Do High ESG Ratings Mitigate Volatility and Tail Risk? Evidence from Canadian and U.S. Equity Markets

by

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We acknowledge and respect the Lekwungen (Songhees and Esquimalt) Peoples on whose territory the university stands, and the Lekwungen and WSANEC Peoples whose historical relationships with the land continue to this day.

Abstract

This essay examines the relationship between environmental, social, and governance (ESG) performance and financial risk in Canadian and U.S. equity markets. Using firm-level ESG data from Refinitiv Workspace, firms are classified into High and Low ESG portfolios based on the ESG Combined Score. Daily stock returns from January 2020 to December 2025 are used to construct equal-weighted portfolio returns, and volatility dynamics are estimated using GARCH-family models, including GARCH, EGARCH, and GJR-GARCH specifications. Conditional volatility, Value-at-Risk, and Expected Shortfall are used to evaluate downside financial risk. The results reveal a significant cross-country contrast. In Canada, High ESG portfolios exhibit higher volatility and greater downside risk than Low ESG portfolios, although sector-neutral sorting reduces part of this difference. In contrast, U.S. High ESG portfolios consistently exhibit lower volatility and lower downside risk, even after controlling for sector composition. These findings suggest that the relationship between ESG performance and financial risk is not uniform across markets and may depend on market structure, diversification, and industry composition.

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1 Introduction

In recent years, environmental, social, and governance (ESG) considerations have become an increasingly prominent component of financial decision-making (Albuquerque et al., 2020; Lins et al., 2017; Broadstock et al., 2021). Institutional investors, asset managers, and regulators have shown growing interest in whether firms with stronger ESG performance exhibit different financial characteristics compared with firms with weaker ESG performance (Oikonomou et al., 2012; Bouslah et al., 2018). One of the most debated questions in this literature concerns risk: do firms with higher ESG ratings exhibit lower volatility and downside risk, or do ESG characteristics simply reflect other firm attributes without materially affecting risk dynamics (Albuquerque et al., 2020; Sassen et al., 2016).

From a theoretical perspective, there are several channels through which ESG performance may influence risk. Firms with strong ESG practices may benefit from improved stakeholder relations, stronger governance structures, and lower regulatory or reputational risk (Godfrey et al., 2009; Lins et al., 2017). These mechanisms could translate into more stable cash flows and lower exposure to extreme negative events. At the same time, ESG characteristics may be correlated with firm size, industry composition, or growth opportunities, which complicates the interpretation of any observed relationship between ESG ratings and financial risk (Oikonomou et al., 2012; Bouslah et al., 2018). This creates an identification challenge, as observed differences in risk may reflect underlying firm characteristics rather than ESG performance itself. As a result, empirical evidence on the link between ESG performance and risk remains mixed.

Most of the existing literature has examined the relationship between ESG characteristics and firm performance using either firm-level regressions or comparisons between ESG-oriented investment products and traditional market indices (Albuquerque et al., 2020; Broadstock et al., 2021). While these approaches provide useful insights, they often obscure the underlying heterogeneity across firms and across markets (Oikonomou et al., 2012). In particular, index-level comparisons may mask important differences within the cross-section of firms, while firm-level analyses frequently focus on a single country or market environment. As a result, prior work tends to overlook cross-country comparisons conducted under a consistent empirical framework, as well as the joint analysis of volatility and downside tail risk and the role of sector composition in shaping ESG–risk relationships.

This essay provides new evidence on whether firms with higher ESG ratings exhibit different volatility and downside tail risk compared with firms with lower ESG ratings. The analysis focuses on two equity markets with distinct institutional and economic environments: Canada and the United States. This comparison is informative because the Canadian market is more concentrated in resource-based sectors such as energy and materials, whereas the U.S. market is more diversified across industries. These structural differences provide a useful setting to examine whether the relationship between ESG performance and financial risk is stable across markets or instead varies with market structure and sector composition.

The empirical analysis is based on firm-level ESG scores obtained from Refinitiv Workspace. Firms are classified into High and Low ESG portfolios based on the top and bottom quartiles of the ESG Combined Score distribution using a single ESG snapshot. Daily stock price data are then used to calculate log returns for each firm, and portfolio returns are constructed as equal-weighted averages of the daily returns of the firms belonging to each ESG group. The dataset covers the period from January 2020 to December 2025 and includes 111 publicly traded firms in Canada and 1,108 firms in the United States. The larger cross-section of firms in the U.S. market allows for greater diversification and more precise estimation of portfolio-level risk measures, while the smaller Canadian sample reflects the more concentrated structure of that market. These differences are important when interpreting the empirical results.

To model volatility dynamics and measure downside risk, the analysis employs several models from the GARCH family, including the standard GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) specifications. These models are widely used in the financial econometrics literature because they capture key features of financial return series, such as volatility clustering, persistence, and asymmetric responses to positive and negative shocks (Bollerslev, 1986; Nelson, 1991; Glosten et al., 1993). Model selection is based on the Bayesian Information Criterion (BIC), which is preferred for its stronger penalty on model complexity and its ability to select parsimonious specifications. Allowing for asymmetric volatility dynamics and heavy-tailed innovation distributions is particularly important in this context, as ESG-related differences may become more pronounced during periods of market stress (Engle, 1982; Fama and French, 1993, 2015).

The estimated volatility processes are then used to compute two commonly used measures of downside risk: Value-at-Risk (VaR) and Expected Shortfall (ES). These measures are especially relevant for investors concerned with exposure to extreme negative returns, such as market crashes or periods of financial stress. In the context of ESG investing, tail risk is of particular interest because ESG-oriented firms are often argued to provide downside protection and greater resilience during adverse market conditions (Lins et al., 2017; Ding et al., 2021). Comparing VaR and ES across ESG portfolios therefore allows for a direct assessment of whether higher ESG scores are associated with reduced exposure to extreme losses.

The results reveal a notable contrast between the Canadian and U.S. equity markets. In Canada, the High ESG portfolio exhibits higher conditional volatility and more severe downside risk compared with the Low ESG portfolio, although sector-neutral sorting reduces part of this difference. In contrast, the U.S. results indicate that firms with higher ESG scores experience lower volatility and reduced tail risk, and this relationship remains robust after controlling for sector composition. These findings indicate that the relationship between ESG performance and financial risk is not uniform across markets. While higher ESG scores are associated with greater volatility in the Canadian sample, they correspond to lower volatility and lower downside risk in the U.S. sample. The sector-neutral robustness analysis further suggests that industry composition explains part of the Canadian result but does not fully account for the pattern observed in the United States.

The contribution of this essay is fourfold. First, it provides firm-level evidence on ESG and financial risk using portfolios constructed from ESG-based sorting. Second, it jointly examines conditional volatility and downside tail risk, offering a more comprehensive view of risk than studies focusing on volatility alone. Third, it introduces a cross-country comparison between Canada and the United States under a consistent empirical framework. Finally, it incorporates a sector-neutral robustness analysis to distinguish ESG effects from industry composition. These elements provide a coherent framework for evaluating how ESG performance relates to financial risk across different market environments.

The remainder of the essay proceeds as follows. Section 2 reviews the related literature on ESG performance, financial risk, and sustainability investing. Section 3 describes the data sources and sample construction. Section 4 presents the econometric methodology used to model volatility and tail risk. Section 5 reports the empirical results for both Canada and the United States, including the sector-neutral robustness analysis. Section 6 discusses the broader interpretation of the findings, and Section 7 concludes.

2 Related Literature

The growing interest in environmental, social, and governance (ESG) considerations in financial markets has generated a substantial body of academic research examining whether firms with stronger ESG performance differ systematically from other firms in terms of financial outcomes. While early studies focused primarily on the relationship between ESG performance and firm profitability, more recent work has increasingly explored whether ESG characteristics influence financial risk. This shift reflects the growing importance of risk management considerations for institutional investors and policymakers. This section reviews the main strands of literature relevant to the relationship between ESG performance and firm risk, including studies that examine stock return volatility and downside tail risk.

2.1 ESG and Firm Risk

A central argument in the ESG literature is that firms with stronger sustainability practices may experience lower exposure to various forms of risk. Godfrey et al. (2009) suggest that corporate social responsibility activities can create what they describe as a form of "moral capital," which may provide firms with a degree of protection during periods of negative events or reputational shocks. From this perspective, strong ESG practices can reduce the likelihood or severity of adverse outcomes by improving relationships with stakeholders such as customers, regulators, and employees (Lins et al., 2017). This mechanism implies that ESG performance may act as an informal risk management tool, particularly during periods of uncertainty.

At the same time, an alternative view emphasizes that ESG-related investments may reflect agency problems, costly signaling, or the allocation of resources toward non-core activities, potentially weakening profitability or complicating the interpretation of risk outcomes (Barnea and Rubin, 2010; Krüger, 2015; Cheng et al., 2014; Servaes and Tamayo, 2013). Under this perspective, ESG expenditures may not necessarily reduce risk and could instead introduce inefficiencies or distort firm behavior. This competing view highlights that ESG activities are not always aligned with shareholder value maximization.

Oikonomou et al. (2012) provide empirical evidence supporting the risk-reduction view by examining the relationship between corporate social performance and firm risk using measures such as idiosyncratic volatility and exposure to systematic risk factors in U.S. equity markets. Their findings indicate that firms with stronger social performance tend to exhibit lower firm-level risk. However, their approach differs from the present essay, which focuses on portfolio-level conditional volatility and tail risk measures derived from GARCH-family models rather than firm-level regression-based risk metrics. As a result, their findings are not directly comparable to time-series volatility estimates.

Similarly, Bouslah et al. (2018) examine the relationship between corporate social responsibility and stock return risk. Using firm-level data from U.S. markets, they find that firms with stronger CSR profiles tend to experience lower total risk and lower systematic risk. Their results are consistent with the idea that ESG-related activities can mitigate certain forms of financial risk by improving corporate governance and strengthening stakeholder relationships. This evidence further supports the argument that ESG performance may influence both firm-specific and market-related risk components.

Despite these findings, the relationship between ESG performance and financial risk is not universally agreed upon. Differences across studies may arise from several factors, including variation in ESG rating methodologies, differences in country-specific institutional environments, sector composition effects, and whether the analysis focuses on crisis or non-crisis periods. In addition, studies employ different measures of risk, ranging from firm-level volatility and factor exposures to downside risk and crash risk metrics, which further contributes to mixed empirical evidence. These differences highlight the importance of carefully specifying both the empirical framework and the definition of risk.

A growing strand of recent literature further emphasizes that the ESG–risk relationship may depend critically on firm characteristics and institutional context. For example, Servaes and Tamayo (2013) show that the value of corporate social responsibility is contingent on customer awareness, suggesting that ESG activities may only translate into lower risk when stakeholders actively respond to such initiatives. Similarly, El Ghoul et al. (2011) find that firms with better social performance enjoy a lower cost of equity capital, which can be interpreted as a reduction in perceived risk by investors. These findings suggest that ESG effects are mediated through market perceptions and investor behavior.

At the same time, Krüger (2015) provide evidence that investors may react negatively to certain ESG-related news, particularly when such initiatives are perceived as value-destroying or driven by managerial self-interest. This highlights the possibility that ESG activities may introduce agency conflicts rather than mitigate risk. These findings reinforce the view that the ESG–risk relationship is complex and may vary depending on firm-level incentives, investor perceptions, and the broader institutional environment.

2.2 ESG and Stock Return Volatility

A closely related strand of literature examines whether ESG characteristics are associated with differences in stock return volatility. Volatility is a central measure of financial risk and plays a key role in both portfolio management and asset pricing. Albuquerque et al. (2020) provide evidence that firms with stronger ESG performance may exhibit lower stock return volatility. Using firm-level ESG ratings and stock return data, they show that high-ESG firms tend to have more stable returns and lower downside risk, particularly during periods of market stress. The authors argue that this relationship may arise because ESG-oriented firms attract a more stable investor base and may be less exposed to regulatory or reputational risks. This interpretation is consistent with the view that ESG performance enhances firm resilience.

Further evidence is provided by Broadstock et al. (2021), who examine ESG performance and financial resilience during the COVID-19 pandemic. Their results suggest that firms with higher ESG scores demonstrated stronger stock price resilience during the crisis, experiencing smaller declines and lower volatility relative to firms with weaker ESG profiles. Similar findings are reported by Ding et al. (2021), who show that firms with stronger pre-crisis characteristics, including ESG-related dimensions, exhibited greater resilience during the COVID-19 shock. These crisis-period results highlight the potential importance of ESG during extreme market conditions.

However, the evidence (Eccles et al., 2014; Khan et al., 2016; Friede et al., 2015) on ESG and volatility is not uniformly supportive of a risk-reduction effect. Some studies find weak or insignificant relationships, while others document that ESG effects depend on market conditions or firm characteristics (Krüger, 2015; Barnea and Rubin, 2010). Moreover, most studies in this area focus on single-country samples or rely on aggregate ESG indices, which may obscure cross-sectional variation within markets. This raises the possibility that differences in sector composition or firm characteristics may play an important role in shaping observed ESG–volatility relationships.

Beyond crisis-period evidence, several studies have examined the ESG–volatility relationship over longer horizons and across different markets. Eccles et al. (2014) document that firms with strong sustainability performance exhibit more stable operating and stock market performance over time. Similarly, Khan et al. (2016) show that firms that perform well on financially material ESG issues tend to experience lower volatility and improved risk-adjusted returns. These findings suggest that the relevance of ESG may depend on the materiality of specific sustainability factors.

However, other studies suggest that the relationship between ESG and volatility is not uniform. Ang et al. (2006) and Campbell et al. (2001) emphasize that firm-level volatility is influenced by a range of structural factors, including firm size, growth opportunities, and sector exposure, which may also be correlated with ESG characteristics. In addition, meta-analyses such as Friede et al. (2015) conclude that while the majority of studies find a non-negative or positive relationship between ESG and financial performance, the magnitude and direction of the effect vary substantially across samples and methodologies. These findings suggest that ESG-related differences in volatility may be context-dependent and sensitive to both market conditions and empirical design.

2.3 ESG and Downside Tail Risk

In addition to volatility, several studies have examined the relationship between ESG performance and downside tail risk. Tail risk refers to the probability and magnitude of extreme negative outcomes in financial returns and is often measured using metrics such as Value-at-Risk (VaR) or Expected Shortfall (ES). These measures are particularly relevant in the ESG context because investors are often concerned with downside protection and resilience during periods of market stress. Sassen et al. (2016) analyze the relationship between corporate sustainability and firm risk using international firm-level data and regression-based measures of risk exposure. Their results suggest that stronger sustainability performance is associated with lower firm risk and a reduced likelihood of extreme negative returns. However, their approach differs from the present essay in that it focuses on firm-level risk indicators rather than portfolio-level tail risk measures derived from time-series volatility models.

Similarly, Bouslah et al. (2018) find that corporate social responsibility performance is negatively associated with measures of crash risk. Their results indicate that firms with stronger ESG profiles may be less prone to extreme negative stock price movements. Additional evidence on downside protection is provided by Lins et al. (2017) and El Ghoul et al. (2011), who show that firms with stronger stakeholder relationships and social performance tend to experience lower downside risk and better resilience during periods of financial stress (Lins et al., 2017; El Ghoul et al., 2011). These findings reinforce the idea that ESG performance may be particularly relevant in adverse market conditions. These findings highlight the importance of examining risk beyond traditional volatility measures. While volatility captures the overall variability of returns, it does not fully reflect the likelihood of extreme losses. For this reason, the present essay jointly examines conditional volatility, Value-at-Risk, and Expected Shortfall in a unified framework. This approach allows for a more comprehensive assessment of ESG-related risk differences.

Recent research has increasingly emphasized the importance of tail-risk measures in understanding the financial implications of ESG performance. Pástor et al. (2021) develop a theoretical framework in which ESG preferences can affect asset prices and risk exposures, particularly in states of the world associated with negative shocks. Their results suggest that ESG characteristics may influence how firms are priced under adverse conditions, thereby affecting tail-risk outcomes. Empirical studies also highlight that ESG-related resilience may be more pronounced during extreme market downturns rather than in normal periods. For example, Ding et al. (2021) show that firms with stronger pre-crisis characteristics experienced smaller declines during the COVID-19 shock. These findings support the idea that ESG performance may play a particularly important role in mitigating extreme downside risk.

2.4 Contribution of This Essay

Although the literature provides important insights into the relationship between ESG performance and financial risk, several gaps remain. First, much of the existing research focuses on a single country or market, making it difficult to determine whether the ESG–risk relationship is consistent across different institutional and economic environments. Second, many studies examine either volatility or firm risk measures but do not explicitly analyze downside tail risk using metrics such as Value-at-Risk or Expected Shortfall. Third, provider-specific ESG sorting and cross-sectional portfolio-based evidence remain relatively underexplored.

This essay contributes to the literature by addressing these limitations through a unified empirical framework. By constructing portfolios based on firm-level ESG scores obtained from Refinitiv, the analysis directly examines cross-sectional differences in risk between high- and low-ESG firms, rather than relying on aggregate index comparisons. The use of GARCH-family models allows for modeling time-varying volatility and asymmetric responses to shocks, addressing limitations in studies that rely on static approaches.

In addition, the joint estimation of volatility, Value-at-Risk, and Expected Shortfall provides a more comprehensive assessment of financial risk, particularly with respect to extreme downside outcomes. Furthermore, the incorporation of sector-neutral portfolio construction allows the analysis to distinguish ESG effects from industry composition. These elements provide a more integrated and robust perspective on the relationship between ESG performance and financial risk across different market environments.

3 Data

This essay combines firm-level ESG information with daily stock price data to analyze the relationship between ESG performance and financial risk. The dataset is constructed using information obtained from Refinitiv Workspace and covers publicly traded firms in Canada and the United States over the period from January 2020 to December 2025. This time span includes both periods of market stability and episodes of elevated volatility, allowing for a comprehensive analysis of risk dynamics. The ESG data are not time-varying over the sample period. Instead, firms are classified into ESG groups based on a single ESG Combined Score snapshot retrieved in February 2026, and these ex-post classifications are linked to the full return sample. This approach ensures consistency in portfolio construction while avoiding issues related to incomplete historical ESG data.

The dataset is constructed using a two-stage process that combines a cross-sectional ESG classification with a high-frequency panel of daily stock returns. The ESG data are obtained as a single snapshot from Refinitiv Workspace in February 2026, while the return data span the period from January 2020 to December 2025. This structure implies that firms are classified ex-post based on their observed ESG standing and then tracked backward over the full return sample. As a result, the analysis should be interpreted as a comparison of historical risk characteristics across firms grouped by ESG quality, rather than a predictive exercise based on time-varying ESG information. This distinction is important for interpreting the empirical results.

3.1 ESG Data

Firm-level ESG information is obtained from Refinitiv Workspace. The primary variable used in the analysis is the ESG Combined Score, which aggregates a firm's environmental, social, and governance performance into a single indicator. The ESG Combined Score reflects both the firm's reported ESG performance and adjustments related to ESG controversies, providing a comprehensive measure of sustainability performance. In addition to the ESG score, several firm identifiers and classification variables are collected from Refinitiv. These include the Refinitiv Instrument Code (RIC), company name, market capitalization, and industry classifications based on the Thomson Reuters Business Classification (TRBC) system. The TRBC classification provides both sector-level and industry-level identifiers, which are later used to implement sector-neutral portfolio construction as a robustness test. These classifications are particularly important for isolating ESG effects from industry-specific risk patterns.

For the Canadian sample, the dataset contains ESG information for 111 firms listed on Canadian equity exchanges, primarily the Toronto Stock Exchange (TSX) and the TSX Venture Exchange (TSXV). For the United States, the ESG dataset includes 1,108 firms listed on U.S. equity exchanges. This substantial difference in sample size reflects the broader and more diversified nature of the U.S. equity market. The difference in sample size has important implications for the analysis. The larger number of firms in the U.S. sample allows for greater diversification within ESG portfolios and reduces sensitivity to firm-specific shocks. In contrast, the smaller Canadian sample implies that ESG portfolios may be more exposed to sector concentration and idiosyncratic variation, which can affect both volatility estimates and tail-risk measures. These differences should be taken into account when interpreting cross-country results.

To ensure data consistency, observations with missing ESG scores or invalid firm identifiers are removed. Each firm is represented by a unique RIC identifier, allowing the ESG data to be merged with the corresponding price data. This matching procedure ensures that ESG characteristics are consistently linked to financial return series. The use of the Refinitiv ESG Combined Score introduces several important features. First, the inclusion of an ESG controversies overlay implies that firms with negative events or reputational issues may receive lower scores even if their underlying ESG disclosures are relatively strong. Second, because the score is based on a single snapshot (FY0), it does not capture time variation in ESG performance. While this simplifies portfolio construction and avoids issues related to missing historical ESG data, it also implies that any changes in ESG quality over time are not reflected in the analysis. This represents a trade-off between data availability and dynamic accuracy. The application of a market capitalization filter greater than USD 5 billion further shapes the sample by focusing on large and relatively liquid firms. This threshold is used as a practical screening rule rather than as a universal cutoff in the literature. The purpose is to exclude very small and thinly traded firms, for which ESG coverage, price histories, and daily return observations may be less reliable or more affected by idiosyncratic noise. Since the analysis relies on daily returns, GARCH-family volatility models, and downside tail-risk measures, including firms with limited liquidity or irregular trading could introduce distortions into the estimated volatility and VaR/ES measures. A large-cap filter also improves comparability between the Canadian and U.S. samples by focusing on firms that are more likely to have consistent Refinitiv ESG coverage and economically meaningful market participation. At the same time, this choice narrows the scope of the analysis. The results should therefore be interpreted as applying primarily to large, publicly traded firms rather than to the full universe of listed companies. Smaller firms may have different ESG disclosure practices, liquidity conditions, volatility dynamics, and risk profiles, so the findings may not generalize directly to that segment of the market.

3.2 Stock Price Data

Daily stock price data are obtained from Refinitiv Workspace. For each firm in the sample, the variable `TR.PriceClose` is used to collect daily closing prices over the period from January 1, 2020 to December 31, 2025. The use of a consistent price variable ensures comparability across firms and markets. The analysis uses raw closing prices obtained from Refinitiv (TR.PriceClose), which are not adjusted for corporate actions such as dividends or stock splits. As a result, discrete price changes associated with events such as ex-dividend dates may be reflected in the return series. While this introduces minor distortions, it is unlikely to materially affect volatility estimation at the daily frequency.

Daily returns are computed as logarithmic returns based on consecutive closing prices. The use of unadjusted prices is standard in high-frequency financial econometrics, particularly in studies focusing on modeling conditional volatility and tail risk using GARCH-type models. At the daily frequency, the impact of dividend adjustments on volatility estimates is generally limited and is unlikely to materially affect the analysis. This justifies the use of raw prices in the present context. The closing price series are matched with the ESG dataset using the RIC identifier. Observations with missing prices, invalid dates, or non-positive price values are excluded to ensure the reliability of the return calculations. These filtering steps are necessary to avoid distortions in volatility estimation.

When daily prices are missing for a given firm, that firm is excluded from the portfolio return calculation on that specific date rather than being carried forward. As a result, the composition of each portfolio varies slightly across trading days. However, firms are not excluded entirely unless they lack sufficient price data to compute returns. This approach minimizes data loss while maintaining accuracy. After merging the ESG and price datasets, the effective sample includes firms with valid ESG scores and available daily price histories over the sample period. A small number of firms are lost during the merge due to missing or incomplete price histories. This reduction is limited and does not materially affect the overall sample structure.

An additional consideration concerns the structure of the U.S. price dataset. Due to the large number of firms, the data were retrieved in multiple batches and subsequently consolidated into a single panel in R. While this multi-step process does not affect the underlying data, it highlights the practical challenges associated with working with large cross-sectional datasets in Refinitiv Workspace. The use of raw closing prices rather than adjusted prices is consistent with much of the financial econometrics literature on high-frequency return dynamics. Because the analysis relies on daily log returns and models conditional volatility rather than long-term investment performance, the absence of dividend and split adjustments is unlikely to materially affect the main results. Nevertheless, this remains a potential limitation when interpreting the economic magnitude of returns.

3.3 Return Construction

Daily stock returns are calculated using logarithmic returns based on consecutive closing prices. For firm i on day t, the return is computed as

$$r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right), \quad (1)$$

where $P_{i,t}$ denotes the closing price of firm i on day t. Logarithmic returns are used because they are time-additive and facilitate aggregation across time and firms.

Firms are sorted into ESG groups based on the ESG Combined Score snapshot retrieved in February 2026. This sorting is fixed over time, meaning that firms remain in the same ESG group throughout the sample period. Based on a quartile-based sorting procedure, firms are classified into High ESG (top 25%) and Low ESG (bottom 25%) groups. This approach emphasizes cross-sectional differences in ESG quality. Daily portfolio returns are constructed as equal-weighted averages of the returns of all firms within each ESG group. Equal weighting is used to ensure that each firm contributes equally to the portfolio return, allowing the analysis to focus on cross-sectional differences in ESG characteristics rather than being dominated by large-cap firms. This approach is widely used in empirical asset pricing when the objective is to isolate firm-level effects. As a robustness consideration, value-weighted portfolios can also be constructed, where firms are weighted by market capitalization. These results are reported in the Appendix. Comparing equal-weighted and value-weighted results provides insight into the role of firm size. Because firm-level price data may occasionally be missing, the number of firms included in each portfolio varies slightly across trading days. However, the average portfolio size remains stable over time, ensuring consistency in the estimation of risk measures.

The choice of equal-weighted portfolio construction plays an important role in the interpretation of the results. By assigning equal weight to each firm, the analysis emphasizes cross-sectional differences in ESG characteristics rather than allowing large-cap firms to dominate the portfolio. This is particularly relevant given that ESG scores may be correlated with firm size. However, equal-weighted portfolios may also place relatively greater emphasis on smaller firms within the large-cap universe, which could influence the observed risk dynamics. To address this concern, alternative value-weighted portfolio constructions are considered as a robustness check and reported in the Appendix. Comparing equal-weighted and value-weighted results provides additional insight into whether the ESG–risk relationship is driven by firm size or reflects broader cross-sectional patterns.

Equal-weighted portfolio construction is also used in recent ESG portfolio-sorting research. For example, Horn and Oehler (2024) construct stock portfolios by sorting firms on ESG ratings from multiple rating providers and compare portfolio outcomes using equally weighted returns, market-cap-weighted returns, and minimum-variance weights. Their approach illustrates that equal-weighted ESG portfolios are useful when the objective is to examine cross-sectional differences across ESG rating groups without allowing the largest firms to dominate portfolio returns. This supports the use of equal-weighted High and Low ESG portfolios in the present essay, where the goal is to compare risk characteristics associated with ESG quality rather than construct a market-cap-weighted ESG index.

Equal-weighted portfolios are also widely used in empirical asset-pricing studies based on firm-characteristic sorting. Fama and French (1992), for example, sort firms into portfolios using characteristics such as size and book-to-market equity and compute equal-weighted portfolio returns. This approach gives each firm within a sorted group the same influence and is useful when the research objective is to examine cross-sectional differences associated with firm characteristics. In the present essay, the same intuition applies: equal-weighted ESG portfolios emphasize differences between High and Low ESG firms rather than allowing portfolio risk measures to be driven primarily by the largest firms.

3.4 Portfolio Characteristics

Applying the quartile-based ESG sorting procedure results in approximately 28 firms in each ESG portfolio for the Canadian sample. In the U.S. sample, the larger cross-section of firms leads to substantially larger portfolios, with roughly 250–275 firms per ESG group depending on data availability across trading days. The larger number of firms in the U.S. sample provides greater diversification within ESG portfolios, reducing the impact of firm-specific shocks and improving the precision of estimated risk measures. In contrast, the smaller Canadian universe implies that ESG portfolios may be more exposed to sector concentration and idiosyncratic shocks, particularly given the relatively large weight of resource-based industries in the Canadian market. This difference plays a key role in explaining cross-country variation in the results.

To further illustrate portfolio composition, summary statistics such as average ESG scores, market capitalization, sector weights, and average returns can be reported. These characteristics provide additional context for interpreting differences in volatility and downside risk across ESG portfolios and help link empirical findings to underlying economic structure. These features highlight the importance of sample construction in shaping the empirical results. Differences in the number of firms, sector composition, and data availability across markets may influence both volatility estimates and tail-risk measures. In particular, the relatively small number of firms in the Canadian sample implies that portfolio-level results may be more sensitive to individual firm behavior and sector-specific shocks, whereas the larger U.S. sample allows for greater diversification and more stable risk estimates. These considerations are important when interpreting cross-country differences in the ESG–risk relationship.

Table 1: Summary Statistics for Canadian High- and Low-ESG Portfolios

Portfolio	Mean Return	Std. Dev.	Min Return	Max Return	Skewness	Kurtosis	Avg. ESG	Firms	Obs.
High ESG	0.00067	0.01409	-0.13962	0.11076	-1.339	19.282	73.10	28	1503
Low ESG	0.00054	0.01222	-0.14363	0.12201	-1.552	35.010	33.86	28	1503

Notes: This table reports summary statistics for the Canadian High- and Low-ESG portfolios. Firms are sorted into High ESG and Low ESG groups based on the top and bottom quartiles of the Refinitiv ESG Combined Score. Portfolio returns are daily equal-weighted log returns over the January 2020–December 2025 sample period. Skewness and kurtosis are computed from the daily portfolio return series.

Table 1 reports summary statistics for the Canadian High- and Low-ESG portfolios. The portfolio construction produces a clear separation in ESG characteristics, with the High ESG portfolio having an average ESG Combined Score of 73.10 compared with 33.86 for the Low ESG portfolio. Both portfolios contain 28 firms and 1,503 daily portfolio return observations, which makes the return comparison balanced across ESG groups. The High ESG portfolio has a slightly higher average daily return, 0.00067 compared with 0.00054 for the Low ESG portfolio. However, it also has a higher standard deviation, 0.01409 compared with 0.01222, suggesting that the Canadian High ESG portfolio exhibits greater unconditional return volatility over the sample period. Both portfolios display negative skewness and high kurtosis, indicating left-tailed and fat-tailed return distributions. These features are consistent with the use of GARCH-family models and downside risk measures such as VaR and Expected Shortfall in the subsequent empirical analysis.

Table 2: Summary Statistics for U.S. High- and Low-ESG Portfolios

Portfolio	Mean	SD	Min	Max	Skew.	Kurt.	ESG	Firms	Obs.
High ESG	0.00033	0.01516	-0.15201	0.10853	-1.091	19.198	70.20	277	1507
Low ESG	0.00045	0.01675	-0.14124	0.10172	-0.850	12.879	27.20	277	1507

Notes: Mean, standard deviation, minimum, maximum, skewness, and kurtosis are computed from daily equal-weighted log portfolio returns. Firms are sorted into High ESG and Low ESG groups based on the top and bottom quartiles of the Refinitiv ESG Combined Score. The sample covers January 2020–December 2025.

Table 2 reports summary statistics for the U.S. High- and Low-ESG portfolios. The portfolio construction generates a clear separation in ESG characteristics, with the High ESG portfolio having an average ESG Combined Score of 70.20 compared with 27.20 for the Low ESG portfolio. Both portfolios contain 277 firms and 1,507 daily portfolio return observations, providing a balanced comparison across ESG groups. The Low ESG portfolio has a slightly higher average daily return, 0.00045 compared with 0.00033 for the High ESG portfolio. However, the Low ESG portfolio also has a higher standard deviation, 0.01675 compared with 0.01516, suggesting that it exhibits greater unconditional return volatility over the sample period. Both portfolios display negative skewness and excess kurtosis, indicating left-tailed and fat-tailed return distributions. These distributional features support the use of GARCH-family models and downside risk measures such as VaR and Expected Shortfall in the subsequent empirical analysis. The summary statistics provide preliminary evidence that, in the U.S. sample, the High ESG portfolio is associated with lower unconditional volatility than the Low ESG portfolio, which is consistent with the later conditional volatility and tail-risk results.

4 Methodology

This section describes the empirical methodology used to analyze the relationship between ESG performance and financial risk. The analysis proceeds in three main steps. First, firms are sorted into ESG-based portfolios using a cross-sectional ranking procedure. Second, the volatility dynamics of these portfolios are modeled using GARCH-family models that allow for time-varying, asymmetric, and heavy-tailed return distributions. Third, the estimated conditional distributions are used to compute measures of downside tail risk, including Value-at-Risk (VaR) and Expected Shortfall (ES). In addition, a sector-neutral portfolio construction procedure is implemented as a robustness test to distinguish ESG-related effects from differences driven by industry composition. These steps provide a comprehensive framework for evaluating both the volatility and tail-risk implications of ESG performance. This structure allows the analysis to move from simple cross-sectional sorting to more advanced time-series modeling of risk dynamics.

The empirical framework follows standard approaches in financial econometrics. The construction of log returns and portfolio aggregation is consistent with Campbell et al. (1997). The volatility modeling framework is based on GARCH-family models developed by Engle (1982), Bollerslev (1986), Nelson (1991), and Glosten et al. (1993). The downside risk measures, including Value-at-Risk and Expected Shortfall, follow the standard definitions presented in McNeil et al. (2015).

4.1 ESG Portfolio Construction

To examine whether firms with stronger ESG performance exhibit different risk characteristics, firms are sorted according to their ESG Combined Scores obtained from Refinitiv. The ESG ranking is based on a single cross-sectional snapshot retrieved in February 2026. This implies that firms are sorted once, and portfolio membership remains fixed throughout the sample period. The analysis therefore compares the historical return dynamics of firms classified ex-post as having high or low ESG performance, rather than tracking changes in ESG ratings over time.

The sorting procedure follows a quartile-based approach commonly used in empirical asset pricing studies. ESG score cutoffs are computed separately within each country using the cross-sectional distribution of ESG scores. Firms with ESG scores below the 25th percentile are classified as Low ESG, while firms above the 75th percentile are classified as High ESG. The remaining firms are assigned to a middle group. Firms in the middle 50 percent of the ESG distribution are excluded from the analysis in order to sharpen the contrast between firms with relatively strong and relatively weak ESG performance. While this exclusion reduces the sample size—particularly in the Canadian sample—it enhances the ability to detect differences in risk characteristics between the two extreme groups. This trade-off between sample size and cross-sectional contrast is standard in portfolio-sorting studies and helps isolate the effect of ESG quality.

The quartile-based approach is retained for both Canada and the United States in order to maintain methodological consistency across markets and ensure comparability of the resulting ESG portfolios. Although the Canadian sample is substantially smaller, using broader classifications such as median splits would reduce the distinction between High and Low ESG firms by including firms with more moderate ESG characteristics. The quartile-based design instead focuses on firms at the tails of the ESG distribution, where differences in sustainability performance are more economically meaningful. This is particularly important given the objective of the essay, which is to examine whether firms with relatively strong ESG characteristics exhibit different volatility and downside risk profiles compared with firms with relatively weak ESG characteristics. While the smaller Canadian sample results in portfolios containing fewer firms, the use of extreme-group sorting helps strengthen the cross-sectional

ESG contrast and improves the interpretability of the risk comparisons.

After the ESG sorting procedure is applied, daily portfolio returns are constructed using equal-weighted averages of firm-level returns. For each trading day t, the portfolio return for a given ESG group is calculated as

$$R_t = \frac{1}{N_t} \sum_{i=1}^{N_t} r_{i,t}, \tag{2}$$

where R_t denotes the portfolio return on day t, $r_{i,t}$ is the daily log return of firm i, and N_t represents the number of firms included in the portfolio on that day. This formulation implies that each firm contributes equally to the portfolio return, regardless of its size, which allows the analysis to focus on cross-sectional ESG differences rather than firm scale.

Equal weighting is used to ensure that each firm contributes equally to the portfolio return, allowing the analysis to focus on cross-sectional ESG effects rather than being dominated by large-cap firms. This is particularly relevant given that ESG scores may be correlated with firm size. As a robustness check, value-weighted portfolios—where firms are weighted by market capitalization—can be constructed and are reported in the Appendix. Comparing the two weighting schemes helps assess whether the results are driven by large firms or reflect broader patterns across the cross-section. Because firm-level price data may occasionally be missing, the number of firms included in each portfolio varies slightly across trading days. However, the average portfolio size remains stable over time, ensuring that the results are not driven by large fluctuations in portfolio composition.

4.2 Volatility Modelling

To analyze the volatility dynamics of the ESG portfolios, this essay employs models from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family. These models are particularly well suited to the portfolio return series used in this essay, as financial returns are known to exhibit volatility clustering, persistence, and asymmetric responses to positive and negative shocks. These features are especially relevant for ESG-sorted portfolios over the 2020–2025 period, which includes episodes of heightened market stress, such as the COVID-19 pandemic and subsequent market adjustments. ESG-related differences may manifest more strongly during such periods, making it important to allow for asymmetric and heavy-tailed volatility dynamics (Campbell et al., 2001; Ang et al., 2006).

The conditional mean of the portfolio return series is specified as

$$r_t = \mu + \varepsilon_t, \tag{3}$$

where r_t denotes the portfolio return at time t, μ is a constant mean return, and ε_t is the innovation term capturing unexpected shocks. This specification assumes that the predictable component of returns remains relatively stable over time, while the primary source of time variation arises through the conditional volatility process. The choice of a constant mean specification is motivated by the focus of the analysis, which is on modeling volatility dynamics and downside tail risk rather than short-run return predictability. In many empirical finance applications using daily return data, the conditional mean is typically small relative to the magnitude of volatility fluctuations, and autoregressive patterns in returns are often weak after aggregation at the portfolio level. Preliminary inspection of the ESG portfolio return series also indicated limited serial correlation, suggesting that more complex autoregressive or moving-average structures would contribute little to the overall analysis.

Using a constant mean specification also helps maintain a parsimonious volatility model and reduces the risk of overfitting the mean equation when the primary objective is conditional variance estimation. This approach is common in the GARCH literature, particularly in studies focused on volatility clustering and tail-risk measurement. Nevertheless, the assumption represents a simplification. If portfolio returns exhibit time-varying expected returns or omitted autoregressive structure, the mean equation may not fully capture all predictable return dynamics. While this is unlikely to materially affect the main volatility estimates at the daily frequency, it remains a potential limitation when interpreting the broader dynamics of portfolio returns. Before estimating the GARCH-family models, stationarity of the daily portfolio return series is assessed using Augmented Dickey–Fuller tests. The results, reported in Appendix Table 15, reject the unit-root null for all four portfolios, supporting the use of GARCH-family models on the return series.

The conditional variance of returns is modeled using three alternative GARCH specifications.

Standard GARCH (sGARCH)

The GARCH(1,1) model specifies the conditional variance as

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{4}$$

where σ_t^2 is the conditional variance at time t, ω is a constant term, α measures the short-run impact of past shocks (ARCH effect), and β captures the persistence of volatility (GARCH effect). The term ε_{t-1}^2 represents the squared innovation from the previous period, while σ_{t-1}^2 is the lagged conditional variance. These components allow volatility to evolve over time in response to both recent shocks and past volatility levels. For stationarity, the condition $\alpha + \beta < 1$ must hold, ensuring that volatility does not explode over time.

Exponential GARCH (EGARCH)

The EGARCH(1,1) model allows for asymmetric effects and is specified as

$$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \alpha \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \gamma \left(\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - E \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| \right), \tag{5}$$

where the logarithmic formulation ensures that the variance remains strictly positive. The parameter α captures the magnitude of standardized shocks, while γ measures asymmetry in the volatility response. A non-zero γ indicates that negative and positive shocks have different effects on volatility, which is particularly important in financial markets where negative returns often increase volatility more than positive returns.

GJR-GARCH

The GJR-GARCH model captures leverage effects and is specified as

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta\sigma_{t-1}^2, \tag{6}$$

where $I(\varepsilon_{t-1} < 0)$ is an indicator function equal to one when the lagged shock is negative and zero otherwise. The coefficient γ measures the additional impact of negative shocks on volatility. This specification allows for leverage effects, meaning that negative shocks can increase volatility more strongly than positive shocks of the same magnitude, which is a common feature in equity return data.

Each model is estimated under alternative innovation distributions, including the Student-t and Generalized Error Distribution (GED), to account for the fat-tailed nature of financial returns. These distributions allow for a higher probability of extreme outcomes compared to the normal distribution, which is essential when modeling financial risk. The choice of distribution is determined jointly with the variance specification using the Bayesian Information Criterion (BIC), ensuring a balance between model fit and parsimony. Model adequacy is assessed using information criteria and residual diagnostic checks. In particular, standardized residuals are examined to evaluate whether remaining serial correlation and ARCH effects are sufficiently limited after estimation. Diagnostic test results are reported in Appendix Table 16. The selected models provide a reasonable representation of the underlying return dynamics and capture the key features of financial return volatility, including persistence, asymmetry, and fat tails.

Table 3 reports the selected GARCH-family specification for each ESG portfolio based on the Bayesian Information Criterion. Across all four portfolios, the selected specifications are asymmetric GARCH models with Student-t innovations. For the Canadian High ESG portfolio, the selected model is GJR-GARCH(1,1) with Student-t innovations, while the Canadian Low ESG portfolio is best described by an EGARCH(1,1) model with Student-t innovations. In the U.S. sample, the High ESG portfolio is best fitted by EGARCH(1,1) with Student-t innovations, whereas the Low ESG portfolio is best fitted by GJR-GARCH(1,1) with

Table 3: Selected GARCH-Family Models Based on BIC

Market	Portfolio	Selected Model	Distribution	Log-likelihood	AIC	BIC
Canada	High ESG	GJR-GARCH(1,1)	Student-t	4572.04	-6.07590	-6.05468
Canada	Low ESG	EGARCH(1,1)	Student-t	5021.58	-6.67409	-6.65287
U.S.	High ESG	EGARCH(1,1)	Student-t	4597.06	-6.09298	-6.07181
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	4348.14	-5.76263	-5.74145

Notes: This table reports the selected GARCH-family model for each ESG portfolio based on the Bayesian Information Criterion (BIC). The candidate models include sGARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1), estimated under Normal, Student-t, and GED innovation distributions. Lower BIC values indicate preferred specifications.

Student-t innovations. These results suggest that both volatility asymmetry and non-Gaussian return innovations are important features of the portfolio return series.

Table 4: Comparison of Heavy-Tailed and Normal Innovation Distributions

Market	Portfolio	Distribution Type	Best BIC
Canada	High ESG	Heavy-tailed	-6.05
Canada	High ESG	Normal	-6.02
Canada	Low ESG	Heavy-tailed	-6.65
Canada	Low ESG	Normal	-6.63
U.S.	High ESG	Heavy-tailed	-6.07
U.S.	High ESG	Normal	-6.05
U.S.	Low ESG	Heavy-tailed	-5.74
U.S.	Low ESG	Normal	-5.73

Notes: This table compares the best BIC obtained under Normal innovations with the best BIC obtained under heavy-tailed innovation distributions, including Student-t and GED. Lower BIC values indicate preferred specifications.

Table 4 compares the best BIC obtained under Normal innovations with the best BIC obtained under heavy-tailed innovation distributions. For all four ESG portfolios, the heavy-tailed specifications produce lower BIC values than the Normal specification. This indicates that the Student-t or GED distributions better capture the empirical distribution of portfolio returns than the Gaussian distribution. This result is consistent with the summary statistics reported earlier, where the return series exhibit negative skewness and high kurtosis. In financial terms, the portfolio returns contain more extreme observations than would be expected under Normal innovations, especially during periods of market stress. Therefore, allowing for heavy-tailed innovations is important for estimating conditional volatility and downside risk measures such as Value-at-Risk and Expected Shortfall.

Table 5: Comparison of Symmetric and Asymmetric GARCH Specifications

Market	Portfolio	Model Type	Best BIC
Canada	High ESG	Asymmetric	-6.05
Canada	High ESG	Symmetric	-6.05
Canada	Low ESG	Asymmetric	-6.65
Canada	Low ESG	Symmetric	-6.64
U.S.	High ESG	Asymmetric	-6.07
U.S.	High ESG	Symmetric	-6.05
U.S.	Low ESG	Asymmetric	-5.74
U.S.	Low ESG	Symmetric	-5.72

Notes: Symmetric models refer to sGARCH(1,1), while asymmetric models include EGARCH(1,1) and GJR-GARCH(1,1). For each portfolio, the table reports the lowest BIC within each model class. Lower BIC values indicate preferred specifications.

The results in Table 5 indicate that asymmetric GARCH specifications generally provide a better BIC-adjusted fit than the symmetric sGARCH model. This pattern is especially clear for the Canadian Low ESG portfolio and both U.S. portfolios. For the Canadian High ESG portfolio, the rounded BIC values for symmetric and asymmetric specifications are very close; however, the selected model in Table 3 is still the asymmetric GJR-GARCH(1,1) specification when the full-precision BIC is used. The model-selection results suggest that portfolio volatility responds asymmetrically to return shocks. This is consistent with the financial intuition that negative shocks may have a stronger impact on future volatility than positive shocks of similar magnitude, reflecting leverage effects, risk-aversion responses, and market stress dynamics.

4.3 Downside Risk Measures

After estimating the volatility models, the conditional return distributions are used to compute two measures of downside risk: Value-at-Risk (VaR) and Expected Shortfall (ES). These measures are computed in-sample using the fitted GARCH models and provide complementary information about the lower tail of the return distribution.

Value-at-Risk at the 5 percent level is defined as

$$\mathrm{VaR}_t(5\%) = \mu_t + \sigma_t q_{0.05}, \tag{7}$$

where μ_t is the conditional mean return, σ_t is the conditional standard deviation, and $q_{0.05}$ is the 5 percent quantile of the standardized innovation distribution. VaR represents the threshold such that there is a 5 percent probability that the return will fall below this level on a given day.

Expected Shortfall is defined as

$$\mathrm{ES}_t(5\%) = \mu_t + \sigma_t E[z_t \mid z_t \leq q_{0.05}], \tag{8}$$

where z_t denotes the standardized innovation. Expected Shortfall measures the average loss conditional on the return being below the VaR threshold, thereby capturing the severity of extreme negative outcomes. Compared with VaR, ES provides a more informative measure of tail risk because it accounts not only for the probability of extreme losses but also for their expected magnitude. The adequacy of VaR estimates is assessed using exceedance rates, defined as the proportion of observations for which realized returns fall below the estimated VaR. These rates are compared to the nominal 5 percent level to evaluate model calibration and ensure that the risk measures are statistically consistent with observed outcomes.

4.4 Sector-Neutral Portfolio Construction

To ensure that observed ESG effects are not driven by sector composition, a sector-neutral sorting procedure is implemented. Firms are grouped according to the TRBC (Thomson Reuters Business Classification) economic sector classification provided by Refinitiv. Within each sector, firms are ranked by ESG score and assigned to High and Low ESG groups based on sector-specific quartiles. ESG cutoffs are therefore computed separately within each sector and within each country, ensuring that firms are evaluated relative to their industry peers rather than across the entire market. This approach helps control for systematic differences in risk across industries.

If a sector contains too few firms to form reliable quartiles—particularly in the Canadian sample—those firms are excluded from the sector-neutral analysis. This avoids constructing ESG portfolios based on very small samples, which could introduce noise and reduce comparability across sectors. Sector-neutral portfolios are then constructed by aggregating firms across sectors. Each sector contributes proportionally based on the number of firms assigned to each ESG group, ensuring that the overall portfolio is not dominated by any single industry. This construction allows for a cleaner identification of ESG effects that are independent of sector composition.

Comparing the results from the standard ESG sorting procedure with those from the sector-neutral approach provides insight into the role of industry composition. If ESG-related differences in volatility and tail risk remain after sector-neutral sorting, this suggests that the relationship is not primarily driven by sector effects. Conversely, if the differences weaken substantially, this indicates that sector composition plays an important role in explaining the observed results.

5 Empirical Results

This section presents the empirical results of this essay. The analysis proceeds in three stages. First, the volatility and downside risk characteristics of ESG portfolios are examined for the Canadian market. Second, the same analysis is conducted for the United States. Finally, a sector-neutral portfolio construction procedure is used as a robustness check to evaluate whether the observed differences in risk across ESG portfolios are driven by industry composition. For each portfolio, the comparison focuses on three key measures derived from the selected GARCH specification: conditional volatility (σ_t), Value-at-Risk (VaR), and Expected Shortfall (ES). These measures provide a comprehensive assessment of both overall risk and extreme downside risk.

5.1 Canada: ESG Portfolios and Risk

The first part of the analysis focuses on the Canadian equity market. Using the ESG-based portfolio construction described in Section 4, firms classified as High and Low ESG are compared in terms of their volatility and downside risk characteristics. Volatility dynamics for the portfolio returns are estimated using GARCH-family models. Model selection based on the Bayesian Information Criterion (BIC) indicates that asymmetric GARCH specifications with heavy-tailed innovation distributions provide the best fit for both portfolios. In particular, the preferred specifications differ across portfolios, reflecting differences in volatility dynamics between High and Low ESG groups.

Table 6 reports the main results. The estimated average conditional volatility for the High ESG portfolio is 0.0124, compared with 0.0095 for the Low ESG portfolio. This implies that the High ESG portfolio is approximately 30 percent more volatile than the Low ESG portfolio, which represents a substantial and economically meaningful difference in risk. The downside risk measures reinforce this finding. The estimated 5 percent Value-at-Risk (VaR) is -0.0189 for the High ESG portfolio and -0.0147 for the Low ESG portfolio. Similarly, the Expected Shortfall (ES) is -0.0263 for the High ESG portfolio and -0.0197 for the Low ESG portfolio. These differences indicate that the High ESG portfolio is exposed to more severe losses in the left tail of the return distribution.

To assess the economic magnitude of these differences, it is useful to compare them relative to overall volatility. The difference in ES corresponds to a substantial increase in expected losses during extreme events, suggesting that the higher risk of the High ESG portfolio is not only statistically detectable but also economically meaningful for investors concerned with downside protection. These results indicate that firms with higher ESG scores in the

Canadian sample exhibit both higher volatility and more severe downside tail risk compared with firms with lower ESG scores. This finding contrasts with the commonly held expectation that stronger ESG performance is associated with lower financial risk.

One potential explanation for this result relates to sector composition. In the Canadian market, high-ESG firms are often concentrated in specific industries, such as financials and certain industrial segments, while low-ESG firms may be more diversified across sectors. In addition, Canada's relatively small and resource-oriented equity market may amplify the impact of sector concentration and firm-specific shocks, contributing to the observed risk differences. The number of observations differs slightly between the Canadian and U.S. portfolios due to differences in trading calendars, market holidays, and data availability after the data-cleaning process. Because the analysis relies on daily return series constructed from exchange-traded equities, non-overlapping holidays between Canadian and U.S. markets may lead to small differences in the number of available trading days. Additional observations may also be lost when firms have missing price data or insufficient return histories on specific dates. These differences are limited and are unlikely to materially affect the comparability of the estimated volatility and downside risk measures across markets.

Table 6: Volatility and Downside Risk Across ESG Portfolios

Country	Portfolio	Avg. σ	VaR (5%)	ES (5%)	Observations
Canada	High ESG	0.0124	-0.0189	-0.0263	1503
Canada	Low ESG	0.0095	-0.0147	-0.0197	1503
U.S.	High ESG	0.0127	-0.0204	-0.0274	1507
U.S.	Low ESG	0.0148	-0.0236	-0.0312	1507

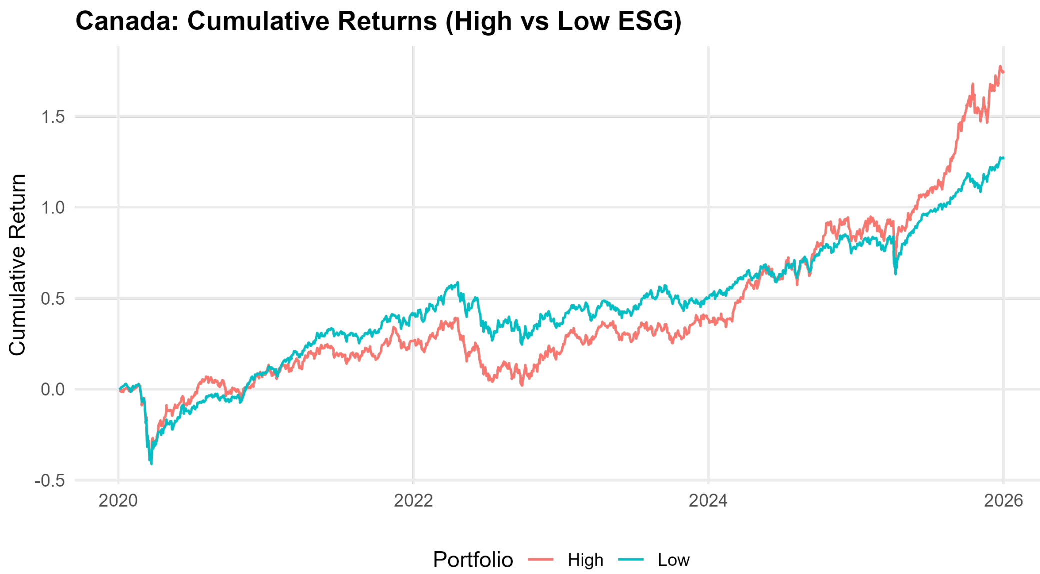


Figure 1: Cumulative returns of High and Low ESG portfolios in Canada.

Figure 1 presents the cumulative returns of the High and Low ESG portfolios in the Canadian market. Both portfolios experience a sharp decline during the early 2020 period, reflecting the impact of the COVID-19 market shock. Following this downturn, the Low ESG portfolio initially recovers more quickly and maintains higher cumulative returns relative to the High ESG portfolio until approximately 2024. However, this pattern reverses in the later part of the sample. Beginning around 2024, the High ESG portfolio exhibits a strong upward trajectory and ultimately outperforms the Low ESG portfolio by a substantial margin. This shift suggests that while High ESG firms may underperform in the earlier recovery phase, they deliver stronger performance in the later period. In addition to differences in performance, the High ESG portfolio displays more pronounced fluctuations over time, indicating greater variability in returns. This visual evidence is consistent with the higher conditional volatility estimates reported in Table 6. The figure highlights both the time-varying nature of ESG-related performance and the higher risk profile associated with High ESG portfolios in the Canadian market.

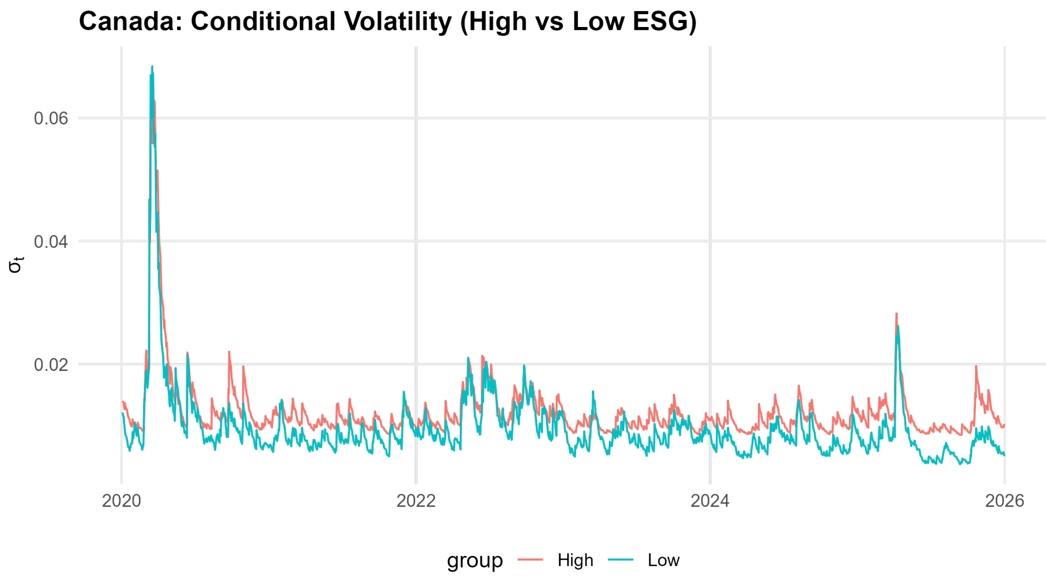


Figure 2: Conditional volatility of High and Low ESG portfolios in Canada under the main ESG sorting procedure.

Figure 2 presents the estimated conditional volatility (σ_t) for the High and Low ESG portfolios in the Canadian market. Both portfolios exhibit a pronounced spike in volatility during early 2020, reflecting the impact of the COVID-19 market shock. Following this period, volatility declines but remains time-varying throughout the sample. A key feature of the figure is that the High ESG portfolio consistently displays higher volatility levels compared to the Low ESG portfolio. In addition, the High ESG portfolio exhibits more frequent and pronounced volatility spikes, particularly during periods of market stress such as 2022 and late in the sample period. In contrast, the Low ESG portfolio shows relatively smoother and more stable volatility dynamics. This visual evidence aligns closely with the quantitative results reported in Table 6, where the average conditional volatility of the High ESG portfolio exceeds that of the Low ESG portfolio. The figure confirms that High ESG portfolios in Canada are associated with greater time-varying risk and are more sensitive to market shocks.

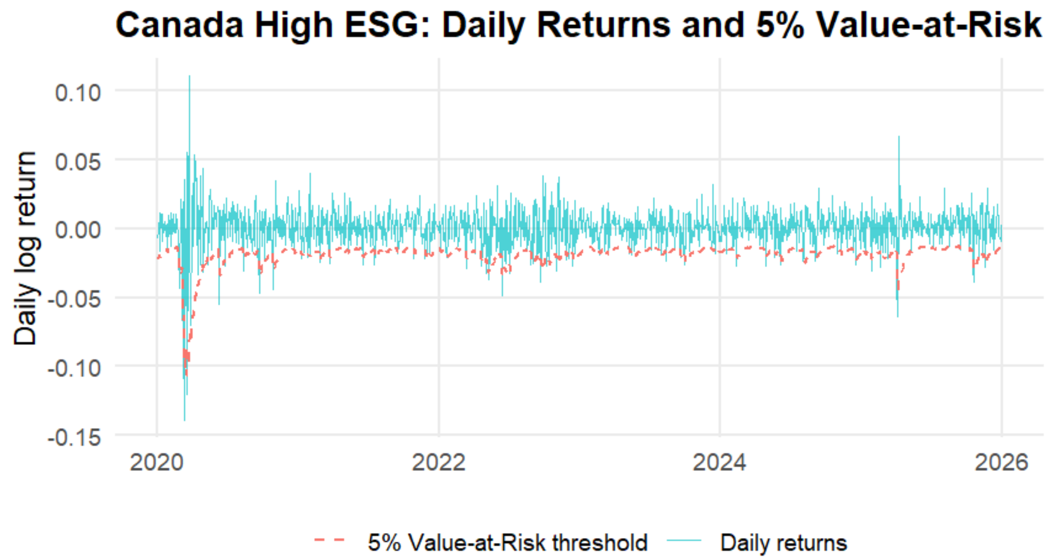


Figure 3: Daily returns and 5% Value-at-Risk for the Canadian High ESG portfolio under the selected GARCH specification.

Figure 3 presents the daily returns of the Canadian High ESG portfolio alongside the estimated 5% Value-at-Risk (VaR) derived from the selected GARCH specification. The figure highlights the time-varying nature of downside risk, with the VaR threshold becoming more negative during periods of heightened market volatility. A prominent feature of the figure is the presence of several large negative return realizations, particularly during the early 2020 period associated with the COVID-19 market shock. During this period, multiple observations fall below the VaR threshold, indicating violations of the predicted risk level. Additional, though less frequent, VaR breaches are observed in later periods, reflecting ongoing exposure to extreme downside events. The clustering of large negative returns and the corresponding adjustments in the VaR threshold provide visual evidence of volatility clustering and fat-tailed behavior in the return distribution. This is consistent with the use of a GARCH model with heavy-tailed innovations, which is designed to capture such features. The figure demonstrates that the High ESG portfolio in Canada is subject to significant tail risk, with occasional extreme losses that exceed the predicted VaR threshold. This supports the earlier finding that High ESG portfolios are exposed to more severe downside risk.

5.2 United States: ESG Portfolios and Risk

The same empirical framework is applied to the U.S. sample. The results differ markedly from those observed in the Canadian market. As shown in Table 6, the High ESG portfolio exhibits an average conditional volatility of 0.0127, compared with 0.0148 for the Low ESG portfolio. This implies that the High ESG portfolio is approximately 14 percent less volatile than the Low ESG portfolio. Downside risk measures display a consistent pattern. The 5 percent Value-at-Risk is -0.0204 for the High ESG portfolio and -0.0236 for the Low ESG portfolio, while the Expected Shortfall is -0.0274 and -0.0312, respectively. These results indicate that firms with stronger ESG performance experience less severe losses in the lower tail of the return distribution.

In contrast to the Canadian findings, the U.S. results are consistent with the view that ESG performance is associated with lower financial risk. One possible explanation is that the larger and more diversified U.S. equity market allows ESG-related characteristics to be reflected more cleanly in firm-level risk profiles, without being dominated by sector-specific effects. In addition, the U.S. market includes a broader range of industries and a larger cross-section of firms, which reduces sensitivity to idiosyncratic shocks and improves the stability of portfolio-level estimates. ESG characteristics in this context may therefore be more closely linked to underlying firm quality, governance, and risk management practices. An additional observation concerns the risk–return trade-off. The Low ESG portfolio exhibits slightly higher average returns but also higher volatility, consistent with the traditional risk–return relationship. In contrast, the High ESG portfolio appears to offer lower risk at the cost of slightly lower average returns.

Figure 4: Cumulative returns of High and Low ESG portfolios in the United States.

Figure 4 presents the cumulative returns of the High and Low ESG portfolios in the U.S. market. Both portfolios experience a sharp decline during early 2020, reflecting the impact of the COVID-19 market shock. Following this period, the portfolios recover steadily over time. In contrast to the Canadian case, the High ESG portfolio exhibits a smoother and more stable growth path throughout the sample period. While the difference in cumulative performance between the two portfolios is not as pronounced as in Canada, the High ESG portfolio generally maintains a slight advantage or closely tracks the Low ESG portfolio. An important feature of the figure is the lower degree of fluctuation in the High ESG portfolio relative to the Low ESG portfolio. The Low ESG portfolio displays more variability and occasional sharper movements, indicating greater instability in returns. The figure suggests that in the U.S. market, High ESG portfolios are associated with more stable return dynamics and comparable, if not slightly superior, long-term performance. This visual evidence is consistent with the empirical results showing lower volatility and reduced downside risk for High ESG firms in the United States.

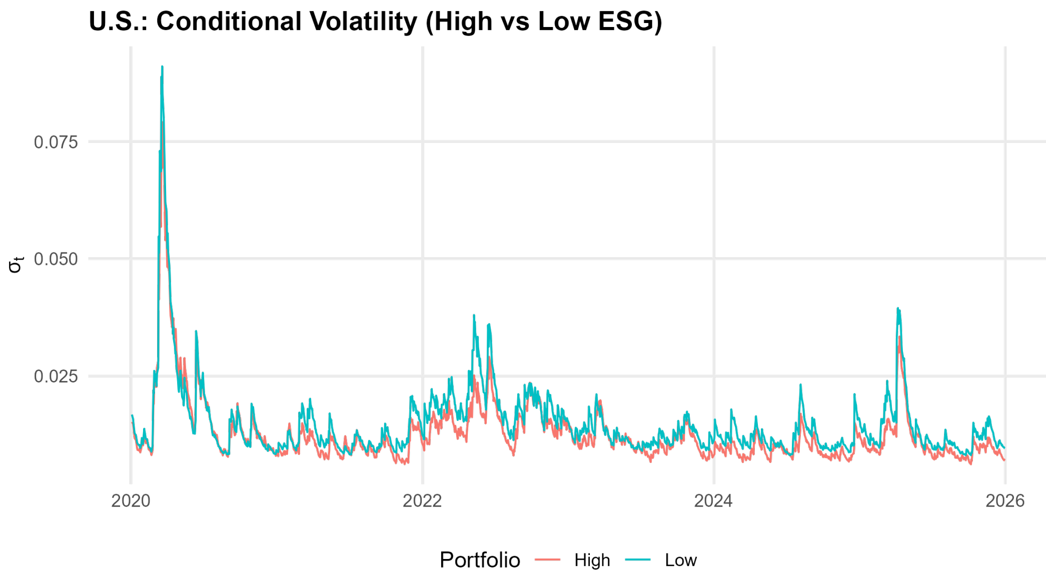


Figure 5: Conditional volatility of High and Low ESG portfolios in the United States under the main ESG sorting procedure.

Figure 5 presents the estimated conditional volatility (σ_t) for the High and Low ESG portfolios in the U.S. market. In contrast to the Canadian case, the figure reveals a clear and persistent pattern in which the Low ESG portfolio exhibits higher volatility levels than the High ESG portfolio throughout the sample period. Although both portfolios show time-varying volatility, consistent with standard financial return dynamics, the Low ESG portfolio shows more frequent and pronounced spikes, indicating greater sensitivity to market fluctuations. In comparison, the High ESG portfolio exhibits smoother volatility dynamics and lower overall variability. Unlike the Canadian market, the difference in volatility between the two portfolios is relatively stable over time and does not appear to be driven by isolated episodes of market stress. Instead, the gap persists across the entire sample, suggesting structurally different risk characteristics between High and Low ESG firms in the U.S. This visual evidence aligns closely with the empirical results reported in Table 6, where the High ESG portfolio is found to have lower average conditional volatility. The figure provides strong support for the view that higher ESG performance is associated with reduced time-varying risk in the U.S. market.

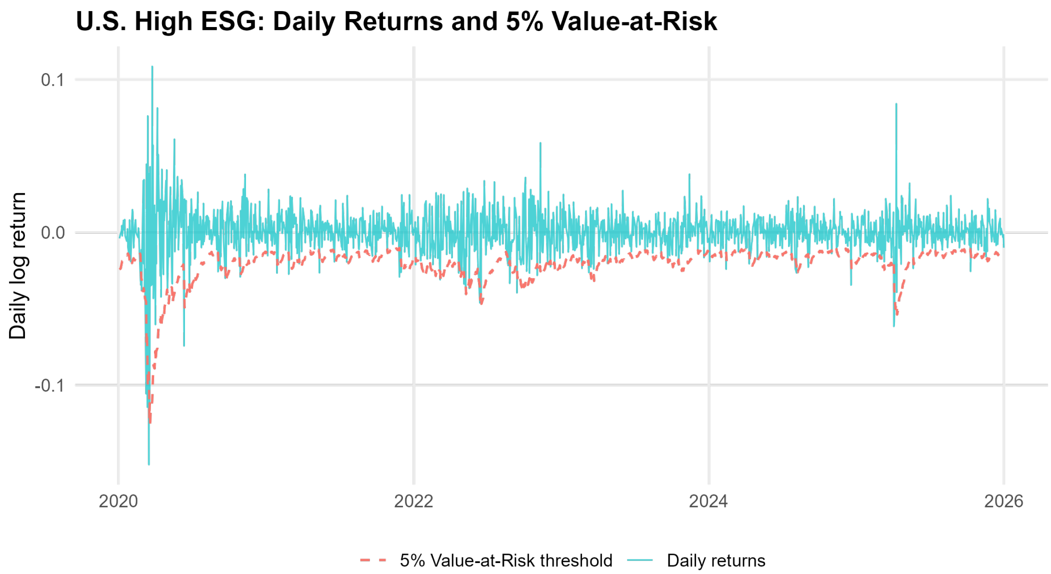


Figure 6: Daily returns and 5% Value-at-Risk for the U.S. High ESG portfolio under the selected GARCH specification.

Figure 6 plots the daily returns of the U.S. High ESG portfolio together with the estimated 5% Value-at-Risk (VaR) from the selected GARCH specification. The figure illustrates the time-varying nature of downside risk, as the VaR threshold adjusts in response to changes in market volatility over the sample period. The most visible period of stress occurs in early 2020, around the COVID-19 market shock, when several large return movements are observed and the VaR threshold becomes more negative. During this period, some realized returns fall below the estimated VaR threshold, indicating VaR violations in which actual losses exceeded the model-implied 5% downside-risk level. In later years, VaR breaches appear less frequent, and the return series is generally more concentrated around zero, suggesting a relatively more stable risk profile after the initial market shock. The clustering of larger return movements during stressed periods and the subsequent adjustment of the VaR threshold are consistent with volatility clustering, which supports the use of GARCH-family models for estimating conditional risk. This visual evidence complements the empirical results reported in Table 6, indicating that the U.S. High ESG portfolio exhibits relatively lower volatility and tail-risk exposure compared with the U.S. Low ESG portfolio.

5.3 Sector-Neutral Robustness Analysis

To evaluate whether the observed ESG-related risk differences are driven by sector composition, a sector-neutral portfolio construction procedure is implemented. The results show distinct patterns across the two markets. In the Canadian sample, the difference in volatility between the High and Low ESG portfolios becomes smaller after controlling for sector composition. Specifically, the average volatility decreases to approximately 0.0102 for the High ESG portfolio and 0.0091 for the Low ESG portfolio, reducing the gap from about 30 percent to roughly 13 percent.

Similarly, the differences in VaR and Expected Shortfall become less pronounced, although the High ESG portfolio continues to exhibit somewhat higher downside risk. These findings suggest that sector composition explains a significant portion of the observed risk differences in Canada, but not all of them. In contrast, the U.S. results remain largely unchanged after sector-neutral sorting. The High ESG portfolio continues to exhibit lower volatility (approximately 0.0127 versus 0.0147) and less severe downside risk compared with the Low ESG portfolio. This indicates that the ESG–risk relationship in the U.S. sample is not primarily driven by sector composition. The persistence of the U.S. results under sector-neutral sorting suggests that ESG characteristics are more directly related to firm-level risk in this market, whereas in Canada, sector effects play a more important role.

Table 7: Sector-Neutral Volatility and Downside Risk Across ESG Portfolios

Country	Portfolio	Avg. σ	VaR (5%)	ES (5%)
Canada	High ESG (Sector-Neutral)	0.0102	-0.0157	-0.0214
Canada	Low ESG (Sector-Neutral)	0.0091	-0.0139	-0.0187
U.S.	High ESG (Sector-Neutral)	0.0127	-0.0204	-0.0271
U.S.	Low ESG (Sector-Neutral)	0.0147	-0.0234	-0.0307

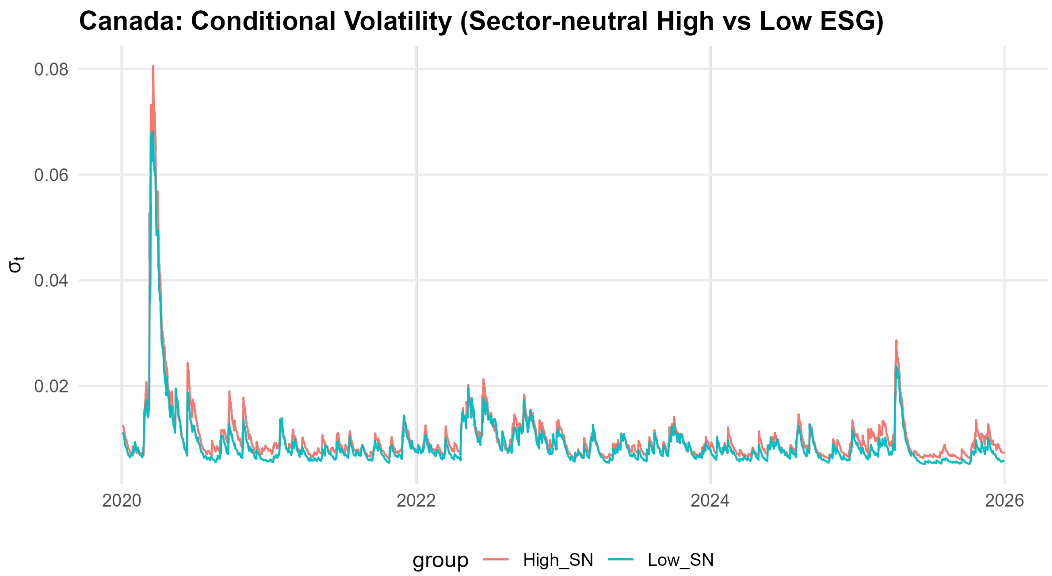


Figure 7: Conditional volatility of High and Low ESG portfolios in Canada under the sector-neutral ESG sorting procedure.

Figure 7 presents the estimated conditional volatility (σ_t) for the Canadian ESG portfolios under the sector-neutral sorting procedure. As in the main specification, both portfolios exhibit a pronounced spike in volatility during early 2020, reflecting the impact of the COVID-19 market shock. Compared to Figure 2, a key difference is the substantial reduction in the volatility gap between the High and Low ESG portfolios. The two series move more closely together over time, and their volatility spikes appear more synchronized. This indicates that controlling for sector composition significantly reduces the observed differences in risk.

However, despite this reduction, the High ESG portfolio continues to exhibit slightly higher volatility than the Low ESG portfolio throughout much of the sample period. This suggests that while sector composition accounts for a large portion of the ESG–risk relationship in Canada, it does not fully explain it. The figure provides strong visual evidence that sector effects play a critical role in shaping the relationship between ESG performance and financial risk in the Canadian market, while also indicating the presence of residual differences that may be attributable to firm-level characteristics.

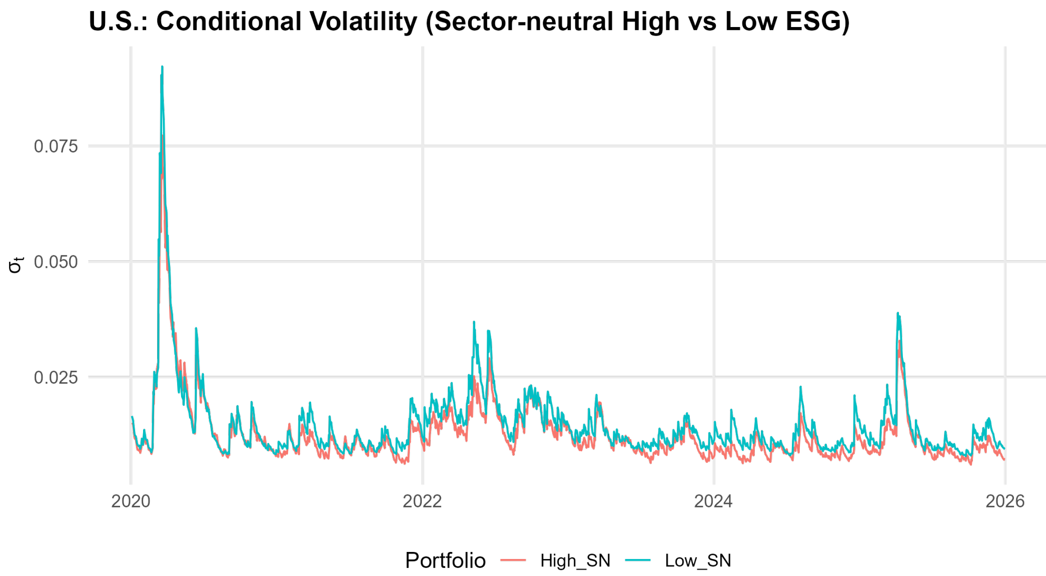


Figure 8: Conditional volatility of High and Low ESG portfolios in the United States under the sector-neutral ESG sorting procedure.

Figure 8 presents the estimated conditional volatility (σ_t) for the U.S. ESG portfolios under the sector-neutral sorting procedure. As in the main specification, both portfolios exhibit a pronounced spike in volatility during early 2020, reflecting the impact of the COVID-19 market shock. In contrast to the Canadian case, the relative ordering of the portfolios remains largely unchanged after controlling for sector composition. The Low ESG portfolio continues to exhibit consistently higher volatility than the High ESG portfolio throughout the sample period. The difference between the two series persists over time, indicating that the volatility gap is not driven by sector-specific effects. Furthermore, the Low ESG portfolio displays more frequent and pronounced volatility spikes, while the High ESG portfolio maintains relatively smoother dynamics. This pattern closely mirrors the results observed in Figure 5. The figure provides strong evidence that the relationship between ESG performance and financial risk in the U.S. market is robust to sector-neutral adjustments. This suggests that ESG characteristics are more directly associated with firm-level risk, rather than reflecting underlying industry composition.

5.4 Cross-Market Comparison

The contrasting results between Canada and the United States suggest that the relationship between ESG performance and financial risk is context-dependent rather than universal. One key factor is market structure. The U.S. equity market is larger and more diversified, allowing ESG-related firm characteristics to be reflected more clearly in risk measures. In contrast, the Canadian market is smaller and more concentrated, with a significant presence of resource-based industries. This concentration can amplify sector-driven effects and weaken the direct relationship between ESG performance and risk.

Another important factor is sector composition. The sector-neutral analysis indicates that industry structure explains a substantial portion of the Canadian ESG–risk relationship, while it has little effect in the U.S. This suggests that ESG scores may be more closely aligned with sector characteristics in Canada than in the United States. Finally, differences in firm heterogeneity and diversification may also contribute to the divergence. The larger cross-section of firms in the U.S. reduces sensitivity to individual firm shocks and improves the precision of estimated risk measures. These findings indicate that ESG performance does not have a uniform relationship with financial risk across markets. Instead, the ESG–risk relationship depends on market structure, sector composition, and the degree of diversification within the equity universe.

6 Discussion

The empirical results of this essay reveal a clear divergence between the Canadian and U.S. equity markets in how ESG performance relates to financial risk. Rather than repeating the direction of the estimates, the key insight is that the ESG–risk relationship appears to be highly sensitive to market-specific characteristics. In particular, the results suggest that ESG classifications may capture different underlying economic or structural features across markets, leading to fundamentally different risk implications for ESG-sorted portfolios.

One possible explanation for the Canadian findings relates to the composition of the Canadian equity market. In the sample used in this essay, firms are distributed across nine TRBC economic sectors, with notable representation in sectors such as Energy, Materials, and Financials. These sectors are known to exhibit distinct volatility patterns and are often more sensitive to commodity price fluctuations and macroeconomic shocks. If higher ESG scores are more prevalent in specific sectors within the Canadian sample, the resulting ESG portfolios may inherit sector-driven risk characteristics. The sector-neutral robustness analysis supports this interpretation, as the difference in volatility between ESG portfolios becomes smaller once sector composition is controlled for. This suggests that part of the observed ESG–risk relationship in Canada reflects the distribution of firms across sectors rather than purely ESG-related effects.

Another possible explanation relates to differences in market size and diversification. The Canadian equity market includes a relatively smaller number of publicly traded firms compared with the U.S. market, and the cross-section is more concentrated across a limited set of industries. As a result, ESG portfolios constructed in Canada may be more sensitive to sector-specific and firm-specific shocks. This does not imply that ESG inherently increases risk, but rather that in a smaller and more concentrated market, ESG classifications may be more closely tied to sector exposure and idiosyncratic variation.

In contrast, the U.S. market provides a much broader and more diversified set of firms across industries. The results indicate that firms with higher ESG scores tend to exhibit lower volatility and less severe downside risk. This evidence is consistent with the argument that stronger ESG profiles may coincide with greater financial stability, potentially through improved governance, better stakeholder relationships, or reduced exposure to regulatory and reputational risks. At the same time, it is important to acknowledge that this relationship may still be influenced by residual confounding factors, such as firm size, industry composition, or other correlated characteristics that are not fully captured by the ESG sorting procedure.

The sector-neutral analysis further reinforces this interpretation in the U.S. context.

Because the volatility difference between ESG portfolios remains largely unchanged after controlling for sector composition, the relationship between ESG performance and financial risk appears to be less driven by industry effects and more closely related to firm-level ESG characteristics. These results suggest that the relationship between ESG performance and financial risk is not universal across markets. Instead, the ESG–risk relationship may depend on market structure, sector composition, and institutional factors. This finding contributes to the broader ESG literature by emphasizing that conclusions drawn from a single market may not necessarily generalize to other financial environments.

At the same time, several limitations of the analysis should be acknowledged. First, this essay relies on ESG Combined Scores obtained from Refinitiv, which represent one of several possible ESG rating methodologies. Different ESG data providers may use alternative scoring frameworks, which could lead to variations in ESG classifications. Second, the portfolio construction approach uses equal-weighted portfolios, which treat all firms equally regardless of market capitalization. While this approach is commonly used in empirical asset pricing studies, value-weighted portfolios could produce somewhat different results. Despite these limitations, the analysis provides useful insights into the relationship between ESG performance and financial risk across two major equity markets. By combining portfolio-based analysis with volatility modeling and tail-risk estimation, this essay contributes to a more nuanced understanding of how ESG characteristics may influence the risk profile of publicly traded firms.

7 Conclusion

This essay investigates the relationship between environmental, social, and governance (ESG) performance and financial risk in equity markets. Specifically, this essay examines whether firms with higher ESG scores exhibit different volatility and downside tail risk characteristics compared with firms with lower ESG scores. The analysis focuses on two markets with distinct institutional environments: Canada and the United States. Using firm-level ESG data obtained from Refinitiv Workspace, firms are sorted into portfolios based on their ESG Combined Scores. High and Low ESG portfolios are constructed using the top and bottom quartiles of the ESG score distribution. Daily stock returns are then calculated using closing price data over the period from January 2020 to December 2025, and equal-weighted portfolio returns are constructed for each ESG group.

To analyze the volatility dynamics of these portfolios, this essay employs several models from the GARCH family, including standard GARCH, EGARCH, and GJR-GARCH specifications. Model selection is based on the Bayesian Information Criterion, and the selected models are used to estimate conditional volatility as well as measures of downside tail risk, including Value-at-Risk and Expected Shortfall. In addition, a sector-neutral portfolio construction approach is implemented as a robustness test to evaluate whether the results are driven by industry composition.

The empirical results reveal a clear contrast between the Canadian and U.S. markets. In the Canadian sample, the High ESG portfolio exhibits higher volatility and more severe downside tail risk compared with the Low ESG portfolio. However, the sector-neutral analysis suggests that part of this difference may be explained by sector composition within the Canadian equity market. In the United States, the results show the opposite pattern. Firms with higher ESG scores exhibit lower volatility and reduced downside risk compared with firms with lower ESG scores. Moreover, the sector-neutral robustness test indicates that this relationship remains largely unchanged after controlling for industry effects. This suggests that ESG characteristics may play a more direct role in shaping firm-level risk dynamics in the U.S. market.

The findings suggest that the relationship between ESG performance and financial risk is not uniform across markets. While stronger ESG performance appears to be associated with lower risk in the United States, the Canadian results indicate that the relationship may be influenced by market structure and sector composition. These findings highlight the importance of considering cross-market differences when evaluating the financial implications of ESG performance. Future research could extend this analysis in several directions. For example, future studies could examine longer sample periods, alternative ESG rating methodologies, or different portfolio construction approaches. In addition, further research could explore whether similar patterns emerge in other international equity markets or under different economic conditions. Understanding the relationship between ESG performance and financial risk remains an important topic for investors, policymakers, and researchers. As ESG considerations continue to play a growing role in investment decision-making, empirical evidence on how sustainability performance relates to financial risk will remain an important area of financial research.

Appendix

A Value-Weighted Portfolio Results

As an additional robustness check, value-weighted ESG portfolios were constructed using firm-level market capitalization weights instead of equal weighting. This approach allows larger firms to contribute more heavily to portfolio returns and helps assess whether the main findings are sensitive to the portfolio weighting scheme. The Canadian results remain consistent with the main equal-weighted specification. The High ESG portfolio continues to exhibit higher conditional volatility and more severe downside risk than the Low ESG portfolio. Similarly, the U.S. results remain qualitatively unchanged: the High ESG portfolio continues to exhibit lower volatility and lower downside risk than the Low ESG portfolio. These findings suggest that the main conclusions are not driven by the use of equal-weighted portfolio returns.

Table 8: Value-Weighted Portfolio Risk Measures

Country	Portfolio	Avg. σ	Median σ	VaR (5%)	ES (5%)	Observations
Canada	High ESG (VW)	0.0112	0.0099	-0.0170	-0.0235	1503
Canada	Low ESG (VW)	0.0094	0.0083	-0.0146	-0.0198	1503
U.S.	High ESG (VW)	0.0132	0.0114	-0.0205	-0.0283	1507
U.S.	Low ESG (VW)	0.0146	0.0126	-0.0223	-0.0310	1507

B Alternative ESG Sorting Cutoffs

The main analysis sorts firms into High and Low ESG portfolios using the top and bottom quartiles of the ESG score distribution. To examine whether the results depend on this specific sorting rule, an alternative cutoff scheme was implemented using the 30th and 70th percentiles. This broader classification includes a larger number of firms in each tail portfolio while preserving the contrast between relatively high- and low-ESG firms. The Canadian results remain consistent under the alternative cutoff rule. The High ESG portfolio continues to display higher volatility and more severe downside tail risk than the Low ESG portfolio. In the U.S. sample, the High ESG portfolio continues to exhibit lower volatility and lower downside risk than the Low ESG portfolio. The persistence of these patterns suggests that the main findings are not sensitive to the exact ESG cutoff thresholds used in the portfolio construction.

Table 9: Risk Measures Under Alternative ESG Sorting Cutoffs (30/70)

Country	Portfolio	Avg. σ	Median σ	VaR (5%)	ES (5%)	Observations
Canada	High ESG (Alt.)	0.0123	0.0110	-0.0187	-0.0260	1503
Canada	Low ESG (Alt.)	0.0091	0.0078	-0.0141	-0.0191	1503
U.S.	High ESG (Alt.)	0.0125	0.0106	-0.0201	-0.0270	1507
U.S.	Low ESG (Alt.)	0.0146	0.0123	-0.0232	-0.0307	1507

C Subperiod Analysis

To assess whether the relationship between ESG performance and financial risk is stable over time, the sample period was divided into two subperiods: 2020–2022 and 2023–2025. This split is useful because the first subperiod includes the COVID-19 shock and its immediate aftermath, while the second reflects a relatively more normal post-pandemic period with different market conditions. The Canadian results remain qualitatively similar across both subperiods. In each period, the High ESG portfolio exhibits higher volatility and greater downside risk than the Low ESG portfolio, although overall volatility is lower in the later period. In the U.S. sample, the opposite pattern is observed in both subperiods: the High ESG portfolio consistently exhibits lower volatility and less severe downside risk than the Low ESG portfolio. These results suggest that the main cross-country contrast documented in the paper is not driven by a particular episode within the sample.

Table 10: Subperiod Risk Measures: Canada

Portfolio	Avg. σ	Median σ	VaR (5%)	ES (5%)	Observations
High ESG (2020–2022)	0.0146	0.0125	-0.0227	-0.0313	750
Low ESG (2020–2022)	0.0122	0.0097	-0.0189	-0.0258	750
High ESG (2023–2025)	0.0103	0.0098	-0.0157	-0.0212	753
Low ESG (2023–2025)	0.0071	0.0068	-0.0108	-0.0145	753

Table 11: Subperiod Risk Measures: United States

Portfolio	Avg. σ	Median σ	VaR (5%)	ES (5%)	Observations
High ESG (2020–2022)	0.0158	0.0134	-0.0254	-0.0337	755
Low ESG (2020–2022)	0.0175	0.0158	-0.0283	-0.0369	755
High ESG (2023–2025)	0.0097	0.0091	-0.0153	-0.0207	752
Low ESG (2023–2025)	0.0119	0.0112	-0.0186	-0.0246	752

D TRBC Sector Composition

Table 12 reports the distribution of firms across TRBC economic sectors for Canada and the United States. The Canadian sample is relatively concentrated in a small number of sectors, particularly Basic Materials, Financials, and Energy. In contrast, the U.S. sample is more diversified, with a large representation in Technology, Industrials, and Financials. These differences in sector composition are important for interpreting the main results, as they help explain why ESG-related risk patterns differ across the two markets.

Table 12: Sector Composition by Country

Sector	Canada (N)	U.S. (N)
Technology	9	219
Industrials	14	183
Financials	20	154
Consumer Cyclicals	6	146
Healthcare	–	118
Real Estate	3	63
Energy	16	60
Basic Materials	30	58
Consumer Non-Cyclicals	5	56
Utilities	8	49
Academic & Educational Services	–	2
Total Firms	**111**	**1108**

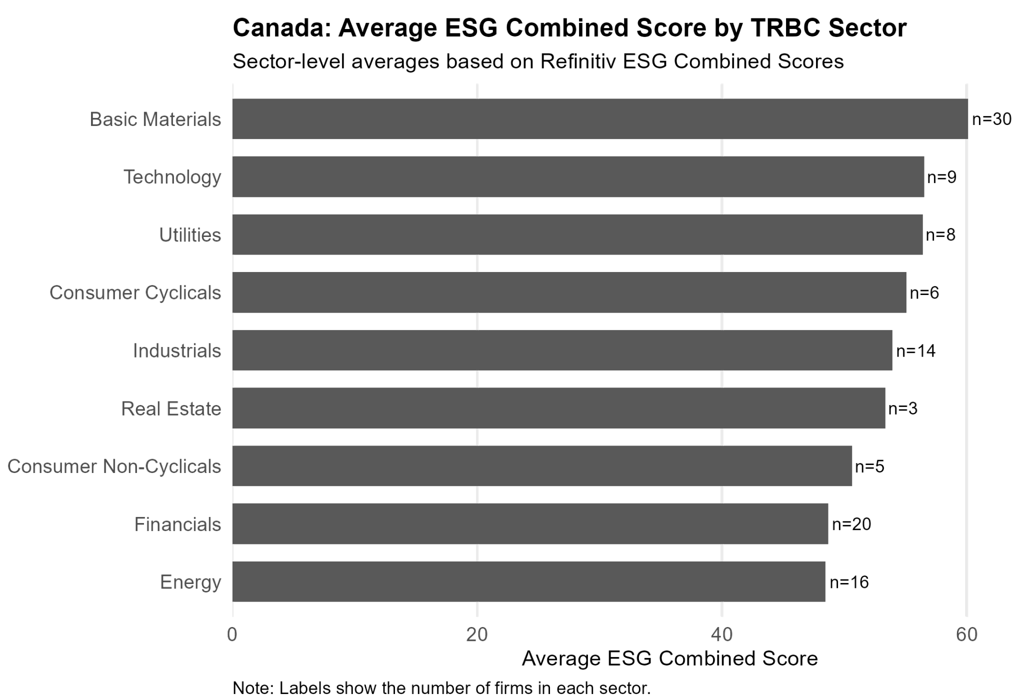


Figure 9: Average ESG Combined Score by TRBC Sector: Canada

Figure 9 shows average ESG Combined Scores by TRBC Economic Sector for the Canadian sample. The figure indicates that ESG scores vary noticeably across sectors, with Basic Materials having the highest average ESG score, followed by Technology and Utilities. By contrast, Financials and Energy have relatively lower average ESG scores. This pattern is important for the thesis because the Canadian sample is relatively small and sector-concentrated, with a meaningful share of firms in Basic Materials, Financials, and Energy. As a result, differences between High- and Low-ESG portfolios in Canada may partly reflect sector composition rather than ESG characteristics alone. This provides useful motivation for the sector-neutral robustness analysis.

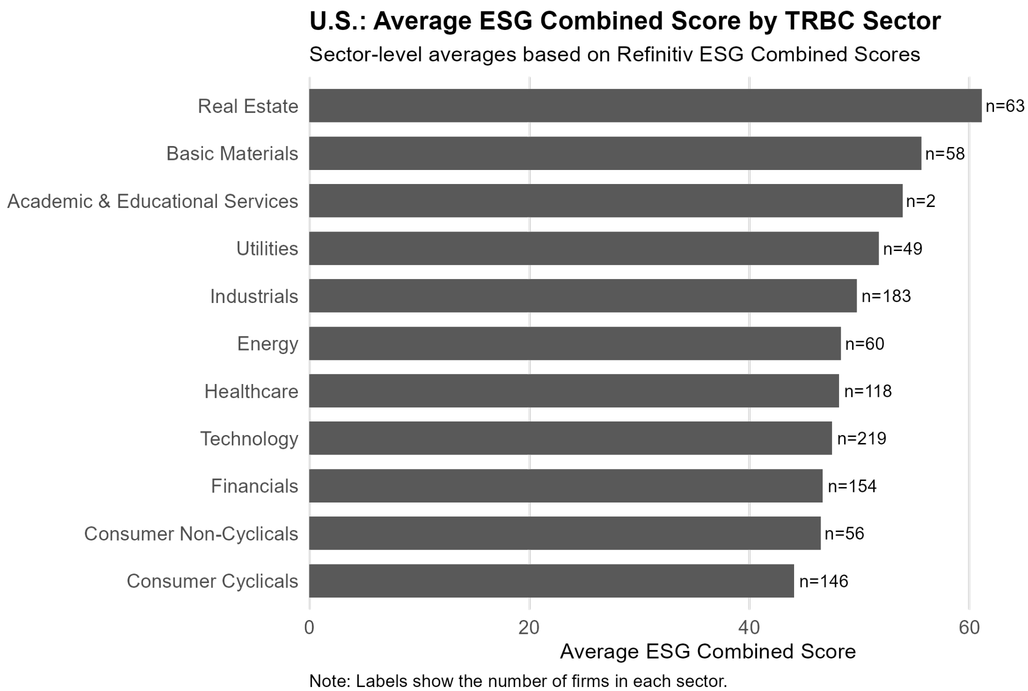


Figure 10: Average ESG Combined Score by TRBC Sector: U.S.

Figure 10 reports average ESG Combined Scores by TRBC Economic Sector for the U.S. sample. The U.S. sample displays broader sector coverage than the Canadian sample, with firms distributed across Technology, Industrials, Financials, Healthcare, Consumer Cyclicals, Real Estate, and other sectors. Real Estate and Basic Materials have the highest average ESG scores, while Consumer Cyclicals and Consumer Non-Cyclicals have relatively lower averages. Compared with Canada, the larger and more diversified U.S. sample reduces the influence of any single sector on the overall High- versus Low-ESG comparison. This broader diversification helps explain why the U.S. ESG–risk relationship is less sensitive to sector composition and remains more stable under sector-neutral sorting.

E Industry Composition (Canada)

Table 13 presents the largest industries in the Canadian sample based on the number of firms. The distribution highlights the strong presence of resource-based industries, particularly Gold and Oil & Gas-related sectors, which is consistent with the structure of the Canadian equity market.

Table 13: Top Industries in Canada (by Number of Firms)

Industry	Number of Firms
Gold	18
Banks	6
Life & Health Insurance	5
Oil & Gas Exploration and Production	5
Diversified Mining	4
Electric Utilities	4
Food Retail & Distribution	4
Oil & Gas Refining and Marketing	4
Oil & Gas Transportation Services	4
Specialty Mining & Metals	4

F Industry Composition (United States)

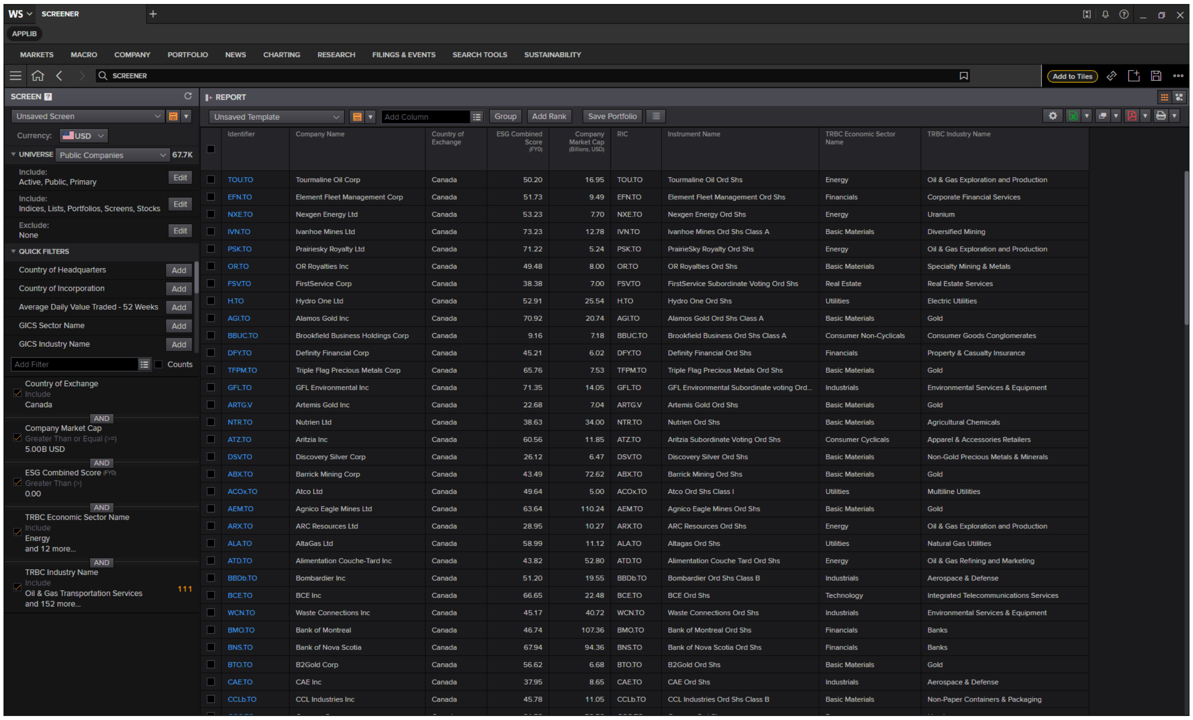
Table 14 reports the largest industries in the U.S. sample. Compared with Canada, the U.S. market exhibits greater diversification, with strong representation across technology, financial, industrial, and healthcare-related industries.

Table 14: Top Industries in the United States (by Number of Firms)

Industry	Number of Firms
Software	55
Banks	44
Industrial Machinery & Equipment	36
Pharmaceuticals	33
Aerospace & Defense	31
Semiconductors	31
Electric Utilities	29
Specialized REITs	29
IT Services & Consulting	28
Biotechnology & Medical Research	26

G Refinitiv Workspace screener (Canada)

Figure 11 represents the Refinitiv Workspace screener used to construct the Canadian ESG sample. Filters include Canada, Company Market Cap greater than 5 billion USD, ESG Combined Score greater than zero to exclude the firms with a N/A ESG score, along with TRBC Economic sector Name and TRBC Industry Name.



Identifier	Company Name	Country of Exchange	ESG Combined Score (FY0)	Company Market Cap (Billions, USD)	RIC	Instrument Name	TRBC Economic Sector Name	TRBC Industry Name
TOU.TO	Tourmaline Oil Corp	Canada	50.20	16.95	TOU.TO	Tourmaline Oil Ord Shs	Energy	Oil & Gas Exploration and Production
EFN.TO	Element Fleet Management Corp	Canada	51.73	9.49	EFN.TO	Element Fleet Management Ord Shs	Financials	Corporate Financial Services
NXE.TO	Nexgen Energy Ltd	Canada	53.23	7.70	NXE.TO	Nexgen Energy Ord Shs	Energy	Uranium
IVN.TO	Ivanhoe Mines Ltd	Canada	73.23	12.78	IVN.TO	Ivanhoe Mines Ord Shs Class A	Basic Materials	Diversified Mining
PSK.TO	Prairiesky Royalty Ltd	Canada	71.22	5.24	PSK.TO	PrairieSky Royalty Ord Shs	Energy	Oil & Gas Exploration and Production
OR.TO	OR Royalties Inc	Canada	49.48	8.00	OR.TO	OR Royalties Ord Shs	Basic Materials	Specialty Mining & Metals
FSV.TO	FirstService Corp	Canada	38.38	7.00	FSV.TO	FirstService Subordinate Voting Ord Shs	Real Estate	Real Estate Services
H.TO	Hydro One Ltd	Canada	52.91	25.54	H.TO	Hydro One Ord Shs	Utilities	Electric Utilities
AGI.TO	Alamos Gold Inc	Canada	70.92	20.74	AGI.TO	Alamos Gold Ord Shs Class A	Basic Materials	Gold
BBUC.TO	Brookfield Business Holdings Corp	Canada	9.16	7.18	BBUC.TO	Brookfield Business Ord Shs Class A	Consumer Non-Cyclicals	Consumer Goods Conglomerates
DFY.TO	Definity Financial Corp	Canada	45.21	6.02	DFY.TO	Definity Financial Ord Shs	Financials	Property & Casualty Insurance
TFPM.TO	Triple Flag Precious Metals Corp	Canada	65.76	7.53	TFPM.TO	Triple Flag Precious Metals Ord Shs	Basic Materials	Gold
GFL.TO	GFL Environmental Inc	Canada	71.35	14.05	GFL.TO	GFL Environmental Subordinate voting Ord...	Industrials	Environmental Services & Equipment
ARTG.V	Artemis Gold Inc	Canada	22.68	7.04	ARTG.V	Artemis Gold Ord Shs	Basic Materials	Gold
NTR.TO	Nutrien Ltd	Canada	38.63	34.00	NTR.TO	Nutrien Ord Shs	Basic Materials	Agricultural Chemicals
ATZ.TO	Aritzia Inc	Canada	60.56	11.85	ATZ.TO	Aritzia Subordinate Voting Ord Shs	Consumer Cyclicals	Apparel & Accessories Retailers
DSV.TO	Discovery Silver Corp	Canada	26.12	6.47	DSV.TO	Discovery Silver Ord Shs	Basic Materials	Non-Gold Precious Metals & Minerals
ABX.TO	Barrick Mining Corp	Canada	43.49	72.62	ABX.TO	Barrick Mining Ord Shs	Basic Materials	Gold
ACOx.TO	Atco Ltd	Canada	49.64	5.00	ACOx.TO	Atco Ord Shs Class I	Utilities	Multiline Utilities
AEM.TO	Agnico Eagle Mines Ltd	Canada	63.64	110.24	AEM.TO	Agnico Eagle Mines Ord Shs	Basic Materials	Gold
ARX.TO	ARC Resources Ltd	Canada	28.95	10.27	ARX.TO	ARC Resources Ord Shs	Energy	Oil & Gas Exploration and Production
ALA.TO	AltaGas Ltd	Canada	58.99	11.12	ALA.TO	Altagas Ord Shs	Utilities	Natural Gas Utilities
ATD.TO	Alimentation Couche-Tard Inc	Canada	43.82	52.80	ATD.TO	Alimentation Couche Tard Ord Shs	Energy	Oil & Gas Refining and Marketing
BBDb.TO	Bombardier Inc	Canada	51.20	19.55	BBDb.TO	Bombardier Ord Shs Class B	Industrials	Aerospace & Defense
BCE.TO	BCE Inc	Canada	66.65	22.48	BCE.TO	BCE Ord Shs	Technology	Integrated Telecommunications Services
WCN.TO	Waste Connections Inc	Canada	45.17	40.72	WCN.TO	Waste Connections Ord Shs	Industrials	Environmental Services & Equipment
BMO.TO	Bank of Montreal	Canada	46.74	107.36	BMO.TO	Bank of Montreal Ord Shs	Financials	Banks
BNS.TO	Bank of Nova Scotia	Canada	67.94	94.36	BNS.TO	Bank of Nova Scotia Ord Shs	Financials	Banks
BTO.TO	B2Gold Corp	Canada	56.62	6.68	BTO.TO	B2Gold Ord Shs	Basic Materials	Gold
CAE.TO	CAE Inc	Canada	37.95	8.65	CAE.TO	CAE Ord Shs	Industrials	Aerospace & Defense
CCLb.TO	CCL Industries Inc	Canada	45.78	11.05	CCLb.TO	CCL Industries Ord Shs Class B	Basic Materials	Non-Paper Containers & Packaging

Figure 11: Refinitiv Workspace screener (Canada)

H Refinitiv Workspace screener (USA)

Figure 12 represents the Refinitiv Workspace screener used to construct the USA ESG sample. Filters include USA, Company Market Cap greater than 5 billion USD, ESG Combined Score greater than zero to exclude the firms with a N/A ESG score, along with TRBC Economic sector Name and TRBC Industry Name.

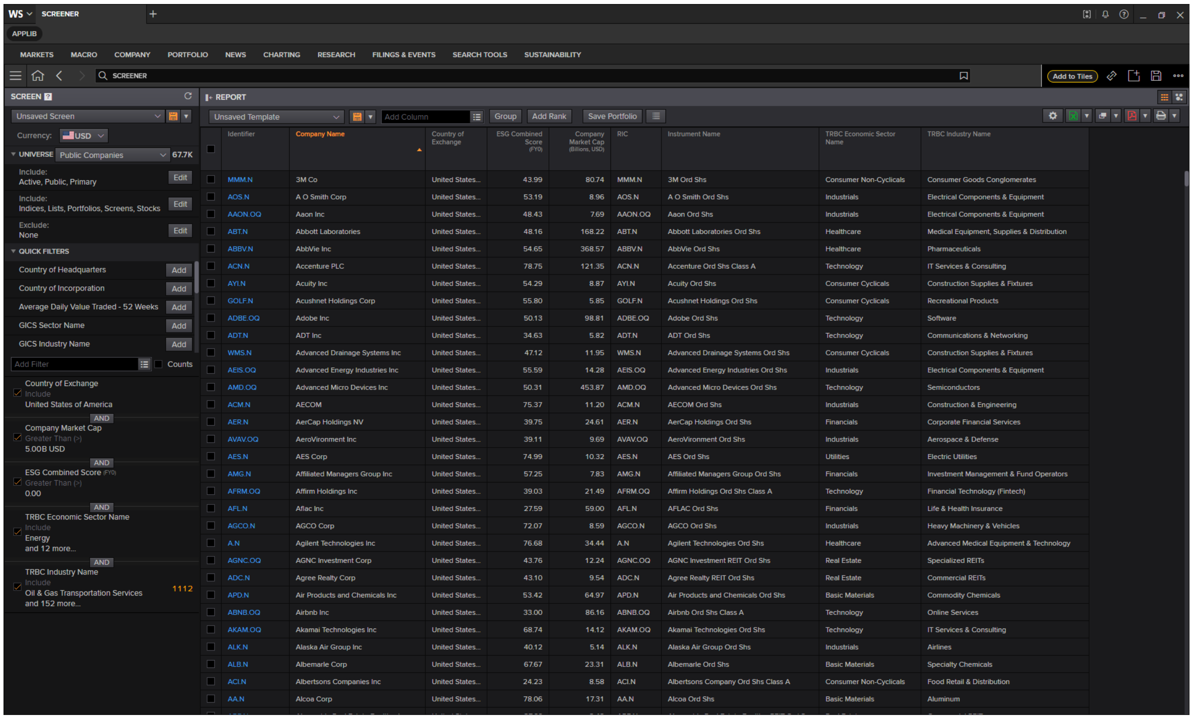


Figure 12: Refinitiv Workspace screener (USA)

I Stationarity tests for portfolio return series

Table 15 reports Augmented Dickey–Fuller tests for the daily portfolio return series used in the GARCH-family models.

Table 15: Stationarity Tests for Portfolio Return Series

Market	Portfolio	Test	Statistic	p-value	Interpretation
Canada	High ESG	ADF test	-10.463	< 0.01	Stationary
Canada	Low ESG	ADF test	-10.648	< 0.01	Stationary
U.S.	High ESG	ADF test	-10.413	< 0.01	Stationary
U.S.	Low ESG	ADF test	-10.211	< 0.01	Stationary

Notes: This table reports Augmented Dickey–Fuller tests for the daily equal-weighted portfolio return series. The null hypothesis of the ADF test is that the series contains a unit root. The reported p-values are shown as < 0.01 because the test output indicates that the p-values are smaller than the printed lower bound. Rejection of the unit-root null supports the stationarity of the portfolio return series.

The ADF test results reject the unit-root null hypothesis for all four portfolio return series at the 1 percent significance level. This indicates that the daily equal-weighted log return series for the Canadian High ESG, Canadian Low ESG, U.S. High ESG, and U.S. Low ESG portfolios are stationary. These results support the use of GARCH-family models, which are estimated on stationary return series rather than non-stationary price levels.

J Post-estimation diagnostic tests

Table 16 reports post-estimation diagnostic tests for the selected GARCH-family models used in the main empirical analysis. These tests are included to assess whether the selected models adequately capture serial dependence and conditional heteroskedasticity in the standardized residuals.

Table 16: Post-Estimation Diagnostic Tests for Selected GARCH Models

Market	Portfolio	Selected Model	Distribution	Diagnostic Test	Statistic	p-value
Canada	High ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box residuals, lag 10	9.432	0.4916
Canada	High ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box residuals, lag 20	14.670	0.7950
Canada	High ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 10	13.583	0.1929
Canada	High ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 20	19.198	0.5090
Canada	High ESG	GJR-GARCH(1,1)	Student-t	ARCH-LM, lag 10	13.201	0.2126
Canada	Low ESG	EGARCH(1,1)	Student-t	Ljung–Box residuals, lag 10	12.176	0.2734
Canada	Low ESG	EGARCH(1,1)	Student-t	Ljung–Box residuals, lag 20	22.623	0.3077
Canada	Low ESG	EGARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 10	14.174	0.1652
Canada	Low ESG	EGARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 20	23.027	0.2874
Canada	Low ESG	EGARCH(1,1)	Student-t	ARCH-LM, lag 10	14.076	0.1695
U.S.	High ESG	EGARCH(1,1)	Student-t	Ljung–Box residuals, lag 10	8.531	0.5771
U.S.	High ESG	EGARCH(1,1)	Student-t	Ljung–Box residuals, lag 20	21.538	0.3661
U.S.	High ESG	EGARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 10	11.910	0.2912
U.S.	High ESG	EGARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 20	21.269	0.3815
U.S.	High ESG	EGARCH(1,1)	Student-t	ARCH-LM, lag 10	10.821	0.3716
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box residuals, lag 10	8.677	0.5630
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box residuals, lag 20	29.614	0.0764
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 10	3.364	0.9715
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	Ljung–Box squared residuals, lag 20	11.682	0.9266
U.S.	Low ESG	GJR-GARCH(1,1)	Student-t	ARCH-LM, lag 10	3.230	0.9755

Notes: This table reports post-estimation diagnostic tests for the selected GARCH-family models. The Ljung–Box tests are applied to standardized residuals and squared standardized residuals at lags 10 and 20. The ARCH-LM test is applied to standardized residuals using 10 lags. The null hypothesis of the Ljung–Box tests is no serial correlation. The null hypothesis of the ARCH-LM test is no remaining ARCH effects. Higher p-values indicate less evidence of remaining serial correlation or conditional heteroskedasticity.

The diagnostic results are reassuring. All reported p-values are above the conventional

5 percent significance level, so the null hypotheses of no residual serial correlation and no remaining ARCH effects cannot be rejected. Although the Ljung–Box test for the U.S. Low ESG standardized residuals at lag 20 is relatively close to significance, it remains above the 5 percent threshold, and the corresponding squared-residual and ARCH-LM tests show no evidence of remaining conditional heteroskedasticity. These results suggest that the selected GARCH-family models provide an adequate representation of the main volatility dynamics in the portfolio return series.

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