRESGS and lagged IVOL, IVOL as well as E(IVOL), indicating that superior ESG performance leads to a reduction in idiosyncratic risk. The EGARCH model demonstrates competence in forecasting IVOL, as evidenced by a 0.37 positive correlation at the 1% level. However, the correlation between lagged IVOL and IVOL is stronger with 0.50 indicating better prediction of IVOL than the EGARCH.

Table 8: Cross-sectional correlation matrix for the full sample (2009–2024)

This table presents the cross-sectional correlation matrix, where first the cross-sectional correlation (Equation (23)) was initially calculated for each point in time and subsequently the time-series average was taken (Equation (24)). This calculation was performed for a range of variables within the full sample for the sample period starting from January 2009 until June 2024. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile. RET is not presented as the correlation is similar to the one of ExRET. Statistical significance is indicated as follows: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

	ExRET	**TRESGS**	**IVOL$_{t-1}$**	**IVOL**	**E(IVOL)**	**ln *MV***
ExRET	1.00***	0.00	-0.02*	-0.06*	0.00	0.05
TRESGS		1.00***	-0.19**	-0.19**	-0.11*	0.60***
IVOL$_{t-1}$			1.00***	0.50***	0.40***	-0.33***
IVOL				1.00***	0.37***	-0.33***
E(IVOL)					1.00***	-0.24***
ln MV						1.00***

Additionally, a negative correlation is observed between any idiosyncratic risk measure and ln MV, suggesting that smaller firms tend to exhibit higher risk compared to larger ones. Findings for the full sample since January 2003 (Appendix B) and high and low ESG stocks (Table 9) are broadly similar to those for the full sample since 2009, with minor variations in the strength of some relationships.

The findings from the present study deviate from those reported by Fu (2009). Fu (2009) utilised RET as opposed to ExRET, which should not be the underlying cause of the observed discrepancy in results. The primary conclusions of Fu (2009) indicated a significant positive correlation between IVOL and E(IVOL) with RET. Additionally, the findings demonstrated a negative relationship between lagged IVOL and RET, which is consistent with the results obtained from the sample employed in this thesis. The observed discrepancy could indicate a shift in IVOL pricing during specific periods or suggest its limitations in providing a comprehensive explanation of returns.

Table 9: Cross-sectional correlation matrix by ESG group (2009–2024)

This table presents the cross-sectional correlation matrix, where first the cross-sectional correlation (equation (23)) was initially calculated for each point in time and subsequently the time-series average was taken (equation (24)). This calculation was performed for a range of variables within the High ESG group, representing the upper half of the correlation matrix, and for the Low ESG group, which corresponds to the lower half of the correlation matrix. The sample period is from January 2009 till June 2024. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile. RET is not presented as the correlation is similar to the one of ExRET. Statistical significance is indicated as follows: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

	ExRET	**TRESGS**	**IVOL$_{t-1}$**	**IVOL**	**E(IVOL)**	**ln *MV***
ExRET	1.00***	0.00	-0.02	-0.08	0.00	0.04
TRESGS	0.00	1.00***	-0.04	-0.04	-0.04	0.25**
IVOL$_{t-1}$	-0.02*	-0.18***	1.00***	0.54***	0.49**	-0.36**
IVOL	-0.06*	-0.18**	0.50***	1.00***	0.45**	-0.37**
E(IVOL)	0.00	-0.11	0.40***	0.36***	1.00***	-0.34*
ln MV	0.06	0.52***	-0.32***	-0.32***	-0.24***	1.00***

5.3 Fama-MacBeth regression

In order to evaluate the explanatory power of factors such as IVOL, E(IVOL) and other variables on stock returns within the sample under consideration, the Fama & MacBeth (1973) two-step regression approach will be introduced in the following paragraphs. However, it should be noted that an additional step is required at the outset, since the factors for the FF5 are constant for each firm in each month t, which does not yield a meaningful result when running a cross-sectional regression. Consequently, prior to initiating the two-step approach, it is necessary to run a time-series regression

$$r_{i,t} = \alpha_i + \beta_{1,i} X1_{i,t} + \beta_{2,i} X2_{i,t} + \cdots + \beta_{k,i} Xk_{i,t} + \varepsilon_{i,t}, \tag{25}$$

where excess returns $r_{i,t}$ will be regressed on the independent variables $X1,\ X2,\ \dots\ ,\ Xk$, such as the FF5 factors, IVOL and/or E(VOL) for each firm i. k represents the kth variable used.

The first step is to perform separate cross-sectional regressions for each month t, whereby the dependent variable is the assets' excess returns, which is regressed on one or more independent variables, such as $X1, X2, \dots, Xk$. However, in the following analysis, the estimated $\beta_{1,i}, \beta_{2,i}, \dots, \beta_{k,i}$ from the time-series regression in Equation (25) are used

$$r_{i,t} = \alpha_t + \gamma_{1,t}\hat{\beta}_{1,i} + \gamma_{2,t}\hat{\beta}_{2,i} + \dots + \gamma_{k,t}\hat{\beta}_{k,i} + \varepsilon_{i,t}. \quad (26)$$

The intercept is denoted by alpha, and the gammas $\gamma_{1,t},\ \gamma_{2,t},\ \dots\ ,\ \gamma_{k,t}$ represent the slopes for the factors.

The second step is to calculate the time-series averages of the periodic cross-sectional regression coefficients, and R^2, form equation (26) as well as the number of observations. Using these results, the final estimate $\hat{\gamma}_k = \frac{1}{T}\sum_{t=1}^{T} \hat{\gamma}_{k,t}$, its variance $Var(\hat{\gamma}_k) = \frac{\sum_{t=1}^{T}(\hat{\gamma}_{k,t} - \hat{\gamma}_k)^2}{T(T-1)}$, the time series standard errors $s.e.(\hat{\gamma}_k) = \sqrt{\frac{Var(\hat{\gamma}_k)}{T}}$, and t-statistic $t(\hat{\gamma}_k) = \frac{\hat{\gamma}_k}{s.e.(\hat{\gamma}_k)}$, are computed. Then, the null hypothesis H_0: $t(\hat{\gamma}_k) = 0$, which evaluates whether the average coefficient is statistically indistinguishable from zero, is tested (Bali et al., 2016; Fu, 2009).

Applying the Fama-MacBeth two-step regression results for the full sample since 2009 (Table 10) provides mixed results regarding the impact of idiosyncratic risk measures on ExRET, with all coefficients being significant at the 1% level. As the application of IVOL and one-period lagged IVOL, both in conjunction with the FF5 and individually, has yielded positive and negative gammas, which may suggest an absence of direct pricing of idiosyncratic risk. It is noteworthy, that the positive gammas are consistently less pronounced, with values of 0.0006 (Model 1) and 0.0005 (Model 4), while the negative relation is consistently stronger. Conversely, the coefficient of -0.0019 for the FF5 augmented by E(IVOL) model and -0.013 for the individual model indicate a negative relationship between E(IVOL) and ExRET coherent.

When considering the explanatory power represented by R^2, idiosyncratic volatility measure always increases the R^2. The most substantial enhancement in explanatory power is observed when incorporating E(IVOL), which increases from 14.41% to 16.57%. However, when considered in isolation, E(IVOL) exhibits the lowest explanatory power at 0.21%, while IVOL exhibits the highest at 0.97%. This finding indicates that realised IVOL possesses the strongest explanatory power, as evidenced by a negative coefficient of -0.0014, which signifies a negative relationship between idiosyncratic risk and ExRET. The findings from the full sample form 2003 (Appendix C) yields similar results.

Table 10: Fama-MacBeth regression results for the full sample (2009–2024)

This table presents the $\gamma \hat{k}$ coefficient, alongside the p-values (presented in brackets), and the R^2 value, derived from the Fama-MacBeth two-step regression approach outlined in Chapter 5.3. Seven distinct factor models have been selected for analysis of the full sample for the sample period starting from January 2009 until June 2024. The initial model comprises the FF5 factors. Subsequent models are variations of the FF5 factors, augmented with one of the following factors: IVOL, IVOLt-1, or E(IVOL). Additionally, each of these factors – IVOL, $IVOL_{t-1}$, or E(IVOL) – is analysed as an independent model. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of all variables used have been winsorized at the 1st and 99th percentile.

Model	Mkt-RF	SMB	HML	RMW	CMA	IVOL	$IVOL_{t-1}$	E(IVOL)	R^2 (%)
1	0.0023	-0.0033	-0.0042	0.0033	-0.0056				14.41
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
2	0.0022	-0.0036	-0.0042	0.0033	-0.0055	0.0006			14.84
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
3						-0.0014			0.97
						(0.0000)			
4	0.0026	-0.0033	-0.0046	0.0031	-0.0054		-0.0020		15.28
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)		
5							0.0005		0.72
							(0.0003)		
6	0.0013	-0.0019	-0.0055	0.0022	-0.0055			-0.0019	16.57
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	
7								-0.0013	0.21
								(0.0000)	

A notable distinction emerges when contrasting the results for the subsamples high ESG (Appendix D) and low ESG (Appendix E). The FF5 model offers a significantly stronger explanatory power for high ESG stocks, while its ability to explain low ESG stocks is comparatively weaker. This observation may be attributed to the earlier finding that high ESG firms are typically larger, with lower idiosyncratic volatility and less variation in it. However, further research is essential to validate this hypothesis.

The findings of more explanatory power for high ESG stocks also apply to the independent models, where IVOL again has the highest R^2 with 1.71%. However, the relation between the coefficient is here positive, in contrast to the low ESG stocks. All other findings are similar to the full sample starting form 2009.

The findings of the Fama-MacBeth regression analysis are not consistent with the results reported by Xu & Malkiel (2004), who found that for the portfolio lagged IVOL and IVOL have consistently positive coefficients. Spiegel & Wang (2005) as well as Fu (2009) also found a significant positive relationship between IVOL and E(IVOL) when applying the Fama-MacBeth methodology. The findings of Guo et al. (2014) have also not been confirmed, as his results for E(IVOL) are all insignificant.

5.4 Cross-sectional portfolio analysis

One of the most used methods for understanding the predictability properties of a factor is portfolio analysis. The initial step involves calculating the periodic breakpoint values, which are employed to divide the sample into distinct portfolios based on the factor under consideration. Subsequently, the excess returns are sorted according to the factor in question. Companies with a factor value below the initial breakpoint are assigned to the first portfolio. If a company's factor values fall between the first and second breakpoints, it is assigned to the second portfolio, and so forth. Finally, companies with factor values that exceed the highest breakpoint are summarised in the last portfolio.

The number of portfolios formed in each period is referred to as n_p, whereby the number of breakpoints being calculated for each period is $n_p - 1$. Both the number of portfolios and the number of breakpoints remain constant across all periods. However, the value of the kth breakpoint usually varies from period to period. The kth breakpoint for the period t is referred to as $B_{k,t}$, where $k \in \{1, 2, \ldots, n_p - 1\}$ applies.

The breakpoints for a period t are determined by the percentiles of the distribution of the sorting variables X at the time t. The kth breakpoint $B_{k,t}$ corresponds to the p_kth percentile of the values of X in the sample, defined as

$$B_{k,t} = Pctl_{p_k}(\{X_t\}), \tag{27}$$

where $\{X_t\}$ comprises the valid values of X during t. The percentiles p_k increase strictly monotonically ($0 < p_1 < p_2 < \cdots < p_{n_p-1,t}$), but this does not guarantee that the breakpoints $B_{k,t}$ also increase strictly.

In the second step, the sample units are divided into portfolios. In the period t, units with sorting variables X that are below or equal to the first breakpoint $B_{1,t}$ are assigned to the first portfolio. The second portfolio contains units with X values between the first and second breakpoints. This process continues until the last portfolio contains all units with X values from the penultimate breakpoint $B_{n_p-1,t}$. In general, portfolio k contains units with $X_{i,t}$ values between $B_{k-1,t}$ and $B_{k,t}$. Formally, portfolio $P_{k,t}$ is defined as

$$P_{k,t} = \{ i \mid B_{k-1,t} \leq X_{i,t} \leq B_{k,t} \}. \tag{28}$$

The first portfolio contains the lowest and the last portfolio the highest X values, whereby these increase with the number of portfolios.

The third step is to calculate the average excess return r for each of the n_P portfolios in each time period t. Either a simple average or a weighted average can be used. The weighting is based on a variable $W_{i,t}$, the market capitalisation, which is referred to as a value-weighted average. For equally weighted portfolios, all $W_{i,t}$ are set to 1, which corresponds to a weighting of $1/n_t$ per company. In general, the average value $r_{k,t}$ for portfolio k in period t is calculated using the formula

$$\bar{r}_{k,t} = \frac{\sum_{i \in P_{k,t}} W_{i,t} r_{i,t}}{\sum_{i \in P_{k,t}} W_{i,t}}, \tag{29}$$

where the totals include all companies in the portfolio $P_{k,t}$. In the following only the equal-weighted portfolios are formed as DeMiguel et al. (2009) have found that no portfolio outperforms the equal-weighted portfolio in terms of Sharpe ratio, certainty-equivalent return, or turnover. Further the difference between the highest and lowest value portfolio of X is calculated

$$\bar{r}_{Diff,t} = \bar{r}_{n_P,t} - \bar{r}_{1,t}, \tag{30}$$

as it is primarily used to determine the cross-sectional relationship between the sort variable X and excess returns r. The difference in average portfolio is also referred to as zero cost portfolio, as the lowest portfolio will be shorted, and the proceeds will be invested in the highest portfolio. Finally, the time-series averages of $\bar{r}_{k,t}$ and $\bar{r}_{Diff,t}$ for each n_p are calculated

$$\bar{r}_k = \frac{\sum_{t=1}^{T} \bar{r}_{k,t}}{T}, \tag{31}$$

$$\bar{r}_{Diff} = \frac{\sum_{t=1} r_{Diff,t}}{T}. \tag{32}$$

To determine whether the variation in a portfolio is sensitive to systematic risk factors, a time-series regression is conducted using the FF5 model. The regression equations are expressed as follows:

$$\begin{aligned} \bar{r}_{k,t} = \alpha_k + \beta_{k,MKT} MKT_t + \beta_{k,SMB}\, SMB_t + \beta_{k,HML}\, HML_t \\ + \beta_{k,RMW}\, RMW_t + \beta_{k,CMA} CMA_t + \varepsilon_{k,t}, \end{aligned} \tag{33}$$

$$\begin{aligned} \bar{r}_{Diff,t} = \alpha_k + \beta_{k,MKT} MKT_t + \beta_{k,SMB}\, SMB_t + \beta_{k,HML}\, HML_t \\ + \beta_{k,RMW}\, RMW_t + \beta_{k,CMA} CMA_t + \varepsilon_{k,t}. \end{aligned} \tag{34}$$

The output are the regression results such as the slopes for the factors as well as the intercept (α). The alpha is also referred to as Jensen (1968)'s alpha, portfolio alpha, or abnormal returns and is interpreted as the average excess returns of the portfolios. The p-value is used to asses if the abnormal returns are statistically significant different from zero (Bali et al., 2016).

Table 11 presents excess returns for the five portfolios formed based on E(IVOL) as well as the zero-cost portfolio (Appendix F presents 10 portfolios sorted based on E(IVOL); Appendix I presents the 5 portfolios starting with a sample period from January 2003). For the full and subsamples a negative relation between E(VOL) and expected excess returns can be implied with average excess returns for the 5-1 portfolio of -0.18% for the full sample. This relation is robust when considering 10 portfolios even though the returns are significantly lower for the full sample and low ESG stocks. When considering the full sample period with 5 portfolios findings are similar for the full sample and low ESG, but for high ESG stocks the excess return for the zero-cost portfolio is close to zero (0.02%).

All portfolio alphas except the zero-cost portfolio of high ESG stocks are significant at the 5% level. Since all of them are negative, no abnormal returns can be observed. However, reversing the 5-1 strategy would yield positive excess returns with a positive alpha. Nonetheless, these findings lack robustness, as the alphas for the zero-cost portfolio are not significant at the 5% level when considering 10 portfolios.

Overall, these findings indicate a robust negative relation between E(IOVL) and expected returns for the full sample and low ESG stocks. For high ESG stocks, a negative relation is also found, but it is not robust. These findings do not confirm the finding of Fu (2009) as the results of Fu`s study indicate a positive relation between E(IVOL) and expected returns.

Table 11: Portfolio returns sorted by E(IVOL) (2009–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable E(IVOL) and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) E(IVOL). Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile.

Group	Variable	1	2	3	4	5	5-1
Full sample	ExRET (%)	0.59	0.77	0.73	0.52	0.41	-0.18
	E(IVOL) (%)	2.36	4.42	5.91	8.23	18.17	15.81
	Alpha (%)	-0.43	-0.28	-0.39	-0.64	-0.88	-0.46
		(0.01)	(0.24)	(0.01)	(0.00)	(0.01)	(2.74)
High ESG	ExRET (%)	0.66	0.66	0.58	0.38	0.49	-0.16
	E(IVOL) (%)	3.19	4.64	5.75	7.4	13.26	10.07
	Alpha (%)	-0.37	-0.44	-0.58	-0.76	-0.85	-0.48
		(0.23)	(0.15)	(0.01)	(0.01)	(1.67)	(16.72)
Low ESG	ExRET (%)	0.57	0.79	0.74	0.59	0.41	-0.16
	E(IVOL) (%)	2.27	4.38	5.94	8.38	18.77	16.51
	Alpha (%)	-0.44	-0.26	-0.37	-0.58	-0.88	-0.44
		(0.02)	(0.64)	(0.02)	(0.00)	(0.01)	(2.70)

Since all the findings so far align more closely with the findings of Ang et al. (2006), which examined the predictability of one-period lagged IVOL, the analysis is extended to explore this relationship further. Table 12 presents the average excess returns for 5 portfolios formed on $IVOL_{t-1}$ over a sample period starting in 2009, Appendix G provides the findings for 10 portfolios, and Appendix J reports results for the full sample period using 5 portfolios. The relationship between one period lagged IVOL and expected excess returns is also negative and stronger with -0.68% for the full sample and similar magnitudes for low ESG.

High ESG regardless of the sample period and number of portfolios formed has consistently the closet average excess returns to zero for the zero-cost portfolio. This aligns with expectations, as the difference in IVOL between portfolios 1 and 5 is the smallest compared to other samples, leading to a weaker effect and returns that are closest to zero.

The findings are robust when looking at all portfolios from 1 to 5 since they highlight a clear negative relationship in which higher IVOL at $t - 1$ leeds to less ExRET at t. Furthermore, all zero-cost portfolios have negative abnormal returns which are all significant the 5% level. Overall, these results confirm the findings of Ang et al. (2006) and highlight slight differences between high and low ESG stocks.

Table 12: Portfolio returns sorted by lagged IVOL (2009–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable $IVOL_{t-1}$ and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) $IVOL_{t-1}$.

Group	Variable	1	2	3	4	5	5-1
Full sample	ExRET (%)	0.83	0.8	0.63	0.41	0.15	-0.68
	$IVOL_{t-1}$ (%)	2.97	4.26	5.58	7.58	13.95	10.98
	Alpha (%)	-0.14	-0.27	-0.49	-0.76	-1.1	-0.96
		(19.94)	(0.45)	(0.00)	(0.00)	(0.00)	(0.10)
High ESG	ExRET (%)	0.81	0.73	0.67	0.34	0.39	-0.43
	$IVOL_{t-1}$ (%)	2.66	3.73	4.75	6.14	10.12	7.46
	Alpha (%)	-0.19	-0.37	-0.48	-0.86	-0.99	-0.80
		(10.07)	(0.48)	(0.56)	(0.00)	(0.53)	(2.89)
Low ESG	ExRET (%)	0.82	0.82	0.6	0.43	0.17	-0.65
	$IVOL_{t-1}$ (%)	3.02	4.33	5.7	7.75	14.25	11.23
	Alpha (%)	-0.14	-0.24	-0.51	-0.74	-1.06	-0.92
		(23.44)	(0.99)	(0.00)	(0.00)	(0.01)	(0.18)

It has been established that a negative relationship exists between E(IVOL) and one period lagged IVOL with expected excess returns. The question that arises from this finding is whether the negative relationship found with E(IVOL) is due to overfitting or inaccurate forecasting of IVOL with the EGARCH model as it opposes previous research. To test the hypothesis, portfolios are formed based on IVOL. This represents the idiosyncratic volatility during the month of the return, which is unavailable to investors and cannot be used for an investment strategy.

The findings for 5 (10) portfolios formed on the sorting variable IVOL are presented in Table 13 (Appendix H). The findings for the full sample starting in 2003 for 5 portfolios are presented in Appendix K. The findings for these portfolios are analogous to those formed on $IVOL_{t-1}$, with the notable difference that the relationship is even stronger. On average, the excess return for the 5-1 portfolio is approximately twice as low compared to one period lagged IVOL ones. However, the finding that due to the lower difference in IVOL for the high ESG sample, the returns of the zero-cost portfolio are closer to zero is not supported. Consequently, no discernible distinction could be identified between high and low ESG stocks.

Consequently, the positive relationship, which would theoretically be consistent with the findings of by Fu (2009) and other scholars, did not materialise. Furthermore, the EGARCH model was able to capture the negative relationship between idiosyncratic risk properly but did a worse job in explaining the cross-section of excess returns than the simple one-lagged IVOL.

Table 13: Portfolio returns sorted by IVOL (2009–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable IVOL and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) IVOL.

Group	Variable	1	2	3	4	5	5-1
Total observations	ExRET (%)	1.05	0.91	0.69	0.36	-0.17	-1.22
	IVOL (%)	2.95	4.23	5.54	7.53	13.87	10.92
	Alpha (%)	0.10	-0.12	-0.43	-0.83	-1.46	-1.56
		(22.13)	(16.05)	(0.01)	(0.00)	(0.00)	(0.00)
High ESG	ExRET (%)	1.12	0.76	0.63	0.6	-0.17	-1.29
	IVOL (%)	2.65	3.71	4.72	6.1	10.05	7.40
	Alpha (%)	0.11	-0.31	-0.54	-0.61	-1.53	-1.65
		(28.06)	(0.68)	(0.03)	(0.19)	(0.00)	(0.00)
Low ESG	ExRET (%)	1.05	0.93	0.67	0.37	-0.15	-1.21
	IVOL (%)	3.00	4.30	5.66	7.7	14.17	11.18
	Alpha (%)	0.11	-0.09	-0.45	-0.82	-1.43	-1.55
		(19.49)	(27.61)	(0.01)	(0.00)	(0.00)	(0.00)

5.5 Cross-sectional portfolio analysis during recessions

Figure 1 displayed E(IVOL) and IVOL over time, where it is clearly visible the idiosyncratic risk spices during the financial crises, which started on October 2007 and lasted until June 2009 and the Covid-19 Pandemic, which lasted from January 2020 until June 2020 both based on U.S. GDP recession data. High ESG stocks further exhibited significantly less idiosyncratic risk, which is why in the following the investment strategies introduced in Chapter 5.4 are applied during the recession periods to determine if this has an impact on the strategy.

Table 14: Portfolio returns sorted by E(IVOL) during recessions

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable E(IVOL) and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for times of recession (October 2007 until June 2009; January 2020 until June 2020) as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding *p*-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) E(IVOL). Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile.

Group	Variable	1	2	3	4	5	5-1
Full sample	ExRET (%)	-2.91	-2.62	-2.35	-2.90	-3.23	-0.32
	E(IVOL) (%)	1.33	3.43	5.06	7.52	19.36	18.03
	Alpha (%)	-1.45	-1.14	-0.75	-1.43	-0.28	1.17
		(4.65)	(5.64)	(11.17)	(2.80)	(75.41)	(13.77)
High ESG	ExRET (%)	-2.52	-1.67	-2.60	-2.50	-2.13	0.38
	E(IVOL) (%)	1.91	3.58	4.81	6.40	14.79	12.88
	Alpha (%)	-0.48	-0.76	-0.38	-0.02	0.08	0.55
		(58.62)	(33.68)	(62.16)	(98.55)	(94.83)	(67.10)
Low ESG	ExRET (%)	-2.93	-2.76	-2.46	-3.00	-3.14	-0.20
	E(IVOL) (%)	1.28	3.40	5.11	7.68	19.78	18.5
	Alpha (%)	-1.55	-1.23	-0.81	-1.78	-0.13	1.42
		(3.04)	(4.69)	(8.46)	(1.40)	(88.80)	(6.47)

Table 14 (Appendix L) presents the average excess returns for 5 (10) formed portfolio based on the sorting criteria E(IVOL). No robust conclusion can be drawn, as the results for the zero-cost portfolio are inverted when comparing portfolios formed with 5 and 10 groups. Especially

when considering all portfolios there is also no clear trend or relationship visible between average monthly excess return and E(IVOL) as it varying substantially.

Table 15 (Appendix M) present the findings for 5 (10) portfolios, sorted according to one-period lagged IVOL. The findings are more robust when compared to the sorting based on E(IVOL), as the zero-cost portfolio for the full sample is 0.00% (-0.08%) when formed on 5 (10) portfolios. This indicates that there is no relationship between expected excess returns and one-period lagged IVOL. However, in contrast to the findings in Chapter 5.4 , High ESG stocks have been found to demonstrate a positive relationship between expected excess returns and one-period lagged IVOL, with an average monthly excess return of 0.82% (2.11%) when 5 (10) portfolios are formed. Furthermore, the formed portfolios for High ESG stocks have been found to exhibit trends. The reasons for this phenomenon require further investigation.

Table 15: Portfolio returns sorted by lagged IVOL during recessions

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable $IVOL_{t-1}$ and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for times of recession (October 2007 until June 2009; January 2020 until June 2020) as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) $IVOL_{t-1}$.

Group	Variable	1	2	3	4	5	5-1
Full sample	ExRET (%)	-2.51	-2.6	-3.19	-2.99	-2.51	0.00
	$IVOL_{t-1}$ (%)	4.59	6.45	8.25	10.77	18.21	13.63
	Alpha (%)	-1.44	-1.05	-1.41	-1.6	0.11	1.54
		(3.11)	(6.15)	(4.78)	(4.35)	(92.43)	(24.86)
High ESG	ExRET (%)	-2.89	-3.71	-1.54	-1.25	-2.07	0.82
	$IVOL_{t-1}$ (%)	4.21	5.60	6.84	8.46	13.18	8.97
	Alpha (%)	-1.04	-2.09	-0.16	1.53	0.61	1.66
		(8.10)	(4.00)	(85.53)	(6.96)	(69.85)	(29.16)
Low ESG	ExRET (%)	-2.47	-2.62	-3.29	-3.01	-2.63	-0.16
	$IVOL_{t-1}$ (%)	4.65	6.56	8.43	11.00	18.56	13.91
	Alpha (%)	-1.51	-1.04	-1.65	-1.59	-0.01	1.50
		(3.93)	(6.72)	(3.51)	(3.63)	(99.04)	(28.42)

6 Research limitations and future directions

The following chapter discusses the main limitations of this study and proposes directions for further research. Chapter 6.1 highlights key challenges, including data constraints and model-specific issues. Chapter 6.2 suggests future studies to validate findings and explore unexplored aspects of idiosyncratic risk measures.

6.1 Limitations

During the study, a number of limitations were identified that served to hinder the informative value of the results. Most significantly, the time horizon over which ESG data is available is limited, extending only as far back as 2002 when utilising data from Workspace Refinitiv. Additionally, the quantity of firms included in the beginning was limited to 250, of which only one was classified as a high ESG. However, this number increased significantly by the end of the sample, with 2484 firms and 254 high ESG firms. It is also important to note that the ESG scores reported in the beginning are likely to be less accurate due to a lack of standardisation and in-depth reporting. A problem that persists to some extent today, though it has improved significantly.

Additionally, the FF5 factors were insufficient for inclusion in certain analyses, such as the cross-sectional correlation matrix, or necessitated an additional step, as in the Fama-MacBeth regression. This is because the factors were not constructed but downloaded and hence were the same value for each company in each month. It can be further argued that the residual value from the FF5 regression does not capture idiosyncratic volatility but is merely the consequence of omitted variables.

A further limitation is that only an EGARCH(1,1) was applied due to a lack of computing power. This is particularly salient given that Fu (2009) tested all EGARCH($p,\ q$) models with $1 \leq p \leq 3$ and $1 \leq q \leq 3$, and the least applied model was the EGARCH(1,1) with 7.41%. However, it should be noted that the application of an EGARCH model may in fact represent an overfitting of the data, given that the numerous time-series of IVOL do not exhibit heteroskedasticity. As further highlighted in Chapter 5.4, EGARCH performed worse than a model taking the lagged one-period IVOL. Consequently, the employment of an alternative model may have yielded superior forecasts.

6.2 Further research

To enhance the understanding of the subject, it is imperative to identify the differences between the time period contemplated in Fu (2009) and the sample period under investigation.

Furthermore, it is important to identify a superior predictor of IVOL, which could be a first-order moving average, as suggested in Chapter 4.2, as it has been demonstrated that IVOL does not follow a white noise process and the relationship between IVOL and $IVOL_{t-1}$ cannot be assumed.

In the distant future, the same analysis should be conducted using more high-quality ESG Score estimates to validate the findings. This will allow for improved validation of the findings related to the positive relationship between $IVOL_{t-1}$ and excess returns for the zero-cost portfolio during crises. A further avenue of interest would be to understand why the variation in excess returns can be so much better explained by the FF5, $IVOL_{t-1}$, and E(IVOL) factors for high ESG stocks than low ESG stocks when looking at the R^2.

Finally, the relationship between idiosyncratic risk measures and stock returns has been extensively studied in the United States and, to a lesser extent, in other developed countries. However, similar studies remain largely unexplored for emerging markets, where the idiosyncratic risk profile may differ significantly from that of developed economies. Understanding potential differences is crucial, making it imperative to conduct such studies in emerging markets.

7 Conclusion

The existing financial literature has established a positive relationship between risk and returns in the stock market. This has been most clearly demonstrated in the CAPM and its various adaptations. Nevertheless, the question of whether this relationship remains valid when idiosyncratic risk is considered remains inconclusive among scholars. The present study aimed to contribute to this ongoing discourse by investigating the relationship between idiosyncratic risk measures and returns. In this study, a new time period was utilised. Furthermore, the role of ESG ratings was examined, as firms prioritising ESG values may be able to hedge ESG-related risks.

The study evaluated the cross-sectional correlation, Fama-MacBeth regression, and cross-sectional portfolio analysis based on idiosyncratic risk measures. The findings revealed a negative relationship between lagged IVOL, IVOL, and E(IVOL). The novel finding of a negative relationship between E(IVOL) and expected returns contradicts the findings of previous research, which predominantly identified a positive relationship. Furthermore, it was determined that E(IVOL) predicted by an EGARCH(1,1) model did not demonstrate a higher degree of predictive capability for IVOL than lagged IVOL.

When ESG ratings are considered, this normally has no substantial effect on the research results. Nevertheless, when analysing recessions exclusively, the relation for high ESG firms is positive, thereby contradicting the findings for the full sample. Additionally, high ESG companies exhibited reduced IVOL, variation in IVOL, and less skewness. These findings are consistent across various periods, including the financial crisis and the recent COVD-19 crisis. Consequently, it can be concluded that investing in ESG is advantageous for companies, as it serves to mitigate risk. These results align with previous research findings.

The findings of this study pose a challenge to risk-based explanations of expected stock returns, underscoring the need for further research attention. This thesis further reveals that investing in companies with lower idiosyncratic risk can result in higher returns for investors. Hence, the formation of zero-cost portfolios, characterised by a long position in low IVOL stocks and a short position in high IVOL, can generate positive abnormal returns.

Appendices

Appendix A: Data cleaning steps and their impact on number of firms and observations

This table details the data cleaning steps undertaken to prepare the dataset, focusing on the number of firms and observations, for analysis over the sample period from January 2003 to June 2024. The cleaning process involved the initial removal of firms and observations with missing values in any variable, followed by the exclusion of firms with missing monthly data. Finally, firms with fewer than 31 months of observations were excluded to ensure the dataset's suitability for proper fitting of the models discussed in the subsequent chapter.

Data cleaning step	**Firms**	**Observations**
Raw Data	3,721	960,018
Removed rows with missing values in any variables	3,712	376,259
Removed all firms with missing monthly data	3,041	301,024
Removed firms with fewer than 30 months of data	2,595	293,320

Appendix B: Cross-sectional correlation matrix for the full sample (2003–2024)

This table presents the cross-sectional correlation matrix, where first the cross-sectional correlation (Equation (23)) was initially calculated for each point in time and subsequently the time-series average was taken (Equation (24)). This calculation was performed for a range of variables within the full sample for the sample period starting from January 2003 until June 2024. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile. RET is not presented as the correlation is similar to the one of ExRET. Statistical significance is indicated as follows: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

	ExRET	**TRESGS**	**$IVOL_{t-1}$**	**IVOL**	**E(IVOL)**	**ln *MV***
ExRET	1.00***	0.00	-0.01	-0.05	0.00	0.05
TRESGS		1.00***	-0.17*	-0.17*	-0.10	0.59***
$IVOL_{t-1}$			1.00***	0.49***	0.37**	-0.31***
IVOL				1.00***	0.34**	-0.31***
E(IVOL)					1.00***	-0.22**
ln MV						1.00***

Appendix C: Fama-MacBeth regression results for the full sample (2003–2024)

This table presents the $\gamma\hat{k}$ coefficient, alongside the p-values (presented in brackets), and the R^2 value, derived from the Fama-MacBeth two-step regression approach outlined in Chapter 5.3. Seven distinct factor models have been selected for analysis to the full sample for the sample period starting from January 2003 until June 2024. The initial model comprises the FF5 factors. Subsequent models are variations of the FF5 factors, augmented with one of the following factors: IVOL, IVOLt-1, or E(IVOL). Additionally, each of these factors – IVOL, $IVOL_{t-1}$, or E(IVOL) – is analysed as an independent model. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of all variables used have been winsorized at the 1st and 99th percentile.

Model	Mkt-RF	SMB	HML	RMW	CMA	IVOL	$IVOL_{t-1}$	E(IVOL)	R^2 (%)
1	0.0005	-0.0030	-0.0040	0.0037	-0.0050				13.06
	(0.0146)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
2	0.0002	-0.0031	-0.0040	0.0037	-0.0048	0.0012			13.42
	(0.2424)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
3						-0.0022			0.83
						(0.0000)			
4	0.0005	-0.0028	-0.0041	0.0037	-0.0048		-0.0009		13.88
	(0.0131)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)		
5							0.0003		0.64
							(0.0028)		
6	-0.0013	-0.0026	-0.0050	0.0026	-0.0049			-0.0020	15.48
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	
7								-0.0013	0.22
								(0.0000)	

Appendix D: Fama-MacBeth regression results for high ESG firms (2009–2024)

This table presents the $\hat{\gamma}_k$ coefficient, alongside the p-values (presented in brackets), and the R^2 value, derived from the Fama-MacBeth two-step regression approach outlined in Chapter 5.3. Seven distinct factor models have been selected for analysis to the high ESG group for the sample period starting from January 2009 until June 2024. The initial model comprises the FF5 factors. Subsequent models are variations of the FF5 factors, augmented with one of the following factors: IVOL, IVOLt-1, or E(IVOL). Additionally, each of these factors – IVOL, $IVOL_{t-1}$, or E(IVOL) – is analysed as an independent model. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of all variables used have been winsorized at the 1st and 99th percentile.

Model	Mkt-RF	SMB	HML	RMW	CMA	IVOL	$IVOL_{t-1}$	E(IVOL)	R^2 (%)
1	-0.0006	0.0015	-0.0042	0.0001	-0.0022				23.24
	(0.0541)	(0.0000)	(0.0000)	(0.3302)	(0.0000)				
2	-0.0016	0.0008	-0.0040	-0.0001	-0.0023	0.0025			24.18
	(0.0000)	(0.0000)	(0.0000)	(0.3880)	(0.0000)	(0.0000)			
3						0.0032			1.71
						(0.0000)			
4	-0.0024	0.0004	-0.0040	0.0004	-0.0026		-0.0005		24.47
	(0.0000)	(0.0398)	(0.0000)	(0.0075)	(0.0000)		(0.0037)		
5							0.0001		1.56
							(0.5789)		
6	-0.0015	0.0008	-0.0045	-0.0004	-0.0026			-0.0024	24.26
	(0.0000)	(0.0001)	(0.0000)	(0.0114)	(0.0000)			(0.0000)	
7								-0.0015	1.09
								(0.0000)	

Appendix E: Fama-MacBeth regression results for low ESG firms (2009–2024)

This table presents the $\gamma\hat{k}$ coefficient, alongside the p-values (presented in brackets), and the R^2 value, derived from the Fama-MacBeth two-step regression approach outlined in Chapter 5.3. Seven distinct factor models have been selected for analysis to the low ESG group for the sample period starting from January 2009 until June 2024. The initial model comprises the FF5 factors. Subsequent models are variations of the FF5 factors, augmented with one of the following factors: IVOL, IVOLt-1, or E(IVOL). Additionally, each of these factors – IVOL, $IVOL_{t-1}$, or E(IVOL) – is analysed as an independent model. Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of all variables used have been winsorized at the 1st and 99th percentile.

Model	Mkt-RF	SMB	HML	RMW	CMA	IVOL	$IVOL_{t-1}$	E(IVOL)	R^2 (%)
1	0.0028	-0.0042	-0.0031	0.0041	-0.0043				14.20
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
2	0.0025	-0.0045	-0.0031	0.0040	-0.0045	0.0011			14.55
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
3						-0.0012			0.89
						(0.0000)			
4	0.0030	-0.0041	-0.0034	0.0037	-0.0043		-0.0014		14.94
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)		
5							0.0007		0.64
							(0.0000)		
6	0.0011	-0.0027	-0.0041	0.0029	-0.0047			-0.0009	16.50
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)	
7								-0.0005	0.16
								(0.0000)	

Appendix F: Portfolio returns sorted by E(IVOL) for 10 portfolios (2009–2024)

This table presents average monthly excess returns for ten equal-weighted portfolios formed based on the variable E(IVOL) and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (10) presents the portfolio based on the lowest (highest) E(IVOL). Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile.

Group	**Variable**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Total observations	ExRET	0.58	0.59	0.78	0.77	0.66	0.81	0.45	0.6	0.28	0.53	-0.05
	E(IVOL)	1.52	3.21	4.07	4.77	5.48	6.33	7.42	9.04	11.99	24.31	22.78
	Alpha	-0.46	-0.4	-0.27	-0.29	-0.45	-0.33	-0.67	-0.61	-1	-0.77	-0.31
		(0.05)	(0.04)	(1.29)	(0.41)	(0.00)	(0.21)	(0.00)	(0.01)	(0.00)	(1.26)	(28.23)
High ESG	ExRET	0.74	0.57	0.74	0.59	0.55	0.61	0.37	0.39	0.46	0.54	-0.20
	E(IVOL)	2.62	3.78	4.38	4.9	5.45	6.07	6.84	7.94	9.79	16.57	13.95
	Alpha	-0.31	-0.43	-0.39	-0.49	-0.64	-0.52	-0.8	-0.72	-0.85	-0.83	-0.52
		(7.26)	(0.33)	(1.41)	(0.75)	(0.02)	(0.77)	(0.02)	(0.23)	(0.77)	(9.08)	(29.49)
Low ESG	ExRET	0.57	0.58	0.77	0.81	0.7	0.79	0.57	0.6	0.28	0.54	-0.03
	E(IVOL)	1.43	3.11	4.02	4.75	5.5	6.39	7.53	9.24	12.35	25.16	23.73
	Alpha	-0.47	-0.4	-0.28	-0.25	-0.41	-0.34	-0.54	-0.62	-1.01	-0.75	-0.28
		(0.06)	(0.06)	(1.17)	(2.62)	(0.03)	(0.30)	(0.00)	(0.01)	(0.00)	(1.23)	(31.63)

Appendix G: Portfolio returns sorted by lagged IVOL for 10 portfolios (2009–2024)

This table presents average monthly excess returns for ten equal-weighted portfolios formed based on the variable $IVOL_{t-1}$ and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (10) presents the portfolio based on the lowest (highest) $IVOL_{t-1}$.

Group	**Variable**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Total observations	ExRET	0.80	0.87	0.78	0.81	0.70	0.56	0.41	0.41	0.35	-0.03	-0.83
	IVOLt-1	2.56	3.37	3.96	4.55	5.2	5.97	6.93	8.24	10.34	17.54	14.98
	Alpha	-0.14	-0.13	-0.26	-0.27	-0.42	-0.56	-0.74	-0.77	-0.89	-1.3	-1.16
		(25.86)	(18.52)	(0.72)	(0.86)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.31)
High ESG	ExRET	0.86	0.78	0.74	0.72	0.75	0.59	0.44	0.24	0.24	0.55	-0.31
	IVOLt-1	2.33	3.02	3.5	3.96	4.47	5.03	5.7	6.57	7.95	12.14	9.82
	Alpha	-0.09	-0.28	-0.35	-0.38	-0.41	-0.55	-0.73	-0.99	-0.98	-0.98	-0.89
		(52.79)	(6.41)	(2.87)	(2.06)	(3.50)	(1.55)	(0.08)	(0.01)	(0.18)	(4.26)	(7.99)
Low ESG	ExRET	0.8	0.85	0.82	0.83	0.69	0.5	0.46	0.40	0.38	-0.02	-0.83
	IVOLt-1	2.61	3.43	4.03	4.63	5.3	6.09	7.08	8.41	10.57	17.92	15.31
	Alpha	-0.13	-0.14	-0.23	-0.26	-0.42	-0.6	-0.7	-0.79	-0.86	-1.26	-1.13
		(30.50)	(20.95)	(2.58)	(1.51)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.47)

Appendix H: Portfolio returns sorted by IVOL for 10 portfolios (2009–2024)

This table presents average monthly excess returns for ten equal-weighted portfolios formed based on the variable IVOL and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2009 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (10) presents the portfolio based on the lowest (highest) IVOL.

Group	**Variable**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Total observations	ExRET	1.09	1.01	0.94	0.89	0.71	0.66	0.44	0.27	-0.02	-0.32	-1.41
	IVOL	2.54	3.35	3.93	4.52	5.16	5.93	6.88	8.19	10.28	17.44	14.9
	Alpha	0.18	0.02	-0.09	-0.15	-0.38	-0.47	-0.74	-0.92	-1.26	-1.66	-1.84
		(4.79)	(78.51)	(32.94)	(10.61)	(0.03)	(0.01)	(0.00)	(0.00)	(0.00)	(0.04)	(0.03)
High ESG	ExRET	1.22	1.01	0.77	0.76	0.66	0.59	0.72	0.48	0.25	-0.54	-1.76
	IVOL	2.31	3	3.48	3.94	4.44	5	5.66	6.53	7.91	12.05	9.73
	Alpha	0.22	0	-0.3	-0.32	-0.43	-0.66	-0.56	-0.65	-1.09	-1.92	-2.14
		(8.02)	(99.32)	(2.58)	(2.96)	(1.85)	(0.04)	(0.83)	(0.59)	(0.08)	(0.03)	(0.01)
Low ESG	ExRET	1.07	1.04	0.95	0.92	0.71	0.62	0.45	0.28	0	-0.3	-1.37
	IVOL	2.59	3.4	4	4.6	5.27	6.05	7.03	8.36	10.5	17.82	15.23
	Alpha	0.16	0.06	-0.08	-0.11	-0.37	-0.53	-0.71	-0.93	-1.25	-1.62	-1.78
		(8.75)	(49.43)	(37.95)	(25.38)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.06)

Appendix I: Portfolio returns sorted by E(IVOL) (2003–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable E(IVOL) and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2003 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) E(IVOL). Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile.

Group	Variable	1	2	3	4	5	5-1
Full sample	ExRET	0.31	0.49	0.46	0.23	0.09	-0.22
	E(IVOL)	2.1	4.07	5.53	7.78	17.27	15.17
	Alpha	-0.47	-0.29	-0.35	-0.59	-0.79	-0.32
		(0.00)	(0.16)	(0.01)	(0.00)	(0.01)	(6.80)
High ESG	ExRET	0.42	0.41	0.44	0.19	0.44	0.02
	E(IVOL)	2.85	4.3	5.4	7.06	12.94	10.08
	Alpha	-0.39	-0.41	-0.36	-0.59	-0.45	-0.07
		(0.54)	(0.72)	(3.01)	(0.17)	(15.20)	(83.28)
Low ESG	ExRET	0.3	0.49	0.46	0.26	0.11	-0.19
	E(IVOL)	2.02	4.04	5.57	7.91	17.77	15.75
	Alpha	-0.47	-0.29	-0.34	-0.57	-0.77	-0.3
		(0.00)	(0.26)	(0.01)	(0.00)	(0.01)	(8.02)

Appendix J: Portfolio returns sorted by lagged IVOL (2003–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable $IVOL_{t-1}$ and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2003 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) $IVOL_{t-1}$.

Group	**Variable**	**1**	**2**	**3**	**4**	**5**	**5-1**
Full sample	ExRET	0.65	0.62	0.45	0.30	0.20	-0.45
	$IVOL_{t-1}$	2.93	4.17	5.41	7.24	12.88	9.95
	Alpha	-0.15	-0.25	-0.47	-0.66	-0.82	-0.68
		(9.81)	(0.21)	(0.00)	(0.00)	(0.01)	(0.31)
High ESG	ExRET	0.55	0.50	0.56	0.37	0.20	-0.39
	$IVOL_{t-1}$	2.93	3.81	4.74	6	9.29	6.51
	Alpha	-0.24	-0.28	-0.19	-0.44	-0.81	-0.68
		(8.56)	(10.34)	(32.06)	(3.39)	(1.08)	(3.75)
Low ESG	ExRET	0.64	0.64	0.41	0.31	0.2	-0.44
	$IVOL_{t-1}$	2.97	4.23	5.5	7.37	13.12	10.15
	Alpha	-0.15	-0.23	-0.52	-0.65	-0.81	-0.65
		(10.39)	(0.55)	(0.00)	(0.00)	(0.01)	(0.48)

Appendix K: Portfolio returns sorted by IVOL (2003–2024)

This table presents average monthly excess returns for five equal-weighted portfolios formed based on the variable IVOL and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for the sample period starting from January 2003 until June 2024 as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (5) presents the portfolio based on the lowest (highest) IVOL.

Group	Variable	1	2	3	4	5	5-1
Total observations	ExRET	0.81	0.72	0.57	0.38	-0.27	-1.08
	IVOL	2.93	4.17	5.4	7.22	12.84	9.91
	Alpha	0.06	-0.12	-0.35	-0.59	-1.36	-1.41
		(37.74)	(10.52)	(0.02)	(0.00)	(0.00)	(0.00)
High ESG	ExRET	0.74	0.64	0.56	0.42	-0.15	-0.94
	IVOL	2.83	3.81	4.74	6	9.27	6.49
	Alpha	-0.05	-0.11	-0.27	-0.41	-1.11	-1.18
		(73.22)	(46.82)	(11.20)	(5.00)	(0.10)	(0.10)
Low ESG	ExRET	0.82	0.73	0.56	0.38	-0.27	-1.08
	IVOL	2.97	4.22	5.49	7.36	13.09	10.12
	Alpha	0.06	-0.11	-0.36	-0.59	-1.35	-1.41
		(38.61)	(15.09)	(0.02)	(0.00)	(0.00)	(0.00)

Appendix L: Portfolio returns sorted by E(IVOL) during recessions for 10 portfolios

This table presents average monthly excess returns for ten equal-weighted portfolios formed based on the variable E(IVOL) and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for times of recession (October 2007 until June 2009; January 2020 until June 2020) as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding *p*-value (in brackets in %) is presented for each portfolio. Portfolio 1 (10) presents the portfolio based on the lowest (highest) E(IVOL). Utilising the methodology outlined in Chapter 3.3 the lowest and highest values of E(IVOL) have been winsorized at the 1st and 99th percentile.

Group	Variable	1	2	3	4	5	6	7	8	9	10	10-1
Total observations	ExRET	-3.01	-2.82	-2.42	-2.82	-2.64	-2.07	-2.99	-2.81	-4.07	-2.39	0.61
	E(IVOL)	0.58	2.08	3.04	3.82	4.62	5.51	6.64	8.39	11.99	26.7	26.12
	Alpha	-1.19	-1.71	-0.89	-1.38	-1.13	-0.37	-1.52	-1.35	-1.78	1.21	2.4
		(11.23)	(2.84)	(14.43)	(9.36)	(5.87)	(42.49)	(1.25)	(13.17)	(3.97)	(33.26)	(5.04)
High ESG	ExRET	-1.36	-3.92	-2.44	-0.91	-2.26	-3.08	-1.91	-3.06	-0.87	-3.17	-1.8
	E(IVOL)	1.33	2.56	3.28	3.9	4.5	5.18	5.86	6.9	9.17	19.82	18.49
	Alpha	1.22	-2.54	-1.44	-0.04	0.14	-1.08	-0.39	0.36	0.03	0.4	-0.81
		(41.90)	(1.46)	(11.38)	(97.66)	(86.80)	(24.18)	(78.07)	(70.02)	(98.44)	(81.17)	(69.34)
Low ESG	ExRET	-3.03	-2.83	-2.35	-3.16	-2.57	-2.36	-2.73	-3.27	-3.87	-2.43	0.6
	E(IVOL)	0.55	2.02	3	3.81	4.64	5.58	6.76	8.6	12.26	27.18	26.63
	Alpha	-1.31	-1.79	-0.72	-1.73	-1.03	-0.59	-1.63	-1.93	-1.47	1.18	2.5
		(7.44)	(2.27)	(24.94)	(4.13)	(9.14)	(19.06)	(2.87)	(3.12)	(8.28)	(35.79)	(3.81)

Appendix M: Portfolio returns sorted by lagged IVOL during recessions for 10 portfolios

This table presents average monthly excess returns for ten equal-weighted portfolios formed based on the variable $IVOL_{t-1}$ and the corresponding zero-cost portfolio. The results were calculated for all three groups – full sample, high ESG, and low ESG – for times of recession (October 2007 until June 2009; January 2020 until June 2020) as described in the chapter 5.4. In addition, Jensen's alpha with the corresponding p-value (in brackets in %) is presented for each portfolio. Portfolio 1 (10) presents the portfolio based on the lowest (highest) $IVOL_{t-1}$.

Group	Variable	1	2	3	4	5	6	7	8	9	10	10-1
Full sample	ExRET	-2.47	-2.55	-2.75	-2.45	-2.9	-3.48	-2.56	-3.43	-2.47	-2.55	-0.08
	$IVOL_{t-1}$	3.98	5.2	6.04	6.87	7.74	8.76	9.96	11.58	14.06	22.36	18.39
	Alpha	-1.51	-1.36	-1.3	-0.8	-0.99	-1.84	-1.43	-1.77	-0.67	0.88	2.39
		(4.81)	(2.67)	(3.01)	(19.52)	(18.05)	(2.19)	(9.05)	(3.20)	(47.23)	(53.57)	(17.67)
High ESG	ExRET	-3.59	-2.01	-4.07	-3.28	-1.92	-0.98	-1.49	-1.08	-2.8	-1.48	2.11
	$IVOL_{t-1}$	3.77	4.74	5.36	5.89	6.54	7.2	7.88	8.93	10.51	15.41	11.64
	Alpha	-1.45	-0.59	-2.52	-1.6	-1.01	1.04	1.69	1.35	-0.52	1.55	3.01
		(10.03)	(49.27)	(1.43)	(22.62)	(37.14)	(44.72)	(15.42)	(35.42)	(71.87)	(46.67)	(18.96)
Low ESG	ExRET	-2.38	-2.56	-2.7	-2.55	-3.23	-3.35	-2.9	-3.13	-2.91	-2.35	0.03
	$IVOL_{t-1}$	4.03	5.28	6.14	6.99	7.91	8.95	10.18	11.81	14.33	22.73	18.7
	Alpha	-1.52	-1.5	-1.23	-0.84	-1.5	-1.8	-1.82	-1.36	-1.17	1.12	2.65
		(6.98)	(2.94)	(3.04)	(19.71)	(6.78)	(3.25)	(3.52)	(8.38)	(25.07)	(42.89)	(15.25)

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