

Louvain School of Management

ESG Integration and Investment Fund Performance

With a Focus on Luxembourg's Post-SFDR Regulatory Context

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Abstract :

This study examines the relationship between ESG integration and financial performance among Luxembourg-domiciled UCITS funds over the period 2019 to 2024. Using a panel of 373 funds and four hypotheses, we test whether ESG integration is associated with higher annual returns, whether this association differs across asset classes, whether fund size moderates it, and whether SFDR implementation in March 2021 constitutes a structural break in ESG-performance dynamics.

Results show that ESG integration is positively associated with annual returns in the random effects specification (coef = +0.077, $p = 0.017$), but not in pooled OLS. It suggests the association is concentrated in the cross-sectional between-fund dimension. The ESG-performance association is significantly stronger in allocation funds than in equity funds (coef = +1.815, $p = 0.003$), contrary to expectations. Fund size does not moderate the association. Most importantly, SFDR implementation coincides with a significant weakening of the ESG-performance association across three estimators (FE: coef = -1.273, $p = 0.008$), consistent with compliance-driven ESG adoption diluting the informational content of ESG ratings as performance predictors.

These findings suggest that the regulatory environment shapes the ESG-performance relationship and raise questions about whether mandatory ESG disclosure frameworks channel capital toward genuinely better-performing sustainable investments or primarily stimulate compliance-driven adoption.

Keywords: ESG integration, fund performance, SFDR, Luxembourg, panel data, sustainable finance.

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GLOSSARY OF ACRONYMS, ABBREVIATION AND FREQUENTLY USED TERMS

AUM	Assets Under Management
CAPM	Capital Asset Pricing Model
ESG	Environmental, Social, and Governance
ETF	Exchange-Traded Fund
EU	European Union
FE	Fixed Effects
GLS	Generalized Least Squares
HC3	Heteroskedasticity-Consistent Standard Errors, Type 3
IR	Information Ratio
IV	Instrumental Variable
MS	Morningstar
NAV	Net Asset Value
OLS	Ordinary Least Squares
PRI	Principles for Responsible Investment
RE	Random Effects
SFDR	Sustainable Finance Disclosure Regulation
SRI	Socially Responsible Investing
Sust	Sustainalytics
TNA	Total Net Assets
UCITS	Undertakings for Collective Investment in Transferable Securities
VIF	Variance Inflation Factor
VRIN	Valuable, Rare, Inimitable, Non-substitutable
Article 6 / 8 / 9 — SFDR fund classification tiers	

Executive Summary

Background and Motivation

The integration of environmental, social, and governance (ESG) criteria into investment management has grown from a niche practice into an institutional requirement particularly following the European Union's Sustainable Finance Disclosure Regulation (SFDR), which came into force in March 2021. Luxembourg, as Europe's second-largest fund domicile managing over five trillion euros in assets, represents a critical but underexplored setting for examining whether ESG integration translates into measurable financial performance advantages at the fund level.

Research Questions and Hypotheses

This thesis tests four hypotheses : (H1) whether higher ESG integration is associated with superior fund performance, (H2) whether this relationship is stronger in equity funds than in fixed income and allocation funds, (H3) whether fund size positively moderates the ESG-performance relationship, and (H4) whether SFDR implementation in March 2021 constitutes a structural break in ESG-performance dynamics.

Data and Methodology

The study uses a panel of 373 Luxembourg-domiciled UCITS funds with annual return data for 303 funds (1,534 observations) collected via automated Python web scraping from Yahoo Finance for 2019-2024. ESG measures are sourced from Morningstar Direct (Morningstar ESG Rating, 1-5 scale) and Sustainalytics (Corporate Sustainability Score). The empirical strategy combines pooled OLS with year fixed effects and fund-clustered standard errors, random effects estimation and two-way fixed effects. The Mundlak (1978) test guides estimator selection for H1-H3, where ESG variables are time-invariant; the Hausman test is used for H4.

Key Findings

H1 Baseline ESG-Performance: ESG integration is positively associated with annual returns in the random effects specification ($p = 0.017$) but not in pooled OLS ($p = 0.750$). The divergence suggests the ESG advantage is structural and cross-sectional rather than temporal.

H2 Asset Class Heterogeneity: The ESG-performance relationship is significantly stronger in allocation funds than in equity funds (coef = +1.815, $p = 0.003$), contrary to the prediction. Fixed income shows no significant difference from equity. ESG integration may generate compounding diversification benefits in multi-asset portfolios.

H3: Fund Size Moderation: Fund size does not significantly moderate the ESG-performance relationship ($p = 0.966$). This likely reflects the commoditization of ESG data following SFDR which has reduced informational barriers that favored larger funds.

H4 SFDR Structural Break: SFDR implementation significantly weakened the ESG-performance relationship (FE: coef = -1.273, $p = 0.008$; OLS: coef = -1.083, $p = 0.016$). This is consistent with compliance-driven adoption diluting the signal quality of ESG ratings as performance predictors in the post-regulatory environment.

Robustness analysis using static Morningstar metrics (Sharpe ratio, Jensen's alpha, information ratio) as of April 2025 reveals a negative and significant relationship between ESG integration and all three metrics which is consistent with the H4 finding that the ESG-performance relationship has weakened post-SFDR.

Implications

For fund managers, ESG integration may still generate performance advantages for multi-asset allocation strategies but conviction-based rather than compliance-driven integration is critical for performance differentiation. As for the regulator, the H4 finding raises fundamental questions about whether mandatory ESG disclosure achieves its intended goal of transferring capital toward better-performing sustainable investments suggesting that disclosure requirements alone may be insufficient without enforcement mechanisms that reward integration quality.

Limitations and Future Research

Key limitations include the time-invariant nature of ESG measures, the absence of SFDR classification data at the fund level, incomplete panel coverage from Yahoo Finance, and the restriction of the sample to Luxembourg-domiciled funds with assets exceeding 100 million euros. Future research should prioritize access to time-varying historical ESG scores, SFDR classification data, and multi-jurisdiction samples.

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Introduction

The integration of environmental, social and governance considerations into investment decision-making has become one of the most consequential developments in modern finance. From its origins in faith-based ethical screening and activist divestment campaigns, ESG investing has evolved into an institutional practice managing trillions of euros in assets globally. This transformation accelerated sharply following the European Union's Sustainable Finance Disclosure Regulation which came into force in March 2021 mandating standardized ESG disclosure across the fund industry and altering the incentives for ESG adoption.

Against this backdrop, a simple question remains unresolved in the academic literature: does ESG integration actually improve investment fund performance? The question is simple because the answer depends critically on how performance is measured, over what time period, across which asset classes and in which regulatory environment. The rapid institutionalization of ESG practices post-SFDR may have fundamentally changed the relationship between ESG commitment and financial outcomes as compliance-driven adoption by fund managers who lack conviction in ESG's financial materiality potentially dilutes the signal quality of ESG ratings as performance predictors.

This thesis addresses these questions through a quantitative empirical study of Luxembourg-domiciled investment funds over the period 2019 to 2024. Luxembourg is selected as the research setting for three reasons. First, it is Europe's second-largest fund domicile managing over five trillion euros in assets. Second, Luxembourg implemented SFDR early, creating an ideal natural experiment for studying the regulatory transition effect. Third, Luxembourg has received little attention in fund-level ESG-performance research despite its prominence.

The study tests four hypotheses. The first examines the baseline relationship between ESG integration and annual fund returns using panel data methods appropriate for the time-invariant nature of ESG ratings. The second tests whether this relationship differs systematically across equity, fixed income, and allocation asset classes. The third examines whether fund size moderates the ESG-performance relationship. The fourth tests whether SFDR implementation in March 2021 constitutes a structural break in the ESG-performance relationship.

The empirical approach combines pooled OLS panel regressions with year fixed effects and fund-clustered standard errors, random effects estimation and two-way fixed effects for the pre/post-SFDR analysis. Annual return data for 303 funds covering 2019-2024 are collected

through an automated Python web scraping procedure from Yahoo Finance, complemented by cross-sectional ESG and performance data from Morningstar Direct.

The remainder of this thesis is structured as follows. Section 2 reviews the historical evolution, theoretical frameworks, and empirical evidence on ESG-performance relationships. Section 3 presents the research questions and hypotheses. Section 4 presents the methodology and data collection. Section 5 presents the empirical results and discussion. Section 6 discusses critical setbacks and implications. The conclusion synthesizes the findings and offers recommendations for practitioners and regulators.

2. Literature Review

2.1. Historical Evolution: From Ethical Exclusion to Strategic Integration

Contemporary ESG investing reflects a long evolution from faith-based screening to financially motivated integration. Early ethical investing such as the Pioneer Fund's 1920s exclusions of sin stocks and Quaker prohibitions against slavery related investments, prioritized moral purity over financial optimization. These approaches established the premise that investors could intentionally constrain portfolios based on non-financial criteria though at potential cost to diversification and returns. The 1960s and 1970s politicization through Vietnam War protest divestment and anti apartheid campaigns introduced a strategic dimension. Investment decisions as instruments for corporate behavior change rather than mere conscience-keeping (Revelli, 2013). This shift is analytically significant because it introduced the possibility that ESG considerations might influence corporate practices and valuations.

Three subsequent developments transformed ESG from an activist movement to an institutional practice. Freeman's (1984) stakeholder theory provided theoretical justification for considering non-shareholder constituencies challenging shareholder primacy. The emergence of ESG rating agencies such as ARESE in 1997 and followed by MSCI ESG and Sustainalytics, created the data infrastructure enabling systematic integration though with methodological diversity that remains problematic today (Berg et al., 2022). The Kyoto Protocol (1997) transformed environmental factors from voluntary considerations to regulatory requirements with material financial implications altering ESG's investment relevance even for purely profit-motivated investors.

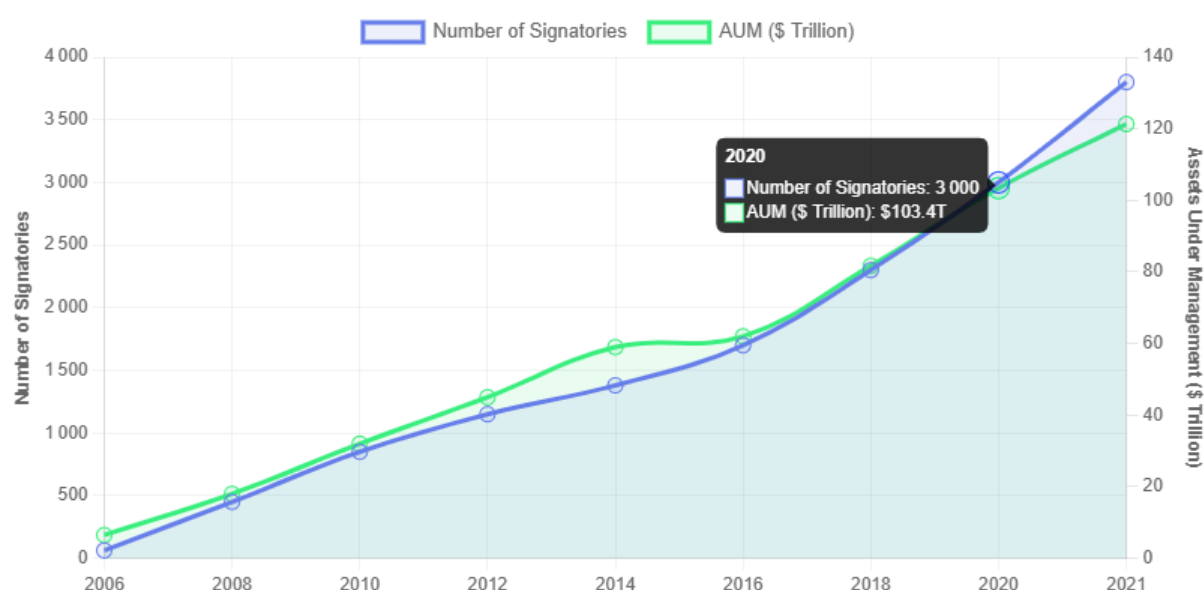
The UN Principles for Responsible Investment, launched in 2006 and growing from 63 signatories managing \$6.5 trillion to over 3,800 signatories managing \$121 trillion by 2021, legitimized ESG integration as consistent with fiduciary duty. The 2015 Paris Agreement and subsequent EU regulatory frameworks such as SFDR (2021), completed ESG's transition from voluntary practice to mandatory consideration for large segments of the financial industry. This regulatory mainstreaming raises the central research question motivating this study, does mandated ESG integration drive value creation or does it produce compliance-focused implementation that adds costs without compensating performance benefits?

This evolution ultimately raises the question of what motivates firms and investors to pursue ESG integration in the first place and whether those motivations translate into measurable financial outcomes. Luxembourg, as Europe's second-largest fund domicile and one of the

earliest adopters of the SFDR framework, provides a unique empirical setting in which these questions can be examined at the fund level. Before turning to the empirical evidence, it is useful to consider the theoretical motivations that prior literature offers for why ESG integration might affect fund performance.

[Figure 1: Evolution of Sustainable Investing, PRI Signatory Growth (2006–2021)]

Source: UN Principles for Responsible Investment (2021). Note: AUM in USD trillion.



2.2 Theoretical Mechanisms Linking ESG to Performance

Prior literature provides several theories illustrating the motivations for firms and investors to pursue ESG investment. For instance, some argue that ESG integration creates stakeholder value that translates into superior financial performance. Others suggest that ESG signals reduce information asymmetries in capital markets and still others think that ESG capabilities represent a source of competitive advantage for fund managers with sufficient resources to implement them effectively. These three perspectives rooted respectively in stakeholder theory, information asymmetry research and the resource-based view generate different predictions about the conditions under which ESG integration should improve performance. Understanding these mechanisms is necessary for interpreting the heterogeneous empirical findings reviewed in Section 3.

2.2.1 Stakeholder Theory: Value Creation Through Stakeholder Management

Stakeholder theory offers one of the most intuitive explanations for why ESG integration might generate superior financial performance. Freeman's (1984) stakeholder theory says that firms managing diverse stakeholder relationships including employees and the environment create sustainable competitive advantages through resource access, legitimacy building, and risk mitigation (Donaldson & Preston, 1995). Applied to investment contexts, funds allocating capital toward stakeholder-oriented companies should capture these value-creation dynamics through portfolio returns. Eccles et al. (2014) provide empirical support, finding that high-sustainability firms demonstrate superior accounting and stock performance over an 18-year horizon particularly in sectors where stakeholder issues are most material. They attribute these results to better risk management, resource efficiency and innovation capabilities. This materiality dimension is critical as stakeholder effects may be stronger where stakeholder issues most directly affect operations and competitive positioning such as extractive industries for environmental factors, labor-intensive sectors for social factors.

However, several challenges complicate stakeholder theory's translation to fund-level performance. Stakeholder value creation often materializes over periods exceeding typical fund performance evaluation windows. It creates temporal misalignment between ESG investments and observable returns. At fund level, the theory also requires that companies with superior stakeholder management offer genuine investment opportunities not already fully reflected in market prices. In reasonably efficient markets, this requires either informational advantages or the ability to identify stakeholder issues before markets do, directly linking stakeholder theory to the information asymmetry perspective examined next. Finally, stakeholder demands sometimes conflict as environmental investments may increase costs while benefiting communities or aggressive supplier negotiations may boost margins while harming supplier relationships. The theory provides limited guidance on navigating these trade-offs which may explain heterogeneous fund-level results even when stakeholder principles are theoretically sound.

2.2.1 Information Asymmetry and Market Efficiency

A second motivation for ESG integration stems from information asymmetry. If ESG factors capture material risks and opportunities that are not fully reflected in market prices, funds with superior ESG research capabilities may identify mispriced securities and generate performance advantages. Under Fama's (1970) efficient market hypothesis, publicly available ESG information should be immediately incorporated into prices leaving ESG-integrated

funds unable to outperform. ESG screening that excludes certain companies or sectors further reduces diversification potentially decreasing returns. This perspective, aligned with Pástor et al.'s (2021) equilibrium model, implies that ESG investing reflects investor preferences rather than profit-seeking based on information advantages.

Substantial evidence challenges this efficient market view, however. Berg et al. (2022) document that ESG rating correlations across major providers average only 0.54, in stark contrast to the 0.99 correlation observed among credit ratings. If professional raters disagree fundamentally with ESG assessments, markets are unlikely to efficiently price this information. Serafeim and Yoon (2022) provide direct evidence of information inefficiency: stock prices react significantly to ESG news, with larger reactions for stocks with higher rating disagreement suggesting that markets resolve ambiguous ESG signals slowly. Climate risk pricing research also shows that people do not give value to the long term effects of climate change. This is what Krueger (Krueger et al., 2020) found. It is like the idea of the Tragedy of the Horizon, where the bad things that can happen in the term are not considered important by the people who make decisions in the market because these things will happen after they are gone. Climate risk pricing research is very important, for understanding climate exposures and climate exposures are a problem.

These findings suggest that funds with superior ESG research capabilities may exploit pricing inefficiencies. Whether such advantages persist as ESG mainstreams remains contested as the rapid proliferation of ESG data providers and the mandatory disclosure introduced by SFDR may be gradually closing the information gaps that once created opportunities. This raises a central question for the contemporary landscape of whether ESG has transitioned from an alpha source to a compliance requirement with different performance implications.

2.2.3 Resource-Based View: ESG Capabilities as Competitive Advantage

A third motivation relates to the organizational capabilities required to implement ESG effectively. Barney's (1991) resource-based view conceptualizes ESG capabilities as strategic resources that may generate competitive advantages when they satisfy the VRIN criteria (valuable, rare, inimitable, and non-substitutable). Investment fund ESG capabilities encompass proprietary analytics, specialized human capital, portfolio company relationships enabling effective engagement and organizational processes that integrate ESG throughout investment workflows (Clark et al., 2015). These potentially satisfied VRIN criteria in ESG's earlier stages, as they were valuable if identifying material risks that traditional analysis misses, rare given significant investment requirements, and inimitable due to the time needed

for expertise and relationship development. As ESG has mainstreamed, many once-rare capabilities have become widely distributed. Major asset managers have built dedicated ESG teams, subscribed to commercial data providers and adopted formal ESG policies. The resource-based view thus predicts that early-mover advantages erode as the field matures, with differentiation increasingly depending on implementation quality rather than mere adoption.

The ESG-performance relationship should vary systematically with fund size and resource access. Larger funds may achieve economies of scale in ESG research by amortizing fixed infrastructure costs over greater assets while smaller funds face capacity constraints in data access, engagement resources and specialized personnel. Empirical evidence supports this scale argument. Ferreira et al. (2013) demonstrate that fund size influences performance outcomes across European markets while Amel-Zadeh and Serafeim (2018) document that larger institutional investors are significantly more likely to integrate ESG information in a sophisticated manner because they possess the analytical infrastructure and human capital that smaller funds cannot afford. However, Chen et al. (2004) caution that scale advantages are not monotonically increasing. At very large asset levels, liquidity constraints and portfolio concentration limits may offset research advantages suggesting a potential non-linear relationship between fund size and ESG-performance dynamics. Luxembourg's fund universe, spanning multi-billion euro UCITS structures to smaller specialized boutiques and providing sufficient size variation to examine whether these scale dynamics materialize empirically.

2.2.4 Synthesis

Taken together, the three frameworks generate distinct predictions. Stakeholder theory predicts superior performance for funds with high ESG integration particularly over sufficiently long-time horizons. The information asymmetry perspective predicts that advantages concentrate among funds with proprietary ESG research capabilities, and that these advantages may decrease as information environments improve. The resource-based view predicts that larger, better-resourced funds demonstrate superior ESG-related outcomes, with performance differentials concentrated among funds with sophisticated rather than superficial implementation. These frameworks are not exclusive, and real-world ESG-performance dynamics may reflect simultaneous operation of all three mechanisms. What distinguishes them empirically is the pattern of heterogeneity they predict, which the empirical analysis in this study is designed to examine.

2.3. ESG Integration and Financial Performance: Empirical Evidence

2.3.1 Meta-Analyses: Aggregate Evidence and Its Limitations

Meta-analytic evidence establishes the aggregate ESG-performance relationship and is a necessary starting point for any review of this topic. However, its primary value for this study lies not in confirming that ESG generates positive returns but in revealing the methodological limitations and heterogeneity that make direct fund-level testing in Luxembourg necessary. The patterns of heterogeneity documented across meta-analyses including variation across geographies, asset classes and methodologies directly motivate the research design choices made in this study.

The ESG-performance literature exhibits a fundamental paradox, increasingly positive aggregate findings alongside persistent heterogeneity and methodological concerns that challenge forward interpretation. Friede et al.'s (2015) landmark meta-analysis of approximately 2,200 studies found that 90% reported non-negative ESG-performance relationships with the majority positive.

However, this interpretation conflates temporal patterns with causation as positive findings may instead reflect publication bias, researcher degrees of freedom or shifting methodologies rather than a strengthening of ESG-performance linkages. More recent meta-analyses reveal the complexity beneath aggregate positivity. Whelan et al. (2021) find that 58% of studies published between 2015 and 2020 show positive ESG-performance relationships, 13% negative and 29% neutral or mixed. They also found that the way studies are done affects the results. For instance studies that look at portfolios tend to show positive results than those that use regression analysis. Also metrics like ROE and ROA tend to show consistent positive results than stock returns.

Atz et al. (2023) directly address publication bias, finding that after adjusting for selective reporting and study quality, the ESG-performance correlation increase from estimates of 0.15 to 0.20 down to approximately 0.10. It suggests that ESG-performance relationships exist but are weaker than raw meta-analyses imply and may be economically modest even when statistically significant.

Crucially, most studies focus on corporate-level ESG performance rather than fund-level ESG integration. This distinction matters for a fundamental reason. Investment funds are the primary vehicle through which capital is allocated to ESG-screened companies and their

ability to generate outperformance depends on factors beyond company-level ESG quality alone, including portfolio construction choices, manager skill, fee structures, and investor flow dynamics. Understanding whether ESG integration at the fund level translates into measurable performance advantages is therefore not merely a replication of corporate-level findings but a distinct and practically important question for the asset management industry. If ESG integration genuinely creates value, funds that implement it most effectively should be identifiable and should demonstrate superior outcomes which is what this study sets out to examine.

2.3.2 Fund-Level Performance: Ambiguous Evidence and Competing Explanations

Fund-level evidence is the most directly relevant to this study's research question, and its ambiguity what motivates a new empirical test. The absence of agreement in the fund-level literature reflects heterogeneity in ESG mechanisms, implementation quality and measurement approaches rather than a failure of the literature. An early consensus emerged from Renneboog et al. (2008) and Bauer et al. (2005), SRI funds neither significantly outperform or underperform conventional funds on a risk-adjusted basis with null findings attributed primarily to diversification costs from negative screening. This no-difference finding became conventional wisdom, but it leaves critical questions unresolved such as, does ESG integration create value that is offset by implementation costs or are ESG factors simply orthogonal to performance under standard measurement approaches?

Contemporary research offers competing refinements consistent with the theoretical frameworks examined in Section 2. Pedersen et al. (2021) find that high-ESG portfolios deliver comparable returns but with lower volatility and risk positioning ESG as risk management rather than alpha generation. This distinction matters methodologically if ESG principally reduces downside risk, Sharpe ratios may detect effects that Jensen's alpha misses which is why this study employs multiple performance metrics. Conversely, Pástor et al. (2021) offer an equilibrium perspective? If widespread ESG preferences cause sustainable assets to trade at premium valuations, ESG funds face lower expected returns, consistent with preference-based rather than fundamental-value explanations.

The fund-level literature's ambiguity may also reflect heterogeneity in ESG integration quality that existing studies fail to capture. Sophisticated integration involving proprietary research, active engagement screening may create value while superficial compliance-driven approaches may add costs without benefits. Existing research typically treats ESG integration

as binary failing to measure implementation depth. This limitation motivates the use of continuous ESG scores rather than binary ESG labels in the present study.

2.3.3 Geographic and Asset Class Variations

Geographic and asset class variations in the ESG-performance relationship provide two forms of justification for this study. First, the European advantage in ESG-performance findings, combined with the absence of systematic post-SFDR analyses justifies focusing on Luxembourg as research setting where regulatory conditions are most advanced and most underexplored. Second, the severe asset class concentration of existing research on equities directly motivates the second hypothesis of this study which predicts that ESG mechanisms operate differently across equity, fixed income and mixed asset funds.

European studies report more favorable ESG-performance relationships than US research (Friede et al., 2015) reflecting stronger regulatory frameworks, longer sustainable investing traditions and the prevalence of stakeholder capitalism norms. The EU's SFDR implementation in March 2021 constitutes the most significant regulatory shift in sustainable finance in recent years and represents a natural experiment for examining whether mandatory standardization strengthens ESG-performance relationships. Yet systematic post-SFDR performance analyses at the fund level remain entirely absent from the literature, a gap this study directly addresses.

The literature also exhibits severe asset class concentration with equity markets dominating fixed income and mixed asset funds understudied despite representing a significant share of total fund assets. This concentration creates analytical problems because the mechanisms linking ESG to performance plausibly differ across asset classes. In equities, stakeholder value creation and reputational channels plausibly link ESG to long-run valuations. In fixed income, credit risk mitigation is the more direct channel, with ESG factors influencing default probabilities and credit spreads. Mixed asset funds face the additional complexity of balancing ESG considerations across asset classes with different materiality profiles. Luxembourg's fund universe spans all three asset classes within a unified regulatory framework, making it uniquely suited to examine whether ESG mechanisms operate uniformly or in asset-class-specific ways.

2.3.4 Fund Manager Incentives and the ESG-AUM Nexus

Understanding why fund managers offer ESG funds is a separate issue from whether these funds outperform but it is analytically necessary for interpreting the empirical results. If managers adopt ESG primarily to attract capital inflows rather than out of conviction in value creation, then the ESG-performance relationship observed in the literature may reflect supply-and-demand dynamics rather than fundamental effects on returns. Fund managers' compensation is typically calculated as a fixed percentage of assets under management, creating a structural incentive to maximize AUM through any means available. Hartzmark and Sussman (2019) provide causal evidence of this dynamic. Being classified as a low-sustainability fund resulted in net capital outflows exceeding \$12 billion, while being classified as a high-sustainability fund generated net inflows of over \$24 billion. This finding establishes that ESG ratings have direct commercial value for managers, creating an incentive to maximize ESG scores regardless of their relationship to returns.

This dynamic creates a potential conflict of interest between maximizing capital inflows and maximizing financial returns. Research by Ceccarelli, Ramelli, and Wagner (2024) shows that managers who improved their sustainability ratings underperformed in their ESG-related trades where in other words, trades made to improve the fund's ESG score were poor trades from a financial standpoint. This suggests that the pursuit of better ESG ratings may come at the expense of performance, constituting a significant source of heterogeneity in the ESG-performance relationship at the fund level. Additionally, evidence on managerial ownership shows that when managers have a significant portion of their own capital invested in the fund, the fund's ESG performance tends to be weaker suggesting that when personal financial incentives are aligned with returns, managers move away from ESG strategies they do not believe are financially advantageous (Riedl & Smeets, 2017).

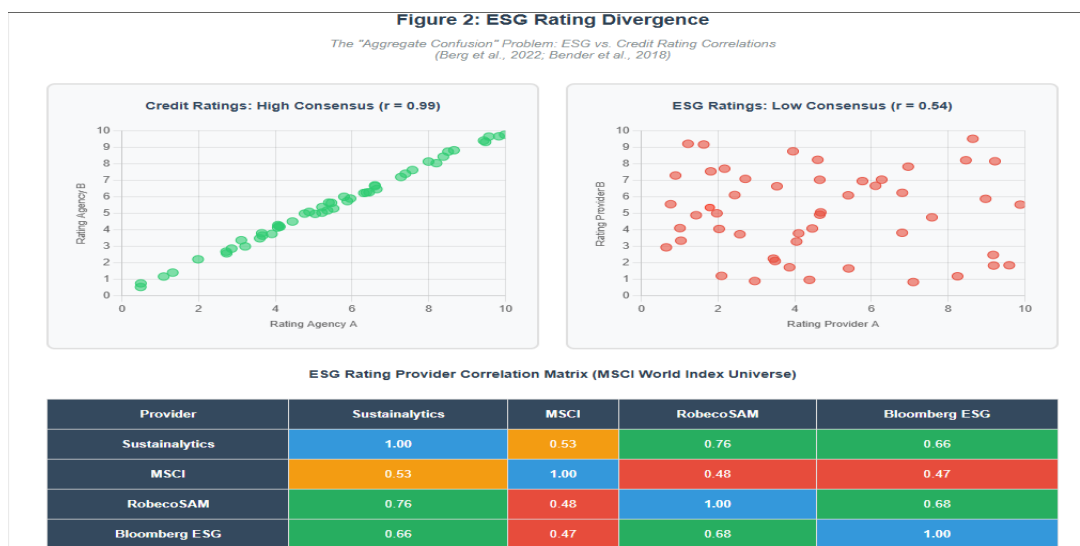
These findings have direct implications for interpreting the results of this study. If a significant portion of the ESG funds in the sample adopt ESG primarily for commercial reasons rather than out of conviction in value creation, then the ESG-performance relationship may be difficult to confirm not because ESG does not create value, but because integration quality is heterogeneous. This observation reinforces the importance of examining fund size as a moderator. Larger funds with sufficient resources are better positioned to distinguish between cosmetic ESG adoption and authentic integration which should translate into a stronger ESG-performance relationship as fund size increases.

2.4. ESG Measurement Challenges

Before moving to the empirical context, it is important to acknowledge the measurement challenges that affect ESG-performance research including this study. Rating divergence across ESG providers is not merely a technical inconvenience. It has direct implications for how ESG integration is operationalized and how results should be interpreted. Unlike standardized financial metrics, ESG encompasses diverse dimensions measured through varied methodologies creating fundamental measurement challenges. Berg et al.'s (2022) systematic analysis reveals ESG rating correlations averaging only 0.54 across major providers, dramatically lower than the 0.99 correlation observed among credit ratings undermining the premise that ESG represents a clearly defined measurable construct. They found three reasons for this. One reason is what they call scope. This means which things are being measured for ESG. Another reason is measurement. This means how they are deciding what the numbers are. The last reason is weighting. This means how important each part of ESG is. When they looked at these things they found that the reason the ratings are different is not because of mistakes in measuring. It is because the companies have ideas about what ESG performance is. They have ideas, about what ESG means.

[Figure 2: The 'Aggregate Confusion' Problem — ESG vs. Credit Rating Correlations]

Source: Berg et al. (2022); Bender et al. (2018).



For this study, rating divergence has a direct implication. Results may be sensitive to the choice of ESG measure. The Morningstar Sustainability Rating and Sustainalytics ESG Risk Score used in this study both draw on the same underlying Sustainalytics methodology which reduces but does not eliminate specific bias. This limitation is acknowledged as a constraint on generalizability and motivates the use of two complementary ESG measures as a partial

robustness check. Rating disagreement itself may also be informative. Gibson Brandon et al. (2022) show that stocks with greater rating divergence exhibit higher volatility and larger ESG news reactions. It suggests that measurement uncertainty creates market inefficiency that sophisticated investors may exploit.

2.5 Luxembourg's Institutional Context and Research Implications

Luxembourg is not simply a convenient data source for this study but a theoretically motivated research setting. Its combination of regulatory sophistication, fund diversity, and institutional investor base creates conditions in which all three theoretical mechanisms examined in Section 2 can be tested together.

2.5.1 Luxembourg as an Underexplored Empirical Setting

Despite managing over €5 trillion in assets (ALFI, 2024) and ranking as Europe's second-largest fund domicile, Luxembourg has received surprisingly attention in fund-specific ESG research. Existing European studies aggregate data across domiciles without examining jurisdiction-specific characteristics, a consequential gap given that Luxembourg's regulatory environment, institutional investor base and cross-border distribution infrastructure differ meaningfully from the domestic fund markets most studied. Luxembourg's UCITS expertise and cross-border distribution infrastructure attract a predominantly institutional and sophisticated investor base which may influence both the demand for genuine ESG integration and the quality of implementation.

Luxembourg's comprehensive SFDR implementation creates a unified regulatory framework within which diverse fund types, including equity, fixed income and mixed assets, operate under identical disclosure and classification requirements. This enables comparative analysis across asset classes and fund sizes that multi-jurisdiction studies cannot achieve. Furthermore, the relatively recent SFDR implementation means that Luxembourg's post-2021 period represents a structural shift in the ESG integration environment whose performance implications remain entirely unexamined in the academic literature.

2.5.2 SFDR and the Regulatory Architecture

SFDR introduces mandatory disclosure requirements and a three-tier fund classification. Article 6 for funds with no sustainability claims, Article 8 for funds promoting ESG

characteristics, and Article 9 for funds pursuing explicit sustainability objectives. This architecture addresses one of literature's most persistent challenges, the absence of clear definitional boundaries between ESG and conventional funds. However, self-classification with limited enforcement creates verification challenges and early evidence of substantial within-category heterogeneity raises the question of whether SFDR categories distinguish integration quality or primarily signal marketing positioning.

2.5.3 Theoretical Intersections in the Luxembourg Context

Within Luxembourg's post-SFDR environment, the three theoretical mechanisms examined in Section 2 intersect in distinctive ways. If stakeholder theory dominates, funds with stronger ESG commitments should outperform regardless of size or asset class. If information asymmetry effects predominate, performance advantages should concentrate among funds with proprietary ESG research capabilities. If resource-based mechanisms matter most, the ESG-performance relationship should be strongest among larger funds and should vary by asset class according to the materiality of ESG mechanisms in each context. These considerations position Luxembourg as a setting that uniquely concentrates the features necessary for testing all three mechanisms simultaneously. Regulatory standardization, sufficient fund universe diversity, and a post-mainstreaming context that enables examination of whether ESG-performance dynamics have shifted as the practice has moved from voluntary differentiator to regulatory requirement.

2.6 Research Gaps and Justification for the Present Study

The foregoing review reveals five interconnected gaps in the ESG-performance literature that motivate direct empirical investigation in Luxembourg's post-SFDR context.

First, fund-level ESG-performance relationships remain understudied relative to corporate-level dynamics. Existing fund studies rarely examine the heterogeneity of implementation quality within ESG categories and tend to treat ESG integration as binary rather than measuring it on a continuous scale. This study addresses this gap using fund-level ESG scores from Morningstar and Sustainalytics directly motivating the first hypothesis.

Second, European fund markets, particularly Luxembourg, are substantially underrepresented in systematic empirical analyses. The post-SFDR period represents a structural shift in the regulatory environment that no existing study has examined in terms of fund-level

performance implications. Luxembourg's position as Europe's second-largest fund domicile with comprehensive SFDR implementation makes it an ideal and largely unexplored setting for addressing this gap.

Third, the severe concentration of ESG-performance research on equity funds leaves fixed income and mixed asset classes empirically underexplored, even though the mechanisms linking ESG to performance plausibly differ across these contexts. Luxembourg's multi-asset fund universe within a unified regulatory framework provides the appropriate conditions for testing whether ESG mechanisms are asset-class-specific which is precisely what the second hypothesis examines.

Fourth, the moderating role of fund size predicted by the resource-based view and supported by evidence from Ferreira et al. (2013) and Amel-Zadeh and Serafeim (2018), remains empirically underexplored in ESG-specific fund research. Whether larger funds translate ESG capabilities into superior performance outcomes is an open empirical question that the third hypothesis addresses directly.

Fifth, methodological concerns including endogeneity, survivorship bias and the measurement of ESG integration depth remain inadequately addressed in most existing fund-level studies. The present study addresses these through the use of continuous ESG measures, a cross-sectional design that controls fund-level characteristics.

3. Hypothesis

The following hypotheses are derived from the theoretical frameworks and empirical gaps identified in this literature review. The first hypothesis tests the baseline prediction of both stakeholder theory and the information asymmetry perspective, namely that stronger ESG integration is associated with superior financial performance. The second tests whether ESG mechanisms are asset-class-specific as predicted by the differential materiality of ESG channels across equity and fixed income contexts. The third tests whether fund size moderates the ESG-performance relationship as predicted by the resource-based view and supported by evidence on scale advantages in ESG integration.

Hypothesis 1: ESG Integration and Financial Performance

The first and primary hypothesis concerns the ESG-performance relationship at the fund level. Drawing on stakeholder theory (Freeman, 1984; Eccles et al., 2014), funds with stronger ESG integration are expected to benefit from superior risk management, reduced exposure to regulatory, reputational shocks and more efficient allocation of capital toward companies with competitive advantages. The information asymmetry perspective adds a complementary prediction. Where ESG-related information remains imperfectly priced as evidenced by the rating divergence documented by Berg et al. (2022) and the market underreaction to ESG news reported by Serafeim and Yoon (2022), funds with sophisticated integration capabilities may identify mispriced risk generating performance advantages over funds with lower ESG integration. ESG integration is operationalized through Morningstar Sustainability Ratings and Sustainalytics ESG Risk Scores. Performance is measured through Sharpe ratios, Jensen's alpha, and information ratios.

H1: *Luxembourg investment funds with higher ESG integration demonstrate superior financial performance compared to funds with lower ESG integration, after controlling for fund size, age, and asset class.*

Hypothesis 2: Asset Class Heterogeneity in ESG-Performance Dynamics

The second hypothesis addresses the concentration of ESG-performance research on equity funds, leaving fixed income and mixed asset classes substantially understudied. As established in Section 2, the mechanisms through which ESG affects performance differ across asset classes. In equity funds, stakeholder value creation, operational efficiency gains, and reputational channels plausibly link ESG quality to long-run valuations. In fixed income funds, credit risk mitigation is the more direct channel, with ESG factors potentially influencing default probabilities and credit spreads. Mixed asset funds must balance ESG considerations across asset classes with different materiality profiles. These mechanism differences generate the prediction that the positive ESG-performance relationship expected in H1 should be stronger among equity funds, where ESG value creation channels are most directly observable. This hypothesis is tested through interaction terms between ESG integration measures and asset class indicators.

H2: *The positive relationship between ESG integration and financial performance is stronger among equity funds than among fixed income and mixed asset funds, reflecting differences in the mechanisms through which ESG factors affect fund-level returns across asset classes.*

Hypothesis 3: Fund Size as a Moderator of ESG-Performance Relationships

The third hypothesis is grounded in the resource-based view (Barney, 1991; Clark et al., 2015). As ESG has mainstreamed, differentiation increasingly depends on implementation quality. The depth of proprietary ESG research, the effectiveness of portfolio company engagement and the sophistication of materiality analysis. These capabilities require sustained investment in human capital and data infrastructure, and are therefore more accessible to larger funds. Ferreira et al. (2013) demonstrate that fund size influences performance outcomes across European markets while Amel-Zadeh and Serafeim (2018) document that larger institutional investors are more likely to integrate ESG information in a sophisticated and systematic manner. However, Chen et al. (2004) caution that scale advantages are not monotonically increasing. At very large asset levels, liquidity constraints may offset research advantages suggesting a potential non-linear relationship. This hypothesis is tested through interaction terms between ESG integration measures and fund size measured by log total net assets with a quadratic term to capture potential non-linearities.

H3: *The positive relationship between ESG integration and financial performance is positively moderated by fund size, with larger funds better positioned to leverage ESG research capabilities into performance outcomes, though this moderating effect may diminish at very large asset levels.*

Hypothesis 4: Impact of SFDR on ESG-Performance Dynamics

Prior to SFDR, ESG integration was largely voluntary and conviction-driven, potentially generating performance advantages for early adopters. Following SFDR's implementation, mandatory ESG consideration may have either strengthened the relationship through improved information quality or weakened it as compliance-driven adoption replaced conviction-based integration.

***H4:** The relationship between ESG integration and financial performance differs significantly between the pre-SFDR period (2019-2020) and the post-SFDR period (2022-2024), with SFDR implementation constituting a structural break in ESG-performance dynamics among Luxembourg-domiciled investment funds.*

4. Methodology

4.1 Research Design

This study employs a quantitative empirical research design to examine the relationship between ESG integration and financial performance among Luxembourg-domiciled investment funds. The dataset has a panel structure, each fund is observed across multiple years from 2019 to 2024, yielding both cross-sectional variation across funds and temporal variation within funds. This panel structure governs the choice of estimation method for all four hypotheses.

The key ESG variables, the Morningstar ESG Rating and the Sustainalytics ESG Score are measured at a single point in time and do not vary across years within the same fund. This has implications for estimator choice across the four hypotheses and the appropriate strategy differs by hypothesis.

For H1, both Pooled OLS with year fixed effects and fund-clustered standard errors, and Random Effects with year fixed effects are estimated and reported. The Mundlak approach was tested to formally guide the choice between these two estimators but was not feasible since ESG_Rating does not vary within funds. Its fund-level mean is identical to the variable itself producing a singular matrix. Random Effects is therefore preferred over Pooled OLS on efficiency grounds as it incorporates fund-level heterogeneity through the random effects variance component making it more efficient than OLS in the presence of unobserved fund-

level characteristics. Both specifications are reported to allow comparison as recommended by the thesis supervisor.

For H2 and H3, two-way fixed effects estimation was tested empirically but is not feasible. Although the variables of interest are interaction terms ESG x D_FI, ESG x D_Alloc, and ESG x Log_TNA, these interactions have zero within-fund variation as confirmed by diagnostic testing. ESG_Rating, the asset class dummies and Log_TNA are all time-invariant at the fund level in this dataset, meaning their interactions are equally time-invariant and fully absorbed by fund fixed effects. The resulting model is empty. Pooled OLS and Random Effects are therefore the only applicable estimators for H2 and H3.

For H4, the interaction term ESG x Post_SFDR varies over time within funds since Post_SFDR switches from 0 to 1 after March 2021. Two-way fixed effects estimation is therefore feasible and is estimated alongside Random Effects and Pooled OLS. The Hausman test is used to guide the choice between Fixed Effects and Random Effects for this hypothesis.

4.2 Sample and Data Collection

4.2.1 Sample Construction

The sample consists of Luxembourg-domiciled open-end mutual funds (UCITS) across three asset classes. Global large-cap equity funds, EUR-denominated fixed income funds, and EUR flexible allocation funds. Inclusion criteria such as fund domicile is Luxembourg, fund type is open-end mutual fund excluding ETFs, fund status is active as of the data collection date, and total net assets per share class exceed 100 million euros. The final cross-sectional sample comprises 373 funds. 125 equity funds, 125 fixed income funds, and 123 allocation funds. For the panel analysis, annual return data are available for 303 funds, yielding 1,534 fund-year observations for H1-H3 and 1,236 fund-year observations for H4.

4.2.2 Data Sources

All fund-level cross-sectional variables are sourced from Morningstar Direct, accessed in April 2025. Annual return data are collected through an automated Python web scraping procedure. For each fund, the Morningstar internal identifier (format 0P0000XXXX) is first retrieved via the Yahoo Finance search API using the fund's ISIN. The Annual Total Return History table on each fund's Yahoo Finance performance page is then accessed programmatically using the Selenium WebDriver library with a headless Chrome browser. Annual return percentages are extracted directly from the rendered HTML for each year 2019 to 2024. A five-second pause between requests prevents server-side rate limiting.

4.3 Variable Definitions and Measurement

Table 4 provides a complete summary of all variables used in the study.

Table 4: Variable Definitions and Data Sources

Variable	Type	Description	Source
Annual_Return	Dependent (panel)	Annual total return of fund <i>i</i> in year <i>t</i> (%)	Yahoo Finance (scraping)
Sharpe	Dependent (robustness)	Sharpe ratio, 12-month trailing as of April 2025	Morningstar Direct
Alpha	Dependent (robustness)	Jensen's alpha, 12-month trailing as of April 2025	Morningstar Direct
IR	Dependent (robustness)	Information ratio, 12-month trailing as of April 2025	Morningstar Direct
ESG_Rating	Independent (main)	Morningstar ESG Rating 1-5 globes (5 = best ESG)	Morningstar / Sustainalytics
ESG_Inv	Independent (robustness)	Sustainalytics score inverted; higher = better ESG	Sustainalytics (inverted)
Log_TNA	Control	Natural log of total net assets (EUR)	Morningstar Direct
Fund_Age	Control	Age in years from inception to 31/12/2024	Morningstar Direct
Fee_Num	Control	Fee level ordinal 1 (Low) to 5 (High); missing = 3	Morningstar Direct
D_FI	Control	Dummy: 1 if Fixed Income, 0 otherwise (ref = Equity)	Morningstar Direct
D_Alloc	Control	Dummy: 1 if Allocation, 0 otherwise (ref = Equity)	Morningstar Direct
Year	Control	Calendar year fixed effects in all models	Calendar
Post_SFDR	Moderator (H4)	0 = pre-SFDR (2019-2020), 1 = post-SFDR (2022-2024)	Constructed

Note: ESG_Inv = max(ESG_Score) - ESG_Score. Fee_Num missing values imputed to 3 (Average). Sharpe, Alpha, IR reflect April 2024-April 2025 window only (robustness check).

4.4 Model Specification

4.4.1 Estimator Selection

For H1, Random Effects is preferred over Pooled OLS on efficiency grounds. Both are reported to allow comparison. The Mundlak test was not feasible due to perfect collinearity between the time-invariant ESG variable and its fund-level mean.

For H2 and H3, two-way fixed effects was tested and found not feasible. All interaction terms (ESG x D_FI, ESG x D_Alloc, ESG x Log_TNA) have zero within-fund variation and are

fully absorbed by fund fixed effects. Pooled OLS and Random Effects are the only applicable estimators.

For H4, the Hausman test between two-way fixed effects and random effects is reported. The interaction term ESG x Post_SFDR varies over time, making fixed effects identification possible.

4.4.2 H1: Baseline ESG-Performance Relationship

$$\text{Return}_{it} = b_0 + b_1 \cdot \text{ESG}_i + b_2 \cdot \text{Log_TNA}_i + b_3 \cdot \text{Fund_Age}_i + b_4 \cdot \text{Fee}_i + b_5 \cdot \text{D_FI}_i + b_6 \cdot \text{D_Alloc}_i + \text{Year_FE} + e_{it}$$

where Return_{it} is the annual return of fund i in year t . H1 predicts $b_1 > 0$.

4.4.3 H2: Asset Class Heterogeneity

$$\text{Return}_{it} = b_0 + b_1 \cdot \text{ESG}_i + b_2 \cdot \text{D_FI}_i + b_3 \cdot \text{D_Alloc}_i + b_4 \cdot (\text{ESG}_i \times \text{D_FI}_i) + b_5 \cdot (\text{ESG}_i \times \text{D_Alloc}_i) + \text{Controls} + \text{Year_FE} + e_{it}$$

H2 predicts $b_4 < 0$ and $b_5 < 0$.

4.4.4 H3: Fund Size as Moderator

$$\text{Return}_{it} = b_0 + b_1 \cdot \text{ESG}_i + b_2 \cdot \text{Log_TNA}_i + b_3 \cdot (\text{ESG}_i \times \text{Log_TNA}_i) + \text{Controls} + \text{Year_FE} + e_{it}$$

H3 predicts $b_3 > 0$.

4.4.5 H4: Pre versus Post-SFDR

$$\text{Return}_{it} = b_0 + b_1 \cdot \text{ESG}_i + b_2 \cdot \text{Post_SFDR}_t + b_3 \cdot (\text{ESG}_i \times \text{Post_SFDR}_t) + b_4 \cdot \text{Log_TNA}_i + b_5 \cdot \text{Fee}_i + \text{Fund_FE} + \text{Year_FE} + e_{it}$$

H4 predicts b_3 differs from zero, with no a priori sign restriction.

4.5 Robustness Checks and Limitations

All specifications are estimated with both ESG measures and use fund-clustered standard errors (OLS) or HC3 robust standard errors (RE). The Hausman test for H4 guides estimator selection between fixed and random effects. For H1-H3, the Mundlak test was not feasible due to the time-invariant nature of the ESG variables. Random Effects is preferred over Pooled OLS on efficiency grounds and both are reported. Supplementary cross-sectional regressions using the static Sharpe ratio, Jensen's alpha and information ratio are reported as robustness checks acknowledging that these metrics reflect only the April 2024 to April 2025 window.

5. Results and Discussion

This section presents the empirical results for each of the four hypotheses. Section 5.0 describes the sample and key variables including descriptive statistics and the correlation matrix. Sections 5.1 through 5.4 present the regression results in turn beginning in each case with the control variables before turning to the ESG coefficients of interest. Section 5.5 presents the robustness analysis using performance metrics separately from the main results. Section 5.6 synthesizes the findings across all hypotheses.

5.0 Sample Description and Descriptive Statistics

Table 1 reports descriptive statistics for the main panel variables across 1,610 fund-year observations covering 2019-2024. The average annual return is 0.91% with substantial cross-year variation ($SD = 7.77\%$) driven by the 2020 COVID shock and the 2022 monetary tightening correction visible in Table 3. The Morningstar ESG Rating averages 3.48 globes out of 5 across all fund-years. The inverted Sustainalytics Score averages 4.55. Both ESG measures are time-invariant cross-sectional variables observed in April 2025. They are not combined but used in parallel specifications. Each hypothesis is tested twice, once with the Morningstar ESG Rating (MS specification) and once with the inverted Sustainalytics Score (Sust specification) using identical control structures. This approach follows Berg et al. (2022), who document that ESG ratings from different providers capture related but distinct dimensions of ESG quality.

Table 1: Descriptive Statistics Panel Variables (2019-2024)

Variable	N	Mean	SD	Min	P25	Median	Max
Annual Return (%)	1,610	0.912	7.769	-24.840	-4.220	1.650	23.640
ESG Rating (1-5)	1,513	3.480	0.899	1.000	3.000	4.000	5.000
ESG Score Inv. (Sust)	1,429	4.546	1.995	0.000	3.120	4.590	16.870
Log(TNA)	1,610	19.415	0.804	18.421	18.823	19.219	23.116
Fund Age (years)	1,610	9.915	6.107	-0.791	5.123	9.105	30.875
Fee Level (1-5)	1,610	2.771	1.311	1.000	1.000	3.000	5.000
D_FI (Fixed Income)	1,610	0.364	0.481	0.000	0.000	0.000	1.000
D_Alloc (Allocation)	1,610	0.356	0.479	0.000	0.000	0.000	1.000
—	—	—	—	—	—	—	—

Notes: Panel H1-H3 (N = 1,610 obs, 309 funds, 2019-2024). ESG Rating is the Morningstar Sustainability Rating (1-5; 5 = best ESG). ESG Score Inv. is the Sustainalytics Corporate Sustainability Score inverted so that higher values indicate better ESG. Both ESG measures are time-invariant cross-sectional variables measured in April 2025. Annual Return (%) collected via Yahoo Finance scraping.

Table 7 reports the correlation matrix. ESG Rating and the inverted Sustainability Score are positively but imperfectly correlated ($r = 0.283$) confirming that they capture related but distinct dimensions of ESG quality and justifying their use as parallel rather than combined measures. The raw correlations between each ESG measure and Annual Return are modest (ESG Rating: $r = +0.084$; ESG Inv.: $r = -0.131$), consistent with the weak unconditional associations documented in meta-analytic reviews and motivating multivariate panel regressions.

Table 7: Correlation Matrix Panel Variables

	Ann. Return	ESG Rating	ESG Inv.	Log(TNA)	Fund Age	Fee Level
Annual Return	1.000	0.084	-0.131	0.079	-0.053	0.022
ESG Rating	0.084	1.000	0.283	-0.078	-0.188	-0.141
ESG Inv. (Sust)	-0.131	0.283	1.000	-0.019	0.076	-0.134
Log(TNA)	0.079	-0.078	-0.019	1.000	0.037	-0.020
Fund Age	-0.053	-0.188	0.076	0.037	1.000	0.134
Fee Level	0.022	-0.141	-0.134	-0.020	0.134	1.000

Notes: Pairwise complete observations. All variables are panel-level (fund-year). ESG variables are time-invariant cross-sectional measures assigned to each fund-year observation.

Figure 8 traces the evolution of key fund characteristics across the sample period. Panel A confirms the year-to-year variation in mean returns that motivates the inclusion of year fixed effects in all specifications. Panel B shows that mean ESG Rating rose modestly between 2019 and 2022 (from 3.42 to 3.51), consistent with the SFDR-driven improvement in ESG disclosure following the March 2021 regulation. Panel C shows a declining fund age trajectory as newer funds entered the sample, while Panel D shows a slight decline in mean fee levels. These trends are controlled for Fund Age and Fee Level regressors in all specifications.

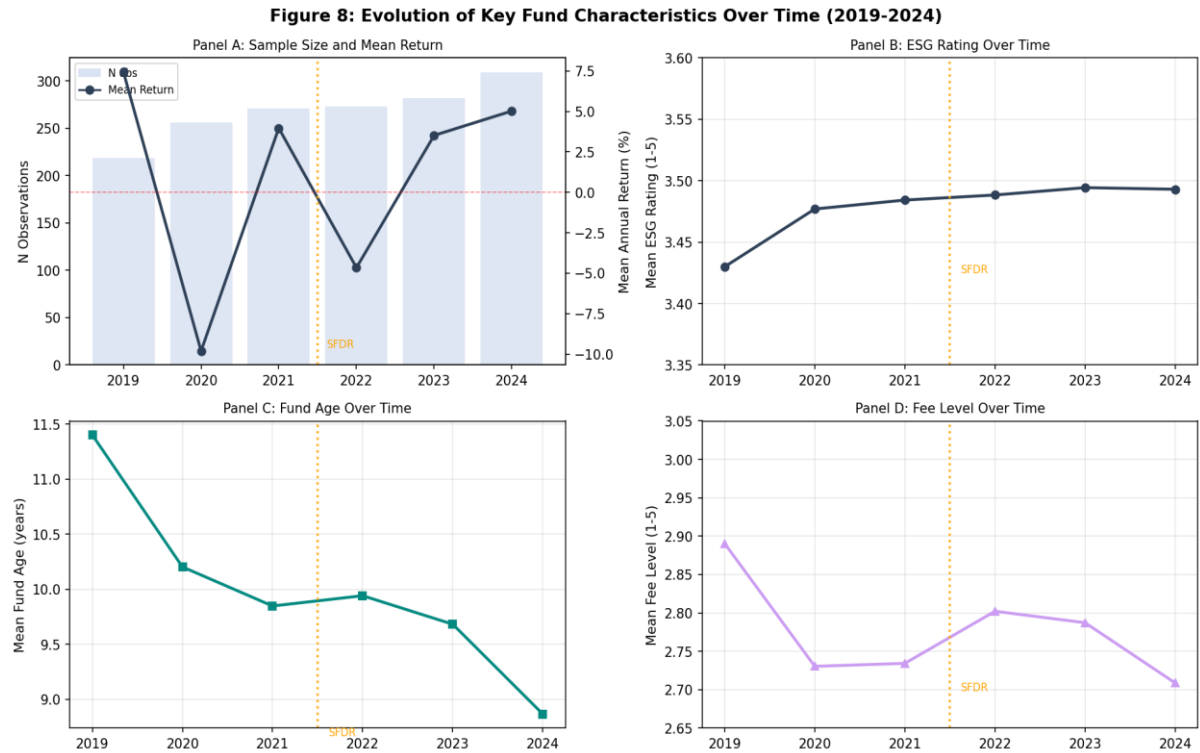


Figure 8: Evolution of Key Fund Characteristics Over Time (2019-2024). Orange dotted line marks SFDR implementation (March 2021). Panel A: sample size and mean annual return. Panel B: mean ESG Rating. Panel C: mean fund age. Panel D: mean fee level.

Table 5: Summary of Regression Results : All Hypotheses

Hypothesis	Estimator	Key Variable	Coef.	p-val	Verdict
H1: ESG → Annual Return	Pooled OLS	ESG_Rating	+0.077	0.750	n.s.
H1: ESG → Annual Return	RE (preferred)	ESG_Rating	+0.077	0.017**	Supported
H2: ESG x Fixed Income	Pooled OLS	ESG x D_FI	-0.468	0.392	n.s.
H2: ESG x Allocation	Pooled OLS	ESG x D_Alloc	+1.815	0.003***	Supported (reversed)
H3: ESG x Log(TNA)	Pooled OLS	ESG x Log_TNA	+0.011	0.966	Not supported
H4: ESG x Post_SFDR	FE two-way	ESG x Post_SFDR	-1.273	0.008***	Supported
H4: ESG x Post_SFDR	RE (preferred)	ESG x Post_SFDR	-1.230	<0.01***	Supported

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. = not significant. OLS: year fixed effects and fund-clustered standard errors. RE: HC3 robust standard errors, Wallace-Hussain estimator. RE is preferred over Pooled OLS on efficiency grounds: it incorporates fund-level heterogeneity through the random effects variance component, making it more efficient than OLS regardless of the Mundlak test outcome. For H4, RE is additionally favoured by the Hausman test ($p = 0.995$ and $p = 0.739$). Full regression tables with all control coefficients follow in Sections 5.1 through 5.5.

With the sample characterized and the main findings visible at a glance, the following sections discuss each hypothesis in detail.

5.1 H1: ESG Integration and Annual Fund Returns

H1 asked whether funds with stronger ESG integration tend to be associated with higher annual returns. Table A1 reports the full results for both ESG measures across OLS and RE estimators.

Control variables. The control variables show patterns consistent with literature. Fund size (Log_TNA) is positive and significant across all specifications (coef = +0.484, $p = 0.042$ in OLS; +0.485, $p < 0.01$ in RE), consistent with Ferreira et al. (2013) who document scale economies in European fund management. Fund age is negative and significant (coef = -0.105, $p = 0.001$) also consistent with Chen et al. (2004) who find that older funds face increasing liquidity constraints and organizational rigidities that erode performance over time. Fee level is negative and significant (coef = -0.582, $p < 0.001$) similar with Carhart (1997) and Jensen (1968), who establish that management costs directly reduce net investor returns. The asset class dummies are large and significant. Fixed income funds generate approximately 13.1 percentage points lower annual returns than equity funds ($p < 0.001$) and allocation funds approximately 8.0 percentage points lower ($p < 0.001$), reflecting their lower systematic risk exposure.

ESG coefficients. In the Pooled OLS specification, the coefficient on ESG Rating is positive but not statistically significant (coef = +0.077, $p = 0.750$). In the Random Effects specification, the same coefficient is positive and statistically significant (coef = +0.077, $p = 0.017$). The sensitivity of the ESG coefficient to estimator choice suggests caution in interpreting the baseline ESG effect. RE is preferred over Pooled OLS on efficiency grounds since it incorporates fund-level heterogeneity through the random effects variance component. Even where the Mundlak test was not feasible due to perfect multicollinearity, RE remains more efficient than OLS and constitutes the preferred estimate.

The RE result suggests a modest positive association between ESG integration and annual returns in the between-fund dimension. Funds with structurally stronger ESG profiles tend to be associated with higher average annual returns. This is in line with stakeholder theory which predicts that ESG advantages build through durable organizational capabilities rather than generating immediate year-to-year return responses.

However, the divergence between the Morningstar and Sustainalytics specifications in the RE model deserves careful attention rather than a passing reference to rating divergence. The

Morningstar ESG Rating (coef = +0.077, $p = 0.017$) and the inverted Sustainalytics Score (coef = -0.060, $p < 0.01$) point in opposite directions. This is not merely a measurement artefact. It reflects a fundamental conceptual difference between the two instruments. The Morningstar ESG Rating is a portfolio-level sustainability rating that aggregates the ESG risk profile of the securities held by the fund measuring how well the fund's holdings manage exposure to ESG-related risks relative to peers. The Sustainalytics Corporate Sustainability Score, by contrast, is a company-level metric that measures the unmanaged ESG risk exposure of individual issuers. When inverted, a higher score indicates that the fund holds companies with lower residual ESG risk at the firm level.

The positive Morningstar coefficient suggests that funds rated as managing their portfolio-level ESG risk well tend to generate higher returns, consistent with a risk-management interpretation. Good portfolio-level ESG governance is associated with better return outcomes. The negative Sustainalytics coefficient suggests that funds holding companies with very low company-level ESG risk exposure (inverted high score) tend to generate lower returns which is consistent with the preference-based asset pricing model of Pastor et al. (2021). Companies with very low ESG risk are held in high demand, trade at premium valuations and therefore offer lower expected returns. These two results are not contradictory, they measure different things. The Morningstar result captures a portfolio management quality premium; the Sustainalytics result captures a valuation premium discount. This distinction demonstrates that the sign of the ESG-performance relationship depends critically on which dimension of ESG is measured and suggests that future research should be more precise about whether ESG ratings measure risk management quality (portfolio level) or ESG risk exposure (company level) as these dimensions can have opposite performance implications.

Three additional limitations apply. First, the ESG Rating is measured in April 2025 and used as a proxy for ESG integration over 2019-2024, introducing potential look-ahead bias. Second, reverse causality cannot be excluded: better-performing funds may invest more in ESG infrastructure, improving their subsequent ratings. Third, the opposing directions of the two ESG specifications underline that H1 should be considered partially supported, with the direction of the effect depending on the ESG dimension operationalized.

Table A1: H1 — ESG Integration and Annual Fund Returns

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	0.077 (0.201)		0.077** (0.214)	

ESG Score (Sustainalytics)		-0.059 (0.090)		-0.060*** (0.071)
Log(TNA)	0.484** (0.189)	0.535** (0.193)	0.485*** (0.205)	0.535*** (0.210)
Fund Age	-0.105*** (0.029)	-0.115*** (0.030)	-0.105*** (0.025)	-0.114*** (0.026)
Fee Level	-0.582*** (0.140)	-0.604*** (0.139)	-0.582*** (0.147)	-0.604*** (0.147)
Fixed Income	-13.137*** (0.391)	-12.751*** (0.376)	-13.137*** (0.431)	-12.750*** (0.421)
Allocation	-8.012*** (0.458)	-7.998*** (0.457)	-8.012*** (0.502)	-7.998*** (0.497)
Year FE	Yes	Yes	Yes	Yes
SE	Clustered	Clustered	HC3	HC3
N	1,554	1,470	1,554	1,470
R ²	0.685	0.688	0.155	0.148

Notes: Dependent variable is annual total return (%). OLS: fund-clustered standard errors. RE: HC3 robust standard errors, Wallace-Hussain estimator. RE is preferred over OLS on efficiency grounds; it incorporates fund-level heterogeneity more efficiently regardless of the Mundlak test outcome. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

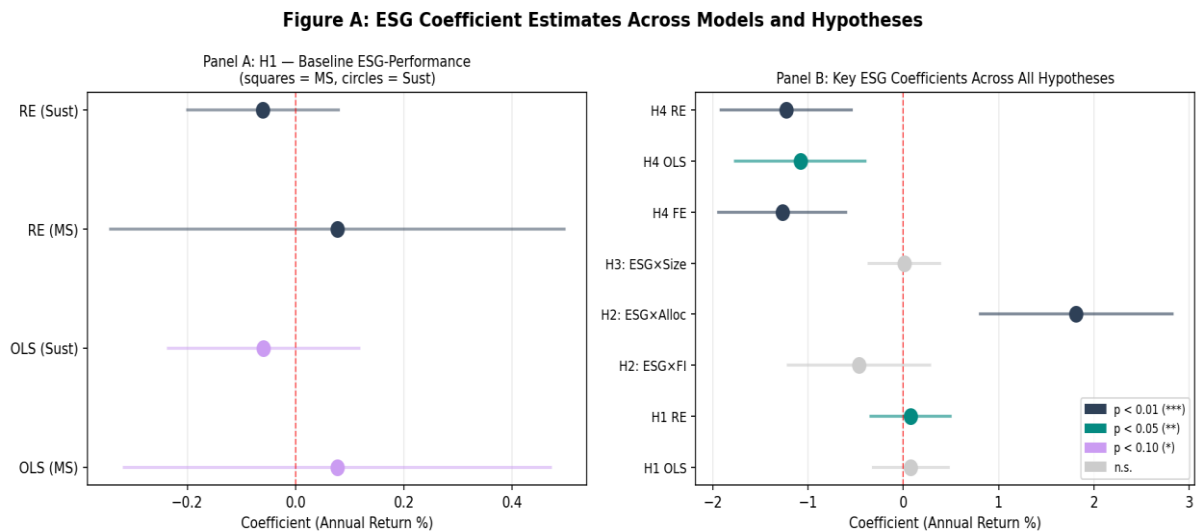


Figure A: ESG Coefficient Estimates Across Models and Hypotheses. Panel A: H1 OLS and RE estimates with 95% confidence intervals. Panel B: key ESG interaction coefficients across all hypotheses, colour-coded by significance level.

5.2 H2: Asset Class Heterogeneity in ESG-Performance Dynamics

H2 predicted a stronger ESG-performance association in equity funds than in fixed income and allocation funds. Table A2 reports the full interaction results. Table 2 below describes the characteristics of each asset class to contextualise the baseline differences.

Table 2: Sample Characteristics by Asset Class

	N	ESG Rating	ESG Score	Log(TNA)	Fund Age	Mean Return
Equity	125	3.47	17.65	19.61	9.5	3.82%
Fixed Income	125	3.04	15.70	19.38	10.0	-2.14%
Allocation	125	3.92	17.80	19.29	9.3	1.05%
Full Sample	373	3.48	17.13	19.43	9.9	0.91%

Notes: Means computed over non-missing observations per asset class. ESG Score is the raw Sustainalytics score (lower = better ESG quality). Mean Return is the unconditional mean annual return across all years 2019-2024.

Control variables. The asset class baseline dummies in Table A2 reveal that fixed income funds generate approximately 11.8 percentage points lower annual returns than equity funds, and allocation funds approximately 14.9 percentage points lower, before accounting for ESG effects. These large and significant differences confirm the importance of asset class controls and are consistent with the risk-return profiles of each asset class. The remaining controls (Log_TNA, Fund Age, Fee Level) maintain the same signs and approximate magnitudes as in H1 confirming the stability of the control structure across specifications.

ESG coefficients and interactions. For fixed income funds, the interaction term ESG x Fixed Income is negative but not significant (coef = -0.468, $p = 0.392$), indicating that the ESG-performance association in bond funds is not statistically distinguishable from that in equity funds. This may reflect post-SFDR convergence in ESG disclosure practices across asset classes reducing the differentiation the credit risk mitigation channel would produce.

The allocation fund result is the most unexpected finding of H2. The interaction ESG x Allocation is positive and highly significant (coef = +1.815, $p = 0.003$) indicating a stronger ESG-performance association in multi-asset funds than in equity funds, the opposite of what H2 predicted. The net ESG effects by asset class are: Equity = -0.227 (not significant), Fixed Income = -0.695 (not significant), Allocation = +1.588 ($p < 0.01$).

Two interpretations are plausible. First, ESG integration in multi-asset funds may operate simultaneously across both equity and fixed income sleeves, generating compounding cross-asset risk reduction effects. Second, managers of ESG-committed allocation funds may exhibit higher overall investment sophistication. The Sustainalytics specification shows a positive but smaller allocation interaction (coef = +0.106, $p < 0.05$ in RE), consistent in direction. Figure B below visualizes the net ESG slopes.

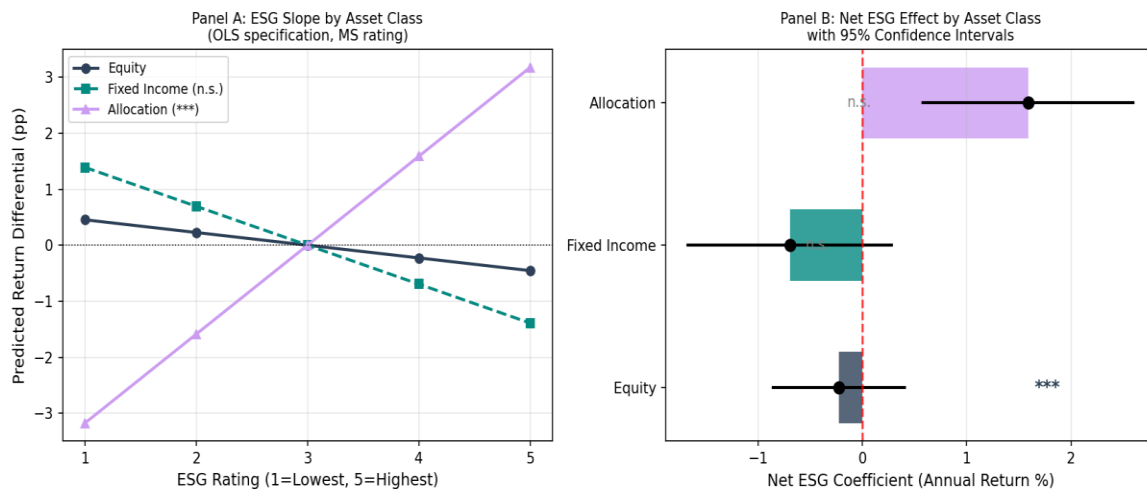
Figure B: H2 — ESG-Performance Relationship by Asset Class

Figure B: ESG-Performance Association by Asset Class. Panel A: predicted ESG-return slopes by asset class (OLS, Morningstar Rating). Panel B: net ESG coefficients with 95% confidence intervals. The Allocation fund ESG premium is large and significant; equity and fixed income effects are not significant.

Table A2: H2 Asset Class Heterogeneity in ESG-Performance Dynamics

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	-0.227 (0.322)		-0.227*** (0.388)	
ESG Score (Sustainalytics)		-0.196 (0.278)		-0.196*** (0.347)
Fixed Income	-11.784*** (1.351)	-13.477*** (1.382)	-11.782*** (1.525)	-13.474*** (1.573)
Allocation	-14.905*** (1.918)	-8.443*** (1.564)	-14.902*** (2.097)	-8.441*** (1.811)
ESG x Fixed Income	-0.468 (0.380)		-0.468*** (0.430)	
ESG x Allocation	1.815*** (0.515)		1.815*** (0.571)	
ESG x FI (Sust)		0.167 (0.301)		0.166*** (0.356)
ESG x Alloc (Sust)		0.106 (0.375)		0.105** (0.436)
Log(TNA)	0.525** (0.185)	0.515** (0.201)	0.525*** (0.200)	0.515*** (0.219)
Fund Age	-0.129*** (0.029)	-0.117*** (0.030)	-0.129*** (0.026)	-0.117*** (0.026)
Fee Level	-0.509*** (0.136)	-0.607*** (0.142)	-0.509*** (0.144)	-0.607*** (0.151)
Net ESG: Equity	-0.227	-0.196	-0.227	-0.196
Net ESG: Fixed Income	-0.695	n.s.	-0.695	n.s.
Net ESG: Allocation	+1.588***	n.s.	+1.588***	n.s.
Year FE	Yes	Yes	Yes	Yes
N	1,554	1,470	1,554	1,470
R ²	0.688	0.688	0.157	0.148

Notes: Dependent variable is annual total return (%). Equity is the reference asset class. Net ESG effects = $b1 + \text{interaction term}$. OLS: fund-clustered standard errors. RE: HC3 robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 H3: Fund Size as a Moderator

H3, grounded in the resource-based view, it predicted that larger funds would show a stronger ESG-performance association. Regarding the quadratic size terms, these were tested empirically and found to produce Variance Inflation Factors exceeding 200 for all relevant terms (ESG_Rating VIF = 482, ESG x Log_TNA VIF = 944), rendering all coefficients statistically non-identifiable. This is an empirically reason for exclusion severe multicollinearity inflates standard errors so that no coefficient can be identified as significant. H3 therefore tests only the linear interaction ESG x Log_TNA.

Control variables. The control variables maintain the expected signs established in H1 and H2. Log_TNA is positive and significant in the Sustainalytics RE specification (coef = +1.094, $p < 0.01$), confirming the size premium. Fund Age and Fee Level are both negative and significant, consistent with prior specifications.

ESG coefficients and interaction. The interaction ESG x Log_TNA is near zero in the Morningstar specification (coef = +0.011, $p = 0.966$). The Sustainalytics RE model shows a small negative interaction (coef = -0.131, $p < 0.01$), suggesting if anything a slight adverse moderating effect though multicollinearity limits confidence in this estimate. Two factors likely account for the null result. First, SFDR-driven standardization of ESG data has reduced the proprietary information advantages that once favored larger funds

Table A3: H3 — Fund Size as Moderator of ESG-Performance

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	-0.140 (3.768)		-0.142 (4.308)	
ESG Score (Sustainalytics)		2.496 (1.879)		2.494*** (1.508)
Log(TNA)	0.446 (0.660)	1.094** (0.447)	0.446*** (0.759)	1.094*** (0.400)
ESG x Log(TNA)	0.011 (0.191)		0.011 (0.219)	
ESG x Log(TNA) (Sust)		-0.131 (0.095)		-0.131*** (0.076)
Fixed Income	-13.140*** (0.404)	-12.695*** (0.381)	-13.140*** (0.444)	-12.695*** (0.424)

Allocation	-8.014*** (0.458)	-7.975*** (0.459)	-8.013*** (0.504)	-7.975*** (0.499)
Fund Age	-0.105*** (0.029)	-0.118*** (0.030)	-0.105*** (0.026)	-0.118*** (0.026)
Fee Level	-0.583*** (0.140)	-0.595*** (0.139)	-0.583*** (0.147)	-0.595*** (0.147)
Year FE	Yes	Yes	Yes	Yes
N	1,554	1,470	1,554	1,470
R ²	0.685	0.688	0.155	0.148

Notes: Dependent variable is annual total return (%). Log_TNA squared and its interaction with ESG are excluded on empirical grounds: VIF values of 482-944 render all coefficients non-identifiable. OLS: fund-clustered standard errors. RE: HC3 robust standard errors. *** p<0.01, ** p<0.05, * p<0.10.

5.4 H4: The Regulatory Transition (Pre versus Post-SFDR)

H4 is the central empirical contribution of this study. It asks whether SFDR implementation in March 2021 coincides with a structural change in the ESG-performance association among Luxembourg funds. Table 3 and Figure 3 first describe the annual return patterns to provide temporal context.

Table 3: Annual Fund Returns by Year and Asset Class (2019-2024)

Year	Period	N (all)	Equity	N_EQ	Fixed Inc.	N_FI	Allocation	N_AL
2019	Pre-SFDR	210	+13.78%	60	+2.97%	85	+7.44%	65
2020	Pre-SFDR	239	-14.29%	75	-5.19%	102	-11.50%	62
2021	Transition	262	+8.48%	80	-0.19%	105	+4.84%	77
2022	Post-SFDR	342	-5.46%	81	-4.85%	100	-3.75%	92
2023	Post-SFDR	290	+6.18%	83	+1.85%	106	+3.05%	93
2024	Post-SFDR	307	+11.06%	88	+0.44%	119	+5.17%	102

Notes: Mean annual total return (%) over funds with non-missing data for the given year. 2021 is the SFDR transition year; included in H1-H3 but excluded from H4. Coverage is lower for 2019-2020 (55-65%) than for 2022-2024 (70-80%) due to Yahoo Finance data availability.

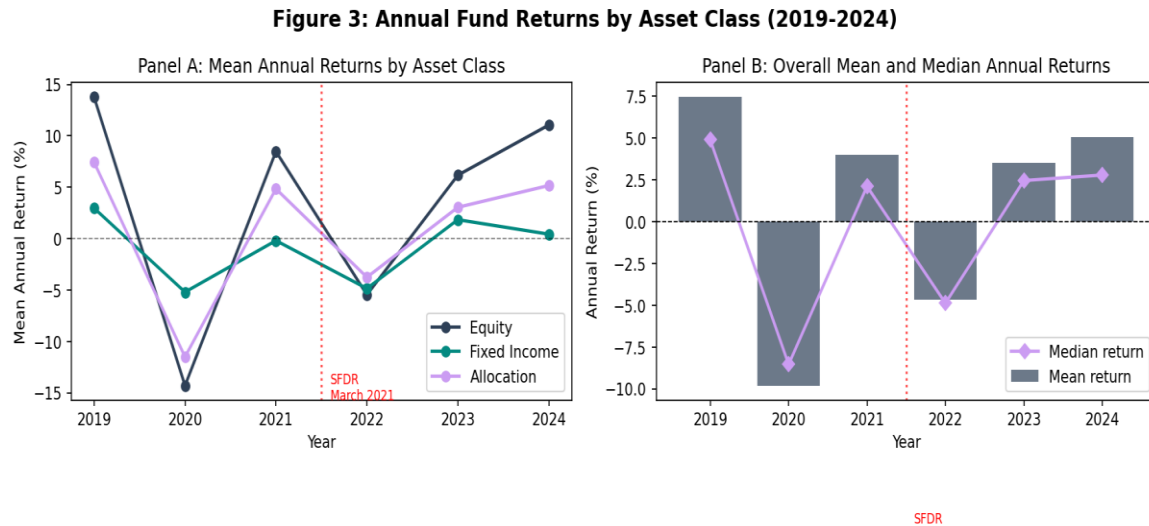


Figure 3: Annual Fund Returns by Asset Class (2019-2024). Panel A: mean returns by asset class; orange dotted line marks SFDR implementation (March 2021). Panel B: overall mean and median returns. The 2020 COVID shock and 2022 monetary tightening correction are clearly visible.

Control variables. The Hausman test ($p = 0.995$ for MS, $p = 0.739$ for Sust) favours Random Effects; RE is the preferred estimator for H4. In the RE specifications, Log_TNA is positive and significant (coef = +0.385 to +0.441, $p < 0.05$), consistent with the scale effects documented in prior hypotheses. Fee Level is negative and significant (coef = -0.303 to -0.320, $p < 0.05$), confirming cost drag. The Post-SFDR dummy is negative and significant in both OLS and RE specifications, reflecting the broader 2022 market correction driven by monetary tightening in addition to any ESG-specific regulatory effect.

ESG coefficient and interaction. The interaction term ESG x Post-SFDR is negative and significant across all three estimators: two-way fixed effects (coef = -1.273, $p = 0.008$), pooled OLS (coef = -1.083, $p = 0.016$), and random effects (coef = -1.230, $p < 0.01$). The consistency across methods with different identification assumptions increases confidence in the finding. The interaction remains negative and significant after controlling for the common Post-SFDR time trend confirming that the shift is specific to the ESG dimension.

In economic terms, a coefficient of -1.083 suggests that for a one-unit increase in ESG Rating, the performance differential between high- and low-ESG funds narrowed by approximately 1.1 percentage points per year after SFDR relative to before. A fund moving from 2 to 4 globes would have seen its performance advantage shrink by approximately 2.2 percentage points annually in the post-SFDR period.

These results are consistent with a regulatory dilution interpretation. Before SFDR, ESG integration was voluntary and conviction-driven and the resulting self-selection may have produced a positive association between ESG commitment and returns. After SFDR, mandatory disclosure prompted industry-wide adoption including by managers motivated by compliance or capital attraction. The resulting dilution of the ESG signal is consistent with Ceccarelli et al. (2024) and Hartzmark and Sussman (2019). Figures C and 5 visualize this shift.

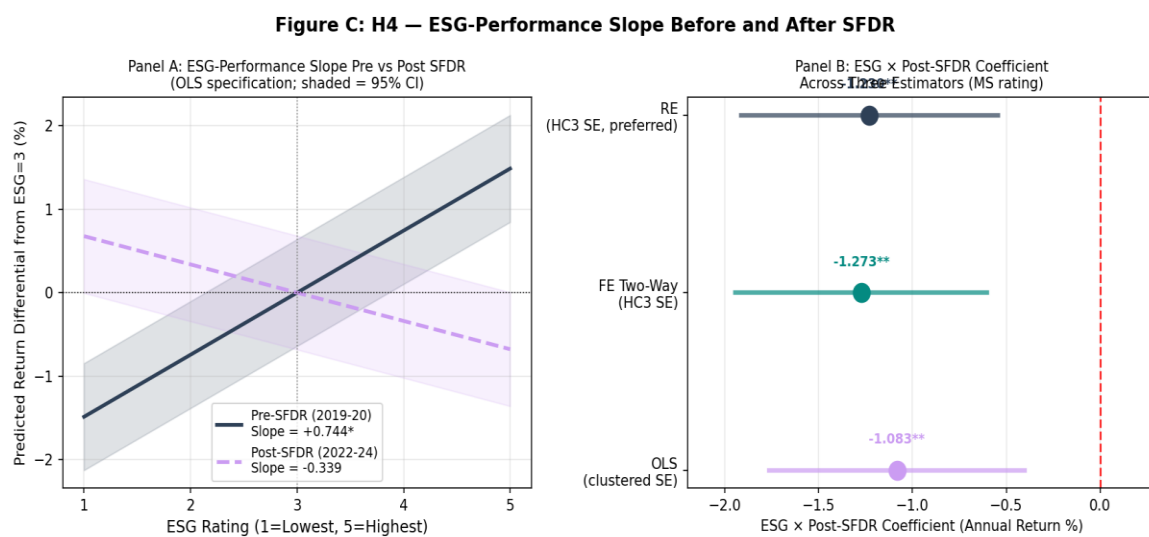


Figure C: Pre/Post-SFDR ESG Slope. Panel A: predicted ESG-return gradient before and after SFDR (OLS, shaded areas = 95% CI). The positive pre-SFDR slope flattens post-SFDR. Panel B: ESG x Post-SFDR coefficient across three estimators, all negative and significant.

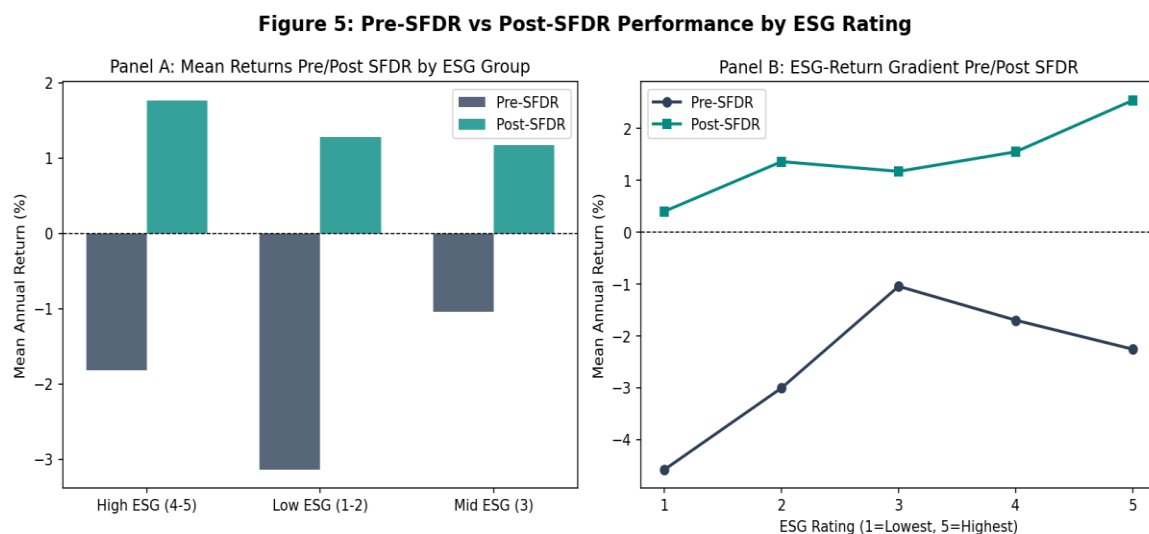


Figure 5: Mean Returns by ESG Group and Regulatory Period. Panel A: mean annual returns by ESG Rating group in pre-SFDR (2019-20) and post-SFDR (2022-24) periods. Panel B: ESG-return gradient by period. The flattening of the gradient post-SFDR is consistent with the H4 finding.

Table A4: H4 — Pre versus Post-SFDR Structural Break

	OLS (MS)	OLS (Sust)	FE (MS)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	0.744* (0.327)		1.616 (n.a.)	0.683** (0.340)	
ESG Score (Sustainalytics)		-0.208 (0.113)			-0.272** (0.128)
Post-SFDR	-1.775 (1.217)	-6.430*** (0.837)		-3.119*** (1.107)	-7.892*** (0.730)
ESG x Post-SFDR (MS)	-1.083** (0.348)		-1.273*** (0.343)	-1.230*** (0.350)	
ESG x Post-SFDR (Sust)		0.218 (0.147)			0.131 (0.127)
Log(TNA)	0.336 (0.193)	0.381 (0.197)		0.385** (0.189)	0.441** (0.192)
Fund Age	-0.089*** (0.027)	-0.094*** (0.028)			
Fee Level	-0.385** (0.130)	-0.400** (0.127)		-0.303** (0.127)	-0.320** (0.124)
Fixed Income	-10.084*** (0.395)	-9.753*** (0.401)			
Allocation	-6.913*** (0.440)	-6.909*** (0.432)			
Fund FE	No	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Hausman p-val				0.995	0.739
N	1,306	1,236	1,306	1,306	1,236
R ²	0.720	0.719	0.007	0.170	0.162

Notes: Panel covers 2019-2020 (pre-SFDR) and 2022-2024 (post-SFDR); 2021 excluded. Hausman test favours RE ($p = 0.995$ for MS; $p = 0.739$ for Sust). Empty cells ("") in the FE column for Post-SFDR and most control variables are expected: two-way fixed effects absorb all time-invariant fund characteristics and all time effects not interacted with ESG, leaving only the interaction term ESG x Post-SFDR identified. ESG_Rating in FE (MS) has inflated standard error due to near-perfect collinearity with fund fixed effects; the interaction ESG x Post-SFDR is identified because it varies over time. OLS: fund-clustered standard errors. FE and RE: HC3 robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.5 Robustness Checks

Having discussed the main results across H1 through H4, this section presents supplementary cross-sectional regressions using three Morningstar performance metrics as dependent variables: the Sharpe ratio, Jensen alpha, and information ratio. The metrics reflect the trailing 12-month window from April 2024 to April 2025 only and cannot be compared directly to the panel results covering 2019-2024.

Control variables. In the robustness regressions, Fee Level is negative and significant for Sharpe ratio (coef = -0.111, $p < 0.01$) and information ratio (coef = -0.230, $p < 0.05$), consistent with the panel findings. Allocation funds show significantly higher Jensen alpha (coef = +3.315, $p < 0.01$) and information ratio (coef = +1.248, $p < 0.01$) than equity funds in the April 2025 snapshot, consistent with the stronger ESG-performance association for allocation funds found in H2.

ESG coefficients. ESG Rating is negatively associated with all three metrics. Sharpe ratio (coef = -0.354, $p < 0.01$), Jensen alpha (coef = -2.164, $p < 0.01$), and information ratio (coef = -0.682, $p < 0.01$). The Sustainalytics specification is directionally consistent. These negative cross-sectional associations in the most recent period extend the H4 finding rather than contradicting the H1 RE result: the ESG-performance association appears to have continued weakening in the post-SFDR environment of 2024-2025. This is consistent with Pastor et al. (2021), who predict that widespread ESG investor preferences compress expected returns on ESG assets over time.

Table A5: Robustness — Static Performance Metrics (April 2025 Snapshot)

	Sharpe (MS)	Sharpe (Sust)	Alpha (MS)	Alpha (Sust)	IR (MS)	IR (Sust)
ESG Rating (Morningstar)	-0.354*** (0.054)		-2.164*** (0.428)		-0.682*** (0.144)	
ESG Score (Sustainalytics)		-0.108*** (0.025)		-0.481*** (0.156)		-0.144*** (0.051)
Log(TNA)	0.032 (0.044)	0.071 (0.046)	0.079 (0.386)	0.320 (0.398)	-0.030 (0.131)	0.046 (0.132)
Fund Age	-0.005 (0.005)	-0.002 (0.006)	0.014 (0.045)	0.033 (0.045)	-0.009 (0.013)	-0.003 (0.014)
Fee Level	-0.111*** (0.031)	-0.074** (0.032)	-0.637** (0.262)	-0.398 (0.267)	-0.230** (0.095)	-0.155 (0.097)
Fixed Income	-1.133*** (0.099)	-0.734*** (0.097)	0.011 (0.803)	2.144*** (0.774)	0.334 (0.306)	0.994*** (0.299)
Allocation	-0.465*** (0.105)	-0.600*** (0.110)	3.315*** (0.866)	2.537*** (0.919)	1.248*** (0.271)	1.005*** (0.298)
SE	HC3	HC3	HC3	HC3	HC3	HC3
N	306	306	306	306	306	306
R ²	0.367	0.304	0.154	0.079	0.155	0.089

Notes: Cross-sectional OLS. Dependent variables are Morningstar trailing 12-month metrics as of April 2025 (window: April 2024 to April 2025). These analyses serve as robustness checks only and cannot be compared to the panel regressions. HC3 heteroskedasticity-robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 4: ESG Rating vs. Risk-Adjusted Performance Metrics (Robustness Sample, April 2025)

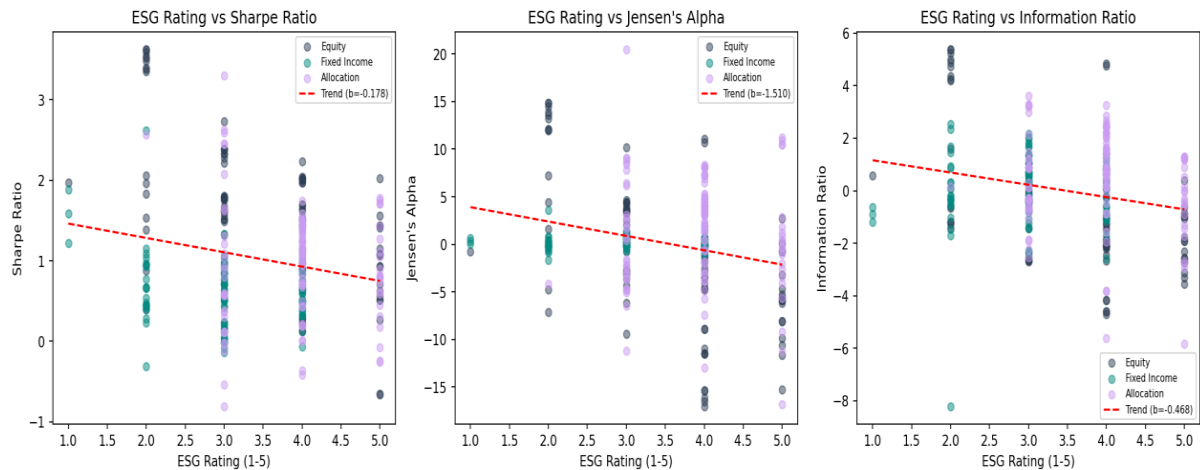


Figure 4: ESG Rating vs. Risk-Adjusted Metrics (Cross-Section, April 2025). Negative trend lines across Sharpe ratio, Jensen alpha, and information ratio are consistent with the post-SFDR ESG alpha dilution documented in H4.

5.6 Overall Discussion and Synthesis

Figure A summarizes the ESG coefficients across all models and hypotheses, making the overall pattern visible immediately.

Figure A: ESG Coefficient Estimates Across Models and Hypotheses

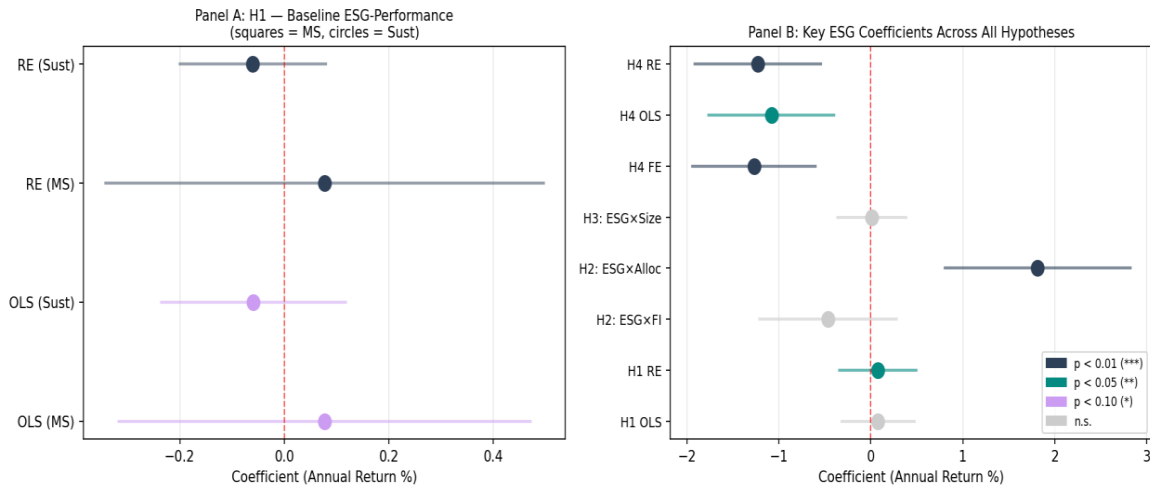


Figure A: ESG Coefficient Estimates Across All Hypotheses. Colour-coded by significance: dark = $p < 0.01$, medium = $p < 0.05$, light = $p < 0.10$, grey = n.s. The contrast between the H4 negative significant coefficients and the non-significant H3 result is the central empirical message.

Four findings emerge from the analysis. First, funds with stronger ESG integration tend to be associated with higher annual returns in the between-fund dimension (H1, RE preferred on efficiency grounds), though this result is sensitive to ESG operationalization and should be interpreted cautiously given look-ahead bias and the possibility of reverse causality. Second, this association is most pronounced in allocation funds rather than equity funds (H2),

suggesting that ESG integration may generate compounding cross-asset risk reduction effects in multi-asset portfolios. Third, fund size does not moderate the ESG-performance association (H3), consistent with post-SFDR commoditization of ESG data. Fourth, SFDR implementation coincides with a significant weakening of the ESG-performance association across three estimators (H4) and the April 2025 robustness checks suggest this trend has continued into the most recent period.

Together, these findings suggest that ESG integration was associated with a performance advantage when it was a voluntary, conviction-driven differentiator in the pre-SFDR period, but that this advantage has diminished significantly following mandatory ESG adoption under SFDR. The central message is that the regulatory environment fundamentally shapes the informational content of ESG ratings as performance predictors, with direct implications for both fund managers and regulators.

6. Critical Setbacks, Limitations and Future Research

This section discusses the practical difficulties encountered during the research process, the methodological constraints that limit the scope and causal interpretation of the findings, and the directions that future research should prioritize to address them.

6.1 Data Collection and Practical Challenges

The most significant practical challenge was the collection of annual return data for the panel analysis. Morningstar Direct does not provide programmatic access to historical annual returns at the fund level without a premium subscription which necessitated the development of an automated web scraping procedure using the Selenium WebDriver library to extract return data from Yahoo Finance performance pages. Although this approach proved effective, it introduced three complications that affect the quality and completeness of the panel dataset.

Coverage is inherently incomplete under this approach as approximately 70-80% of funds in the sample have return data for 2022-2024 and only 55-65% for 2019-2020. This structure reduces statistical power for the pre-SFDR period which serves as the baseline for H4. The asymmetry between 449 pre-SFDR and 939 post-SFDR observations means that the pre-period estimate is less precisely identified which is a relevant limitation when interpreting the

magnitude of the ESG x Post-SFDR coefficient. Additionally, Yahoo Finance uses internal identifiers rather than standard ISINs requiring a two-step matching procedure that produced incorrect share class assignments. Finally, Yahoo Finance return figures may differ marginally from official NAV-based calculations due to differences in dividend reinvestment assumptions. Access to Morningstar Direct's full historical performance module or Bloomberg's UCITS fund database would resolve all three of these complications and is recommended for future replications of this study.

A second practical challenge relates to the Mundlak test, which was intended to guide the choice between Random Effects and Pooled OLS for H1-H3. The test was not feasible because the time-invariant ESG variables are perfectly collinear with their fund-level means, producing a singular matrix that prevents estimation of the augmented model. This is not a computational error but a consequence of the research design. When a variable does not vary within a fund over time, its fund-level mean is identical to the variable itself making the Mundlak augmentation redundant by construction. Random Effects is therefore retained as the preferred estimator on the grounds that it is the only specification capable of identifying the effect of a time-invariant variable while preserving the panel structure and because it is more efficient than Pooled OLS in the presence of fund-level heterogeneity.

6.2 Methodological Limitations and Future Research

Beyond the practical challenges above, the study is subject to several methodological constraints that limit the causal interpretation of the findings and point toward specific improvements for future research.

The most fundamental limitation concerns the time-invariant nature of the ESG variables. Both the Morningstar ESG Rating and the Sustainalytics Score are measured at a single point in time, April 2025, and assigned uniformly to all fund-years in the panel. This creates two related problems. First, if a fund's ESG quality improved between 2019 and 2025, the April 2025 rating states its ESG integration in early years and understates it in later years, introducing a form of look-ahead bias that may distort the estimated panel coefficients in ways that are difficult to characterize without historical ESG data. Second, the time-invariant structure prevent the use of fund fixed effects which would otherwise offer the most credible approach to controlling unobserved fund-level characteristics. Both problems would be resolved by using annual ESG scores which Sustainalytics and MSCI make available through

professional data subscriptions and this represents the single most impactful improvement available to future researchers working on similar questions.

A related concern is reverse causality. The positive H1 RE coefficient is consistent with the interpretation that stronger ESG integration is associated with better performance but the causal direction cannot be established with the current design. It is equally plausible that better-performing funds generate higher fee revenues and capital inflows that are subsequently reinvested in ESG capabilities, analyst capacity, and engagement programs, leading to improved ESG ratings without ESG integration being the performance driver. Distinguishing these channels would require an instrumental variable that affects ESG ratings without directly affecting fund returns such as exogenous changes in ESG rating methodology at Sustainalytics or a regression discontinuity design exploiting fund-size thresholds that trigger differential regulatory scrutiny. These approaches are beyond the scope of this study but represent credible identification strategies for future research.

The absence of SFDR fund classification data represents a third structural limitation. The Post-SFDR dummy in H4 captures the aggregate time effect of SFDR implementation across all funds in the sample, but it cannot distinguish between funds that genuinely modified their investment processes in response to SFDR and funds whose practices were already SFDR-compliant before March 2021. A more precise test of SFDR's effects would compare financial performance across Article 6, Article 8 and Article 9 funds directly which is the most policy-relevant research question in European sustainable finance today. Fund-level SFDR classifications are increasingly accessible through data providers such as MSCI FactSet, and a study designed around this classification would offer substantially more granular regulatory insights than the pre/post dummy approach used here.

The divergence between the Morningstar and Sustainalytics specifications in H1 also deserves acknowledgment as a methodological limitation rather than merely a robustness observation. The fact that these two measures which are both derived from Sustainalytics underlying data, produce coefficients of opposite sign in the RE model indicates that the ESG-performance relationship is not stable across operationalizations. As discussed in Section 5.1, this likely reflects the different levels of aggregation at which the two measures operate with Morningstar capturing portfolio-level ESG governance quality and Sustainalytics capturing company-level ESG risk exposure. Future research should treat these as distinct constructs and test their implications separately under different theoretical frameworks, rather than treating them as interchangeable proxies for a single latent concept of ESG quality.

Finally, the scope of the sample limits the external validity of the findings. The restriction to Luxembourg-domiciled UCITS funds with assets exceeding 100 million euros means that the results apply directly to large institutionally distributed European fund products. Smaller funds, funds domiciled in Ireland, France, or Germany, and non-UCITS structures may exhibit different ESG-performance dynamics. A multi-jurisdiction comparative study spanning Ireland, Luxembourg, France and Germany within the same post-SFDR regulatory framework would be well-positioned to examine whether the H4 finding of ESG alpha dilution is specific to Luxembourg or reflects a broader European phenomenon. Similarly, extending the panel backward to 2015-2018 would provide a richer pre-SFDR baseline, enabling a more robust examination of whether the ESG-performance association was itself evolving in the years preceding SFDR's adoption, which would bring additional light on the conviction-driven early-adopter narrative that underlies the H4 interpretation.

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Appendix

Appendix A: Descriptive Statistics and Correlation Matrix

Table 1: Descriptive Statistics — Panel Variables (2019-2024)

Variable	N	Mean	SD	Min	P25	Median	Max
Annual Return (%)	1,610	0.912	7.769	-24.840	-4.220	1.650	23.640
ESG Rating (1-5)	1,513	3.480	0.899	1.000	3.000	4.000	5.000
ESG Score Inv. (Sust)	1,429	4.546	1.995	0.000	3.120	4.590	16.870
Log(TNA)	1,610	19.415	0.804	18.421	18.823	19.219	23.116
Fund Age (years)	1,610	9.915	6.107	-0.791	5.123	9.105	30.875
Fee Level (1-5)	1,610	2.771	1.311	1.000	1.000	3.000	5.000
D_FI (Fixed Income)	1,610	0.364	0.481	0.000	0.000	0.000	1.000
D_Alloc (Allocation)	1,610	0.356	0.479	0.000	0.000	0.000	1.000
—	—	—	—	—	—	—	—

Notes: Panel H1-H3 (N = 1,610 obs, 309 funds, 2019-2024). ESG Rating is the Morningstar Sustainability Rating (1-5; 5 = best ESG). ESG Score Inv. is the Sustainalytics Corporate Sustainability Score inverted so that higher values indicate better ESG. Both ESG measures are time-invariant cross-sectional variables measured in April 2025.

Table 7: Correlation Matrix — Panel Variables

	Ann. Return	ESG Rating	ESG Inv.	Log(TNA)	Fund Age	Fee Level
Annual Return	1.000	0.084	-0.131	0.079	-0.053	0.022
ESG Rating	0.084	1.000	0.283	-0.078	-0.188	-0.141
ESG Inv. (Sust)	-0.131	0.283	1.000	-0.019	0.076	-0.134
Log(TNA)	0.079	-0.078	-0.019	1.000	0.037	-0.020
Fund Age	-0.053	-0.188	0.076	0.037	1.000	0.134
Fee Level	0.022	-0.141	-0.134	-0.020	0.134	1.000

Notes: Pairwise complete observations. ESG variables are time-invariant cross-sectional measures assigned to each fund-year observation.

Figure 8: Evolution of Key Fund Characteristics Over Time (2019-2024)

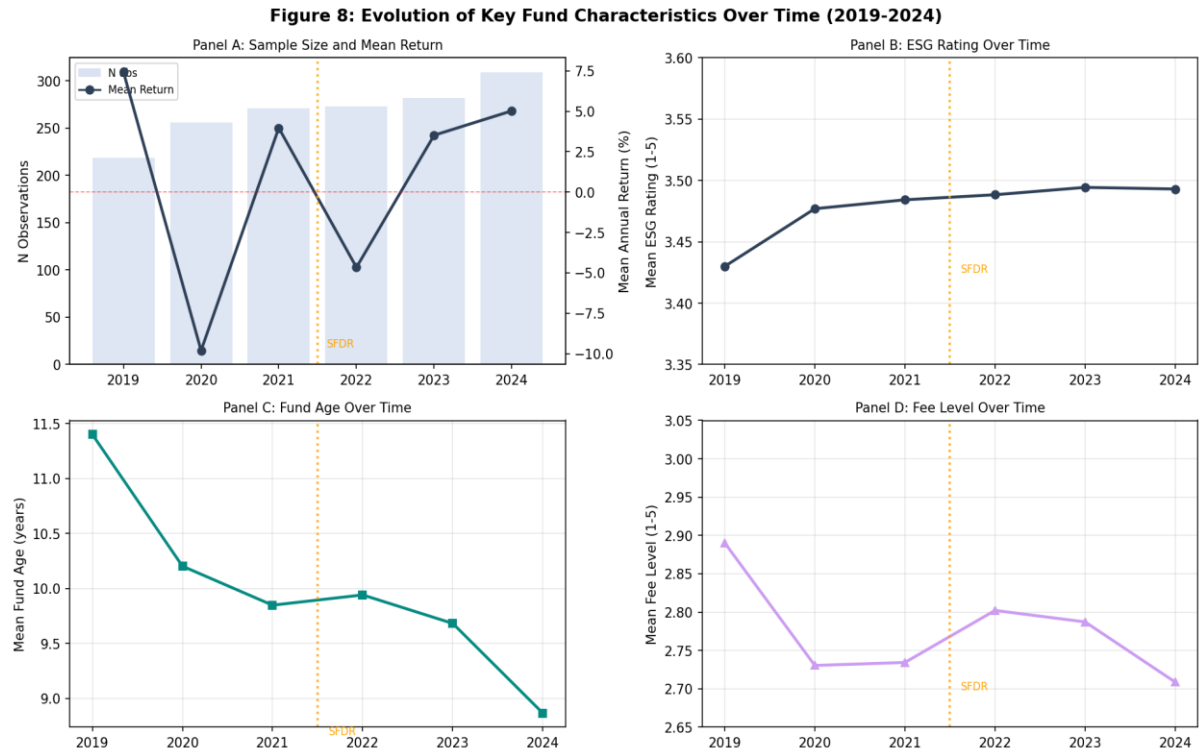


Figure 8: Evolution of key fund characteristics. Panel A: sample size and mean annual return. Panel B: mean ESG Rating. Panel C: mean fund age. Panel D: mean fee level. Orange dotted line = SFDR implementation (March 2021).

Appendix B: Summary of Regression Results

Table 5: Summary of Regression Results — All Hypotheses

Hypothesis	Estimator	Key Variable	Coef.	p-val	Verdict
H1: ESG → Annual Return	Pooled OLS	ESG_Rating	+0.077	0.750	n.s.
H1: ESG → Annual Return	RE (preferred)	ESG_Rating	+0.077	0.017**	Supported
H2: ESG x Fixed Income	Pooled OLS	ESG x D_FI	-0.468	0.392	n.s.
H2: ESG x Allocation	Pooled OLS	ESG x D_Alloc	+1.815	0.003***	Supported (reversed)
H3: ESG x Log(TNA)	Pooled OLS	ESG x Log_TNA	+0.011	0.966	Not supported
H4: ESG x Post_SFDR	FE two-way	ESG x Post_SFDR	-1.273	0.008***	Supported
H4: ESG x Post_SFDR	RE (preferred)	ESG x Post_SFDR	-1.230	<0.01***	Supported

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, n.s. = not significant. OLS: year fixed effects and fund-clustered standard errors. RE: HC3 robust standard errors. RE is preferred over Pooled OLS on efficiency grounds. For H4, RE is additionally favoured by the Hausman test ($p = 0.995$ and $p = 0.739$).

Figure A: ESG Coefficient Estimates Across All Models and Hypotheses

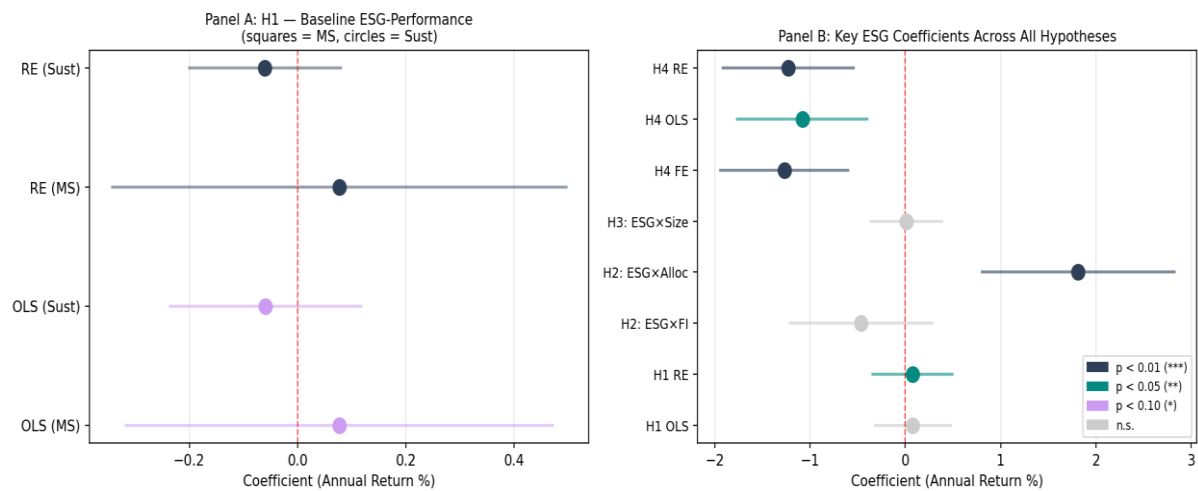
Figure A: ESG Coefficient Estimates Across Models and Hypotheses

Figure A: ESG coefficient estimates with 95% confidence intervals. Colour-coded by significance level: dark = $p < 0.01$, medium = $p < 0.05$, light = $p < 0.10$, grey = n.s.

Appendix C: Full Regression Results — H1

Table A1: H1 — ESG Integration and Annual Fund Returns

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	0.077 (0.201)		0.077** (0.214)	
ESG Score (Sustainalytics)		-0.059 (0.090)		-0.060*** (0.071)
Log(TNA)	0.484** (0.189)	0.535** (0.193)	0.485*** (0.205)	0.535*** (0.210)
Fund Age	-0.105*** (0.029)	-0.115*** (0.030)	-0.105*** (0.025)	-0.114*** (0.026)
Fee Level	-0.582*** (0.140)	-0.604*** (0.139)	-0.582*** (0.147)	-0.604*** (0.147)
Fixed Income	-13.137*** (0.391)	-12.751*** (0.376)	-13.137*** (0.431)	-12.750*** (0.421)
Allocation	-8.012*** (0.458)	-7.998*** (0.457)	-8.012*** (0.502)	-7.998*** (0.497)
Year FE	Yes	Yes	Yes	Yes
SE	Clustered	Clustered	HC3	HC3
N	1,554	1,470	1,554	1,470
R ²	0.685	0.688	0.155	0.148

Notes: Dependent variable is annual total return (%). OLS: fund-clustered SE. RE: HC3 robust SE, Wallace-Hussain estimator. RE is preferred over OLS on efficiency grounds. Mundlak test not feasible due to perfect collinearity between time-invariant ESG and fund mean. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix D: Full Regression Results — H2

Table 2: Sample Characteristics by Asset Class

	N	ESG Rating	ESG Score	Log(TNA)	Fund Age	Mean Return
Equity	125	3.47	17.65	19.61	9.5	3.82%
Fixed Income	125	3.04	15.70	19.38	10.0	-2.14%
Allocation	125	3.92	17.80	19.29	9.3	1.05%

Full Sample	373	3.48	17.13	19.43	9.9	0.91%
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Notes: Means computed over non-missing observations per asset class. ESG Score is the raw Sustainalytics score (lower = better ESG quality). Mean Return is the unconditional mean annual return across 2019-2024.

Table A2: H2 — Asset Class Heterogeneity in ESG-Performance Dynamics

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	-0.227 (0.322)		-0.227*** (0.388)	
ESG Score (Sustainalytics)		-0.196 (0.278)		-0.196*** (0.347)
Fixed Income	-11.784*** (1.351)	-13.477*** (1.382)	-11.782*** (1.525)	-13.474*** (1.573)
Allocation	-14.905*** (1.918)	-8.443*** (1.564)	-14.902*** (2.097)	-8.441*** (1.811)
ESG x Fixed Income	-0.468 (0.380)		-0.468*** (0.430)	
ESG x Allocation	1.815*** (0.515)		1.815*** (0.571)	
ESG x FI (Sust)		0.167 (0.301)		0.166*** (0.356)
ESG x Alloc (Sust)		0.106 (0.375)		0.105** (0.436)
Log(TNA)	0.525** (0.185)	0.515** (0.201)	0.525*** (0.200)	0.515*** (0.219)
Fund Age	-0.129*** (0.029)	-0.117*** (0.030)	-0.129*** (0.026)	-0.117*** (0.026)
Fee Level	-0.509*** (0.136)	-0.607*** (0.142)	-0.509*** (0.144)	-0.607*** (0.151)
Net ESG: Equity	-0.227	-0.196	-0.227	-0.196
Net ESG: Fixed Income	-0.695	n.s.	-0.695	n.s.
Net ESG: Allocation	+1.588***	n.s.	+1.588***	n.s.
Year FE	Yes	Yes	Yes	Yes
N	1,554	1,470	1,554	1,470
R ²	0.688	0.688	0.157	0.148

Notes: Dependent variable is annual total return (%). Equity is the reference asset class. Net ESG effects = b1 + interaction term. OLS: fund-clustered SE. RE: HC3 robust SE. *** p<0.01, ** p<0.05, * p<0.10.

Figure B: ESG-Performance Association by Asset Class

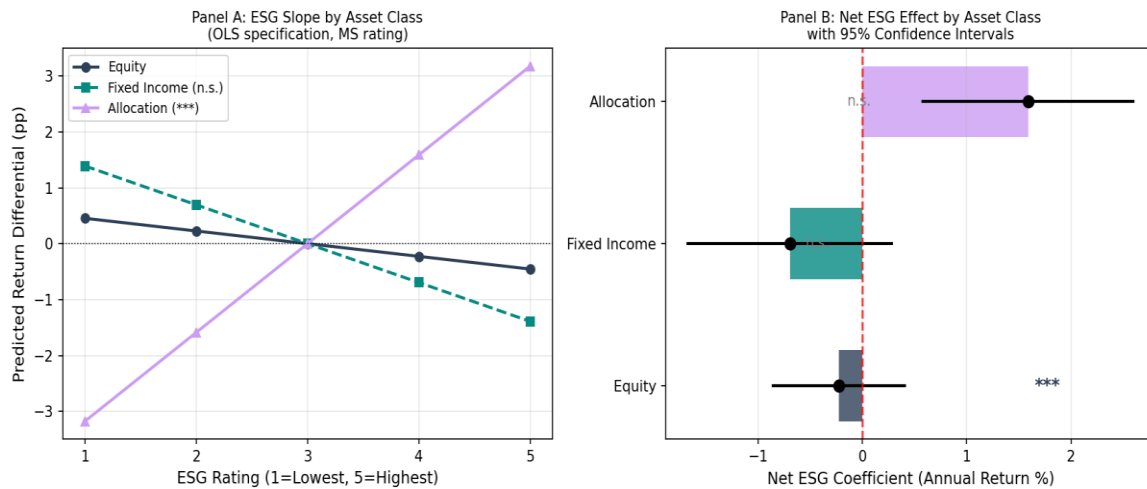
Figure B: H2 — ESG-Performance Relationship by Asset Class

Figure B: Net ESG coefficients by asset class with 95% confidence intervals. The Allocation fund ESG premium is significant; equity and fixed income effects are not.

Appendix E: Full Regression Results — H3

Table A3: H3 — Fund Size as Moderator of ESG-Performance

	OLS (MS)	OLS (Sust)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	-0.140 (3.768)		-0.142 (4.308)	
ESG Score (Sustainalytics)		2.496 (1.879)		2.494*** (1.508)
Log(TNA)	0.446 (0.660)	1.094** (0.447)	0.446*** (0.759)	1.094*** (0.400)
ESG x Log(TNA)	0.011 (0.191)		0.011 (0.219)	
ESG x Log(TNA) (Sust)		-0.131 (0.095)		-0.131*** (0.076)
Fixed Income	-13.140*** (0.404)	-12.695*** (0.381)	-13.140*** (0.444)	-12.695*** (0.424)
Allocation	-8.014*** (0.458)	-7.975*** (0.459)	-8.013*** (0.504)	-7.975*** (0.499)
Fund Age	-0.105*** (0.029)	-0.118*** (0.030)	-0.105*** (0.026)	-0.118*** (0.026)
Fee Level	-0.583*** (0.140)	-0.595*** (0.139)	-0.583*** (0.147)	-0.595*** (0.147)
Year FE	Yes	Yes	Yes	Yes
N	1,554	1,470	1,554	1,470
R ²	0.685	0.688	0.155	0.148

Notes: Dependent variable is annual total return (%). Log(TNA)² and its interaction with ESG excluded on empirical grounds: VIF values of 482-944 render all coefficients non-identifiable. OLS: fund-clustered SE. RE: HC3 robust SE. *** p<0.01, ** p<0.05, * p<0.10.

Appendix F: Full Regression Results — H4

Table 3: Annual Fund Returns by Year and Asset Class (2019-2024)

Year	Period	N (all)	Equity	N_EQ	Fixed Inc.	N_FI	Allocation	N_AL
2019	Pre-SFDR	210	+13.78%	60	+2.97%	85	+7.44%	65
2020	Pre-SFDR	239	-14.29%	75	-5.19%	102	-11.50%	62
2021	Transition	262	+8.48%	80	-0.19%	105	+4.84%	77
2022	Post-SFDR	342	-5.46%	81	-4.85%	100	-3.75%	92
2023	Post-SFDR	290	+6.18%	83	+1.85%	106	+3.05%	93
2024	Post-SFDR	307	+11.06%	88	+0.44%	119	+5.17%	102

Notes: Mean annual total return (%) over funds with non-missing data. 2021 is the SFDR transition year; included in H1-H3 but excluded from H4.

Figure 3: Annual Fund Returns by Asset Class (2019-2024)

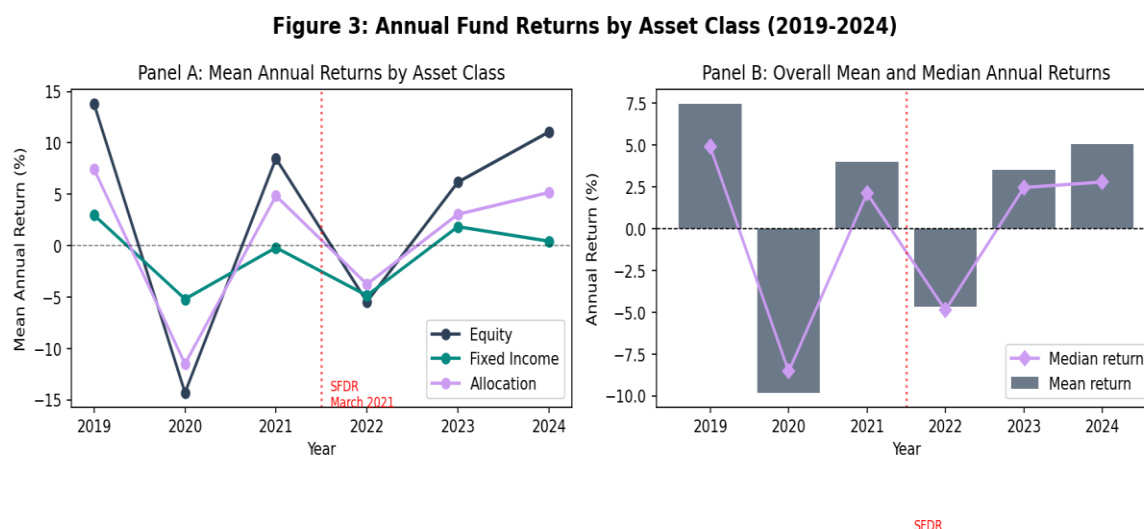


Figure 3: Annual Fund Returns by Asset Class. Panel A: mean returns by asset class; orange dotted line marks SFDR implementation. Panel B: overall mean and median returns.

Figure C: Pre/Post-SFDR ESG-Performance Slope

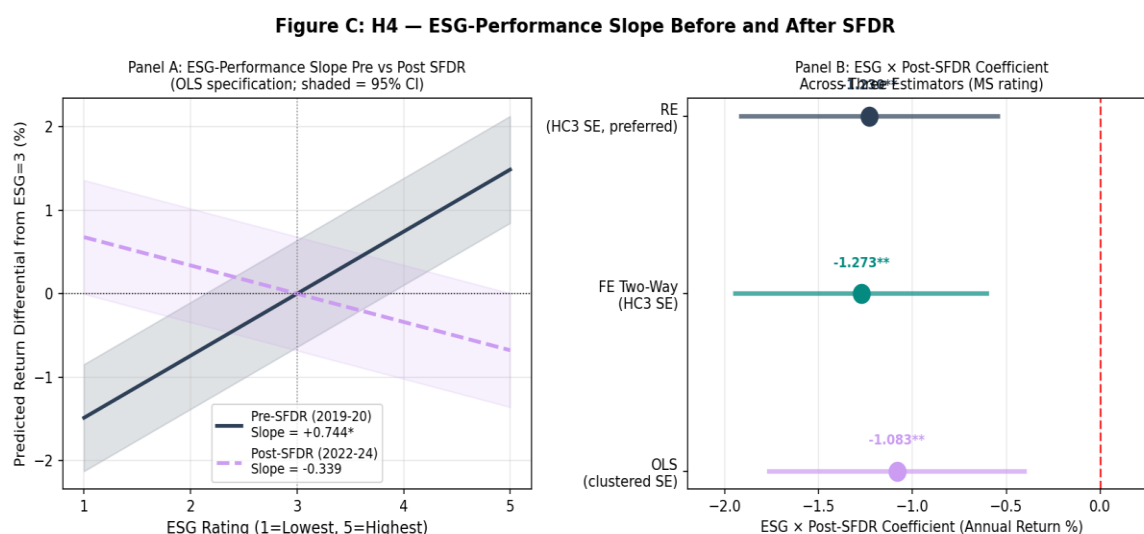


Figure C: Pre/Post-SFDR ESG slope. Panel A: predicted ESG-return gradient before and after SFDR with 95% CI. Panel B: ESG x Post-SFDR coefficient across three estimators.

Figure 5: Mean Returns by ESG Group and Regulatory Period

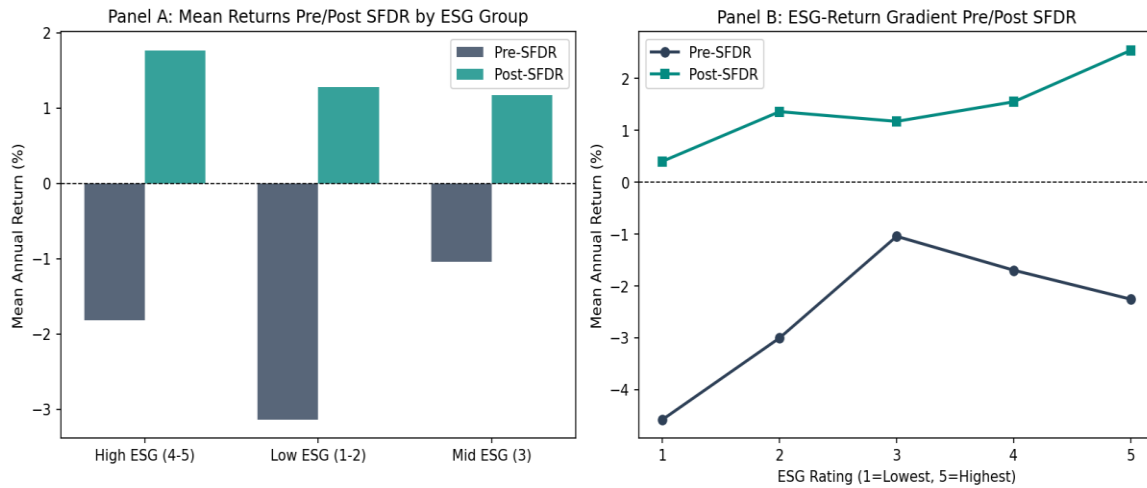
Figure 5: Pre-SFDR vs Post-SFDR Performance by ESG Rating

Figure 5: Mean annual returns by ESG Rating group in pre-SFDR (2019-20) and post-SFDR (2022-24) periods. The flattening of the ESG-return gradient post-SFDR is consistent with the H4 finding.

Table A4: H4 — Pre versus Post-SFDR Structural Break

	OLS (MS)	OLS (Sust)	FE (MS)	RE (MS)	RE (Sust)
ESG Rating (Morningstar)	0.744* (0.327)		1.616 (n.a.)	0.683** (0.340)	
ESG Score (Sustainalytics)		-0.208 (0.113)			-0.272** (0.128)
Post-SFDR	-1.775 (1.217)	-6.430*** (0.837)		-3.119*** (1.107)	-7.892*** (0.730)
ESG x Post-SFDR (MS)	-1.083** (0.348)		-1.273*** (0.343)	-1.230*** (0.350)	
ESG x Post-SFDR (Sust)		0.218 (0.147)			0.131 (0.127)
Log(TNA)	0.336 (0.193)	0.381 (0.197)		0.385** (0.189)	0.441** (0.192)
Fund Age	-0.089*** (0.027)	-0.094*** (0.028)			
Fee Level	-0.385** (0.130)	-0.400** (0.127)		-0.303** (0.127)	-0.320** (0.124)
Fixed Income	-10.084*** (0.395)	-9.753*** (0.401)			
Allocation	-6.913*** (0.440)	-6.909*** (0.432)			
Fund FE	No	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Hausman p-val				0.995	0.739
N	1,306	1,236	1,306	1,306	1,236
R ²	0.720	0.719	0.007	0.170	0.162

Notes: Panel covers 2019-2020 (pre-SFDR) and 2022-2024 (post-SFDR); 2021 excluded. Hausman test favours RE ($p = 0.995$ for MS; $p = 0.739$ for Sust). Empty cells in FE column are expected: two-way fixed effects absorbs time-invariant variables. OLS: fund-clustered SE. FE/RE: HC3 robust SE. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix G: Robustness Checks

Table A5: Robustness — Static Performance Metrics (April 2025 Snapshot)

	Sharpe (MS)	Sharpe (Sust)	Alpha (MS)	Alpha (Sust)	IR (MS)	IR (Sust)
ESG Rating (Morningstar)	-0.354*** (0.054)		-2.164*** (0.428)		-0.682*** (0.144)	
ESG Score (Sustainalytics)		-0.108*** (0.025)		-0.481*** (0.156)		-0.144*** (0.051)
Log(TNA)	0.032 (0.044)	0.071 (0.046)	0.079 (0.386)	0.320 (0.398)	-0.030 (0.131)	0.046 (0.132)
Fund Age	-0.005 (0.005)	-0.002 (0.006)	0.014 (0.045)	0.033 (0.045)	-0.009 (0.013)	-0.003 (0.014)
Fee Level	-0.111*** (0.031)	-0.074** (0.032)	-0.637** (0.262)	-0.398 (0.267)	-0.230** (0.095)	-0.155 (0.097)
Fixed Income	-1.133*** (0.099)	-0.734*** (0.097)	0.011 (0.803)	2.144*** (0.774)	0.334 (0.306)	0.994*** (0.299)
Allocation	-0.465*** (0.105)	-0.600*** (0.110)	3.315*** (0.866)	2.537*** (0.919)	1.248*** (0.271)	1.005*** (0.298)
SE	HC3	HC3	HC3	HC3	HC3	HC3
N	306	306	306	306	306	306
R ²	0.367	0.304	0.154	0.079	0.155	0.089

Notes: Cross-sectional OLS. Dependent variables are Morningstar trailing 12-month metrics as of April 2025 (window: April 2024 to April 2025). HC3 heteroskedasticity-robust standard errors. Cannot be compared to panel regressions. *** p<0.01, ** p<0.05, * p<0.10.

Figure 4: ESG Rating vs. Risk-Adjusted Metrics (Cross-Section, April 2025)

Figure 4: ESG Rating vs. Risk-Adjusted Performance Metrics (Robustness Sample, April 2025)

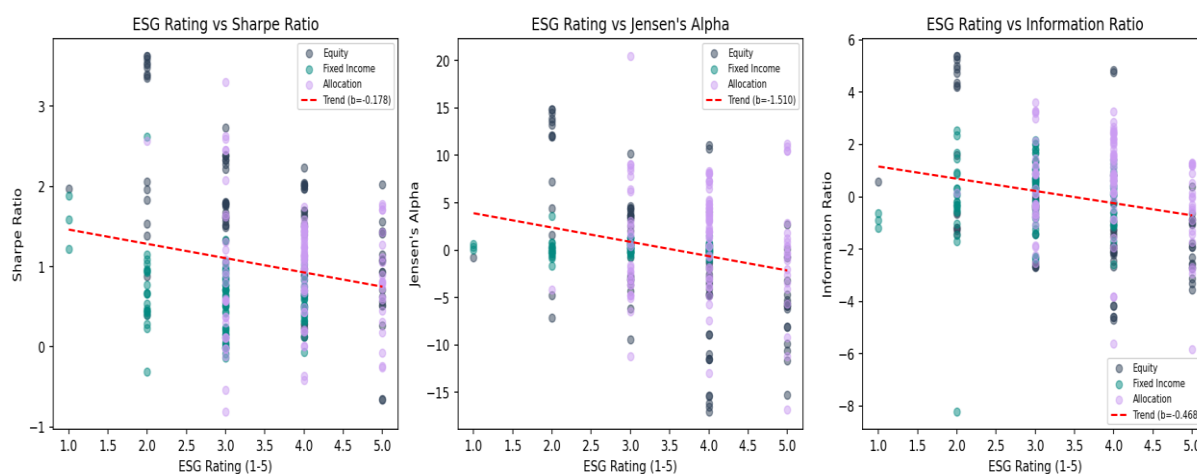


Figure 4: ESG Rating vs. Sharpe ratio, Jensen alpha, and information ratio. Negative trend lines are consistent with the post-SFDR ESG alpha dilution documented in H4.

Appendix H: R Analysis Code

The following R code was used for all statistical analyses in this thesis.

```
Required packages:
# install.packages(c("readxl","dplyr","tidyr","plm","lmtest",
#                    "sandwich","stargazer","ggplot2","lfe"))
# =====

library(readxl)
library(dplyr); library(tidyr)
library(plm); library(lmtest); library(sandwich)
library(stargazer); library(ggplot2)

# — SOURCE DES DONNEES —————
df_raw <- panel_with_returns_v6
cat("Funds loaded:", nrow(df_raw), "\n")

# =====
# SECTION 1: DATA PREPARATION
# =====

df <- df_raw %>%
  rename(
    ISIN      = Ticker,
    ESG_Rating = `Morningstar ESG Risk Rating for Funds`,
    ESG_Score  = `Corporate Sustainability Score`,
    Sharpe     = `Sharpe Ratio (1Y Monthly)`,
    Alpha      = `Alpha (1Y Monthly)`,
    IR         = `Information Ratio (1Y)`,
    TNA        = `Total Net Assets for Share Class`,
    Inception  = `Inception Date`,
    Fee_Level  = `Fee Level: Distribution`,
    Category   = `Morningstar Category`
  ) %>%
  mutate(
    Log_TNA   = log(TNA),
    Log_TNA2  = Log_TNA^2,

    Fund_Age = as.numeric(difftime(
      as.Date("2024-12-31"), as.Date(Inception), units = "days")) / 365.25,

    Fee_Num = case_when(
      Fee_Level == "Low"           ~ 1,
      Fee_Level == "Below Average" ~ 2,
      Fee_Level == "Average"       ~ 3,
      Fee_Level == "Above Average" ~ 4,
      Fee_Level == "High"          ~ 5,
      TRUE ~ NA_real_),

    # Missing fee -> imputed to 3 (Average)
    # to preserve panel observations
    Fee_Num_imp = ifelse(is.na(Fee_Num), 3, Fee_Num),

    D_FI      = as.integer(Asset_Class == "Fixed Income"),
    D_Alloc   = as.integer(Asset_Class == "Allocation"),

    # Sustainalytics score inverted: lower raw = better ESG
    # Inversion: higher values = stronger ESG integration
    # consistent with Morningstar ESG Rating
    # Les deux mesures reposent sur Sustainalytics :
    # ESG_Rating = version catégorielle 1-5 globes (Morningstar),
    # ESG_Inv    = score numérique continu inverted (Sustainalytics).
    ESG_Inv     = max(ESG_Score, na.rm = TRUE) - ESG_Score
  )
```

```

cat("Asset classes:\n")
print(table(df$Asset_Class))

# =====
# SECTION 2: VARIABLE DEFINITIONS TABLE
# =====

cat("\n===== \n")
cat("TABLEAU DE DEFINITIONS DES VARIABLES\n")
cat("===== \n")

var_def <- data.frame(
  Variable = c("Sharpe", "Alpha", "IR", "Annual_Return",
               "ESG_Rating", "ESG_Inv",
               "Log_TNA", "Log_TNA2", "Fund_Age", "Fee_Num",
               "D_FI", "D_Alloc", "Year", "Post_SFDR"),
  Type = c("Dep.", "Dep.", "Dep.", "Dep. panel",
           "Indep.", "Indep.",
           "Controle", "Controle", "Controle", "Controle",
           "Controle", "Controle", "Controle", "Moderateur H4"),
  Description = c(
    "Ratio de Sharpe 12 mois (rendement exces / ecart-type)",
    "Alpha de Jensen 12 mois (CAPM)",
    "Information Ratio 12 mois (rendement actif / tracking error)",
    "Rendement annuel total du fonds (annee t)",
    "Note ESG Morningstar 1-5 globes (5 = meilleur, cross-sectionnel)",
    "Score Sustainalytics inverse (max - score brut; plus eleve = meilleur ESG)",
    "Log(actifs nets totaux EUR); corrige la skewness",
    "Log(TNA)^2; effets non-lineaires de taille",
    "Age du fonds en annees au 31/12/2024",
    "Frais ordinal 1 (Low) a 5 (High); Morningstar Fee Level",
    "1 si Fixed Income, 0 sinon (ref = Equity)",
    "1 si Allocation, 0 sinon (ref = Equity)",
    "Annee calendaire; inclus comme FE dans tous les modeles",
    "0 = pre-SFDR (2019-2020), 1 = post-SFDR (2022-2024); 2021 exclu"),
  Source = c(
    "Morningstar Direct", "Morningstar Direct", "Morningstar Direct",
    "Yahoo Finance (scraping)",
    "Morningstar / Sustainalytics", "Sustainalytics (inverted)",
    "Morningstar", "Calcule", "Morningstar", "Morningstar",
    "Morningstar", "Morningstar", "Calendaire", "Construit"),
  stringsAsFactors = FALSE)

print(var_def, row.names = FALSE)

# =====
# SECTION 3: DESCRIPTIVE STATISTICS
# =====

cat("\n===== \n")
cat("STATISTIQUES DESCRIPTIVES\n")
cat("===== \n")

desc_vars <- c("Sharpe", "Alpha", "IR", "ESG_Rating", "ESG_Score",
              "Log_TNA", "Fund_Age", "Fee_Num")

desc_table <- data.frame(
  Variable = desc_vars,
  N = sapply(desc_vars, function(v) sum(!is.na(df[[v]]))),
  Mean = sapply(desc_vars, function(v) round(mean(df[[v]], na.rm=TRUE), 3)),
  SD = sapply(desc_vars, function(v) round(sd(df[[v]], na.rm=TRUE), 3)),
  Min = sapply(desc_vars, function(v) round(min(df[[v]], na.rm=TRUE), 3)),
  Max = sapply(desc_vars, function(v) round(max(df[[v]], na.rm=TRUE), 3))
)
print(desc_table)

cat("\nMeans by Asset Class:\n")

```

```

print(df %>% group_by(Asset_Class) %>%
      summarise(N = n(),
                Mean_ESG      = round(mean(ESG_Score, na.rm=TRUE), 2),
                Mean_Sharpe    = round(mean(Sharpe, na.rm=TRUE), 3),
                Mean_Alpha     = round(mean(Alpha, na.rm=TRUE), 3)))

# =====
# SECTION 4: PANEL DATASET CONSTRUCTION
# =====

cat("\n=====\\n")
cat("CONSTRUCTION DU PANEL LONG\\n")
cat("=====\\n")

return_cols <- paste0("Return_", 2019:2024)
available_cols <- return_cols[return_cols %in% names(df)]

panel_long <- df %>%
  select(ISIN, Asset_Class, ESG_Rating, ESG_Score, ESG_Inv,
         Log_TNA, Log_TNA2, Fund_Age, Fee_Num, Fee_Num_imp,
         D_FI, D_Alloc, all_of(available_cols)) %>%
  pivot_longer(cols = all_of(available_cols),
               names_to = "Year_Label",
               values_to = "Annual_Return") %>%
  filter(!is.na(Annual_Return)) %>%
  mutate(
    Year = as.integer(sub("Return_", "", Year_Label)),

    Post_SFDR = case_when(
      Year %in% c(2019, 2020) ~ 0L,
      Year == 2021 ~ NA_integer_,
      Year %in% c(2022, 2023, 2024) ~ 1L
    ),

    # Interaction terms for H2 (asset class heterogeneity)
    ESG_R_x_FI = ESG_Rating * D_FI,
    ESG_R_x_Alloc = ESG_Rating * D_Alloc,
    ESG_S_x_FI = ESG_Inv * D_FI,
    ESG_S_x_Alloc = ESG_Inv * D_Alloc,

    # Interaction terms for H3 (fund size moderator)
    ESG_R_x_Size = ESG_Rating * Log_TNA,
    ESG_S_x_Size = ESG_Inv * Log_TNA,
    ESG_R_x_Size2 = ESG_Rating * Log_TNA2,
    ESG_S_x_Size2 = ESG_Inv * Log_TNA2,

    # Interaction terms for H4 (pre vs post-SFDR)
    ESG_R_x_Post = ESG_Rating * Post_SFDR,
    ESG_S_x_Post = ESG_Inv * Post_SFDR,

    # Year as factor for OLS year fixed effects
    Year_f = factor(Year)
  )

# Sub-panels
panel_h123 <- panel_long
panel_h4 <- panel_long %>% filter(!is.na(Post_SFDR))

cat("Panel H1/H2/H3 (2019-2024):", nrow(panel_h123), "obs |",
    length(unique(panel_h123$ISIN)), "fonds\\n")
cat("Distribution by year:\\n")
print(table(panel_h123$Year))

cat("\\nPanel H4 (excl. 2021):", nrow(panel_h4), "obs |",
    "Pre-SFDR:", sum(panel_h4$Post_SFDR == 0),
    "| Post-SFDR:", sum(panel_h4$Post_SFDR == 1), "\\n\\n")

```

```

# pdata.frame pour modeles RE
pdata_h123 <- pdata.frame(panel_h123, index = c("ISIN","Year"))
pdata_h4    <- pdata.frame(panel_h4,    index = c("ISIN","Year"))

# =====
# KEY METHODOLOGICAL NOTE
# =====
# ESG_Rating et ESG_Inv sont TIME-INVARIANT (mesure unique par
# per fund, cross-sectional). Within-fund FE absorbs them
# entirely -> "empty model". Estimator strategy:
#
#   Model 1: Pooled OLS + year FE + fund-clustered SE
#             (main estimator; exploits cross-fund variation)
#   Model 2: Random Effects + year FE
#             (panel estimator; assumes: fund effects non
#             correlated with regressors)
#   Hausman: test RE vs OLS via Mundlak approach
#             (fund-level means added as regressors)
#
# For H4 only: Post_SFDR varies over time -> two-way FE
# (fund + year) is feasible and estimated.
# =====

cat("=====\n")
cat("NOTE: ESG time-invariant -> Pooled OLS + RE (not within FE)\n")
cat("=====\n\n")

# =====
# MUNDLAK TEST FUNCTION (guides OLS vs RE choice for H1-H3)
# =====
# The Mundlak approach adds fund-level means as regressors.
# If the Wald test on these means is significant (p<0.05),
# fund effects are correlated with regressors -> prefer OLS.
# Otherwise, RE is efficient.
#

mundlak_test <- function(formula_rhs, panel_df, pdata_obj, label="") {

  # — 1. Clean formula for plm: remove Year_f
  #   Year_f causes singularity in plm RE
  #
  clean_rhs <- function(rhs) {
    terms <- trimws(unlist(strsplit(rhs, "\\|")))
    terms <- terms[!grepl("Year_f|factor\\|(", terms)]
    paste(terms, collapse = " + ")
  }
  rhs_re <- clean_rhs(formula_rhs)

  # — 2. Eligible variables for Mundlak means
  vars <- trimws(unlist(strsplit(rhs_re, "\\|")))
  vars <- vars[vars %in% names(panel_df)]

  # Exclude dummies, interactions, Post_SFDR
  interactions <- grep("_x_", vars, value=TRUE)
  exclude <- c("D_FI","D_Alloc","Post_SFDR", interactions)
  candidates <- vars[!vars %in% exclude]
  candidates <- candidates[
    sapply(candidates,
           function(v) is.numeric(panel_df[[v]]) && v %in% names(panel_df))
  ]

  if (length(candidates) == 0) {
    cat("Mundlak [", label, "] : aucune variable eligible -> RE retenu\n\n")
    return("re")
  }

  # — 3. Fund-level means
  means_df <- panel_df %>%

```

```

group_by(ISIN) %>%
  summarise(across(all_of(candidates),
    ~mean(.x, na.rm=TRUE),
    .names = "mean_{col}"),
    .groups = "drop")

panel_mundlak <- panel_df %>% left_join(means_df, by="ISIN")
mean_vars <- paste0("mean_", candidates)
mean_vars <- mean_vars[mean_vars %in% names(panel_mundlak)]

pdata_mundlak <- pdata.frame(panel_mundlak, index=c("ISIN","Year"))

# — 4. Base RE and Mundlak RE (effect="twoways" handles year effects)
re_base <- tryCatch(
  plm(as.formula(paste("Annual_Return ~", rhs_re)),
    data=pdata_obj, model="random", effect="twoways",
    random.method="walhus"),
  error = function(e) {
    cat("RE base impossible [", label, "]:", e$message, "\n\n")
    return(NULL)
  })

if (is.null(re_base)) return("re")

re_mundlak <- tryCatch(
  plm(as.formula(paste("Annual_Return ~", rhs_re, "+",
    paste(mean_vars, collapse=" + "))),
    data=pdata_mundlak, model="random", effect="twoways",
    random.method="walhus"),
  error = function(e) {
    cat("RE Mundlak impossible [", label, "]:", e$message, "\n\n")
    return(NULL)
  })

if (is.null(re_mundlak)) return("re")

# — 5. Wald test on Mundlak terms
tryCatch({
  fttest <- waldtest(re_base, re_mundlak)
  cat("\n--- Test Mundlak [", label, "] ---\n")
  cat("H0 : effets fonds non correlated with regressors (RE valide)\n")
  print(fttest)
  p_mundlak <- fttest$`Pr(>Chisq)`[2]
  if (!is.na(p_mundlak) && p_mundlak < 0.05) {
    cat("-> p<.05: correlated effects -> Pooled OLS preferred\n\n")
    return("pooled")
  } else {
    cat("-> p>.05: RE valid and efficient\n\n")
    return("re")
  }
}, error = function(e) {
  cat("Test Mundlak indisponible [", label, "]:", e$message,
    "\n-> RE retenu par default\n\n")
  return("re")
})
}

# Fund-clustered SE for Pooled OLS
se_clustered <- function(mod, cluster_var, data) {
  tryCatch(
    sqrt(diag(vcovCL(mod, cluster = ~ISIN, data = data))),
    error = function(e) sqrt(diag(vcovHC(mod, type="HC3")))
  )
}

se_plm <- function(mod) {
  tryCatch(
    sqrt(diag(vcovHC(mod, type="HC3", cluster="group"))),

```

```

    error = function(e) sqrt(diag(vcovHC(mod, type="HC3")))
  )
}

# =====
# SECTION 5: H1 – ESG INTEGRATION AND ANNUAL RETURNS (POOLED OLS + RE)
# =====

cat("=====\n")
cat("H1: ESG -> Annual Fund Returns\n")
cat("=====\n\n")

rhs_h1_r <- "ESG_Rating + Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc +
Year_f"
rhs_h1_s <- "ESG_Inv + Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc +
Year_f"

# Mundlak test
cat(">> Test Mundlak H1 (ESG_Rating):\n")
h1_mundlak_r <- mundlak_test(rhs_h1_r, panel_h123, pdata_h123, "H1 ESG_Rating")
cat(">> Test Mundlak H1 (ESG_Inv):\n")
h1_mundlak_s <- mundlak_test(rhs_h1_s, panel_h123, pdata_h123, "H1 ESG_Inv")

# Model 1: Pooled OLS with year FE + clustered SE
h1_ols_r <- lm(as.formula(paste("Annual_Return ~", rhs_h1_r)),
              data = panel_h123)
h1_ols_s <- lm(as.formula(paste("Annual_Return ~", rhs_h1_s)),
              data = panel_h123)

# Model 2: Random Effects with year FE
rhs_h1_re_r <- "ESG_Rating + Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc"
rhs_h1_re_s <- "ESG_Inv + Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc"

# Wallace-Hussain estimator: requires only N > K
# Default Swamy-Arora needs T > K, which fails here
# (6 periods <= 7 coefficients)
h1_re_r <- plm(as.formula(paste("Annual_Return ~", rhs_h1_re_r)),
              data = pdata_h123, model = "random", effect = "twoways",
              random.method = "walhus")
h1_re_s <- plm(as.formula(paste("Annual_Return ~", rhs_h1_re_s)),
              data = pdata_h123, model = "random", effect = "twoways",
              random.method = "walhus")

# SE
se_h1_ols_r <- se_clustered(h1_ols_r, "ISIN", panel_h123)
se_h1_ols_s <- se_clustered(h1_ols_s, "ISIN", panel_h123)

cat("\n--- ESG Coefficients H1 ---\n")
cat("Pooled OLS, ESG_Rating:\n")
print(summary(h1_ols_r)$coefficients["ESG_Rating",])
cat("Pooled OLS, ESG_Inv:\n")
print(summary(h1_ols_s)$coefficients["ESG_Inv",])
cat("RE, ESG_Rating:\n")
print(summary(h1_re_r)$coefficients["ESG_Rating",])

print(modelsummary(
  list("OLS (MS)"=h1_ols_r, "OLS (Sust)"=h1_ols_s,
        "RE (MS)"=h1_re_r, "RE (Sust)"=h1_re_s),
  vcov = list(se_h1_ols_r, se_h1_ols_s, se_plm(h1_re_r), se_plm(h1_re_s)),
  stars = c("***=0.1", "**=0.05", "*=0.01"),
  coef_map = c("ESG_Rating"="ESG Rating (MS)", "ESG_Inv"="ESG Score (Sust)",
                "Log_TNA"="Log(TNA)", "Fund_Age"="Fund Age",
                "Fee_Num_imp"="Fee Level", "D_FI"="Fixed Income",
                "D_Alloc"="Allocation"),
  coef_omit = "Year_f",
  gof_map = c("nobs", "r.squared", "adj.r.squared"),
  output = "dataframe"))

```

```

cat("\n--- H1 RESULTS ---\n")
cat("Preferred estimator (Mundlak): ESG_Rating =", h1_mundlak_r,
    "\n| ESG_Inv =", h1_mundlak_s, "\n")
p_h1 <- summary(h1_ols_r)$coefficients["ESG_Rating", "Pr(>|t|)"] # OLS -> t
c_h1 <- coef(h1_ols_r)["ESG_Rating"]
if (!is.na(p_h1) && p_h1 < 0.05 && c_h1 > 0) {
  cat("H1 SUPPORTED: ESG_Rating positive and significant (p=",
    round(p_h1, 3), ")\n")
} else if (!is.na(p_h1) && p_h1 < 0.1 && c_h1 > 0) {
  cat("H1 PARTIALLY SUPPORTED: marginally significant (p=", round(p_h1, 3), ")\n")
} else {
  cat("H1 NOT SUPPORTED: not significant (p=", round(p_h1, 3), ")\n")
}

# =====
# SECTION 6: H2 - ASSET CLASS HETEROGENEITY
# =====

cat("\n===== \n")
cat("H2: Asset Class Heterogeneity\n")
cat("===== \n\n")

rhs_h2_r <- "ESG_Rating + D_FI + D_Alloc + ESG_R_x_FI + ESG_R_x_Alloc + Log_TNA
+ Fund_Age + Fee_Num_imp + Year_f"
rhs_h2_s <- "ESG_Inv + D_FI + D_Alloc + ESG_S_x_FI + ESG_S_x_Alloc + Log_TNA +
Fund_Age + Fee_Num_imp + Year_f"

cat(">> Test Mundlak H2 (ESG_Rating):\n")
h2_mundlak_r <- mundlak_test(rhs_h2_r, panel_h123, pdata_h123, "H2 ESG_Rating")
cat(">> Test Mundlak H2 (ESG_Inv):\n")
h2_mundlak_s <- mundlak_test(rhs_h2_s, panel_h123, pdata_h123, "H2 ESG_Inv")

h2_ols_r <- lm(as.formula(paste("Annual_Return ~", rhs_h2_r)), data=panel_h123)
h2_ols_s <- lm(as.formula(paste("Annual_Return ~", rhs_h2_s)), data=panel_h123)

rhs_h2_re_r <- "ESG_Rating + D_FI + D_Alloc + ESG_R_x_FI + ESG_R_x_Alloc +
Log_TNA + Fund_Age + Fee_Num_imp"
rhs_h2_re_s <- "ESG_Inv + D_FI + D_Alloc + ESG_S_x_FI + ESG_S_x_Alloc + Log_TNA
+ Fund_Age + Fee_Num_imp"

h2_re_r <- plm(as.formula(paste("Annual_Return ~", rhs_h2_re_r)),
  data=pdata_h123, model="random", effect="twoways",
  random.method="walhus")
h2_re_s <- plm(as.formula(paste("Annual_Return ~", rhs_h2_re_s)),
  data=pdata_h123, model="random", effect="twoways",
  random.method="walhus")

print(modelsummary(
  list("OLS (MS)"=h2_ols_r, "OLS (Sust)"=h2_ols_s,
    "RE (MS)"=h2_re_r, "RE (Sust)"=h2_re_s),
  vcov = list(se_clustered(h2_ols_r, "ISIN", panel_h123),
    se_clustered(h2_ols_s, "ISIN", panel_h123),
    se_plm(h2_re_r), se_plm(h2_re_s)),
  stars = c("***=0.1, ***=0.05, ****=0.01),
  coef_map = c("ESG_Rating"="ESG Rating (MS)", "ESG_Inv"="ESG Score (Sust)",
    "D_FI"="Fixed Income", "D_Alloc"="Allocation",
    "ESG_R_x_FI"="ESG x Fixed Income", "ESG_R_x_Alloc"="ESG x
Allocation",
    "ESG_S_x_FI"="ESG x Fixed Income (Sust)", "ESG_S_x_Alloc"="ESG x
Allocation (Sust)",
    "Log_TNA"="Log (TNA)", "Fund_Age"="Fund Age", "Fee_Num_imp"="Fee
Level"),
  coef_omit = "Year_f",
  gof_map = c("nobs", "r.squared", "adj.r.squared"),
  output = "dataframe"))

cat("\n--- Net ESG effects by asset class ---\n")
b <- coef(h2_ols_r)

```

```

cat("Equity      :", round(b["ESG_Rating"], 4), "\n")
cat("Fixed Income:", round(b["ESG_Rating"] + b["ESG_R_x_FI"], 4), "\n")
cat("Allocation  :", round(b["ESG_Rating"] + b["ESG_R_x_Alloc"], 4), "\n")

cat("\n--- H2 RESULTS ---\n")
cat("Preferred estimator (Mundlak): ESG_Rating =", h2_mundlak_r, "\n")
tryCatch({
  p_fi <- summary(h2_ols_r)$coefficients["ESG_R_x_FI", "Pr(>|t|)"]
  p_al <- summary(h2_ols_r)$coefficients["ESG_R_x_Alloc", "Pr(>|t|)"]
  c_fi <- coef(h2_ols_r)["ESG_R_x_FI"]
  c_al <- coef(h2_ols_r)["ESG_R_x_Alloc"]
  cat(" ESG x Fixed Income : coef=", round(c_fi,4), "p=", round(p_fi,3), "\n")
  cat(" ESG x Allocation   : coef=", round(c_al,4), "p=", round(p_al,3), "\n")
  if ((p_fi < 0.1 && c_fi < 0) || (p_al < 0.1 && c_al < 0)) {
    cat("H2 SUPPORTED: weaker ESG effect in FI or Allocation\n")
  } else {
    cat("H2 NOT SUPPORTED: interactions not significant\n")
  }
}, error=function(e) cat("Erreur:", e$message, "\n"))

# =====
# SECTION 7: H3 – FUND SIZE AS MODERATOR
# =====

cat("\n===== \n")
cat("H3: Fund Size as Moderator\n")
cat("===== \n\n")

rhs_h3_r <- "ESG_Rating + Log_TNA + ESG_R_x_Size + D_FI + D_Alloc + Fund_Age +
Fee_Num_imp + Year_f"
rhs_h3_s <- "ESG_Inv + Log_TNA + ESG_S_x_Size + D_FI + D_Alloc + Fund_Age +
Fee_Num_imp + Year_f"

cat(">> Test Mundlak H3 (ESG_Rating):\n")
h3_mundlak_r <- mundlak_test(rhs_h3_r, panel_h123, pdata_h123, "H3 ESG_Rating")
cat(">> Test Mundlak H3 (ESG_Inv):\n")
h3_mundlak_s <- mundlak_test(rhs_h3_s, panel_h123, pdata_h123, "H3 ESG_Inv")

h3_ols_r <- lm(as.formula(paste("Annual_Return ~", rhs_h3_r)), data=panel_h123)
h3_ols_s <- lm(as.formula(paste("Annual_Return ~", rhs_h3_s)), data=panel_h123)

rhs_h3_re_r <- "ESG_Rating + Log_TNA + ESG_R_x_Size + D_FI + D_Alloc + Fund_Age +
Fee_Num_imp"
rhs_h3_re_s <- "ESG_Inv + Log_TNA + ESG_S_x_Size + D_FI + D_Alloc + Fund_Age +
Fee_Num_imp"

h3_re_r <- plm(as.formula(paste("Annual_Return ~", rhs_h3_re_r)),
  data=pdata_h123, model="random", effect="twoways",
  random.method="walhus")
h3_re_s <- plm(as.formula(paste("Annual_Return ~", rhs_h3_re_s)),
  data=pdata_h123, model="random", effect="twoways",
  random.method="walhus")

print(modelsummary(
  list("OLS (MS)"=h3_ols_r, "OLS (Sust)"=h3_ols_s,
    "RE (MS)"=h3_re_r, "RE (Sust)"=h3_re_s),
  vcov = list(se_clustered(h3_ols_r, "ISIN", panel_h123),
    se_clustered(h3_ols_s, "ISIN", panel_h123),
    se_plm(h3_re_r), se_plm(h3_re_s)),
  stars = c("***=0.1", "**=0.05", "*=0.01"),
  coef_map = c("ESG_Rating"="ESG Rating (MS)", "ESG_Inv"="ESG Score (Sust)",
    "Log_TNA"="Log(TNA)", "ESG_R_x_Size"="ESG x Log(TNA)",
    "ESG_S_x_Size"="ESG x Log(TNA) (Sust)",
    "D_FI"="Fixed Income", "D_Alloc"="Allocation",
    "Fund_Age"="Fund Age", "Fee_Num_imp"="Fee Level"),
  coef_omit = "Year_f",
  gof_map = c("nobs", "r.squared", "adj.r.squared"),
  output = "dataframe"))

```

```

cat("\n--- H3 RESULTS ---\n")
cat("Preferred estimator (Mundlak): ESG_Rating =", h3_mundlak_r, "\n")
tryCatch({
  p_sz <- summary(h3_ols_r)$coefficients["ESG_R_x_Size", "Pr(>|t|)"]
  c_sz <- coef(h3_ols_r)["ESG_R_x_Size"]
  cat(" ESG x Log(TNA) : coef=", round(c_sz,4), "p=", round(p_sz,3), "\n")
  if (p_sz < 0.05 && c_sz > 0) {
    cat("H3 SUPPORTED: positive size moderation\n")
  } else {
    cat("H3 NOT SUPPORTED (p=", round(p_sz,3),")\n")
  }
}, error=function(e) cat("Erreur:", e$message, "\n"))

# =====
# SECTION 8: H4 – PRE vs POST-SFDR
# Post_SFDR varies over time -> two-way FE feasible
# =====

cat("\n===== \n")
cat("H4: Pre vs Post-SFDR (2021 excluded)\n")
cat("===== \n\n")

# Hausman test: FE vs RE (Post_SFDR est time-varying -> FE faisable)
run_hausman_h4 <- function(formula_str, pdata_obj, label="") {
  fe <- plm(as.formula(formula_str), data=pdata_obj,
    model="within", effect="twoways")
  re <- plm(as.formula(formula_str), data=pdata_obj, model="random")
  ht <- phtest(fe, re)
  cat("\n--- Hausman test [", label, "] ---\n")
  print(ht)
  if (ht$p.value < 0.05) {
    cat("-> p < .05 : Fixed Effects prefere\n\n")
    list(fe=fe, re=re, preferred="fe", hausman=ht)
  } else {
    cat("-> p > .05 : Random Effects prefere\n\n")
    list(fe=fe, re=re, preferred="re", hausman=ht)
  }
}

h4_haus_r <- run_hausman_h4(
  "Annual_Return ~ ESG_Rating + Post_SFDR + ESG_R_x_Post + Log_TNA +
  Fee_Num_imp",
  pdata_h4, "H4 ESG_Rating")
h4_haus_s <- run_hausman_h4(
  "Annual_Return ~ ESG_Inv + Post_SFDR + ESG_S_x_Post + Log_TNA + Fee_Num_imp",
  pdata_h4, "H4 ESG_Inv")

# Pooled OLS
h4_ols_r <- lm(Annual_Return ~ ESG_Rating + Post_SFDR + ESG_R_x_Post +
  Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc + Year_f,
  data=panel_h4)
h4_ols_s <- lm(Annual_Return ~ ESG_Inv + Post_SFDR + ESG_S_x_Post +
  Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc + Year_f,
  data=panel_h4)

# FE two-way
h4_fe_r <- plm(Annual_Return ~ ESG_Rating + Post_SFDR + ESG_R_x_Post +
  Log_TNA + Fee_Num_imp,
  data=pdata_h4, model="within", effect="twoways")
h4_fe_s <- plm(Annual_Return ~ ESG_Inv + Post_SFDR + ESG_S_x_Post +
  Log_TNA + Fee_Num_imp,
  data=pdata_h4, model="within", effect="twoways")

# RE
h4_re_r <- plm(Annual_Return ~ ESG_Rating + Post_SFDR + ESG_R_x_Post +
  Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc,
  data=pdata_h4, model="random", random.method="walhus")
h4_re_s <- plm(Annual_Return ~ ESG_Inv + Post_SFDR + ESG_S_x_Post +

```

```

Log_TNA + Fund_Age + Fee_Num_imp + D_FI + D_Alloc,
data=pdata_h4, model="random", random.method="walhus")

cat("\n--- H4 Table (Pooled OLS) ---\n")
print(modelsummary(
  list("OLS (MS)"=h4_ols_r, "OLS (Sust)"=h4_ols_s),
  vcov      = list(se_clustered(h4_ols_r,"ISIN",panel_h4),
                  se_clustered(h4_ols_s,"ISIN",panel_h4)),
  stars     = c("*"=0.1, "***"=0.05, "****"=0.01),
  coef_map  = c("ESG_Rating"="ESG Rating (MS)", "ESG_Inv"="ESG Score (Sust)",
                "Post_SFDR"="Post-SFDR", "ESG_R_x_Post"="ESG x Post-SFDR (MS)",
                "ESG_S_x_Post"="ESG x Post-SFDR (Sust)", "Log_TNA"="Log(TNA)",
                "Fund_Age"="Fund Age", "Fee_Num_imp"="Fee Level",
                "D_FI"="Fixed Income", "D_Alloc"="Allocation"),
  coef_omit = "Year_f",
  gof_map   = c("nobs", "r.squared", "adj.r.squared"),
  output    = "dataframe"))

cat("\n--- H4 Table (FE + RE) ---\n")
print(modelsummary(
  list("FE (MS)"=h4_fe_r, "FE (Sust)"=h4_fe_s,
        "RE (MS)"=h4_re_r, "RE (Sust)"=h4_re_s),
  vcov      = list(se_plm(h4_fe_r), se_plm(h4_fe_s),
                  se_plm(h4_re_r), se_plm(h4_re_s)),
  stars     = c("*"=0.1, "***"=0.05, "****"=0.01),
  coef_map  = c("ESG_Rating"="ESG Rating (MS)", "ESG_Inv"="ESG Score (Sust)",
                "Post_SFDR"="Post-SFDR", "ESG_R_x_Post"="ESG x Post-SFDR (MS)",
                "ESG_S_x_Post"="ESG x Post-SFDR (Sust)", "Log_TNA"="Log(TNA)",
                "Fee_Num_imp"="Fee Level"),
  gof_map   = c("nobs", "r.squared", "adj.r.squared"),
  output    = "dataframe"))

cat("\n--- H4 RESULTS ---\n")
tryCatch({
  # FE two-way uses t-statistic
  p_h4 <- summary(h4_fe_r)$coefficients["ESG_R_x_Post", "Pr(>|t|)"]
  c_h4 <- coef(h4_fe_r)["ESG_R_x_Post"]
  cat(" FE : ESG x Post-SFDR : coef=", round(c_h4,4), "p=", round(p_h4,3),
      "\n")
  if (!is.na(p_h4) && p_h4 < 0.05) {
    if (c_h4 > 0) cat("H4: ESG-performance association STRONGER post-SFDR\n")
    else          cat("H4: ESG-performance association WEAKER post-SFDR\n")
  } else {
    cat("H4: no significant structural break (p=", round(p_h4,3),")\n")
  }
}, error=function(e) cat("Erreur H4:", e$message, "\n"))

# =====
# SECTION 9: RESULTS SUMMARY
# =====

cat("\n===== \n")
cat("RESULTS SUMMARY\n")
cat("===== \n")

safe_coef <- function(mod, nm) tryCatch(round(coef(mod)[nm],4),
error=function(e) NA)
safe_pval <- function(mod, nm) tryCatch({
  coef_table <- summary(mod)$coefficients
  # RE utilise z-stat -> "Pr(>|z|)" ; OLS/FE utilisent t-stat -> "Pr(>|t|)"
  col_name <- if ("Pr(>|z|)" %in% colnames(coef_table)) "Pr(>|z|)" else
  "Pr(>|t|)"
  round(coef_table[nm, col_name], 4)
}, error=function(e) NA)
sig <- function(p) ifelse(is.na(p), "NA",
  ifelse(p<0.01, "****", ifelse(p<0.05, "***", ifelse(p<0.1, "**", "n.s."))))

results <- data.frame(

```

```

Hypothese = c(
  "H1 OLS : Annual_Return ~ ESG_Rating",
  "H1 OLS : Annual_Return ~ ESG_Inv",
  "H1 RE : Annual_Return ~ ESG_Rating",
  "H2 OLS : ESG_Rating x Fixed Income",
  "H2 OLS : ESG_Rating x Allocation",
  "H3 OLS : ESG_Rating x Log(TNA)",
  "H4 FE : ESG_Rating x Post_SFDR",
  "H4 OLS : ESG_Rating x Post_SFDR"
),
Estimateur = c("Pooled OLS", "Pooled OLS", "RE", "Pooled OLS", "Pooled OLS",
               "Pooled OLS", "FE two-way", "Pooled OLS"),
Coef = c(
  safe_coef(h1_ols_r, "ESG_Rating"),
  safe_coef(h1_ols_s, "ESG_Inv"),
  safe_coef(h1_re_r, "ESG_Rating"),
  safe_coef(h2_ols_r, "ESG_R_x_FI"),
  safe_coef(h2_ols_r, "ESG_R_x_Alloc"),
  safe_coef(h3_ols_r, "ESG_R_x_Size"),
  safe_coef(h4_fe_r, "ESG_R_x_Post"),
  safe_coef(h4_ols_r, "ESG_R_x_Post")
),
P_Value = c(
  safe_pval(h1_ols_r, "ESG_Rating"),
  safe_pval(h1_ols_s, "ESG_Inv"),
  safe_pval(h1_re_r, "ESG_Rating"),
  safe_pval(h2_ols_r, "ESG_R_x_FI"),
  safe_pval(h2_ols_r, "ESG_R_x_Alloc"),
  safe_pval(h3_ols_r, "ESG_R_x_Size"),
  safe_pval(h4_fe_r, "ESG_R_x_Post"),
  safe_pval(h4_ols_r, "ESG_R_x_Post")
)
)

results$Sig <- sapply(results$P_Value, sig)
print(results, row.names=FALSE)

cat("\n--- Specification tests summary ---\n")
cat("H1 Mundlak (ESG_Rating):", h1_mundlak_r, "\n")
cat("H2 Mundlak (ESG_Rating):", h2_mundlak_r, "\n")
cat("H3 Mundlak (ESG_Rating):", h3_mundlak_r, "\n")
cat("H4 Hausman (ESG_Rating):", h4_haus_r$preferred, "\n")

# =====
# SECTION 10: ROBUSTNESS - SHARPE RATIO, JENSEN ALPHA, IR
# =====
# Note: Sharpe, Alpha and IR are pre-computed Morningstar fields
# on a 12-month rolling window as of April 2025.
# They reflect only April 2024 - April 2025.

# These cross-sectional regressions serve as robustness checks
# only; they are not the main results.

# =====

cat("\n===== \n")
cat("SECTION 10: ROBUSTNESS - SHARPE / ALPHA / IR\n")
cat("(Note: trailing 12-month metrics as of April 2025 only)\n")
cat("===== \n\n")

cs <- df %>%
  filter(!is.na(Sharpe), !is.na(Alpha), !is.na(IR),
         !is.na(ESG_Rating), !is.na(ESG_Score),
         !is.na(Log_TNA), !is.na(Fund_Age))

h_rob_sharpe_r <- lm(Sharpe ~ ESG_Rating + Log_TNA + Fund_Age + Fee_Num_imp +
  D_FI + D_Alloc, data=cs)
h_rob_sharpe_s <- lm(Sharpe ~ ESG_Inv + Log_TNA + Fund_Age + Fee_Num_imp +
  D_FI + D_Alloc, data=cs)

```

```

h_rob_alpha_r <- lm(Alpha ~ ESG_Rating + Log_TNA + Fund_Age + Fee_Num_imp +
D_FI + D_Alloc, data=cs)
h_rob_alpha_s <- lm(Alpha ~ ESG_Inv + Log_TNA + Fund_Age + Fee_Num_imp +
D_FI + D_Alloc, data=cs)
h_rob_ir_r <- lm(IR ~ ESG_Rating + Log_TNA + Fund_Age + Fee_Num_imp +
D_FI + D_Alloc, data=cs)
h_rob_ir_s <- lm(IR ~ ESG_Inv + Log_TNA + Fund_Age + Fee_Num_imp +
D_FI + D_Alloc, data=cs)

library(modelsummary)

models_rob <- list(
  "Sharpe (MS)" = h_rob_sharpe_r,
  "Sharpe (Sust)" = h_rob_sharpe_s,
  "Alpha (MS)" = h_rob_alpha_r,
  "Alpha (Sust)" = h_rob_alpha_s,
  "IR (MS)" = h_rob_ir_r,
  "IR (Sust)" = h_rob_ir_s
)

tab_rob <- modelsummary(models_rob,
  vcov = "HC3",
  stars = c("***=0.1", "**=0.05", "***=0.01"),
  coef_map = c(
    "ESG_Rating" = "ESG Rating (MS)",
    "ESG_Inv" = "ESG Score (Sust)",
    "Log_TNA" = "Log(TNA)",
    "Fund_Age" = "Fund Age",
    "Fee_Num_imp" = "Fee Level",
    "D_FI" = "Fixed Income",
    "D_Alloc" = "Allocation",
    "(Intercept)" = "Intercept"
  ),
  gof_map = c("nobs", "r.squared", "adj.r.squared"),
  output = "dataframe")

print(tab_rob)

cat("\nLIMITATION: These metrics reflect only the window\n")
cat("April 2024 - April 2025 and cannot be used\n")
cat("for performance analysis over the 2019-2024 panel period.\n")

cat("\n=====\n")
cat("Script complete.\n")
cat("=====\n")

TEST OF QUADRATIC TERMS H3
# Check whether Log_TNA2 remains significant despite multicollinearity
# =====

cat("\n=== TEST H3 WITH QUADRATIC TERMS ===\n")

rhs_h3_quad_r <- "ESG_Rating + Log_TNA + Log_TNA2 + ESG_R_x_Size + ESG_R_x_Size2
+ D_FI + D_Alloc + Fund_Age + Fee_Num_imp + Year_f"
rhs_h3_quad_s <- "ESG_Inv + Log_TNA + Log_TNA2 + ESG_S_x_Size + ESG_S_x_Size2 +
D_FI + D_Alloc + Fund_Age + Fee_Num_imp + Year_f"

h3_quad_r <- lm(as.formula(paste("Annual_Return ~", rhs_h3_quad_r)), data =
panel_h123)
h3_quad_s <- lm(as.formula(paste("Annual_Return ~", rhs_h3_quad_s)), data =
panel_h123)

cat("--- Coefficients quadratiques (ESG_Rating) ---\n")
print(summary(h3_quad_r)$coefficients[c("Log_TNA", "Log_TNA2", "ESG_R_x_Size", "ESG
_R_x_Size2"),])

cat("\n--- VIF (multicollinearite) ---\n")
library(car)
print(vif(h3_quad_r))

```

```

cat("\n--- Coefficients quadratiques (ESG_Inv) ---\n")
print(summary(h3_quad_s)$coefficients[c("Log_TNA", "Log_TNA2", "ESG_S_x_Size", "ESG_S_x_Size2"),])

# =====
# COMPLETE DESCRIPTIVE STATISTICS + CORRELATION
# =====

cat("\n=== DESCRIPTIVE STATISTICS BY YEAR ===\n")
panel_h123 %>%
  group_by(Year) %>%
  summarise(
    N = n(),
    Mean_Return = round(mean(Annual_Return, na.rm=TRUE), 2),
    SD_Return = round(sd(Annual_Return, na.rm=TRUE), 2),
    Mean_ESG = round(mean(ESG_Rating, na.rm=TRUE), 2),
    Mean_TNA = round(mean(Log_TNA, na.rm=TRUE), 2),
    Mean_Age = round(mean(Fund_Age, na.rm=TRUE), 2),
    Mean_Fee = round(mean(Fee_Num_imp, na.rm=TRUE), 2)
  ) %>% print()

cat("\n=== CORRELATION MATRIX (main variables) ===\n")
cor_vars <-
c("Annual_Return", "ESG_Rating", "ESG_Inv", "Log_TNA", "Fund_Age", "Fee_Num_imp")
cor_data <- panel_h123[, cor_vars]
cor_matrix <- round(cor(cor_data, use="pairwise.complete.obs"), 3)
print(cor_matrix)

cat("\n=== PANEL DESCRIPTIVE STATISTICS (all variables) ===\n")
panel_h123 %>%
  summarise(
    across(c(Annual_Return, ESG_Rating, ESG_Inv, Log_TNA, Fund_Age, Fee_Num_imp,
              D_FI, D_Alloc),
            list(N=~sum(!is.na(.)), Mean=~round(mean(., na.rm=T), 3),
                 SD=~round(sd(., na.rm=T), 3),
                 Min=~round(min(., na.rm=T), 3),
                 Max=~round(max(., na.rm=T), 3)),
            .names="{.col}_{.fn}")
  ) %>% t() %>% print()

cat("\n=== CONTROLS: SIGNS AND MAGNITUDES ===\n")
cat("Log_TNA :", round(coef(h1_ols_r)["Log_TNA"], 4),
    "| p =", round(summary(h1_ols_r)$coefficients["Log_TNA", "Pr(>|t|)"], 4), "\n")
cat("Fund_Age :", round(coef(h1_ols_r)["Fund_Age"], 4),
    "| p =", round(summary(h1_ols_r)$coefficients["Fund_Age", "Pr(>|t|)"], 4), "\n")
cat("Fee_Num :", round(coef(h1_ols_r)["Fee_Num_imp"], 4),
    "| p =", round(summary(h1_ols_r)$coefficients["Fee_Num_imp", "Pr(>|t|)"], 4),
    "\n")
cat("D_FI :", round(coef(h1_ols_r)["D_FI"], 4),
    "| p =", round(summary(h1_ols_r)$coefficients["D_FI", "Pr(>|t|)"], 4), "\n")
cat("D_Alloc :", round(coef(h1_ols_r)["D_Alloc"], 4),
    "| p =", round(summary(h1_ols_r)$coefficients["D_Alloc", "Pr(>|t|)"], 4), "\n")

# =====
# H2 WITH TWO-WAY FIXED EFFECTS
# =====
cat("\n=== H2 FIXED EFFECTS ===\n")

h2_fe_r <- plm(Annual_Return ~ ESG_R_x_FI + ESG_R_x_Alloc +
  Log_TNA + Fee_Num_imp,
  data = pdata_h123,
  model = "within",
  effect = "twoways")

h2_fe_s <- plm(Annual_Return ~ ESG_S_x_FI + ESG_S_x_Alloc +
  Log_TNA + Fee_Num_imp,
  data = pdata_h123,
  model = "within",
  effect = "twoways")

cat("H2 FE (MS):\n")
print(summary(h2_fe_r)$coefficients)

```

```

cat("\nH2 FE (Sust):\n")
print(summary(h2_fe_s)$coefficients)

# =====
# H3 WITH TWO-WAY FIXED EFFECTS
# =====
cat("\n=== H3 FIXED EFFECTS ===\n")

h3_fe_r <- plm(Annual_Return ~ ESG_R_x_Size + Log_TNA + Fee_Num_imp,
data = pdata_h123,
model = "within",
effect = "twoways")

h3_fe_s <- plm(Annual_Return ~ ESG_S_x_Size + Log_TNA + Fee_Num_imp,
data = pdata_h123,
model = "within",
effect = "twoways")

cat("H3 FE (MS):\n")
print(summary(h3_fe_r)$coefficients)

cat("\nH3 FE (Sust):\n")
print(summary(h3_fe_s)$coefficients)

# =====
# HAUSMAN TEST H2 AND H3
# =====
cat("\n=== HAUSMAN H2 ===\n")
h2_re_r_simple <- plm(Annual_Return ~ ESG_R_x_FI + ESG_R_x_Alloc +
Log_TNA + Fee_Num_imp,
data = pdata_h123, model = "random",
random.method = "walhus")
print(phtest(h2_fe_r, h2_re_r_simple))

cat("\n=== HAUSMAN H3 ===\n")
h3_re_r_simple <- plm(Annual_Return ~ ESG_R_x_Size + Log_TNA + Fee_Num_imp,
data = pdata_h123, model = "random",
random.method = "walhus")
print(phtest(h3_fe_r, h3_re_r_simple))

# Check temporal variation of interaction terms
cat("=== TEMPORAL VARIATION OF INTERACTION TERMS ===\n")

check_variation <- panel_h123 %>%
group_by(ISIN) %>%
summarise(
var_ESG_R_x_FI = var(ESG_R_x_FI, na.rm=TRUE),
var_ESG_R_x_Alloc = var(ESG_R_x_Alloc, na.rm=TRUE),
var_ESG_R_x_Size = var(ESG_R_x_Size, na.rm=TRUE),
var_ESG_S_x_FI = var(ESG_S_x_FI, na.rm=TRUE),
var_ESG_S_x_Alloc = var(ESG_S_x_Alloc, na.rm=TRUE),
var_ESG_S_x_Size = var(ESG_S_x_Size, na.rm=TRUE),
) %>%
summarise(across(starts_with("var_"),
~sum(. > 0, na.rm=TRUE),
.names = "n_varying_{.col}"))

print(check_variation)

```