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Understanding the mediating role of volatility between ESG momentum and stock returns: a sector-level analysis

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ABSTRACT

How does ESG momentum influence stock return predictability across sectors, given their distinct ESG profiles, considering the mediating role of stock volatility? I study the U.S. market between 2006 and 2020 using mediation theory, classifying the market into three super-sectors based on their business cycle sensitivity: Cyclical, Sensitive and Defensive. I observe mediation 8 out of 12 times across the 3 sectors and 4 data types - E, S, G and ESG. Of these, 6 out of 8 cases represent full mediation, occurring in the Cyclical and Sensitive sectors. The remaining two cases of partial mediation occur in the Defensive sector. The results are particularly true for Environmental momentum, which is significant in all sectors and at the market level. This suggests that stock volatility mediates the relationship between ESG momentum and stock returns more effectively in more sensitive sectors but with varying effects across the four data types.

Keywords: ESG momentum, Mediation-analysis, stock returns, volatility, sector analysis

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CHAPTER 1 Introduction

In January 2004, the Chief Administrative Officer of the United Nations, Kofi Annan reached out to the CEOs of 55 leading global financial institutions. The goal was to develop guiding principles on how to implement Environmental, Social, and Governance (ESG) considerations into the financial industry and associated research. This led to the "Who Cares Wins" initiative, which aimed to make the case that embedding ESG factors into investing in capital markets creates better outcomes for societies. Since then, academics have started developing theories to reconcile the interaction between ESG scores, investor demand and stock returns (Pedersen et al., 2021). These guidelines, published in December 2004, emphasized the importance of the transparent and consistent reporting of ESG data. It was a major step towards encouraging the financial industry to consider factors beyond the traditional financial metrics, recognizing that ESG factors could significantly influence investment returns in the long run. This initiative laid the foundation for the Principles for Responsible Investment, which was set in motion in April 2006. This further synthesized the initial principles into a unified framework for both institutional- and retail investors, with an emphasis on responsible investing as a way to both manage risks and increase returns. These events marked a turning point in the financial market which fundamentally changed its structure. However, the world of ESG is not without its controversies. Recently, Larry Fink, the CEO of the biggest asset management firm BlackRock, stated that he now tries to refrain from using the term ESG due to its increasingly politicized nature (Müller, 2023).

The impact of firm-level ESG ratings on stock return predictability using a mediation theory has been investigated in the literature so far. Darolles et al. (2023) employ a causal mediation strategy between ESG scores on stock return predictability, using institutional ownership as the mediator variable, and show that the relationship between the two variables of interest is negative and that investor demand explains a high degree of variation in this relationship. Another study by Pástor et al. (2021a) shows that ceteris paribus, green assets with a higher ESG rating have lower expected returns than brown assets, partially because those investors who invest in such assets derive non-monetary benefits from them, and additionally, these can provide a hedge against climate risk. On the contrary, Giese et al. (2019) show that those firms with high ESG momentum, defined as the annual change in ESG score, perform better in terms of costs of capital, valuations and overall risk profile compared to those with low ESG momentum. They claim, that given these insights, ESG momentum can also be a useful indicator of performance. These studies are important, because they broaden the horizons of both researchers and practitioners regarding the influence of sustainable investing on financial markets, and can provide insights into how ESG ratings or ESG preferences influence asset pricing or stock demand. Lastly, Pedersen et al. (2021) developed a theoretical framework that explains how investors factor in their ESG considerations in their portfolio choice. They also introduced the concept of the ESG-efficient frontier, a tool for maximizing the Sharpe ratio at various levels of ESG preference, and showed how these ESG considerations can inform both the selection of optimal portfolios and the equilibrium asset prices, bridging the gap between traditional financial objectives and responsible investing.

Despite the exponentially increasing literature on ESG ratings and ESG momentum and the robustness of the results, currently, there are no studies investigating the relationship between ESG momentum and stock return predictability using stock volatility as the mediator on an industry level. However, previous studies have shown that there is a well-established difference in stock return predictability between different sectors, as shown by Park and Newaz (2023). For example, the authors show that on average, sectors with higher volatilities have more predictable returns. While ESG risks are relevant to all industries, some industries such as agriculture, mining, oil and gas are more exposed to ESG risks than others due to the nature of their business. Observe that these industries not only face elevated ESG risks but also display higher volatility and cyclical behaviour due to their direct interaction with natural resources. Based on these insights, it is plausible that sector-specific volatility may mediate the relationship between ESG momentum and stock return predictability. Motivated by this, the main research question that my thesis will investigate is the following: *„How does ESG momentum influence stock return predictability across sectors, given their distinct ESG profiles, with a particular focus on the mediating role of stock return volatility?"*

I will study the relationship between ESG momentum and stock returns, using stock return volatility as a mediator on a super-sector level. I will obtain the yearly ESG score using the Refinitiv Asset4 database between 2006 through year-end 2020 and quarterly stock return data from Compustat following Darolles et al. (2023). To increase the granularity of my analysis, I will also retrieve the scores for each pillar. Following Giese et al. (2019), I define ESG momentum as the 12-month change in ESG score. For the stock volatility, I will use Compustat using the same time horizon. For the industry classifications, I will use the industry SIC codes. The intuition behind mediation analysis is that it quantifies a process that allows the influence of an independent variable (Z) on a dependent variable (Y) through a mediator variable (M). This happens by decomposing the total effect of Z on Y into a direct and indirect effect. The direct effect refers to the part of the relationship between Z and Y that is not mediated by M, while the indirect effect captures the portion of the relationship that operates through M (Baron and Kenny, 1986). The main dependent variable in my model will be excess stock return and the mediator variable will be 4-quarter stock return volatility. The main independent variable will be ESG momentum, and for the super-sector level analysis, I will use the Cyclical, Sensitive and Defensive Morningstar super-sectors, as defined by Park and Newaz (2023).

In my research, I expect that none of the coefficients of interest will be significant. Specifically, I anticipate that the effect of ESG momentum on stock returns, the effect of ESG momentum on stock volatility, and the mediating effect of stock volatility between ESG momentum and stock returns will not be significant. Additionally, I expect the same insignificance for the individual ESG pillars. This approach aims to prevent my research from falling into confirmation bias, which occurs when a researcher tends to favour information that supports their prior beliefs (Nickerson, 1998). This research is different from the perspective of Park and Newaz (2023) who do not consider ESG variables in their research and also from the work of Darolles et al. (2023), who use a different predictor and also conduct their analysis on a market. This advances the current scientific understanding of the relationship between ESG and future stock return behaviour by investigating their relationship using two flow variables, rather than one stock and one flow. This also opens the debate of whether ESG momentum is a more suitable predictor variable of stock returns compared to ESG score. To summarize, these findings are important both for academics who would like to investigate this in their research, and also for practitioners who would use this to make more informed investing decisions.

In my study, I investigate three hypotheses. The first one is related to the association between ESG momentum and excess returns and the second is related to the relationship between ESG momentum and return volatility. The third one outlines the mediation relationship between ESG momentum and stock returns using volatility as the mediator. For the first hypothesis, I find that the association between Environmental- and aggregate ESG momentum and returns is statistically significant and positive in the Defensive sector. Additionally, there is a significant and negative association between the Governance momentum and returns in the Sensitive sector. For the second hypothesis, the Environmental momentum had a statistically significant, positive relationship with volatility in all three sectors. In the Sensitive sector, aggregate ESG momentum and Social momentum also show the same relationship. In the Cyclical sector, the association between Governance momentum and volatility is negative. For the last hypothesis regarding the mediation relationship, I measure mediation 8 out of 12 times for the 4 data types across the 3 sectors.

I structure the remainder of the paper the following way. Firstly, I will outline the theoretical framework behind ESG, stock volatility and stock returns and show how they are related in Chapter 2. Then, I will continue by providing some information about the data in Chapter 3, and in Chapter 4 I will describe the methodology and formulate the hypotheses. In Chapter 5 I analyze the results and discuss them as well. Lastly, I conclude in Chapter 6 by summarizing the most important findings and making recommendations for future researchers. The Appendix provides all the tables discussed.

CHAPTER 2 Theoretical Framework

2.1 Conceptual foundations of ESG, stock return predictability and volatility

2.1.1 ESG ratings and ESG momentum

Before I investigate the literature on ESG momentum within the context of asset pricing, I find it important to mention some key characteristics of ESG scores, given that they are directly derived from them. Furthermore, to provide a more comprehensive picture, I also depict the status quo regarding ESG providers and the ESG preferences of market participants

Nowadays, an increasing number of investors also consider non-financial metrics in their portfolio choice, driven by what Starks (2023) describes as "increasingly broad interest in ESG investing". However, this rate of interest is different from investor to investor both theoretically and empirically (Pedersen et al., 2021). More specifically, this difference of interest can depend on whether we consider retail, or institutional investors (Darolles et al., 2023) and their underlying motivations, also known as whether they care more about "value or values", coined by Starks (2023). Here, value motivators are synonymous with the focus on financial returns, climate change risk benefits and other economic benefits derived from ESG investing. Values motivators relate to investing which is guided by personal or ethical beliefs, where the decisions are influenced by non-economic factors such as environmental impact and social justice. Most importantly, these ESG investment decisions and ESG scores can also be influenced by different geographic regions and industry characteristics. For example, Cai et al. (2016) find that variation between countries in company ESG or CSR scores is more attributable to differences in countries due to country-specific factors such as per capita income, the legal system, cultural harmony, and cultural autonomy, rather than characteristics specific to individual firms.

Furthermore, investors interested in ESG investing often face significant challenges due to the uncertain nature of a firm's true ESG profile. This uncertainty stems from unreliable measures of actual ESG performance, and most importantly due to the lack of standardized methodologies between the ESG rating agencies (Avramov et al., 2021). Recent studies such as the article by Avramov et al. (2021) provide evidence of the implications of this uncertainty about corporate ESG profiles on asset pricing and portfolio choices. They explored how ESG uncertainty impacts market premiums, investor demand for stocks, the CAPM alpha and stock return predictability among others. In this study, they show that the effect of ESG uncertainty on stock return predictability is negative. Furthermore, their article also suggests that higher ESG ratings are generally associated with better stock performance. On the same note, there are six leading ESG rating agencies, which are consistently used in the literature (Avramov et al., 2021), (Darolles et al., 2023). These are Bloomberg, MSCI KLD, MSCI IVA, Asset4 (Refinitiv), RobecoSAM and Sustainalytics which all differ in their ESG evaluation in some way.

Berg et al. (2022c) dissect the components of divergence between these agencies into three categories. They identify a divergence based on scope, which means that different agencies include different ESG factors in their ratings, which contributes to 38% of the total divergence. Moreover, a 56% divergence is based on measurement, which arises from varying methodologies and indicators used to measure the same ESG factors. For example, some agencies may put more emphasis on using a "best-in-class" approach, comparing companies within the same industry, while others may use an "absolute" approach, evaluating companies without industry-specific benchmarks. Lastly, a 6% divergence due to different weightings assigned to each ESG factor by different agencies. Another significant finding of Berg et al. (2022c) is the "rater effect", where a rater's general perception of a company influences the measurement of specific pillars. For example, if a firm performs well in the environmental component, then this introduces an upward bias for the perceived performance of other categories. In sociology and psychology, this is also known as the "halo effect" (Shrout and Fleiss, 1979). The presence of this effect indicates that ratings are not solely determined by objective criteria but are also influenced by the rater's subjective viewpoint. As a consequence, of this, there can be considerable variations in the ESG scores of a single company between different rating agencies. These discrepancies highlight the subjective nature of ESG assessments, which, as noted by Edmans (2023), differ fundamentally from more objective measures such as credit ratings, which are more easily quantifiable. He argues, "An ESG rating isn't fact; it's opinion."

I would also like to briefly touch upon the regional differences regarding the importance of ESG metrics in the stock selection process, specifically focusing on Europe and the U.S. For example, in the U.S., investors are more likely to perceive the ESG scores of a firm as insurance and see it as a protection against downside risk, according to Bannier et al., (2019), who also find significantly negative abnormal returns for portfolios going long on high ESG stocks and short on low ESG stocks. They find that the downside risk protection characteristic of high ESG firms is mainly driven by the Environmental factor in the U.S. and by the Social factor in the EU. In contrast, in the findings of Drei et al. (2019), ESG is a source of alpha in North America, however in the Eurozone ESG factors are priced as risk factors.

Lastly, Nagy et al. (2015) explore how potentially ESG momentum and ESG tilt strategies could be a source of abnormal returns. In their study, they define ESG momentum as the annual change in a firm's ESG score, and the ESG momentum strategy as a portfolio which overweights such firms. On the other hand, the ESG tilt strategy, which is more long-term focused, simply overweights stocks with high ESG scores. In their analysis, they conclude that both ESG momentum and ESG tilt outperform the MSCI World Index by 2.2% and 1.1% respectively. Most importantly, these abnormal returns were also not fully explained by traditional risk factors, implying that the strategy added value beyond what could be attributed to conventional factor exposures.

2.1.2 Stock return predictability and the importance of sector-level analysis

One of the most important questions in financial economics is the degree to which stock prices – and by extension stock returns - are predictable, based on historical information. One of the leading schools of thought regarding this has been developed by Fama (1970), who formulated the efficient market hypothesis

(EMH), stating that financial markets are efficient in the sense that they reflect all available information. This is strongly associated with the notion that stock prices follow a random walk, meaning that current price movements do not depend on past price movements. An implication of this is that it is impossible to consistently "beat the market", and any market outperformance is a consequence of chance rather than investor skill. Since then, the EMH has been challenged and revisited many times in the literature, both by academics in asset pricing and behavioural finance. To mention a few concrete examples, Rozeff (1984) shows that future stock returns and dividend yields are significantly and positively related using a constant dividend growth model. Furthermore, Ang et al. (2001) show that short-term interest rate is a robust short-term predictor of excess returns. This is a consistent finding across geographies, indicating a generalizable effect, which is not consistent with the EMH. Others, such as Lim and Brooks (2011) assert that market efficiency is more dynamic, evolving over time and changing under different conditions such as market structure, investor behaviour and global economic events. They build on the Adaptive Market Hypothesis (AMH) developed by Lo (2004) who attempts to reconcile the EMH with behavioural economics, suggesting that financial markets constantly change and are influenced by the interactions of market participants, each acting in their self interest based on the limited information and bounded rationality available to them.

There are several variables identified in the research as predictors of stock returns beyond these metrics. One of them is economic policy uncertainty (EPU), which was shown to predict excess stock returns (Phan et al., 2018). The authors however note that this depends on both the country and the sector that is being investigated. In other words, EPU is more important for the predictability of some sectors, such as the consumer services, financials, industrials, telecommunications, and oil & gas industries than for others. This finding that some sectors, such as consumer staples, consumer discretionary, telecommunications, financials, industrials (and also technology) sectors are more predictable than other sectors is also highlighted in the work of Phan et al. (2015), who used crude oil prices and other important economic predictors to predict stock returns. In contrast, they identified that sectors such as energy, healthcare, materials, and utilities show less predictability, indicating that crude oil prices are not as effective in forecasting returns in these sectors. On the same note, market return predictability can be even weaker than sector-level predictability, as shown by the work of Bannigidadmath and Narayan (2016), which underscores the importance of industry-level analysis over market-level analysis. The researchers show that both economically and statistically significant profits can be made on the market using the dividend-payout ratio and dividend yield among other financial ratios.

2.1.3 Stock return volatility

Stock return volatility refers to the fluctuations in stock prices for a specific asset. It is also a frequently used financial metric which is used to measure predictability of stock returns (Devpura et al., 2018). Most importantly, in the paper of Park and Newaz (2023), the authors find that both on a sector level and also on a market level, volatility serves as a good predictor of stock returns using a fixed effects model. Furthermore, using a model with a Dynamic Common Correlated Effects estimator, stock volatility proves to be a statistically significant variable for predicting stock returns for both developed and emerging markets and also for cyclical, sensitive and defensive super-sectors. Their study evaluates the economic benefits of sector selection based on several indicators, such as dividend yield, trading volume and firm size among others. They find that investors can generate higher returns by focusing on more predictable sectors, which they also test by creating momentum and buy and hold portfolios.

Furthermore, one of the most commonly investigated anomalies in stock markets is their excess volatility. To explain this excess volatility, Timmermann (1993) argues that this is due to learning effects among traders. During periods of high stock volatility, investors may struggle to incorporate excessive information into their models, which leads to less accurate predictions. This happens because when investors are uncertain about the true parameters of the dividend process, their continuous adjustments to these estimates can cause greater fluctuations in stock prices than what would occur under a rational expectations model. This effect is more pronounced for smaller sample sizes, but gradually decreases as the sample size becomes larger because investors can accumulate more data over time and update their models as a result.

Another paper of interest which discusses stock volatility is one by Baek et al. (2020), who analysed the U.S. stock market during the COVID-19 crisis period. In their paper, they find that specific economic indicators such as the VIX, Federal Target Range (FTR) and the Economic Policy Uncertainty Index (EPUI) significantly influence stock market volatility in the crisis period. They also find that both positive and negative COVID-19 news impact market volatility, however, negative news has a more pronounced effect, indicating a negativity bias. They also highlight industry heterogeneity in the increases of systemic risk, which was larger for the petroleum, natural gas and lodging industries.

Additionally, one of the important characteristics of equity volatility, is that it can propagate across countries and across industries. In their seminal paper, Diebold et al. (2009) present a simple, but robust framework for measuring the interdependence of asset returns and volatilities through the development of return and volatility spillover indexes. In their global analysis they highlight the different dynamics of volatility and return spillovers across countries, noting that while return spillovers often exhibit a gradual upward trend indicative of increasing financial integration, volatility spillovers are marked by pronounced bursts linked to specific economic crises. In their method, they use vector autoregressions and variance decompositions to quantify the extent of spillovers across equity markets. The key economic indicators identified as influential in explaining volatility changes include global market shocks, regional economic disturbances, and policy shifts, all of which underscore the complex and dynamic nature of financial market interdependencies. Overall, they provide a framework for understanding how shocks in one country can affect others, both in times of stability and turbulence.

Building on their paper, Sita (2013) analyzes the complex relationships between 30 U.S. industries with a focus on volatility spillovers. Utilizing the volatility spillover index proposed by Diebold et al. (2009), the study quantifies both leading and lagging impacts across these industries. The analysis reveals a persistent, time-varying pattern of volatility interdependence, with significant increases since 1999. The manufacturing, business equipment and financial industries emerge as leading industries, exerting substantial influence on others. Interestingly, while these leading industries impact many sectors, they are also influenced by a multitude of others, creating a complex feedback loop. The paper highlights how this strong web between the industries can increase idiosyncratic volatility, suggesting a need for adaptive regulatory policies to mitigate systemic risk in the U.S. market.

2.2 Relationships between ESG, stock returns and volatility

2.2.1 Relationship between ESG variables and stock returns

One of the most important economic frameworks, which provides both a theoretical explanation and empirical evidence between ESG score and stock return predictability has been developed by Pedersen et al. (2021). They argue that the relationship between these two variables can be described by two transmission channels. The first, direct channel is known as the "fundamentals or profitability channel". The intuition behind this channel is simply that high ESG scores can reflect underlying firm characteristics that could affect the firm's future profitability and risk. For instance, better governance could imply more effective management, resulting in more effective employee performance and better firm performance as a consequence. However, this relationship can be positive, not significantly different from zero or negative, depending on the magnitude of the costs incurred to improve the ESG score and the potential future payoffs. Also, there can be no significant effect, if the ESG policy is not a significant determinant of potential future cashflows.

The second channel is indirect and can be negative or not significantly different from zero which is known as the "investor demand channel", outlining the ESG preferences and investor behaviour of market participants. Pedersen et al. (2021) argue that there are essentially three types of investors. Firstly, there are "ESG-unaware investors", who are not influenced by the firm's ESG rating, secondly, "ESG-aware investors" who are more sensitive to ESG-related firm information and lastly, "ESG-motivated investors" who derive non-monetary gains from holding green assets. The consequence of this is that when the market participants are chiefly ESG-unaware investors, then high ESG scores will simply translate into high stock returns on a firm level. This is because, high ESG scores could signal strong firm fundamentals, as argued previously, however, this is not reflected in the market prices due to the ESG awareness distribution of market participants (Pedersen et al., 2021). As soon as more ESG-aware investors enter the market, the demand for stocks with high ESG scores increases, which increases the price of these assets. However, this increase in prices may not be aligned with firm fundamentals, rather reflecting more optimism than warranted. Over time, the market will correct this, driving prices downwards and normalizing returns. This mechanism is taken a step further when ESG-motivated investors also enter the market, which will result in a decrease in returns through the same process, given that the negative indirect impact of the "investor demand channel" will become stronger than the initial direct positive effect of the "fundamentals channel" (Pedersen et al., 2021). In the final analysis, Pedersen et al. (2021) found that ESG scores negatively affect stock returns, indicating that higher ESG scores do not necessarily translate into higher future returns for stocks.

In contrast, Giese et al. (2019), show that companies experiencing positive ESG momentum, indicated by improvements in their ESG scores, tend to have higher valuations and higher profitability, indicating better fundamentals, compared to those with negative or no changes in their scores. In their paper, they examine three different transmission channels. These are the cash-flow channel, the idiosyncratic risk channel and the valuation channel. The intuitive explanation behind the cash-flow channel is that ESG leader firms are more competitive than their peers (Gregory et al., 2014). This allows them to manage their innovations better and use their resources more efficiently, which turns into higher cashflows in the long run.

As for the idiosyncratic risk channel, these firms also typically have better risk management frameworks, thanks to the fact that they adhere to stricter regulatory standards than laggards, which consequently means a lower risk of severe incidents and lower tail risk for leaders, which are empirically shown by Giese et al. (2019). Lastly, for the valuation channel, as argued by Giese et al. (2019), companies with a strong ESG profile have higher returns, because they have a broader investor base. This is because, ESG-aware investors do not invest in firms with a lower ESG profile, which have a smaller pool of investors, lower demand, and lower prices as a result. This finding highlights the relationship between ESG momentum, ESG score and stock returns, suggesting that changes in ESG ratings can also be a useful financial indicator.

Moreover, a global study by Alves et al. (2024) on ESG and stock returns, using a broad dataset covering over 16,000 stocks across 48 countries reveals little to no evidence that ESG ratings correlate with global stock returns. This finding is consistent across different geographical regions, time periods, and for different ESG strategies as well. The researchers also examine potential influences such as ESG rating uncertainty and various country-specific factors like ESG disclosure standards and regulations, yet these do not significantly alter the ESG-stock return relationship. Their comprehensive study challenges the notion that higher ESG ratings necessarily translate into better financial performance, suggesting that ESG investment strategies have not historically penalized investors financially, nor have they offered substantial advantages.

In the final analysis, under the Pedersenian framework, we can see these two effects of fundamentals and investor demand as two "competing forces" (Darolles et al., 2023) between ESG variables and stock return predictability, which can also provide some evidence behind the contradictory findings in the literature between ESG variables and asset returns.

2.2.2 Relationship between ESG variables and stock volatility

ESG score and volatility are also related. For example, in the paper of Ng and Rezaee (2020), the authors find that ESG performance factors increase idiosyncratic volatility, and make firm market value a stronger predictor of earnings. Furthermore, this relationship is even stronger for those firms which publish their sustainability ratings more often. Additionally, the relationship between ESG indicators and idiosyncratic volatility also becomes more dominant for underperforming firms. This could indicate that the non-financial ESG score of a firm becomes more important for investors as it starts to perform financially poorly. On the contrary, Wang et al. (2023b) find a negative relationship between ESG performance and stock price fragility (SPF), which is the "anticipated volatility of non-fundamental demand" as defined by Greenwood and Thesmar (2011). It is important to note that SPF is highly positively correlated with volatility (Wang et al., 2023b). In their research Wang et al. (2023b) also claim that a lower ESG metric increases the investors' sensitivity to stock performance, indirectly supporting the findings of Ng and Rezaee (2020). This is because investors will start to overweigh the higher metric (between financial- and non-financial metrics) in their firm evaluation if the other metric starts to decrease. This negative relationship is further supported by Burger et al. (2022), who examine how ESG performance is related to both implied and historical volatility. This also holds across various time frames, with ESG leaders exhibiting lower volatility compared to laggards, even during the heightened market uncertainty caused by COVID-19. Additionally, the study shows that during the pandemic, the volatility increase was less pronounced for companies with high ESG ratings, emphasizing how important strong ESG metrics could be during turbulent markets. To conclude, the literature again presents a mixed relationship between two variables, in this case between the ESG variables and stock return volatility.

2.2.3 Relationship between stock volatility and stock returns

I find it important to emphasize that in the financial literature, there are a number of ways to measure or define volatility. In this paper, I use the definition of the standard deviation of returns, rather than beta, which is the covariance between an asset and the market over the market variance. Using the same definition of volatility, in their paper, French et al. (1987) find evidence that the the predictable component of stock volatility has a positive relationship with the expected market risk premium, which is the difference between the return of a stock portfolio and the treasury bill yield. The interpretation of this is that, when market participants expect high market volatility, they also expect higher excess returns in compensation for bearing additional risk. Furthermore, Zhang et al. (2023) find strong in-sample and out-of-sample predictability of stock returns using a tailored industry volatility spillover index. The forecasting power of this industry volatility index persists even when accounting for well-known economic variables, and can yield significant expected excess returns up to 4.14%, and even a mean-variance investor can achieve significant economic gains. However, as noted by Van Vliet et al. (2011), the empirical evidence is not as clear, given that many studies report a negative or flat, not only a positive relationship between risk and return. They argue that historically the positive relation could be due to look-forward bias, which happens when a researcher violates the temporal dimension of their model and uses information that would not have been available at the actual time of the analysis. For example, if a model uses data from January to predict stock returns in February, but also includes some information from February as well. They also build on the findings of Blitz and Van Vliet (2007) who find that stocks with lower volatility tend to yield higher risk-adjusted returns compared to their higher volatility peers, challenging the findings in the traditional asset pricing literature.

CHAPTER 3 Data

3.1 Databases and description of data

In my research, I collected quantitative data from four databases: Refinitiv Asset4 database for the ESG scores and ESG pillars, the Compustat North America database for the fundamentals data except the number of shares owned by institutional investors, which I obtained from the Thomson Reuters Institutional (13f) Holdings database. Lastly, I collected the risk-free rate from the Federal Reserve Economic data website. For a detailed description of my sample and the variable definitions, please refer to Table B.1 in the appendix.

My main motivation for using the Refinitiv Asset4 database is that it offers detailed information on over 10,000 companies which cover over 90% of the global market capitalisation, representing over 75 countries (London Stock Exchange Group, 2023). The database compiles data from publicly available sources, including company reports, regulatory filings, and news articles, and provides standardized ESG metrics that facilitate comparative analysis across companies and sectors, which is crucial in my analysis, given my mediator variable. The ESG scores are derived from over 450 individual data points across ten main categories, which are grouped into the 3 pillars of E, S and G. Each pillar score is calculated based on a weighted average of the underlying category scores, which are then combined to produce an overall ESG score for each company which is a percentage value between 0 and 100. As for the industry comparison, Refinitiv uses a "best in class" methodology, meaning that firms are evaluated in comparison to their peer group in their industry. The Refinitiv ESG database also categorizes companies based on their ESG performance and transparency into four quartiles. Scores ranging from 0 to 25 (First Quartile) mean poor ESG performance and low transparency in reporting. Scores between 26 and 50 (Second Quartile) indicate satisfactory performance with moderate transparency. Companies scoring from 51 to 75 (Third Quartile) are seen as having good performance and above-average transparency. Lastly, scores from 76 to 100 (Fourth Quartile) represent perfect ESG performance and high reporting transparency. Although the ESG scores of the Refinitiv database are not absolute, due to the unstandardized nature of ESG measurement, Berg et al. (2022b), who examined the six major ESG rating agencies still consider them to be the most suitable for research purposes compared to alternative providers. Because of these reasons, it has been popular among researchers.

Both researchers and practitioners in the financial industry have used the Compustat database extensively in the last 50 years. It provides accounting and market information on both active and inactive firms, starting as early as the 1950s. As a global database, it covers a wide range of geographic regions encompassing over 100 countries, but in my analysis, I will exclusively focus on U.S. firms which are listed on three major U.S. stock exchanges: NYSE, NASDAQ and AMEX. This is to increase the internal validity of my data and make it more comparable to Darolles et al. (2023), who also used the same restriction in their study. For the analysis, I will use data from 2006 to 2020. As for the data frequency, I will use yearly data for ESG scores and their related variables and quarterly for all other variables.

For the industrial classification, I will use the Global Industry Classification Standard (GICS) and the supersector classification of Morningstar following Park and Newaz (2023), which both classify the market into 11 sectors. Moreover, Morningstar (2010) groups the market into three super sectors based on their sensitivity to the business cycle: cyclical, sensitive and defensive. The industries are grouped into super sectors as follows:

1. Cyclical Super Sector: This consists of the materials, consumer discretionary, financial services, and real estate industries.
2. Sensitive Super Sector: This includes the communication services, energy, industrials, and technology industries.
3. Defensive Super Sector: This comprises the consumer staples, healthcare, and utilities industries.

I deleted those observations which have missing data points, which is known as listwise deletion. According to Kang (2013), this approach can be followed if the sample size is large enough where power is not a problem, and there is no systematic missingness in the data. After failing to identify any systematic missingness, and deleting the missing observations, my sample consists of 138118 observations across 1686 unique firms. The number of observations in the cyclical, sensitive and defensive supersectors are 55651, 50432 and 32035 respectively. A more detailed overview can be seen under Table B.2 in the appendix.
The institutional ownership of a firm is calculated by dividing the number of shares owned by institutional investors by the total number of common shares outstanding. Similarly to Darolles et al. (2023), I remove those observations in the institutional ownership variable which are above 200%, but not those between 100% and 200%. There are two reasons for this. Firstly, there could be a delay in updating the data in the 13F database. This could be because although the 13F database asks institutions to report their holdings every quarter, some firms may lag behind, leading to errors in the calculation. Secondly, in the case of short selling, a lender might lend shares to a borrower who then sells them to a buyer. Now, if both the buyer and the lender claim that they own the shares in question, this will lead to double counting. Given these arguments, it is therefore theoretically possible that the institutional ownership of a firm is greater than 100%. However, as argued by Darolles et al. (2023), once a 200% upper bound is reached, the observation can be seen as too imprecise for the analysis, which is therefore discarded. This makes the mean of the institutional ownership variable in my sample relatively high, around 77%. I use logarithmic returns over simple returns, which is recommended for modelling stock prices rather than wealth (Hudson and Gregoriou, 2014). This is because simple returns exhibit more excess skewness and kurtosis than logarithmic returns. Additionally, to ensure that the control variables do not suffer from multicollinearity, I also log-transformed the Common/Ordinary Equity control variable. I did this, after observing a high correlation with both the Total Assets control variable (0.82) and the Common Shares Outstanding control variable (0.75). Brooks (2008) mentions that control variable transformations could be a feasible alternative to simply dropping control variables in the presence of multicollinearity, which could potentially lead to omitted variable bias.

3.2 Alternative definition of ESG momentum and interesting findings

In their research, Giese et al. (2019) calculated ESG momentum as the annual percentage change in the ESG metric. Empirically two potential issues could arise with this definition, which I illustrate below. The primary concern with constructing ESG momentum as the year-on-year percentage change is that while it takes the proportions of the ESG scores into account, their magnitude is not captured properly in the computation. For example, an ESG score increase from 1% to 2% and an ESG score increase from 40% to 80% are both an increase by 100% in percentage terms. However, the second case is much greater in magnitude, which is not taken into account. A secondary concern could be that positive ESG momentum can theoretically be unlimited, whereas a negative ESG momentum is bounded between 0 and -100%. Consider the following numerical example. If in the first year, the ESG score of a firm is 0.01, and in the second year it increases to 100, then this yields an increase of:

$$\frac{100\% - 1\%}{1\%} = 99 = 9900\%$$

Note that 0% will never be in the denominator in empirical research, because ESG values of 0 are removed in the data cleaning process. The intuitive explanation behind this is that all firms must comply with minimal legal and regulatory requirements to operate a functioning firm, which increases their ESG score. As for the negative ESG momentum, the most extreme theoretical scenario is when the ESG score of a firm declines from 100 to 0:

$$\frac{0 - 100\%}{100\%} = -1 = -100\%$$

Because of these, I will use an alternative measure which is the absolute change in the ESG score over a year, that is, it is a percentage point, which is the difference between two percentages. This keeps the intuition behind ESG momentum intact, at the same time, this will not be limited by the previously mentioned constraints. Lastly, I also define and analyze the momentum for each pillar which will become "Environmental Momentum", "Social Momentum" and "Governance Momentum". For brevity, I will collectively refer to "ESG momentum", "Environmental Momentum", "Social Momentum" and "Governance Momentum" as ESG momentum.

During the data merging process, there were some interesting findings. These include that for example, most of the data which were not matched during the merging process of ESG variables and institutional ownership came from the earlier years of the analysis (2006) and the proportion of missingness decreased as the years went on. Furthermore, in my analysis, the firm with the largest market capitalization in my sample is Apple Inc., with a market capitalization of $2.23 trillion, which makes the distribution of the market capitalization variable highly right-skewed, with other tech giants also contributing to this skewness.

[Include here - Table A.1: Descriptive statistics]

Table A.1 above provides descriptive statistics about the sample data. Most importantly, the average Environmental momentum is the highest among the three pillars, indicating that firms increase their Environmental score the most on average. This could be because of increasing regulations related to environmental protection or because green assets also provide a hedge against climate risk (Pástor et al., 2021a). Note that the median is lower than the mean, suggesting that the distribution is right-skewed, indicating that the majority of the firms in the sample are still catching up to the ESG leaders.

CHAPTER 4 Method

4.1 Mediation theory

To analyze the data that I have collected and to answer the three hypotheses to come, I will use mediation analysis. This framework is typically used in psychology and related areas, however, lately, researchers have also adopted to use it in economics (Bardos et al., 2020). The overarching intuition behind mediation theory is that it assumes that a direct, global effect between a predictor (denoted by Z) and an outcome variable (denoted by Y) can be split into a direct effect between the predictor and the outcome and an indirect effect which runs through a mediator variable (denoted by M). This relationship is also illustrated in Figure C.1 in the appendix. Sometimes multiple mediator variables can be used, however, I will only consider one. In the literature, multiple statistical methods have been established to model mediation. Mackinnon et al. (2002) identified that they fit into 3 broad categories. Firstly, mediation strategies which involve causal steps, secondly strategies which utilize differences in coefficients and lastly strategies which identify mediation by the product of coefficients. In my analyses, I will use a product of coefficients method, following Darolles et al. (2023).

If Z is the predictor variable, M is the mediator variable, Y is the outcome variable and X = X1, ..., Xn are the control variables, then this will yield a system of equations of the following form (Baron and Kenny, 1986):

$$Y = \gamma_0 + \gamma \cdot Z + \gamma_X' \cdot X + \varepsilon_1 \qquad (1)$$

$$M = \alpha_0 + \alpha \cdot Z + \alpha_X' \cdot X + \varepsilon_2 \qquad (2)$$

$$Y = \beta_0 + \beta \cdot M + \gamma' \cdot Z + \beta_X' \cdot X + \varepsilon_3 \qquad (3)$$

Where I will use equation (3) to answer my first hypothesis, equation (2) to answer my second hypothesis, and all three equations to answer my third hypothesis which I will formulate later.

My motivation for using mediation theory is that it allows for modelling a more complex, relationship between the variables. This complexity cannot be effectively captured by a single equation, such as equation (3), which does not take into account whether Z is associated with the mediator. To add to the previously discussed direct and indirect effects, the indirect effect between the main predictor variable and the outcome variable is $\alpha \cdot \beta$, that is, the effect of the predictor variable on the mediator variable times the effect of the mediator variable on the outcome variable, controlling for relevant control variables in both cases. Furthermore, the direct effect is the coefficient γ' in equation (3), which measures how the predictor influences the outcome, neutralized to the other control variables, with the mediator included. Therefore, the total effect on Y will be $\widehat{\alpha} \cdot \widehat{\beta} + \widehat{\gamma'} = \hat{\gamma}$.

At this point is important to mention that in mediation analysis a control variable is a variable which falls into one of the following criteria. Firstly, it has an impact on Z and M. Alternatively, it has an impact on Z and Y. Alternatively, it has an impact on M and Y (Darolles et al., 2023). In the analysis that follows I will

use institutional ownership, market value, common shares outstanding, common equity, total assets and Tobin's Q as control variables after Darolles et al. (2023).
Therefore, in my thesis, the system of equations will become:

$$R_{i,t+1,j} = \gamma_0 + \gamma \cdot \text{ESG momentum}_{i,t,j} + \gamma_X' \cdot \mathbf{controls}_{i,t,j} + \varepsilon_{i,t,j} \tag{4}$$

$$\ln(\text{vol})_{i,t,j} = \alpha_0 + \alpha \cdot \text{ESG momentum}_{i,t,j} + \alpha_X' \cdot \mathbf{controls}_{i,t,j} + \epsilon_{i,t,j} \tag{5}$$

$$R_{i,t+1,j} = \beta_0 + \beta \cdot \ln(\text{vol})_{i,t,j} + \gamma' \cdot \text{ESG momentum}_{i,t,j} + \beta_X' \cdot \mathbf{controls}_{i,t,j} + v_{i,t,j} \tag{6}$$

where $R_{i,t,j}$ is the excess returns of stock i, i = 1, ..., I at time t, t = 1,...,T, in a specific super-sector j = 1,2,3 for cyclical-, sensitive- and defensive super-sectors respectively. Additionally, $\mathbf{controls}_{i,t,j}$ is a vector of the control variables.
Motivated by the discussion above, now I elaborate on the 5 types of mediation, introduced by Zhao et al. (2010) and discuss how they relate to my third hypothesis. Zhao et al. (2010) classify mediation into:

1. Indirect-only mediation: The mediated effect exists. There is no direct effect. This is also known as full mediation (Baron and Kenny, 1986).
2. Complementary mediation: The mediated effect and the direct effect exist and have the same sign.
3. Competitive mediation: The mediated effect and the direct effect exist but have the opposite sign.
4. Direct-only nonmediation: The mediated effect does not exist, only the direct effect.
5. No-effect nonmediation: Neither effects exist.

Where the mediated effect is $\alpha \cdot \beta$ and the direct effect is γ'. Moreover, complementary- and competitive mediation is classified as partial mediation in Baron and Kenny's (1986) work, which is directly related to my third hypothesis, which states that super-sector level volatility mediates the relationship between ESG momentum and stock returns.

4.2 Model assumptions

There are several important assumptions which are necessary to ensure the internal validity of a mediation model. According to Baron and Kenny (1986), these are the following. Firstly, there is no measurement error in the mediator and secondly, the dependent variable can not cause the mediator, in other words, there is no reverse causality between M and Y.
I ensured that the first assumption holds by obtaining the stock price data from the Compustat North America database, a widely recognized source among researchers for its data accuracy. For calculating stock volatility, I employed the rolling window method, a standard approach when volatility is defined as the standard deviation of stock returns. These ensure that the potential measurement error in the mediator is minimized. The second assumption states that stock returns can not influence stock volatility. Currently, there is some existing literature regarding a so-called "volatility feedback" effect (Bollerslev et al., 2006).

This means that although volatility influences stock returns, stock returns also influence stock volatility, creating a feedback loop. Fortunately, this phenomenon only lasts for several days in high-frequency data, and given that my data is quarterly, this assumption is also met.

Beyond these assumptions, the regressions that were used to model mediation also meet the five Classical Linear Regression Model assumptions, as described by Brooks (2008). These are as follows. Firstly, the expectation of the error term is zero. Although the detection of the violation of this assumption is typically not possible, fortunately, the constant term, which is not analyzed in mediation, absorbs the error (Brooks, 2008). Secondly, to ensure that the second CLRM assumption of homoskedasticity, that is the error terms have constant variance is also met, heteroskedasticity robust standard errors have been used. Thirdly, industry-clustered standard errors have been employed to account for the cross-sectional dependence in the data, which accounts for the cross-sectionally correlated errors. Most crucially, the fourth assumption is of exogeneity, which has two other forms next to the previously described reverse causality: Omitted Variable Bias (OVB), and measurement error of the independent variables. To address OVB, I control for six variables which have been theoretically supported in the literature as being associated with ESG or excess returns. According to the work of Pedersen et al. (2021) and Darolles et al. (2023), the institutional ownership variable represents the demand channel, which is one of the two main transmission channels next to the fundamental channel in the relationship between ESG score and stock returns, as outlined in the theoretical framework. The common shares outstanding variable is directly related to institutional ownership, given that if the number of common shares outstanding increases, the share price decreases, which makes share participation more accessible to retail investors. In the same vein, market value, common/ordinary equity, total assets and Tobin's Q serve as control variables which represent the fundamentals channel. Additionally, in the panel data regressions, I use fixed effects, which account for time-invariant OVB. Secondly, I ensured that the assumption of no measurement error in the independent variables was met by obtaining my data from reputable and trusted data providers and by using standardized procedures to calculate them. The fifth CLRM assumption is that the residuals are normally distributed. The potential violation of assumption is not of concern given the large sample size for each supersector and data type. Because of the large sample sample size "violation of the normality assumption (of the error term) is virtually inconsequential" (Brooks, 2008, p. 164). As a result, the estimators' sampling distribution is going to be the standard normal distribution, thanks to the Central Limit Theorem.

Lastly, there is a final mediation-specific assumption, which is outlined by MacKinnon (2008), namely the assumption of temporal precedence, that is, the mediator occurs before the dependent variable. In my analysis, the mediator variable is 4-quarter stock return volatility, which was calculated with a rolling-window method after Park and Newaz (2023). This method is always backwards-looking, calculating the standard deviation of stock returns over the last 4 quarters. For my dependent variable, I used forward returns in excess of the risk-free rate, which means that the assumption of temporal dependence is met.

4.3 The necessity for bootstrapping and the bootstrapping process

To estimate the significance of the indirect effect in the mediation analysis, we require at least a Sobel test, as recommended by Baron and Kenny (1986), which is a statistical test specifically designed for this reason. However, the Sobel test is considered to have low power (Zhao et al., 2010), that is, the probability of correctly rejecting a false null hypothesis is lower, which means that it makes Type II errors more often. This is because it assumes that the probability distribution of ($\hat{\alpha} * \hat{\beta}$) is normal, however, in reality, it is right-skewed (Aroian, 1947). As a result researchers (Zhao et al., 2010) often recommend bootstrapping instead, which does not rely on the assumption of normality. This process involves repeatedly drawing samples from the data with replacement, typically at least 1000 times (Preacher and Hayes, 2008). At each sampling, the indirect effect is estimated, from which a distribution is constructed. This distribution is then used to estimate the significance level of the indirect effect.

4.4 Hypotheses

Given the above-mentioned literature review and methodology, I formulate three hypotheses regarding ESG momentum and stock returns, ESG momentum and stock volatility, and whether stock volatility mediates the relationship between ESG momentum and stock returns on a supersector level.

H_1: *An increase in ESG momentum, defined as the annual change in ESG score affects stock returns in at least one supersector for at least one data type.*

Which is tested by equation (6) by examining the coefficient γ' using a two-sided test. This measures the direct effect of ESG momentum on excess stock returns while controlling for all variables, including the mediator.

The rationale behind my first hypothesis is related to the work of both Giese et al. (2019), from whom I borrow the definition of ESG momentum, and also to the seminal meta-analysis of Friede et al. (2015), who provide the largest literature review between ESG criteria and corporate financial performance (CFP), and find that approximately 90% of 2200 individual studies find either no relationship or a positive relationship between ESG and CFP.

Moreover, related to my second hypothesis, in the paper of Jo and Na (2012), the authors examine how corporate social responsibility (CSR), which is closely related to ESG, influences firm volatility both in controversial and non-controversial industry sectors. Overall, the authors find that engaging in CSR practices helps firms in their risk management efforts, using a system equation approach. They also note that this is more prominent in controversial sectors, again highlighting the importance of industry-level analysis. Given their findings, I formulate my second hypothesis regarding the relationship between ESG momentum and stock volatility. This is closely related to the second transmission channel of Giese et al. (2019), also known as the idiosyncratic risk channel. As discussed before, they empirically show that those firms with strong ESG practices have lower tail risk thanks to their robust risk management frameworks. Motivated by their findings and the findings of Jo and Na (2012), my second hypothesis is as follows:

H_2: *An increase in ESG momentum, defined as the annual change in ESG score affects stock return volatility in at least one supersector for at least one data type.*

This is estimated by equation (5) by examining the coefficient α using a two-sided test. This measures the effect of ESG momentum on stock volatility.
Lastly, for the third hypothesis, which encompasses the entire mediation relationship between ESG momentum and stock returns using stock return volatility as the mediator variable, I propose the following argument. Drawing on the insights of Park and Newaz (2023), who emphasize the importance of industry-level analysis in understanding the effect of return volatility on stock returns, and Jo and Na (2012), who illustrate the significant impact of CSR (which is closely related to ESG) on stock volatility, it becomes evident that sector-specific factors play a crucial role in stock return predictability. Additionally, Giese et al. (2019) demonstrate how ESG momentum serves as a valuable financial metric for forecasting stock returns. In addition, as stated before, certain industries, for example, oil, gas, agriculture and mining exhibit both higher ESG risks and more cyclical behaviour, due to their direct interaction with natural resources. Motivated by these, I propose the third hypothesis:

H_3: *Stock return volatility mediates the relationship between ESG momentum and stock returns in at least one supersector for at least one data type.*

Which is estimated by equations (4), (5) and (6) in the following way. The main coefficients of interest are α in equation (5) and β in equation (6), where the null hypothesis of no mediation is H_0: $\alpha \cdot \beta = 0$, and the alternative hypothesis is H_1: $\alpha \cdot \beta \neq 0$, indicating a two-sided test. Furthermore, the main coefficient of interest in equation (4) is γ, which determines the type of mediation as discussed by Zhao et al. (2010).

CHAPTER 5 Results & Discussion

In what follows I report the analyses of the results obtained from the regressions and the mediation analysis. First, I will report the results from the panel data regressions between ESG momentum and excess stock returns, to answer the first hypothesis. Then, I will continue by examining the results that were obtained from the regressions between ESG momentum and stock volatility. Lastly, I will answer the third hypothesis by examining the regression results of stock returns on ESG momentum and stock volatility and the controls and also by elaborating on the results from the bootstrapping procedure. Each regression contains institutional ownership, market value, common shares outstanding, common equity, total assets and Tobin's Q as control variables.

5.1 Hypothesis 1 – Direct effect

5.1.1 Theoretical interpretation and discussion on model performance

The interpretation of the results in Table A.6 and Table A.7 is as follows. Considering the fact that the dependent variable has been log-transformed by taking the natural logarithm, we can interpret the effect of ESG momentum on excess returns as a semi-elasticity. Normally, this would mean that a unit increase in X increases/decreases excess returns by $100\gamma'$ %. Given the previous discussion on ESG momentum variables regarding why their calculation as an annual percentage change is problematic, ESG momentum variables represent a percentage point change, which is simply the difference between two percentages. For example, if the ESG momentum coefficient is 0.1, that means that a 1 percentage point change in ESG momentum is associated with a 10% increase in excess returns.

[Include here – Table A.7: Panel Regression showing the effect of ESG momentum variables and 4 quarter return volatility on excess returns with fixed effects]

By looking at the between R^2 of the models in Table A.6, we can observe that the Social Momentum in the Defensive supersector has the lowest R-squared of 0.162. This means that this random effects model explains 16.2% of the variation in excess returns. The highest R-squared in Table A.6 is for the Environmental Momentum in the Defensive supersector which is 0.350. As for the fixed effects models, the lowest within R-squared is 0.022, which surprisingly belongs to the Environmental Momentum in the Defensive supersector, and the highest R-squared is 0.089 in the Cyclical super sector for the Social- and Governance momentum. In Table A.7, we can see a clear trend that the R-squared consistently decreases as the cyclicality of the supersector decreases. Also, in Table A.6, we can observe that the highest R-squared within a supersector always belongs to the Environmental momentum datatype.

5.1.2 Discussing ESG momentum and answering Hypothesis 1

Let me discuss some important observations regarding the significance and magnitude of the regression coefficients by looking at Table A.7. Firstly, only three regression coefficients are significant, Governance momentum in the Sensitive sector and ESG momentum in the Defensive sector at a 5% level, and Environmental momentum in the Defensive supersector at a 10% level. The coefficient is negative in the Sensitive sector, but positive in the Defensive sector, and greater in magnitude in the Defensive sector. It is also the smallest in magnitude for Governance momentum and larger for Environmental and ESG momentum. I interpret the (0.263*) coefficient for the Environmental momentum in the Defensive sector as follows. In the Defensive sector when a firm's Environmental momentum increases by 1 percentage point, the associated change in its excess returns is 26.3%. Therefore, not the Environmental score is changing, but the change in the Environmental score changes by 1 percentage point. That is, the rating agency is increasing the score for the Environmental pillar at an increasing rate. This result is both statistically and economically significant. However, I argue that this interpretation is not very useful in an applied setting, both due to the complex nature of ESG momentum and due to the magnitude of the effects. Rather, it is more applicable to interpret the coefficients by comparing them across sectors and data types, than to view it in isolation. These results are partially supported by Table A.6, which should be interpreted more carefully due to potential time-invariant OVB.

In light of the recent discussion and by looking at the results in Table A.7 and Table A.6, the first null hypothesis which states that an increase in ESG momentum does not affect stock returns in at least one supersector for at least one datatype is rejected. This could be the consequence of the fact that those firms who experience an increasing increase in ESG scores have better fundamentals, which transforms into better profitability, as suggested by Pedersen et al. (2021). I find it important to emphasize that this is not a universal result, as it failed to reject in specific sectors for specific data types. Nonetheless, I conclude that my first hypothesis is rejected.

5.1.3 Comparison with literature and market level robustness check

The most similar analysis on ESG is of Darolles et al. (2023), who analyzed the mediating effect of institutional ownership between ESG score and stock returns. Upon comparing the results for the Environmental momentum, it can be immediately observed that they have significant and negative results, whereas I have either not significantly different from zero, or positive results. My results are therefore consistent with the theoretical framework developed by Pedersen et al. (2021). For the Social momentum, both Darolles et al. (2023) and I observe a result which is not significantly different from zero with a FEs model. For the Governance momentum, my results are also consistent with theirs, being not significantly different from zero, except for the Sensitive sector, which is negative. Lastly, for the ESG momentum, the results also differ, but only in the Defensive sector, otherwise, both of us have results which are not significantly different from zero. For the larger scientific discussion, this could mean that in the Defensive sector, ESG momentum can be considered an equally sound ESG variable as ESG score, because of the theoretical soundness of the results.

To check the robustness of the results obtained from my analysis, I conduct a robustness check on a market level for all three hypotheses. First, I will analyze Tables A.7 and A.12. Not surprisingly, for the first hypothesis, the results seem to average out on a market level, in terms of magnitude. For the Environmental pillar, the market-level analysis supports the findings for the Defensive sector only. Moreover, on a market level, the FEs model shows a 1% significance for the Social pillar, however, this completely disappears on an industry level. On the contrary, the Governance pillar is only significant in the Sensitive sector, but not on a market level. Lastly, the ESG momentum coefficient on a market level appears to be the average of the sector-level coefficients both in terms of magnitude and significance. For Table A.6, the results are supported by the robustness check for the Environmental and Social momentum, and discrepancies only appear for the remaining datatypes.

5.2 Hypothesis 2 - Volatility on ESG momentum

5.2.1 Theoretical interpretation and discussion on model performance

For the regressions between ESG momentum and 4-quarter return volatility, the interpretation is as follows. Considering that volatility has also been transformed using the natural logarithm, the coefficients are interpreted as semi-elasticity, just as before. In other words, in Table A.4 and Table A.5, a percentage point increase in ESG momentum increases/decreases stock volatility by 100α%.

[Include here – Table A.5: Panel Regression showing the effect of ESG momentum variables on 4 quarter return volatility with fixed effects]

The models which depict the regressions for the second hypothesis can be seen in Table A.4 and A.5. For Table A.4, the lowest between R-squared is 0.033, corresponding to the Governance momentum in the Cyclical super sector, and the highest R-squared is 0.426, which is associated with the ESG momentum of the Defensive super sector. This means that the ESG momentum model explains 42.6% of the variation in excess returns in the Defensive super sector. Again, in Table A.4 we see a clear difference between the supersectors in terms of R-squared, which constantly increases as the cyclicality of the supersector decreases. In Table A.5, all within R-squared values are near zero, indicating that the ESG momentum models (including the controls) do not explain a lot of within-panel variation in stock volatility with a fixed effects model. Just as before, the Environmental momentum model is always the best in explaining within-panel variation in 4-quarter return volatility, now for a fixed effects model.

5.2.2 Discussing ESG momentum and answering Hypothesis 2

In Table A.5, the regression results show the associations between the ESG momentum variables and volatility, which can be interpreted as follows. Firstly, the Environmental momentum is significant in all sectors, however, the Sensitive sector shows the most significant result at a 5% level. Furthermore, all coefficients are positive, except the Governance momentum in the Cyclical sector, however, this coefficient has the smallest effect size. I interpret this (-0.073**) coefficient as a one percentage point increase in Governance momentum being associated with a decrease in return volatility by 7.3% in the Cyclical sector. Again, these results should be interpreted in comparison to other sectors, for example, a 1% point change in Environmental momentum is associated with a similar increase in stock volatility in the three sectors, given their similar magnitude. The results of Table A.5 are also economically significant and are supported by Table A.4 with the REs specification.

Based on the results of the panel regressions between return volatility and ESG momentum in Table A.5, I conclude that the second null hypothesis which states that an increase in ESG momentum does not affect stock return volatility in at least one supersector for at least one datatype is rejected. However, in contrast to the existing literature developed by Giese et al. (2019), the results show that a 1% point increase in ESG momentum is associated with an increase in return volatility for the specific data types and sectors, and only shows a decrease for the Governance momentum in the Cyclical sector.

5.2.3 Comparison with literature and market level robustness check

For the second hypothesis, the most comparable literature is of Burger et al. (2022), who regress the aggregate ESG score of 4 raters on historical volatility, finding almost exclusively significant and negative results. However, for the 360-day historical volatility for Refinitiv, they find results which are not significantly different from zero, and oddly enough this metric is the most related to my 4-quarter return volatility. In Table A.5, I find either not significantly different from zero results for the Cyclical and Defensive sectors, but significantly positive results for the Sensitive sector using the FEs model. For the REs model, the Cyclical sector also becomes significant for aggregate ESG momentum. This sector level divergence suggests a different interaction between ESG momentum and volatility, highlighting the importance of sector level analysis, as discussed by Park and Newaz (2023), which can be a motivation for the larger scientific community to conduct industry level analyses next to market level research.

For the second hypothesis, the market level robustness check strongly supports the results of Table A.4 and A.5 for the Environmental momentum. This can be because, on a sector level, there are little deviations in the coefficient of the Environmental momentum on volatility both in terms of significance and magnitude. The robustness check only confirms the findings on Social momentum in the Sensitive sector but for both specifications. Furthermore, the market level analysis and the sector level analysis are exactly the same for the Governance momentum on volatility, but only for the Sensitive and the Defensive sectors, because both of them show coefficients which are not significant and also have small magnitude. Lastly, the robustness of the findings on ESG momentum on volatility is confirmed, only for the Sensitive sector, which shows that the results are the most robust for the sensitive sector.

5.3 Hypothesis 3 - Mediation

5.3.1 Theoretical interpretation and discussion on model performance

The theoretical interpretation of H3 differs substantially from the previous interpretations. The most convenient and elegant interpretation of mediation has been developed by Zhao et al. (2010), who use a decision tree to determine whether mediation has been established, and if yes, then what is the type of mediation. Firstly, to determine mediation, one should look at the results of the bootstrapping procedure in Table A.8 and Table A.9. If the indirect effect coming from the bootstrapping procedure is significant, then, according to Zhao et al. (2010), mediation is established. After this, one should observe the coefficient of ESG momentum in Tables A.6 and A.7, measuring the direct effect between ESG momentum and stock returns. This determines whether pure (indirect only) or partial mediation is established. Indirect-only mediation happens when the ESG momentum coefficient is *not* significant. Lastly, from Table A.2 and A.3, one could determine the type of partial mediation: if $\gamma*\beta*\gamma'$ is positive, we measure complementary mediation, otherwise, competitive mediation.

[Include here – Table A.9: Direct and indirect effects between ESG variables and returns with fixed effects]

For the bootstrapping procedure, I would like to discuss the SEs obtained. In Table A.9, for the fixed effects models, the SEs for the indirect effect are between 0.01 and 0.02. For the total effects, they fall between 0.04 and 0.10. This increase in SEs makes sense both statistically and intuitively, because for the total effect, the bootstrapping procedure is estimating both the direct and the indirect effect, and it sums them up, leading to larger SEs. In Table A.8, for the models without fixed effects, the same general trend is observed. In Tables A.2 and A.3 which are necessary to determine the type of mediation, a low R-squared can be seen between ESG momentum and excess stock returns for both the REs and for the FEs model. This is especially true for the Cyclical supersector, where the highest R-squared is 0.041, which is for the Social Momentum with the REs specification, indicating that the model merely explains a 4.1% between panel variation for excess returns.

5.3.2 Discussing mediation analysis and answering Hypothesis 3

To discuss the mediation analysis, I will examine Table A.9, containing the models with FEs and support the observed results by Table A.8, which contains the bootstrapping results of the REs regressions. According to Table A.9, by looking at the significance levels, mediation is established 8 out of 12 times for the sectors according to the data types. From these, 6 out of 8 is considered full mediation in the case of the Cyclical and the Sensitive sectors, because the direct effect (coefficient of ESG momentum on excess returns, controlling for volatility) is not significant. According to Zhao et al. (2010), this means that for the specific data types and sectors, an omitted mediator is not likely and that the theoretical framework that volatility mediates ESG momentum and returns is consistent. Also, partial mediation is only established in the Defensive sector, 2 out of 8 times, both of which are complementary by using the framework of Zhao et al. (2010). They claim that in this case there could be an omitted mediator and that the theoretical framework is incomplete for these sectors and datatypes. Table A.8 partially supports these findings, where we observe mediation 8 out of 12 times, from which 7 overlap with Table A.9. This suggests that stock return volatility mediates ESG momentum on excess stock returns for the specific sectors and datatypes. Additionally, the total effect of ESG momentum and volatility on stock returns is significant 10 out of 12 times for the FEs model. For the REs model, there is only one instance where the total effect is not significant: the Governance momentum in the Defensive sector. This could be, because this is the least volatile sector and traditional investors tend to invest in more volatile sectors, with the aim to earn higher returns, as supported by Sharpe (1964).

By looking at the results of the mediation analysis in Table A.9 and Table A.8, I state that the third null hypothesis, which states that stock return volatility does not mediate the relationship between ESG momentum and stock returns in at least one sector for at least one datatype is rejected. To reiterate, this result is not rejected for every single data type and sector combination, just in specific ones, as seen in Table A.9. These results highlight sector level differences, as advocated by Park and Newaz (2023), which would have been lost, had this analysis been on a market level.

5.3.3 Comparison with literature and market level robustness check

Although Darolles et al. (2023) use institutional ownership as the mediator in their research between ESG score and excess returns, it is still the most similar paper on the topic of ESG and mediation, thus I compare my results to theirs. For the Environmental momentum, I always find a significant and positive indirect effect. In contrast, they find a significant and negative indirect effect through institutional ownership, although their Environmental score has the greatest magnitude. For the larger scientific discussion, these findings suggest that Environmental momentum may play a more prominent role in influencing stock returns compared to Social and Governance factors even after using different mediator variables. My results mean that volatility acts as a mediating variable between Environmental momentum and stock returns, that is, Environmental momentum is positively associated with stock volatility, and this translates into a positive association with stock returns. Darolles et al. (2023) find significant and negative indirect effects for all datatypes with a FEs model. I only find this result for the Governance momentum in the Cyclical sector in my analysis.

For the robustness check regarding the mediation analysis, I will primarily focus on Table A.13 and compare it with Tables A.9 and A.8. According to Table A.13, mediation is only present for the Environmental momentum, Social momentum and ESG momentum, both for the REs and FEs. Based on Table A.13, the analysis for the Sensitive sector and the Environmental momentum is the most consistent, but only for the indirect and total effects. In the Defensive sector, the mediation results for the ESG momentum are supported, that is, both on a market level and in the Defensive sector the relation between ESG momentum and returns is mediated by volatility.

CHAPTER 6 Conclusion

In my thesis, I have looked at how stock volatility mediates the relationship between ESG momentum, the annual absolute change in ESG score, and excess stock returns. Previous research has shown statistically significant causal effects between ESG variables and volatility (Burger et al., 2022), between ESG variables and stock returns using mediation theory (Darolles et al., 2023) and between volatility and stock returns Van Vliet et al. (2011). Furthermore, several economic theories have also been developed around these concepts which enabled me to conduct research which is both statistically and theoretically supported. However, despite prior research so far, it remained unclear how these variables interact on a sector level. More specifically, until now no literature exists that examines this mediating relationship on a sector level, or on a market level. Thus, the research question that I investigated in my dissertation was: *„How does ESG momentum influence stock return predictability across sectors, given their distinct ESG profiles, with a particular focus on the mediating role of stock return volatility?"*

6.1 Research methods, results and takeaways

To answer this question, I used mediation analysis using the traditional mediation approach of Baron and Kenny (1986), as Darolles et al. (2023) have done, using U.S. data across 1686 unique firms between 2006 and 2020, which have been categorized into three sectors using the Morningstar supersector classification. Additionally, I formulated three hypotheses, the first on the relationship between ESG momentum and returns, the second between ESG momentum and volatility, and the third on whether volatility mediates the relationship between ESG momentum and stock returns. The panel data analysis using regressions with fixed effects showed that ESG momentum has a statistically significant and positive effect on returns in the Defensive sector for the Environmental momentum and the aggregate ESG momentum, but a significant and negative in the Sensitive sector for the Governance momentum. Furthermore, for the second hypothesis, Environmental momentum has a significant and positive relationship with return volatility in all three sectors. For the Sensitive sector, the association is also significant and positive for the Social momentum and the aggregate ESG momentum as well. Lastly, in the Cyclical sector, the association is significant and negative between Governance momentum and volatility. For my third hypothesis on mediation, I measure mediation 8 out of 12 times for the 3 sectors across the 4 data types, from which 6 out of 8 is considered full mediation. The remaining two partial mediations are complementary according to the mediation framework of Zhao et al. (2010).

This research therefore concludes that stock return volatility does mediate the relationship between ESG momentum and excess stock returns both in specific super-sectors and also on a market level, as seen by the robustness tests. The results are specifically true to Environmental momentum, which is significant in all sectors and also on a market level. The results in the Sensitive sector are closest to the results at the market level. Furthermore, ESG momentum does have a significant association with excess returns, and also with return volatility, both on the market level and on a sector level for specific data types and sectors. However, the results on a sector level are not necessarily stronger in contrast to the findings of Park and Newaz (2023).

6.2 Limitations and recommendations for future research

This research has (at least) two limitations that I would like to outline briefly: one statistical and one in terms of data. Firstly, the statistical limitation of my study is the potential temporal dependence in my panel data, which I could not address due to how more sophisticated SE models, such as Driscoll Kraay or Newey-West – which is more appropriate to time series data (Brooks, 2008) – and bootstrapping methods interact within Stata. The second limitation is that for the scope of this research, the data has only been obtained from one ESG rating agency, which is Refinitiv. Because of this, there is a high possibility that completely different results would have been obtained, if I had used the ESG scores of a different rating agency, given the differences between the scores of different ESG raters (Berg et al., 2022c). Moreover, my data only covers U.S. listed firms from three major exchanges, not firms internationally, and from prior research of Alves et al. (2023), this could be the factor that determines whether statistically significant results between ESG variables and stock returns are determined or not. Therefore, global claims about causality or mediation can not be made at all. Nonetheless these limitations, it would be interesting to see the results of the same research which uses the data of Alves et al. (2023) with 7 major rating agencies using over 16 000 stocks in 48 countries.

My recommendations for future researchers are twofold. Firstly, researchers could develop an accessible global ESG database that creates an aggregate ESG score from the ESG scores of the 7 major ESG providers, combining the work of Alves et al. (2023) and Burger et al. (2022) in terms of data. This combined score could potentially reduce the ESG divergence for future research, given that now we would obtain more consistent data across different studies, enabling more robust conclusions regarding the influence of ESG variables on financial performance. Secondly, with this aggregate ESG score, the same analysis could be expanded to include both ESG score and ESG momentum as the main independent variables. This would potentially enable us to differentiate the effect of ESG score and ESG momentum on returns using mediation theory.

REFERENCES

Alves, R., Krueger, P., & van Dijk, M. A. (2023). *Drawing Up the Bill: Are ESG Ratings Related to Stock Returns Around the World?* (SSRN Scholarly Paper 4674146). https://doi.org/10.2139/ssrn.4674146

Ang, A., & Bekaert, G. (n.d.). *Stock Return Predictability: Is it There?*

Aroian, L. A. (1947). The Probability Function of the Product of Two Normally Distributed Variables. *The Annals of Mathematical Statistics*, *18*(2), 265–271. https://doi.org/10.1214/aoms/1177730442

Avramov, D., Cheng, S., Lioui, A., & Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, *145*(2, Part B), 642–664. https://doi.org/10.1016/j.jfineco.2021.09.009

Bannier, C. E., Bofinger, Y., & Rock, B. (2019). *Doing safe by doing good: ESG investing and corporate social responsibility in the U.S. and Europe* (Working Paper 621). CFS Working Paper Series. https://www.econstor.eu/handle/10419/200161

Bannigidadmath, D., & Narayan, P. K. (2016). Stock return predictability and determinants of predictability and profits. *Emerging Markets Review*, *26*, 153–173. https://doi.org/10.1016/j.ememar.2015.12.003

Bardos, K. S., Ertugrul, M., & Gao, L. (n.d.). *Corporate Social Responsibility, Product Market Perception, and Firm Value*.

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance*, *26*(6), 1315–1344. https://doi.org/10.1093/rof/rfac033

Blitz, D. C., & van Vliet, P. (2007). *Lower risk without lower return.*

Bollerslev, T. (2006). Leverage and Volatility Feedback Effects in High-Frequency Data. *Journal of Financial Econometrics*, *4*(3), 353–384. https://doi.org/10.1093/jjfinec/nbj014

Brooks, C. (2008). *Introductory Econometrics for Finance* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511841644

Burger, E., Grba, F., & Heidorn, T. (2022). *The impact of ESG ratings on implied and historical volatility* (Working Paper 230). Frankfurt School - Working Paper Series. https://www.econstor.eu/handle/10419/251516

Cai, Y., Pan, C. H., & Statman, M. (2016). Why do countries matter so much in corporate social performance? *Journal of Corporate Finance*, *41*, 591–609. https://doi.org/10.1016/j.jcorpfin.2016.09.004

Confirmation Bias: A Ubiquitous Phenomenon in Many Guises—Raymond S. Nickerson, 1998. (n.d.). Retrieved May 24, 2024, from https://journals.sagepub.com/doi/10.1037/1089-2680.2.2.175

Darolles, S., Le Fol, G., & He, Y. (2023). Understanding the Effect of ESG Scores on Stock Returns Using Mediation Theory. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4634699

Devpura, N., Narayan, P. K., & Sharma, S. S. (2018). Is stock return predictability time-varying? *Journal of International Financial Markets, Institutions and Money*, *52*(C), 152–172.

Diebold, F. X., & Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal*, *119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Drei, A., Le Guenedal, T., Lepetit, F., Mortier, V., Roncalli, T., & Sekine, T. (2019). *ESG Investing in Recent Years: New Insights from Old Challenges* (SSRN Scholarly Paper 3683469). https://doi.org/10.2139/ssrn.3683469

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383-417. https://doi.org/10.2307/2325486

Frank, J. (2023, June 26). *Black Rock CEO Larry Fink "ashamed" to be part of ESG political debate*. Axios. https://www.axios.com/2023/06/26/larry-fink-ashamed-esg-weaponized-desantis

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, *19*(1), 3–29. https://doi.org/10.1016/0304-405X(87)90026-2

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210–233. https://doi.org/10.1080/20430795.2015.1118917

Giese, G., Lee, L.-E., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of ESG Investing: *How ESG Affects Equity Valuation, Risk, and Performance*. *The Journal of Portfolio Management*, *45*(5), 69–83. https://doi.org/10.3905/jpm.2019.45.5.069

Gregory, A., Tharyan, R., & Whittaker, J. (2014). Corporate Social Responsibility and Firm Value: Disaggregating the Effects on Cash Flow, Risk and Growth. *Journal of Business Ethics*, *124*(4), 633–657.

Hudson, R. S., & Gregoriou, A. (2015). Calculating and comparing security returns is harder than you think: A comparison between logarithmic and simple returns. *International Review of Financial Analysis*, *38*, 151–162. https://doi.org/10.1016/j.irfa.2014.10.008

Jo, H., & Na, H. (2012). Does CSR Reduce Firm Risk? Evidence from Controversial Industry Sectors. *Journal of Business Ethics*, *110*(4), 441–456. https://doi.org/10.1007/s10551-012-1492-2

Kang, H. (2013). The prevention and handling of the missing data. *Korean Journal of Anesthesiology*, *64*(5), 402–406. https://doi.org/10.4097/kjae.2013.64.5.402

London Stock Exchange Group. (n.d.). LSEG ESG scores methodology. https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis* (pp. x, 477). Taylor & Francis Group/Lawrence Erlbaum Associates.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods*, *7*(1), 83–104. https://doi.org/10.1037/1082-989x.7.1.83

Morningstar, Inc. (n.d.). Morningstar stock sector structure: Factsheet. https://www.morningstar.com/content/dam/marketing/apac/au/pdfs/Legal/StockSectorStructure_Factsheet.pdf

Nagy, Z., Kassam, A., & Lee, L.-E. (2016). Can ESG Add Alpha? *An Analysis of ESG Tilt and Momentum Strategies*. *The Journal of Investing*, *25*(2), 113–124. https://doi.org/10.3905/joi.2016.25.2.113

Ng, A. C., & Rezaee, Z. (2020). Business sustainability factors and stock price informativeness. *Journal of Corporate Finance*, *64*, 101688. https://doi.org/10.1016/j.jcorpfin.2020.101688

Park, J. S., & Newaz, M. K. (2023). Time-Series Predictability for Sector Investing. *Financial Analysts Journal*, *79*(3), 136–154. https://doi.org/10.1080/0015198X.2023.2208028

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571. https://doi.org/10.1016/j.jfineco.2020.12.011

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*, *142*(2), 572–597. https://doi.org/10.1016/j.jfineco.2020.11.001

Phan, D. H. B., Sharma, S. S., & Narayan, P. K. (2015). Stock return forecasting: Some new evidence. *International Review of Financial Analysis*, *40*, 38–51. https://doi.org/10.1016/j.irfa.2015.05.002

Phan, D. H. B., Sharma, S. S., & Tran, V. T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Markets, Institutions and Money*, *55*, 134–150. https://doi.org/10.1016/j.intfin.2018.04.004

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Rozeff, M. S. (1984). Dividend yields are equity risk premiums. Journal of Portfolio Management, 25(2), 68-75. https://doi.org/10.2139/ssrn.6454

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, *86*(2), 420–428. https://doi.org/10.1037/0033-2909.86.2.420

Starks, L. T. (2023). Presidential Address: Sustainable Finance and ESG Issues—Value versus Values. *The Journal of Finance*, *78*(4), 1837–1872. https://doi.org/10.1111/jofi.13255

Timmermann, A. G. (1993). How Learning in Financial Markets Generates Excess Volatility and Predictability in Stock Prices. *The Quarterly Journal of Economics*, *108*(4), 1135–1145. https://doi.org/10.2307/2118462

United Nations Environment Programme Finance Initiative (UNEP FI). (2004). Who cares wins: Connecting financial markets to a changing world. https://www.unepfi.org/fileadmin/events/2004/stocks/who_cares_wins_global_compact_2004.pdf

Van Vliet, P., Blitz, D., & Van Der Grient, B. (2011). Is the Relation between Volatility and Expected Stock Returns Positive, Flat or Negative? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1881503

Wang, H., Shen, H., & Li, S. (2023). ESG performance and stock price fragility. *Finance Research Letters*, *56*, 104101. https://doi.org/10.1016/j.frl.2023.104101

Zhang, Y., He, M., & Wen, D. (2023). Industry volatility spillover and aggregate stock returns. *The European Journal of Finance*, *0*(0), 1–30. https://doi.org/10.1080/1351847X.2023.2271054

Zhao, X., Lynch, J., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis. *Journal of Consumer Research*, *37*, 197–206. https://doi.org/10.1086/651257

APPENDIX A Main Tables

Table A.1 Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min.	5%	95%	Max.
Environmental Momentum	0.0298	0.0087	0.0964	-0.5908	-0.0776	0.2192	0.722
Social Momentum	0.0241	0.0058	0.0823	-0.4699	-0.0708	0.1822	0.7446
Governance Momentum	0.0187	0.0133	0.1330	-0.5642	-0.1918	0.2445	0.8104
ESG Momentum	0.0248	0.0151	0.0692	-0.3448	-0.0701	0.1489	0.5637
Institutional Ownership	0.7725	0.8079	0.2060	0.0001	0.3426	1.0330	1.9841
Market Value ($ billion)	19.0787	4.5698	56.5979	0.0053	0.2586	81.4839	2232.28
Common Shares Outstanding (million)	355.0565	110.5700	873.1923	1.1610	14.2110	1378.1870	16976.76
Common/Ordinary Equity ($ billion)	7.0708	1.75	20.2057	0.0027	0.1432	27.592	250.136
Total Assets ($ billion)	31.0215	5.3271	156.4974	0.0022	0.3603	109.706	3386.071
Tobin's Q	1.9710	1.5034	1.627	0.3031	0.9426	4.6824	35.6144
Excess Return	0.0868	0.0182	0.6185	-2.4881	-0.7931	1.2790	5.4885
4-Quarter Return Volatility	0.1756	0.1339	0.1432	0.0006	0.0418	0.4427	2.7977

Note. E, S, G and ESG momentum variables are measured as percentage points. Institutional ownership is measured in percentage. Table B.1 in the appendix defines all the variables used.

Table A.2 Panel Regression showing the global effect of ESG momentum variables on excess returns without fixed effects

	Excess Returns											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.444***				0.323***				0.375***			
	(0.12)				(0.12)				(0.10)			
Social momentum		0.229*				0.342***				0.310**		
		(0.12)				(0.13)				(0.13)		
Governance momentum			-0.072				-0.118***				0.045	
			(0.10)				(0.04)				(0.03)	
ESG momentum				0.206*				0.266				0.427***
				(0.12)				(0.17)				(0.06)
Constant	0.483	0.374	0.384	0.374	0.605	0.409	0.414	0.400	0.104	0.154	0.156	0.147
	(0.22)	(0.10)	(0.11)	(0.10)	(0.13)	(0.10)	(0.10)	(0.09)	(0.12)	(0.07)	(0.17)	(0.07)
R^2 (between)	0.001	0.041	0.034	0.039	0.049	0.108	0.085	0.112	0.161	0.050	0.052	0.063
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions without fixed effects between excess returns on ESG variables across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.3 Panel Regression showing the global effect of ESG momentum variables on excess returns with fixed effects

	Excess Returns											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.364*				0.275				0.299*			
	(0.15)				(0.13)				(0.09)			
Social momentum		0.183				0.307				0.287		
		(0.11)				(0.14)				(0.15)		
Governance momentum			-0.089				-0.146**				0.022	
			(0.11)				(0.04)				(0.03)	
ESG momentum				0.115				0.180				0.381**
				(0.16)				(0.19)				(0.29)
Constant	1.145***	0.936**	0.945**	0.936**	1.013*	0.828	0.827	0.829	0.234	0.030	0.031	0.016
	(0.15)	(0.25)	(0.26)	(0.25)	(0.41)	(0.45)	(0.45)	(0.46)	(0.32)	(0.19)	(0.20)	(0.19)
R^2 (within)	0.033	0.026	0.026	0.026	0.013	0.011	0.010	0.010	0.013	0.015	0.014	0.016
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions with fixed effects between excess returns on ESG variables across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.4 Panel Regression showing the effect of ESG momentum variables on 4-quarter return volatility without fixed effects

	ln(volatility)											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.388***				0.373***				0.366***			
	(0.14)				(0.09)				(0.02)			
Social momentum		0.148				0.368***				0.065		
		(0.12)				(0.13)				(0.13)		
Governance momentum			-0.058***				0.057				0.017	
			(0.02)				(0.05)				(0.03)	
ESG momentum				0.179***				0.455***				0.179
				(0.07)				(0.10)				(0.17)
Constant	-1.457***	-1.726***	-1.721***	-1.730***	-1.157***	-1.314***	-1.307***	-1.313***	-2.205***	-2.115***	-2.117***	-2.123***
	(0.22)	(0.24)	(0.24)	(0.23)	(0.17)	(0.15)	(0.15)	(0.15)	(0.20)	(0.23)	(0.23)	(0.23)
R^2 (between)	0.062	0.034	0.033	0.036	0.176	0.201	0.191	0.202	0.355	0.423	0.423	0.426
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions without fixed effects between 4 quarter return volatility on ESG variable s across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.5 Panel Regression showing the effect of ESG momentum variables on 4-quarter return volatility with fixed effects

	ln(volatility)											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.329*				0.358**				0.343**			
	(0.14)				(0.09)				(0.04)			
Social momentum		0.136				0.323*				0.052		
		(0.12)				(0.11)				(0.15)		
Governance momentum			-0.073**				0.050				0.008	
			(0.02)				(0.05)				(0.03)	
ESG momentum				0.123				0.404**				0.152
				(0.06)				(0.10)				(0.19)
Constant	-1.003**	-1.266***	-1.259***	-1.268***	-1.064***	-1.231**	-1.231**	-1.229**	-2.051***	-2.091***	-2.091***	-2.097***
	(0.25)	(0.15)	(0.15)	(0.15)	(0.25)	(0.21)	(0.21)	(0.22)	(0.11)	(0.10)	(0.09)	(0.10)
R^2 (within)	0.035	0.023	0.023	0.023	0.025	0.020	0.019	0.021	0.011	0.005	0.004	0.005
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions with fixed effects between 4 quarter return volatility on ESG variables across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.6 Panel Regression showing the effect of ESG momentum variables and 4-quarter return volatility on excess returns without fixed effects

	Excess Returns											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.352***				0.251**				0.333***			
	(0.08)				(0.10)				(0.09)			
Social momentum		0.195**				0.258**				0.299***		
		(0.09)				(0.13)				(0.11)		
Governance momentum			-0.062				-0.129***				0.042	
			(0.09)				(0.05)				(0.03)	
ESG momentum				0.155				0.166				0.401***
				(0.11)				(0.16)				(0.04)
ln(volatility)	0.235***	0.253***	0.254***	0.254***	0.211***	0.199***	0.201***	0.199***	0.124***	0.126***	0.127***	0.125***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.759***	0.838***	0.847***	0.840***	0.817***	0.677***	0.682***	0.671***	0.389***	0.444***	0.449***	0.438***
	(0.14)	(0.05)	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)	(0.06)	(0.10)	(0.06)	(0.06)	(0.06)
R^2 (between)	0.332	0.286	0.277	0.282	0.269	0.241	0.225	0.244	0.350	0.162	0.166	0.174
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions without fixed effects between excess returns on 4-quarter return volatility and ESG variables across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1 , **p < 0.05, ***p < 0.01.

Table A.7 Panel Regression showing the effect of ESG momentum variables and 4-quarter return volatility on excess returns with fixed effects

	Excess Returns											
	Cyclical Super Sector				Sensitive Super Sector				Defensive Super Sector			
Variable	E	S	G	ESG	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.297				0.201				0.263*			
	(0.13)				(0.11)				(0.08)			
Social momentum		0.149				0.239				0.281		
		(0.09)				(0.14)				(0.13)		
Governance momentum			-0.070				-0.157**				0.021	
			(0.11)				(0.05)				(0.03)	
ESG momentum				0.084				0.096				0.363**
				(0.16)				(0.18)				(0.06)
ln(volatility)	0.206***	0.251***	0.251***	0.251***	0.205***	0.209***	0.211***	0.210***	0.105**	0.117***	0.117**	0.116***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	1.351***	1.254**	1.261**	1.254**	1.231**	1.085*	1.087*	1.087*	0.451	0.275	0.276	0.260
	(0.19)	(0.24)	(0.25)	(0.25)	(0.38)	(0.40)	(0.40)	(0.41)	(0.34)	(0.23)	(0.24)	(0.23)
R^2 (within)	0.072	0.089	0.089	0.088	0.049	0.049	0.049	0.048	0.022	0.027	0.025	0.026
Observations	10978	14891	14891	14891	10838	13198	13198	13198	6430	8535	8535	8535

Note. This table reports the results of the regressions with fixed effects between excess returns on 4-quarter return volatility and ESG variables across the three Morningstar supersectors. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1 , **p < 0.05, ***p < 0.01.

Table A.8

Direct and indirect effects between ESG variables and returns without fixed effects

	Direct effect	Indirect effect	Total effect
Panel A: Cyclical super sector			
E momentum on returns	0.352***	0.091***	0.443***
	(0.08)	(0.02)	(0.06)
S momentum on returns	0.195**	0.038**	0.233***
	(0.09)	(0.02)	(0.07)
G momentum on returns	-0.062	-0.015	-0.076*
	(0.09)	(0.01)	(0.04)
ESG momentum on returns	0.155	0.045**	0.200**
	(0.11)	(0.02)	(0.08)
Panel B: Sensitive super sector			
E momentum on returns	0.251**	0.079***	0.330***
	(0.10)	(0.14)	(0.06)
S momentum on returns	0.258**	0.073***	0.331***
	(0.13)	(0.01)	(0.07)
G momentum on returns	-0.129***	0.011	-0.117***
	(0.05)	(0.01)	(0.04)
ESG momentum on returns	0.166	0.090***	0.256***
	(0.17)	(0.02)	(0.08)
Panel C: Defensive super sector			
E momentum on returns	0.334***	0.046***	0.380***
	(0.09)	(0.01)	(0.08)
S momentum on returns	0.299***	0.008	0.307***
	(0.11)	(0.01)	(0.07)
G momentum on returns	0.042	0.002	0.044
	(0.03)	(0.01)	(0.05)
ESG momentum on returns	0.401***	0.022**	0.423***
	(0.04)	(0.01)	(0.09)

Note. This table reports the results of the bootstrapping procedure for the indirect and total effect between excess returns on ESG momentum variables across the three Morningstar supersectors. The results for the direct effect were obtained from panel regressions. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.9

Direct and indirect effects between ESG variables and returns with fixed effects

	Direct effect	Indirect effect	Total effect
Panel A: Cyclical super sector			
E momentum on returns	0.297	0.068***	0.364***
	(1.13)	(0.01)	(0.06)
S momentum on returns	0.149	0.034*	0.183*
	(0.09)	(0.02)	(0.07)
G momentum on returns	-0.070	-0.018*	-0.089**
	(0.11)	(0.01)	(0.04)
ESG momentum on returns	0.084	0.031	0.115
	(0.16)	(0.02)	(0.08)
Panel B: Sensitive super sector			
E momentum on returns	0.201	0.074***	0.275***
	(0.12)	(0.01)	(0.06)
S momentum on returns	0.239	0.068***	0.307***
	(0.14)	(0.01)	(0.07)
G momentum on returns	-0.157**	0.011	-0.146***
	(0.05)	(0.01)	(0.04)
ESG momentum on returns	0.096	0.085***	0.180**
	(0.18)	(0.02)	(0.08)
Panel C: Defensive super sector			
E momentum on returns	0.263*	0.036***	0.299***
	(0.08)	(0.01)	(0.08)
S momentum on returns	0.281	0.006	0.287***
	(0.13)	(0.01)	(0.07)
G momentum on returns	0.021	0.001	0.022
	(0.03)	(0.01)	(0.05)
ESG momentum on returns	0.363**	0.018*	0.381***
	(0.06)	(0.01)	(0.10)

Note. This table reports the results of the bootstrapping procedure for the indirect and total effect between excess returns on ESG momentum variables across the three Morningstar supersectors. The results for the direct effect were obtained from panel regressions. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.10 Panel Regression showing the global effect of ESG momentum variables on excess returns on a market level

	Excess Returns							
	Random effects				Fixed effects			
Variable	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.389***				0.326***			
	(0.07)				(0.07)			
Social momentum		0.296***				0.261***		
		(0.06)				(0.07)		
Governance momentum			-0.061				-0.084	
			(0.04)				(0.05)	
ESG momentum				0.288***				0.216**
				(0.07)				(0.08)
Constant	0.416***	0.305***	0.311***	0.302***	0.875***	0.620**	0.626**	0.618**
	(0.12)	(0.06)	(0.07)	(0.06)	(0.21)	(0.24)	(0.24)	(0.24)
R^2	0.006	0.053	0.042	0.056	0.017	0.013	0.012	0.012
Observations	28246	36624	36624	36624	28246	36624	36624	36624

Note. This table reports the results of the regressions without and with fixed effects between excess returns on ESG momentum variables on a market level. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.11 Panel Regression showing the effect of ESG momentum variables on 4-quarter return volatility on a market level

	4 quarter return volatility							
	Random effects				Fixed effects			
Variable	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.376***				0.350***			
	(0.06)				(0.05)			
Social momentum		0.206***				0.184**		
		(0.08)				(0.08)		
Governance momentum			0.001				-0.011	
			(0.03)				(0.03)	
ESG momentum				0.277***				0.236***
				(0.07)				(0.07)
Constant	-1.520***	-1.723***	-1.719***	-1.728***	-1.284***	-1.516***	-1.514***	-1.520***
	(0.16)	(0.17)	(0.17)	(0.17)	(0.16)	(0.13)	(0.13)	(0.13)
R^2	0.131	0.146	0.142	0.149	0.021	0.011	0.011	0.011
Observations	28246	36624	36624	36624	28246	36624	36624	36624

Note. This table reports the results of the regressions without and with fixed effects between ESG momentum variables and return volatility on a market level. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

Table A.12 Panel Regression showing the effect of ESG momentum variables and 4-quarter return volatility on excess returns on a market level

	Excess Returns							
	Random effects				Fixed effects			
Variable	E	S	G	ESG	E	S	G	ESG
Environmental momentum	0.317***				0.260***			
	(0.06)				(0.07)			
Social momentum		0.248***				0.222***		
		(0.06)				(0.06)		
Governance momentum			-0.062				-0.081	
			(0.04)				(0.05)	
ESG momentum				0.223***				0.166*
				(0.08)				(0.08)
ln(volatility)	0.203***	0.209***	0.210***	0.208***	0.187***	0.214***	0.214***	0.214***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	0.708***	0.696***	0.702***	0.694***	1.115***	0.944***	0.950***	0.943***
	(0.09)	(0.06)	(0.06)	(0.06)	(0.21)	(0.23)	(0.23)	(0.23)
R^2	0.275	0.233	0.224	0.235	0.049	0.054	0.054	0.054
Observations	28246	36624	36624	36624	28246	36624	36624	36624

Note. This table reports the results of the regressions without and with fixed effects between excess returns on ESG momentum variables and volatility on a market level. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0 .01.

Table A.13

Direct and indirect effects between ESG variables and excess returns on a market level

	Direct effect	Indirect effect	Total effect
Panel A: Random Effects			
E momentum on returns	0.317***	0.077***	0.393***
	(0.06)	(0.01)	(0.04)
S momentum on returns	0.248***	0.043***	0.291***
	(0.06)	(0.01)	(0.04)
G momentum on returns	-0.062	0.001	-0.062**
	(0.04)	(0.01)	(0.03)
ESG momentum on returns	0.223***	0.058***	0.280***
	(0.08)	(0.01)	(0.05)
Panel B: Fixed Effects			
E momentum on returns	0.260***	0.065***	0.326***
	(0.07)	(0.01)	(0.04)
S momentum on returns	0.222***	0.039***	0.261***
	(0.06)	(0.01)	(0.04)
G momentum on returns	-0.081	-0.002	-0.084***
	(0.05)	(0.01)	(0.03)
ESG momentum on returns	0.166*	0.051***	0.216***
	(0.08)	(0.01)	(0.05)

Note. This table reports the results of the bootstrapping procedure for the indirect and total effect between excess returns on ESG momentum variables on a market level. The results for the direct effect were obtained from panel regressions. Table B.1 in the appendix defines all the variables used. Standard errors are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.

APPENDIX B Supporting Tables

Table B.1 General information regarding the main variables

Variable	Definition	Periodicity	Number of observations
Environmental Momentum	Year-on-year absolute change in the Environmental score of a firm with a one-year lag.	Yearly	30469
Social Momentum	Year-on-year absolute change in the Social score of a firm with a one-year lag.	Yearly	38652
Governance Momentum	Year-on-year absolute change in the Governance score of a firm with a one-year lag.	Yearly	38652
ESG Momentum	Year-on-year absolute change in the ESG score of a firm with a one-year lag.	Yearly	38652
Institutional Ownership	Total shares owned by institutional investors divided by common shares outstanding	Quarterly	174257
Market Value ($ billion)	Quarter-end share price multiplied by the number of common shares outstanding. Also includes non-trading securities	Quarterly	174257
Common Shares Outstanding (million)	Total number of common shares outstanding excluding treasury shares	Quarterly	174257
Common/Ordinary Equity ($ billion)	Sum of Common/Ordinary stock, capital share premium reserve, retained earnings less treasury stock	Quarterly	174257
Total Assets ($ billion)	Includes current assets plus net PPE plus other tangible assets	Quarterly	174257
Tobin's Q	Market value of equity plus preferred stock equity plus total debt divided by book value of total assets	Quarterly	174257
Excess Return	logarithmic return of quarterly close prices	Quarterly	166315

4-Quarter Return Volatility	less logarithmic return of 3-month US treasury bill standard deviation of logarithmic forward returns calculated with 4-step rolling windows	Every 4 quarters	144412

Table B.2 Number of Observations for Industries Grouped by Super Sectors

Super Sector	Industry	Number of Observations
Cyclical	Basic Materials	14029
Cyclical	Consumer Cyclical	27866
Cyclical	Financial Services	27402
Cyclical	Real Estate	1865
Defensive	Consumer Defensive	11590
Defensive	Healthcare	18820
Defensive	Utilities	9586
Sensitive	Communication Services	3640
Sensitive	Energy	10363
Sensitive	Industrials	31130
Sensitive	Information Technology	17966

APPENDIX C Supporting Figures

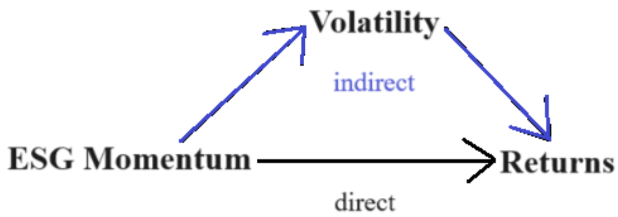

Figure C.1 Triangular relationship between ESG momentum, volatility and returns