Are Article 9 Funds Superior? - A Comprehensive Empirical Analysis of the SFDR Regulation on its Efficacy, Flows and Performance.

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Abstract (English)

Title: *Are Article 9 Funds Superior? - A Comprehensive Empirical Analysis of the SFDR Regulation on its Efficacy, Flows and Performance.*

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This master's dissertation examines the impact of the Sustainable Finance Disclosure Regulation (SFDR) on mutual equity funds domiciled in the Eurozone, specifically those governed by Article 9, and the ensuing behavioural repercussions on investors.

This academic endeavour contributes to the growing empirical evidence positing the SFDR regulation as an effective bulwark against greenwashing. This is substantiated through the analysis of cross-sectional data procured from two independent ESG data providers, Refinitiv and MSCI, demonstrating that funds governed by Article 9 consistently deliver superior ESG metrics.

Further, this dissertation probes the propensity of investors to allocate a greater quantum of capital towards Article 9 funds and ventures into a detailed analysis of the inherent characteristics of these investors. Utilising a panel data dataset and deploying a difference-in-differences model revealed that investors demonstrate a preference for Article 9 funds preceding the final implementation date of 10th March 2021. Additionally, these investors exhibit signs of higher resilience.

Lastly, this research assesses performance disparities by deploying the Fama and French 3-Factor Model. The analysis suggests that Article 9 funds are characterised by heightened factor exposure to growth investments. Nevertheless, during the observation period spanning 2018 to 2022, SFDR 9 funds do not exhibit a positive alpha. However, when assessed through a difference-in-differences lens, these funds demonstrate a significantly higher alpha than their counterparts.

Keywords: Mutual Funds, Equity Funds, ESG, SFDR, Sustainability Ratings, Fund Flows, Investor Characteristics, Fund Performance

Abstract (Portuguese)

Título: *Os Fundos do Artigo 9º São Superiores? - Uma Análise Empírica do Regulamento SFDR Sobre a sua Eficácia, Fluxos e Desempenho.*

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Esta dissertação analisa o impacto do Regulamento relativo à divulgação de informações sobre finanças sustentáveis (Sustainable Finance Disclosure Regulation - SFDR) nos fundos de investimento em ações da zona euro, especificamente nos fundos regidos pelo Artigo 9.

Esta tese contribui para as crescentes provas empíricas que apontam o regulamento SFDR como um baluarte eficaz contra greenwashing. Isto é comprovado através da análise de dados transversais obtidos de dois fornecedores independentes de dados ESG, Refinitiv e MSCI, demonstrando que os fundos regidos pelo Artigo 9 consistentemente alcançam métricas ESG superiores.

Além disso, esta dissertação investiga a propensão dos investidores para afetarem um maior volume de capital aos fundos do Artigo 9 e analisa as características inerentes a estes investidores. A utilização de um conjunto de dados de painel e a aplicação de um modelo de diferenças em diferenças revelaram que os investidores demonstram uma preferência pelos fundos do Artigo 9 antes da data de implementação final de 10/03/2021. Além disso, estes investidores apresentam sinais de maior resiliência.

Por último, este estudo avalia as disparidades de desempenho através da aplicação do modelo de 3-fatores de Fama e French. A análise sugere que os fundos do Artigo 9 se caracterizam por uma maior exposição a fatores de investimento em crescimento. Ainda assim, durante o período de observação de 2018-2022, os fundos SFDR 9 não apresentam um alfa positivo. No entanto, quando avaliados através de uma lente de diferença nas diferenças, estes fundos demonstram um alfa significativamente mais elevado do que os seus homólogos.

Palavras-chave: Fundos Mútuos, Fundos de Acções, ESG, SFDR, Ratings de Sustentabilidade, Fluxos de Fundos, Características dos Investidores, Desempenho dos Fundos

Table of Abbreviations

CAGR	Compound Annual Growth Rate
DJSI	Dow Jones Sustainability Index
DNSH	Do Not Significant Harm
ESG	Environmental, Social and Governance
EU	European Union
GNPO	Government and Nonprofit Organization
HML	High Minus Low
KPI	Key Performance Indicator
PAI	Principle Adverse Impacts
RTS	Regulatory Technical Standards
SFAP	Sustainable Finance Action Plan
SFDR	Sustainable Finance Disclosure Regulation
SMB	Small Minus Big
TNA	Total Net Assets

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1. Introduction

In the past year, a seismic shift rippled through the financial sector. This disturbance was provoked by revelations from U.S. prosecutors, asserting that a substantial number of investments managed by Deutsche Bank's DWS division, which holds almost €1 trillion in assets, exhibited a complete disregard for environmental, social, and governance (ESG) factors, contradicting their promotional claims (Reuters, 2022). Moreover, this case brought to the fore the potential for greenwashing within sustainable investments, particularly in the absence of regulatory oversight.

Academics have persistently cautioned that without a robust, government regulated labelling system, the risk of greenwashing in sustainable investments is alarmingly high (Berg et al., 2022; Capota et al., 2022). In response to these concerns and to mitigate greenwashing, directing capital flows towards sustainable investments, and aligning financial activities with the objectives of the Green Deal, the European Union (EU) introduced the Sustainable Finance Disclosure Regulation (SFDR) in March 2021. The development of SFDR has been a subject of consideration since 2019, and the regulation aims to alter patterns within the financial sector and channel capital towards environmentally sound investments.

The SFDR framework also provides a classification system for financial products of three categories depending on the degree of ESG integration: Article 9 (characterised as "dark green products"), Article 8 ("light green"), and Article 6 ("conventional products") and thus the EU meets the demands for a state-regulated labelling system for sustainable investments.

Nevertheless this, the following questions remain unanswered so far: Is the SFDR regulation manifest efficacy in the markets, and is it perceived as a hallmark of sustainability concerning financial instruments, thereby raising the barrier against greenwashing? What has been the investors' response to the introduction of the SFDR regulation in their flow behaviour? Do disparities exist among investors, and if so, what is the nature of these disparities across the various classifications? Finally, to what degree do investment strategies and financial performance diverge?

Numerous academics have undertaken analyses of the repercussions of sustainable interventions in financial products and elaborated on the impact of other sustainable metrics.

However, there remains an evident lacuna in examining the effects in the abovementioned areas in relation to the SFDR classifications. This gap in research underscores the novelty and importance of this study in contributing to understand the implications of SFDR regulation on financial products and investor behaviour.

Consequently, this work addresses the abovementioned queries in the context of the ensuing empirical investigation. Particular attention is paid to Article 9 funds, whose superiority over their counterparts is repeatedly called into question. However, before embarking on the empirical dissection, an introduction of the theoretical underpinnings of the SFDR regulation, its implementation, and its critiques will be presented. In addition, a comprehensive review of state-of-the-art academic findings regarding capital flows, performance, and non-financial motivations concerning sustainable investments is provided.

Broadly, the empirical analysis is bifurcated into two sections, each corresponding to different underpinning datasets, to assess the influence of the SFDR implementation on mutual equity funds domiciled in the Eurozone.

The inaugural section investigates whether the regulation confers a quality seal concerning sustainability and thereby scrutinises the regulation's impact on greenwashing. To this end, the ESG metrics of SFDR 9 funds are explored by examining a cross-sectional dataset procured from two independent data providers, Refinitiv and MSCI.

The subsequent section hinges on a panel data dataset encapsulating monthly data spanning a five-year interval from 2018 to 2022, sourced from Refinitiv. This section delves into the examination of three distinct hypotheses. First, the study investigates whether the regulation enhances value for investors and introduces novel information to market participants. In the realm of sustainable investment, a plethora of ESG ratings is available to the public, although academic consensus shows divergent approaches and results. Additionally, fresh ESG information invariably provides added value to investors and engenders corresponding capital flows, as recent studies illustrated with the introduction of Morningstar ratings (Ammann et al., 2019; Hartzmark & Sussman, 2019). This section examines whether Article 9 funds consequently attract superior capital inflows post-implementation of the regulation. Second, the work scrutinises investor characteristics in greater detail, analysing disparities in the flow relationship of Article 9 funds and juxtaposing the findings with results based on other examinations of ESG funds. Finally, this work investigates the discrepancies in investment strategies using the Fama and French 3-Factor Model and ultimately explores performance disparities across different classifications.

2. Background Information

The centrepiece of the European Green Deal of the European Union (EU) is the goal of being climate-neutral by 2050. The EU argues that this goal is consistent with commitments made under the Paris Agreement to keep the global temperature rise below 2°C and to make efforts to limit the rise to 1.5°C. To transform all areas of society and the economy, the EU aims to take the lead in critical areas such as industrial policy, finance and research, while simultaneously ensuring social justice among EU citizens (European Commission, 2023a).

To take action, the EU published a Sustainable Finance Action Plan (SFAP) in 2018 to channel capital flows to solutions and businesses that address social and environmental issues. Empirical research suggests that allocating financial resources towards such companies can facilitate the transition to a greener economy. This is particularly true for equity markets, which have demonstrated their effectiveness in providing capital for developing and implementing green projects (De Haas & Popov, 2019). Simultaneously, the EU aimed to improve disclosure to make sustainability opportunities more transparent on the one hand, and to assess the financial risks arising from Environmental, Social and Governance ESG issues easier on the other hand. (European Commission, 2020).

3. European Union’s Sustainable Finance Disclosure Regulation (SFDR)

The EU’s SFDR is a key component of the SFAP. It is a measure to reduce greenwashing and to enable a better comparison of financial products, especially investment funds and similar products, by increasing the transparency of products. Regulators are also responding to increasing academic demands for a standardized definition of ESG funds and a regulatory label to identify ESG funds accurately to make qualitative differences easily tangible (Berg et al., 2022; Capota et al., 2022).

The SFDR regulation is simply an addition to the general regulatory frameworks already in place. It increases the obligation for fund managers and financial advisors to disclose the extent to which they consider sustainability goals in their investment process. Specifically, it increases the level of disclosure that fund managers and financial advisors must provide for their funds' key ESG performance indicators (KPI). Additionally, it provides guidance on how to manage investment risks that affect sustainability factors and ultimately impact investment value. All in all, the SFDR regulation raises the bar for investment products (Morningstar U.K., 2021).

Furthermore, the SFDR regulation segments the financial products into three types with different disclosure and sustainability quality levels: Products that do not show any sustainable focus (Article 6 products), products that promote an environmental or social investment strategy (Article 8 products) or, ultimately, products with a sustainable investment objective (Article 9 funds) (Lysak et al., 2021).

3.1. Classification Categories of SFDR

Products that are referred to as Article 6 products do not have any sustainability focus in their investment strategy. According to the SFDR regulation, such products classify that they are neither aligned with the disclosure criteria for Article 8 products nor Article 9 products. In detail, there is no clear definition of Article 6 products. However, the EU Commission sets boundaries for an Article 8 product towards an Article 6 product (Joint Committee of the European Supervisory Authorities, 2021b). All in all, Article 6 products can be considered the least sustainable products, tier 3 products.

The boundary that classifies a product as an Article 8 product is that such a product includes information towards sustainability-related financial product standards and labels and uses one of the common investment process tools, such as screening, exclusion, and best-in-class strategies (Joint Committee of the European Supervisory Authorities, 2021b). Correspondingly, Article 8 products are known as "light green" products and promote environmental or social characteristics in their product information or product name. Additionally, products can be classified as Article 8 if they invest a portion in so-called sustainable investments. However, then the products should support reaching the communicated attributes of their investment in the long run to prevent greenwashing. This must be proven by sharing the EU taxonomy alignment of their sustainable investments, or their general alignment with the Do Not Significant Harm (DNSH) criteria and the Principle

Adverse Impacts (PAI) (Joint Committee of the European Supervisory Authorities, 2021b). All three classifications are EU regulations. The EU Taxonomy is a standard classification system to identify sustainable economic activities, hence so-called sustainable investments (European Commission, 2023b). The DNSH is linked to the EU Taxonomy and secures a minimum safeguard regarding general sustainable objectives, such as the reduction of greenhouse gas emissions, the reduction of water usage, and the protection of biodiversity and ecosystems (European Commission, 2021). The PAIs are the negative ESG impacts caused by an investment or a financial activity. These impacts may be environmental, social and labour concerns, respect for human rights, anti-corruption and anti-bribery. It involves assessing and disclosing them for each asset (Deloitte, 2023). In other words, Article 8 products can be considered tier 2 products in sustainable investing.

Article 9 products are considered as "dark green" products. It must only invest in sustainable investments to qualify as such. The classification of sustainable investments is again secured through the EU Taxonomy, for which an Article 9 product has to disclose its full alignment (Joint Committee of the European Supervisory Authorities, 2021b). Therefore, Article 9 funds can be seen as the most sustainable ones and therefore as tier 1 products in the product universe of sustainable investments. Ramos et al. (2023) also emphasize this in their study in which they researched the coherence of the signals sent by government and non-profit organisations (GNPOs) labels and of private sector labels. They find that Article 9 products are more aligned with GNPO labels and tend to exhibit ESG terminology (Ramos et al., 2023). Thus, my first hypothesis posits that:

Hypothesis 1: Article 9 products are a signal of a high ESG focus in their investment process and therefore show a significantly higher alignment with common ESG metrics.

3.2. SFDR Timeline

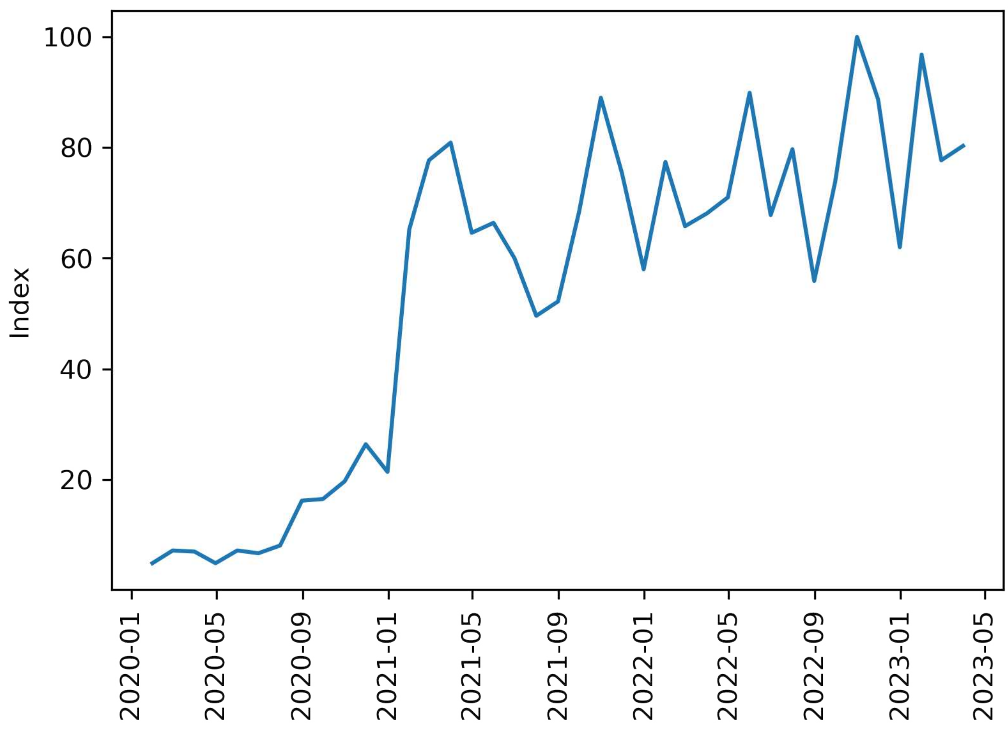
The implementation of the SFDR regulation follows a step-by-step process. First, financial market participants, product owners and advisors were required to publish information on their websites and in their product prospectus about their SFDR alignment. This became active on the 10th of March 2021.

The precise enforcement timeline of the SFDR was marked by considerable ambiguity as regulatory bodies grappled with numerous external challenges. Most notably, the upheaval was elicited by the Corona pandemic, resulting in significant delays in technical requirements threatening the implementation of the SFDR regulation. Finally, however, the definitive implementation date was revealed in a letter issued by the European Commission towards the end of October 2020 (i.e., 20th of October 2021) and the previously published criteria were upheld. This clarification enabled market participants to meticulously prepare for the regulation's application, which was slated for the 10th of March, 2021 (Berrigan, 2020). Hence, market participants were able to publish their alignment already before the regulation became active in March.

Figure 1 shows the monthly worldwide search volume of the keyword "SFDR" on Google per month, with the highest month indexed to 100. Accordingly, the introduction of the SFDR regulation has led to a steep increase in search volume and a steady increase until today (Google Trends, 2023).

Figure 1: Monthly Search Volume of Keyword "SFDR".

Figure 1 depicts the normalised monthly Google search volume for the keyword "SFDR". Data spans the period from January 2020 through March 2023. The monthly measure is determined by summing the weekly search volumes and indexing them by the month with the maximum search volume.



Source:(Google Trends, 2023). Own Illustration.

Later in the same year, from the end of June 2021, participants must start reporting using the templates on PAI and DNSH or disclose their EU Taxonomy alignment of their product (European Parliament and Council, 2019). The regulators have continuously worked on and finalised the Regulatory Technical Standards (RTS), which provide more detailed guidance on the content and presentation of the required disclosures of the PAI, DNSH and EU Taxonomy. The 1st of January 2023 marks the application date of the finalised RTS, and since then market participants must comply with the RTS (Joint Committee of the European Supervisory Authorities, 2021a). According to Morningstar, this has produced a large downgrade wave to Article 8 from Article 9, hence the final RTS increased disclosure pressure on Article 9 products (Hortense Bioy, CFA et al., 2023).

3.3. Criticism Regarding SFDR

However, introducing the SFDR regulation also resulted in criticism among market participants and academics. The characterization of products under the SFDR regulation could have been clearer from the beginning. It contained vague wording that made it challenging for market participants to understand the requirements and left many questions unanswered. Indeed, the SFDR regulation was still one of the major projects of the European Securities and Markets Authority in 2022 (Lysak et al., 2021). Additionally, incorporating consistent ESG data in the investment decision process is a major issue (Doyle, 2018). Many providers and ESG rating agencies such as Sustainalytics, Moody`s ESG (Vigeo-Eiris), Refinitiv, and MSCI have integrated ESG data on different bases and the literature shows differences in the ratings (Chatterji et al., 2016; Dimson et al., 2020; Berg et al., 2022). Scholars showed that this is due to heterogeneous approaches regarding the methodology used to measure ESG standards (Delmas & Blass, 2010; Rekker et al., 2021).

Additionally, there is a significant difference in ESG scores with respect to size and geographical areas. First, ratings diverge between small-sized and large-sized companies. Respectively, this also translates into small-cap and large-cap funds, in which small-cap funds show the tendency of lower ESG scores. Ultimately, this leads to a large-cap bias in using ESG scores as a screening criterion (Dolvin et al., 2017; Doyle, 2018). This assumption is supported by the finding that European funds with a higher sustainability score carry a negative, statistically significant difference in loading on the Small Minus Big (SMB) factor of the Fama and French 3-factor model. This implies that funds with a high sustainability focus are more heavily weighted towards large companies than their counterpart with low sustainability focus (Auran & Kristiansen, 2016). Second, a geographical bias exists, since ESG ratings differ across geographies depending on the stringency of disclosure requirements. For example, ESG scores in Europe are higher than in America (Doyle, 2018). As the SFDR regulation further increases the disclosure standards it will exacerbate these biases.

4. Literature Review

Many causative evidence and scholarly perspectives exist addressing whether investors assign value to sustainability attributes embedded in financial instruments. An extensive corpus of literature dedicated to sustainable finance delves into these aspects, particularly emphasising the influence of sustainability and its bearing on mutual funds.

The forthcoming chapter collates and succinctly delineates the existing academic understanding of sustainability's impact on financial instruments. Initially, it presents empirical findings that discern the impact of a sustainable investment profile on capital inflows from investors. Subsequently, the chapter elaborates on the flow of relationship discoveries, illuminating investor characteristics.

The chapter will then articulate the academic comprehension of the motivational factors underlying investor movements towards ESG investments. This will be dissected into two principal segments. The first segment will expound upon the financial motives, particularly performance-driven ones. The second segment will delve into non-financial motives, thus focusing on non-pecuniary factors that drive investor decisions.

4.1. Empirical Evidence on ESG-Related Fund Flows

Flow refers to capital inflows, positive flows, and capital outflows, negative flows, made by any investor in the financial markets. This is typically measured by the difference in total net assets (TNA) from one period to the subsequent period minus the return of the period (Ammann et al., 2019; Sirri & Tufano, 1998). Generally speaking, a flow response to any fund-specific characteristic, such as ESG characteristics or ratings, indicates investors' sensitivity. Conversely, unlike mutual funds, an individual stock is fixed in supply in the short run. Accordingly, if investors see mutual funds as more desirable because of any fund-specific characteristic, money will flow into them. On the contrary, if investors view a fund-specific characteristic as unattractive, they will disinvest, and consequently, money will flow out of the fund. In other words, flows into mutual funds can be considered an ideal laboratory to examine investors' revealed preferences (Madhavan et al., 2021).

Studies reveal a propensity among investors to allocate capital to funds with strong ESG characteristics, a trend observed among individual and institutional market participants (Capota et al., 2022; Pastor & Vorsatz, 2020). Additionally, Hartzmark & Sussman (2019) show similar results in their work. They examine how the introduction of the Morningstar sustainability rating affects inflows into equity and fixed income funds that demonstrate different levels of ESG in their funds' investment strategy. This event disclosed the ESG profile of the different funds. Ultimately, they show that being categorised in Morningstar's low sustainability category resulted in outflows, while being categorised in the high sustainability category led to inflows in the following months. This solidifies the evidence that investors seek sustainability characteristics in mutual funds and align their investment strategy with these characteristics. Ammann et al. (2019) supported this finding with their identical event analysis. As pointed out, Article 9 funds can be considered superior regarding sustainability characteristics by definition. A preliminary analysis on the implementation of the SFDR classification by Becker et al. (2022) has shown that Article 8 and 9 funds experience inflows using a time horizon of three months. Consequently, if investors currently value the sustainability characteristics in a way, as Hartzmark & Sussman (2019), Ammann et al. (2019) and Becker et al. (2022) showed, the SFDR regulation might also have impacted flows in the following months after its introduction. Thus, my second hypothesis posits that:

Hypothesis 2: Article 9 products show significantly higher inflows in the months after the introduction of the SFDR regulation.

A vast amount of literature has studied the reaction of investors to past returns, i.e. the flow performance relationship, for conventional equity and bond funds (Chen et al., 2010; Goldstein et al., 2017; Yong Chen & Nan Qin, 2017). There is consensus in the academic literature that the flow-performance relationship of funds with high ESG characteristics differs from conventional funds. The studies showed that investors in such funds with high ESG characteristics exhibit a weaker flow-performance relationship. In detail, investors in such funds react more resiliently to poor past returns (Capota et al., 2022; El Ghoul & Karoui, 2017; Renneboog et al., 2011).

Capota et al. (2022) examine the differences in the flow-performance relationship of ESG equity and bond funds compared to their unconventional counterparts. They identify ESG funds by searching for ESG-related words in the funds' names. In general, in the absence of a standardised ESG classification and the divergences between ESG scores, researchers either identify ESG products with their ESG scores from several databases (Abate et al., 2021; Steen et al., 2020) or by specific keywords in the product names (Capota et al., 2022; Ramos et al., 2023). The main finding in Capota et al. (2022) flow analysis was that ESG equity and bond funds showed a weaker flow-performance relationship in the years 2016-2020. In particular, investors show higher resilience towards negative past returns. This indicates the long-term investment focus of investors who consider ESG motives because they expect ESG products to deliver better risk-adjusted performance in the future (Capota et al., 2022).

On the other hand, this also ensures a stable source of funding for the green transition and reduces risks for fund managers as it provides financial stability (Capota et al., 2022). Moreover, in their work, Hartzmark & Sussman (2019) confirm that investors' flows towards ESG mutual funds are less volatile, hence showing higher investor resilience. Accordingly, my third hypothesis entails that:

Hypothesis 3: Article 9 products show a higher resilience, defined as lower flow relationship towards negative signals, such as excess returns, negative return, and negative flow over the last twelve months.

4.2. Empirical Evidence on ESG-Related Fund Performance

There are two reasons investors are interested in funds with higher ESG factor exposure regarding performance. First, specific ESG characteristics may be linked to positive factor exposures. This means that such positive factors have been empirically shown to lead to excess returns, called alphas. In this case, such products with high ESG characteristics carry a higher likelihood of high excess returns (Madhavan et al., 2021). Assuming that investors are aware of this positive factor, they might naturally prefer products that are associated with such a characteristic. Madhavan et al. (2021) additionally argues that if such positive ESG factors exist today, then these factors did in the past, even if they were not observable. Second, the literature proposes to assess fund performances correctly to compare risk-adjusted returns while taking into account factor exposures (Jensen, 1968) and reflecting that funds with high ESG characteristics mean that they might underperform their benchmark on an absolute scale but might beat their benchmark on a risk-adjusted basis considering factor relationships (Madhavan et al., 2021).

There is evidence in favour and against excess returns, positive alphas, of securities with high ESG characteristics and the impact of an exposure towards ESG factors on mutual funds. Several researchers found that ESG-related securities, in this case, common shares, are linked towards higher returns (Khan, 2020; Serafeim, 2020). In their study, Ashwin Kumar et al. (2016) investigated ESG factors' influence on to the risk-adjusted stock performance of several companies included in the Dow Jones Sustainability Index (DJSI) versus the risk-adjusted stock performance of companies outside of the index over two years. They build industry-specific portfolios and reference groups to control the different ESG levels in different industries. As a result, the ESG stocks outperformed 75% of the industries in terms of risk-adjusted returns.

Taking common shares as a starting point, there is also evidence of excess returns in the mutual fund universe, respectively, funds with high ESG standards. Verheyden et al. (2016) researched the impact of ESG screenings. On the one hand, ESG screenings limit the investment horizon, respectively diversification, but on the other hand, they add another quality check of the investment. They divided funds that perform ESG screenings into different portfolios based on the funds' target markets and compared them to unscreened benchmarks. Interestingly, they found that the risk-adjusted portfolio returns of the funds pursuing ESG screenings exceed those of the unscreened portfolios. Additionally, when analysing the deviation of the return distribution, the authors also found that ESG funds showed lower tail risk. In other words, ESG funds showed a lower risk in terms of the likelihood and impact of extreme events (Verheyden et al., 2016).

Some studies support the argument that mutual funds with high ESG characteristics carry excess returns. However, these studies only find this to be the case in times of financial distress, i.e. in times of crisis. Nofsinger & Varma (2014) present such evidence by analysing U.S.-based mutual funds with high ESG characteristics. They show that such funds outperform conventional funds in periods of crisis, respectively, in the financial crisis of 2008-2009. Moreover, Verheyden et al. (2016) link this pattern to the impact of screening in ESG funds. More specifically, ESG funds that performed positive screenings.

Regarding mutual funds, Lesser et al. (2016) studied the performance of international funds starting from the results of Nofsinger & Varma (2014). They found these results are not generalisable to global markets and that they are due to the excessive management of U.S. funds in periods of crisis. Their results show that highly sustainable ESG mutual funds show no outperformance regardless of the market situation. This is in line with Gibson et al. (2019) who promoted the finding that investments with high ESG characteristics neither outperform nor underperform other types of investments in both market situations. Additionally, Dolvin et al. (2017) study the relationship between Morningstar sustainability scores of mutual funds in the U.S and performance. They also find that funds with high Morningstar sustainability scores do not yield excess returns over their low-score counterparts. This is evidence that funds with high sustainability scores have the same risk-adjusted returns as other funds.

On the contrary, some studies on other securities show a general negative relationship between ESG scores and return (Cheng et al., 2013) and others show evidence of negative excess returns of portfolios constructed on ESG scores (Chan et al., 2020). Concentrating on mutual funds, some academics state that funds with high ESG characteristics underperform their conventional counterparts (Ammann et al., 2019; Das et al., 2018; Ferriani & Natoli, 2021; Pastor & Vorsatz, 2020). For example, Das et al. (2018) built three different portfolios, respectively a high ESG, medium ESG and low ESG portfolio of funds, and measured the differences in portfolios' returns. They find that the high ESG portfolio generally carries negative returns. However, the same portfolio yields excess returns during a financial crisis (Das et al., 2018).

Correspondingly to the findings of the majority of researchers, my fourth hypothesis states that:

Hypothesis 4: Article 9 products do not show statistically higher risk-adjusted returns.

4.3. Non-Pecuniary Investor Motives

The divergent empirical findings in the literature, which show higher flows toward funds exhibiting strong ESG characteristics without corresponding significant outperformance, are a contradiction. The performance expectations hypothesis posits that higher flows should result from superior returns, but existing research has yet to substantiate this relationship. Instead, scholars have attributed this discrepancy to nonpecuniary, noneconomic motives that drive investor behaviour, such as altruism, warm-hearted giving, or social considerations. Consequently, distinguishing between these hypotheses anticipates future performance. The following chapter touches on the main principles of these.

Some argue that investors in sustainable funds fundamentally value sustainability more than performance. Such investors are committed to a specific concept of value (Bauer et al., 2021; Döttling & Kim, 2022; Hartzmark & Sussman, 2019). This concept also takes into account non-financial payoffs and is consistent with evidence and theories that some people strive to increase social welfare (Charness & Rabin, 2002; Fehr & Schmidt, 1999). According to the concepts of altruism and warm glow, investments with high ESG characteristics can result in higher non-financial value for investors. This value stems from the fact that they, as investors, are responsible for benefiting others (Andreoni, 1990). In fact, Hartzmark & Sussman (2019) see evidence that altruism is a primary driver of investors' resource allocation next to the products' expected performance and risk profile.

Additionally, Krueger et al. (2020) show similar results among institutional investors in their market research. Investors nowadays consider climate risk in their portfolios, firstly to be protected from reputational losses, secondly because of their moral considerations when investing, and thirdly due to regulatory obligations. Moreover, a focus on high ESG investments stems from other social motives, such as to impress others or to reduce the risk of social backlash (Calhoun et al., 2012; DellaVigna et al., 2015).

Investors are interested in funds with high ESG characteristics because they usually pursue a longer investment horizon (Döttling & Kim, 2022; Riedl & Smeets, 2017). For example, the weaker flow-performance relationship measured by Capota et al. (2022) is according to the authors evidence for that. Following this time horizon, investors are driven by the belief that investments with high ESG characteristics will yield higher future returns, even if they have not shown this in the past (Capota et al., 2022). This belief is supported by the fact that climate risks come into play in portfolios that do not consider them. This suggests that investors believe that performance and risk are positively correlated, whereas there is no doubt that they were negatively correlated in the financial markets in the past. However, this is consistent with research in psychology. For example, the affect heuristic, a concept from behavioural economics and decision-making, has been used to explain various cases where risks and benefits have a positive correlation but are perceived as unfavourable by individuals (Loewenstein et al., 2001; Slovic et al., 2007). In a nutshell, people rely on affect and emotion in decision-making and sustainability ratings positively influence their investment decision process as they assume such funds carry higher returns and lower risk (Hartzmark & Sussman, 2019). This also aligns with the results of Hartzmark & Sussman (2019) and Ammann et al. (2019), which show that after introducing ESG ratings, funds with high ESG ratings generated superior flows.

Therefore, these nonpecuniary investor motives support the rationale of hypotheses two, three and four, i.e., higher flow without higher financial reward.

5. Data Sources and Initial Dataset Construction

The empirical analysis is premised on two distinct datasets. The first hypothesis is primarily tested on a cross-sectional dataset grounded in fund characteristics which is described and analysed in the succeeding Chapter 5. The subsequent hypotheses draw upon a panel dataset comprising time-series data for multiple mutual funds spanning a five-year period, specifically from January 2018 to December 2022. The process of constructing and analysing the latter is elaborated in Chapter 6. However, both datasets stem from the same sources, which are described in this chapter. Additionally, identical preparation steps of both datasets are illustrated in the following. Generally, the preparation steps have been carried out using Python.

Data for this study is sourced from the Lipper Refinitiv database, providing time-series data, i.e. TNA and return index, as well as cross-sectional fund characteristics. The return index represents the cumulative growth of a fund, predicated on the assumption that dividends are reinvested to acquire additional units at the closing price on the ex-dividend date. In other words, the return index mirrors the value growth through both price increments and fund pay-outs. Specifically, the fund characteristics data is retrieved as of March 30, 2023. All data in this study is retrieved in Euros as the base currency unless not mentioned otherwise. To ensure the robustness of the results, particularly concerning ESG scores, MSCI ESG data serves as an auxiliary data stream. This is crucial given the documented ESG data discrepancies across various providers (Berg et al., 2022; Chatterji et al., 2016; Dimson et al., 2020). Note that the MSCI data is also retrieved as of March 30, 2023 and therefore before the shake-off in ratings by the update of MSCI scores in the beginning of April (Glow, 2023). The research covers equity funds domiciled in the euro area, with an investment focus on global, European, or emerging markets. This ensures the analysis is conducted on a homogenous group of funds and excludes those with single-country investment focuses.

The SFDR classification, a vital fund characteristic in this study, is also obtained from the Lipper Refinitiv database. It categorises funds into Article 9, Article 8, Article 6, unclassified ("blank"), or not reported. Owing to the missing boundary between Article 6 funds and unclassified funds, unclassified and Article 6 funds are consolidated in this study into the category *other*. Note that the SFDR classification *other* is meant when referring to other funds in the subsequent analysis. However, funds without reported SFDR classification are excluded from the study. This approach carries two potential risks. First, a fund with an unclassified SFDR classification could be an Article 8 or Article 9 fund, thereby confounding the dataset. Second, there is a risk of classification change over the observation period, which the cross-sectional SFDR data would not capture. This lack of precision is particularly relevant given the wave of downgrades following the final RTS publication in the second half of 2022, potentially blurring the distinction between the classifications, albeit more likely diminishing than amplifying it.

Two different variables have been created that are part of all subsequent datasets. First, the variable, *esg*[1], has been introduced in line with the common academic practice for identifying ESG funds (Capota et al., 2022; Ramos et al., 2023). This dummy variable determines whether a fund's name contains any ESG-related keywords such as "ESG", "SRI", "Social", "Environment", "Climate", "Sustainable", "Green", "Governance", "Transition", "Ecology", "Responsible", "Durable", "Ethical", "SDG" in English, German, Italian, Spanish, or French.

Second, the variable *age* has been incorporated in the datasets. Literature has shown

[1] The appendix Chapter I.B. describes all dummies and selected other variables.

that fund age has an impact on investor behaviour. For example, the level of flows into a fund is lower with increasing age (Ammann et al., 2019; Capota et al., 2022; Chevalier & Ellison, 1997; Huang et al., 2007). The variable age is calculated as

$$age_{i,t} = date_t - date_{launch_i} \quad (1^2)$$

where $date_t$ is the date of the last day in month t[3], and $date_{launch_i}$ is the launch date of fund *i.*

To maintain the integrity of the analysis, a set of inclusion criteria has been established for the funds. Specifically, funds are considered for inclusion only if they have *TNA*s exceeding one million euros and are at least one year old. This selection process is crucial in mitigating the potential for incubation bias (Ammann et al., 2019; Capota et al., 2022; Hartzmark & Sussman, 2019). However, funds are incorporated in both samples independent of their asset status, active, liquidated or merged, to avoid any survivorship bias in the results. The analysis is conducted at the fund portfolio level, with the initial sample encompassing 3,270 equity funds.

6. SFDR Classification and ESG Metrics Alignment

The following section scrutinises Hypothesis 1 regarding the alignment of funds' SFDR classification with ESG scores, particularly the classification of SFDR 9 as superior in sustainability. Initially, the underpinning dataset's construction is outlined, accompanied by an exposition of the corresponding descriptive statistics. Ultimately, the comprehensive validation process for Hypothesis 1 is articulated and conducted.

6.1. Construction and Description of the Cross-Section Dataset

Two cross-sectional datasets of various ESG scores and fund characteristics have been compiled. These datasets are rooted in different ESG data sources, i.e., Refinitiv and MSCI, to enhance the robustness of the results as the divergence of different ESG score sources is

[2] The appendix Chapter I.A. lists all formulas used in this study.
[3] Note, that $date_t$ is the 30.03.2023 for the cross-section dataset and the last day of each month in the panel-data dataset.

widely shown (Berg et al., 2022; Chatterji et al., 2016; Dimson et al., 2020). However, these datasets only vary regarding their ESG score sources and coverage. Other fund characteristics, such as *TNA*, *esg*, and *age*, share the same original source from Refinitiv.

The first dataset is primarily based on ESG scores from the Refinitiv Lipper Database. Specifically, the combined ESG score and isolated scores for the environmental pillar (E-score), the social pillar (S-score), and the governance pillar (G-score) were of interest. The combined ESG score comprehensively assesses a company's ESG performance and factors in significant ESG controversies. Furthermore, it employs internally reported data and external information captured by global media sources, thereby aiming for a transparent and objective measure of a company's relative ESG performance, commitment, and effectiveness (Refinitiv, 2022).

The second dataset is predicated on ESG ratings and scores from MSCI. MSCI employs a rating scale akin to the familiar rating classification for financial instruments. These ratings, ranging from CCC (laggard) to AAA (leader), are based on the weighted average score of ESG scores of each of the fund's holdings. Furthermore, the ESG score of the holdings is determined by the interplay between a company's core business and industry-specific issues among 35 key ESG issues (MSCI, 2023).The dataset was enriched with the fund-weighted average carbon intensity data from MSCI. This metric displays the weighted average carbon emissions in CO2-equivalents per one million revenue of a funds holding (Frankel et al., 2015).

In both datasets, all scores were normalised to generally transform the skewed distribution of the scores and control for the different methodologies in scores between 0 and 1. This is crucial when comparing different ESG ratings (Kakogiannis et al., 2023). Additionally, the funds are divided into three quantiles based on their score: 0% to 15% (laggard), 15% to 85% (average), and 85% to 100% (leader). A similar approach is used by (Kim & Li, 2021).

Subsequently, only funds with ESG data were retained, yielding 1,769 equity funds in the Refinitiv dataset and 1,529 equity funds in the MSCI dataset. The funds listed in those datasets are neither distinct nor mutually inclusive, stemming from different ESG coverages by the two separate data sources. However, it is worth noting that this approach carries the risk of bias. This is due to the large-cap bias of ESG scores shown in the literature (Dolvin et al., 2017; Doyle, 2018). Additionally, the likelihood of ESG coverage towards liquidated or merged funds is relatively low, leading to a potential survivorship bias in this sample. However, since the scope of this sample is to regress fund characteristics and not behaviour over a time horizon, this bias has a negligible impact. Moreover, albeit using two different data sources for ESG ratings, there exists the potential risk that a different data provider not included yields other results.

6.2. Summary Statistics

The subsequent paragraph encapsulates the summary statistics derived from our two datasets described above. Panel A in Table 1 presents statistics for the Refinitiv ESG dataset, which incorporates 1,769 funds, while Panel B delineates the statistics for the MSCI ESG dataset with 1,529 corresponding funds.

In the Refinitiv ESG dataset, we discern that Article 9 funds comprise 10% of the sample, Article 8 funds embody 50% and the remaining 40% are classified as other. Notably, 20% of all funds incorporate an ESG-related keyword in their names. Most funds, representing 73%, have a global investment focus, trailed by those emphasising the Eurozone and emerging markets. The average fund size amounts to €409 million[4], with a discernible disparity across classifications. Article 9 funds exhibit the largest size of €640 million on average, succeeded by Article 8 funds (€460 million) and other funds (€280 million). This discrepancy implies a potential size bias towards SFDR 9 funds, a phenomenon documented in prior research examining ESG scores and fund size (Dolvin et al., 2017; Doyle, 2018). Conversely, the average fund age measures 4,670 days, with Article 9 funds being the youngest (3,683 days), followed by Article 8 funds (4,454 days), and other funds being the oldest (5,191 days). It is crucial to underscore that continuous variables *TNA* and *age* exhibit positive skewness and leptokurtosis. Accordingly, in line with other studies, a natural logarithm is applied to these variables to achieve a better approximation to a normal distribution (Ammann et al., 2019; Capota et al., 2022; Hartzmark & Sussman, 2019). Interestingly, these general fundamental characteristics do not manifest significant differences compared to the MSCI ESG dataset (see Appendix 2).

[4] Note that this is a snapshot as of March 30, 2023 and differs to the weighted-average fund size over the time period in the panel data dataset.

Table 1: Summary Statistics - ESG Datasets.

Table 1, with a split into Panel A and Panel B, presents summary statistics[5] derived from the Refinitiv ESG data (Panel A) and the MSCI ESG data (Panel B). These statistics showcase the key fund characteristics which form the foundation for the subsequent regression analysis investigating the ESG alignment of SFDR 9 funds, as stipulated in Hypothesis 1. Notably, in Panel B, only those columns not previously displayed in Panel A are included for clarity and brevity. Furthermore, it's important to note that the MSCI ESG data in Panel B is available only for 1,529 funds. In contrast, the Refinitiv ESG data in Panel A covers a broader set of 1,769 sample funds.

Panel A: Refinitiv ESG Data

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
sfdr_9	1,769	0.10	0.30	0	0	0	0	1	2.62	7.89	0
sfdr_8	1,769	0.50	0.50	0	0	0	1	1	0.01	1.00	0
sfdr_other	1,769	0.40	0.49	0	0	0	1	1	0.41	1.17	0
esg_comb_score	1,769	0.65	0.11	0	0.58	0.66	0.73	1	-0.62	4.31	0
esg	1,769	0.20	0.40	0	0	0	0	1	1.49	3.22	0
esg_comb_score_2	1,769	0.15	0.36	0	0	0	0	1	1.96	4.83	0
esg_comb_score_1	1,769	0.70	0.46	0	0	1	1	1	-0.87	1.76	0
esg_comb_score_0	1,769	0.15	0.36	0	0	0	0	1	1.96	4.83	0
tna	1,769	408.47	1,108.96	5.01	34.16	105.88	345.85	20,236.95	8.95	115.09	0
age	1,769	4,670.11	3,341.58	374	1,702	3,977	7,418	19,343	0.80	3.49	0
EuroZone	1,769	0.21	0.41	0	0	0	0	1	1.44	3.08	0
Global	1,769	0.73	0.45	0	0	1	1	1	-1.02	2.04	0
EmergingMarkets	1,769	0.07	0.25	0	0	0	0	1	3.53	13.45	0

Panel B: MSCI ESG Data

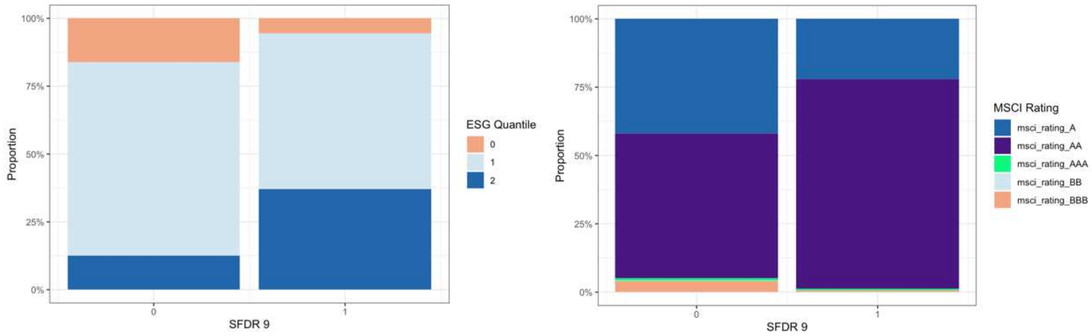
	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
msci_quality_score	1,529	0.63	0.14	0	0.57	0.64	0.73	1	-0.72	4.07	0
msci_rating_AAA	1,529	0.01	0.09	0	0	0	0	1	10.71	115.62	0
msci_rating_AA	1,529	0.56	0.50	0	0	1	1	1	-0.23	1.05	0
msci_rating_A	1,529	0.40	0.49	0	0	0	1	1	0.42	1.18	0
msci_rating_BBB	1,529	0.04	0.19	0	0	0	0	1	4.93	25.34	0
msci_rating_BB	1,529	0.001	0.04	0	0	0	0	1	27.60	762.50	0
msci_carbon	1,529	128.36	105.44	1.99	68.86	108.90	148.85	1,128.06	3.17	19.88	0

Concerning ESG scores, preliminary evidence appears to substantiate our first hypothesis. The average normalised ESG combined score is 0.65, with Article 9 funds leading at 0.72, Article 8 funds following at 0.67, and other funds lagging at 0.61. As illustrated in Figure 2, using Refinitiv data, Article 9 funds comprise a larger portion of the highest ESG quantile and represent a substantially smaller segment of the lowest ESG quantile. This observation suggests that most Article 9 funds display above-average ESG data, and their risk of falling within the lower quantile is markedly reduced. Therefore, initial findings affirm the inherent ESG-related superiority of Article 9 funds. However, the strength of these conclusions requires further empirical testing and statistical validation.

[5] The appendix Chapter I.B. describes all dummies and selected other variables.

Figure 2: Proportion of ESG Quantiles and MSCI Ratings by Article 9 Fund Classification.

Figure 2 demonstrates the distribution of quantiles of the Refinitiv ESG combined score (0%, 15%, 85%, 100%) and MSCI ratings across funds, distinguishing between those classified as Article 9 funds (1) and those not (0). The proportions are shown for both cross-sectional datasets.



In Panel B of Table 1, we delve into the distribution of MSCI rating clusters. A notable concentration exists within clusters A and AA, accounting for 96% of the data. This skewness insinuates that MSCI ESG rating data might be constrained in its analytical scope, urging a focus on the MSCI ESG quality score. Like the Refinitiv ESG dataset, the MSCI ESG quality score also varies amongst classifications, registering 0.69 for Article 9 funds, 0.65 for Article 8 funds, and 0.60 for other funds. This is a similar distribution in comparison with the Refinitiv scores indicating similar distribution of the scores. Parallel examination utilising MSCI ratings reaffirms the interpretations deduced from the Refinitiv data in Figure 2. Article 9 funds demonstrate a larger representation within the AA rating class than non-Article 9 funds. However, an observable concentration of funds, irrespective of SFDR classification, within the AA and A rating classes limits the applicability of MSCI ratings in differentiating ESG metric disparity. Consequently, hereafter quantiles of the underlying MSCI quality score are used in the analysis. Intriguingly, the dataset shows that Article 8 funds have the lowest weighted average carbon intensity at 118t CO_2e/\$M, Article 9 funds at 122 CO_2e/\$M, and other funds at 146 CO_2e/\$M. This observation underlines an important differential aspect of ESG-focused funds regarding their carbon footprint.

6.3. Analysis and Results: Article 9 Funds - A Label of Superiority in Terms of Sustainability

The ensuing discussion seeks to elucidate whether Article 9 funds, based on empirical data, are genuinely superior in terms of their ESG metrics. This chapter presents the results on the study of the correlation between Article 9 funds and various ESG metrics. The SFDR 9 classification, by definition, should indicate higher ESG metrics for funds caused by its strong sustainability orientation (Article 9 funds). Conversely, funds lacking such a focus should display lower ESG metrics.

Preliminary observations indicate a disparity in ESG metrics among differing SFDR classifications (see summary statistics). In both datasets, Article 9 funds register the highest average ESG metrics. However, the significance of this disparity is yet to be statistically corroborated. Nevertheless, a comparison between the ESG scores of Article 9 funds and all other funds reveals a propensity for superior ESG metrics in the former.

To extrapolate the influence of diverse fund characteristics on SFDR classification and affirm Hypothesis 1, an initial base logit regression employing the SFDR 9 fund dummy was utilised:

$$SFDR_{9_i} = \beta_1 ESG\ Score_{Refinitiv_i} + \beta_2 esg_i + \beta_3 \log tna_i + + \beta_3 \log age_i + \varepsilon_i \qquad (2)$$

Column 1 of Table 2 shows that all variables based on Refinitiv data yielded statistical significance at the 1% level, affirming their instrumental role in Article 9 fund identification. In addition, positive coefficients were noted for ESG scores, fund size, and the presence of an ESG keyword in the fund's name, suggesting an increased likelihood of SFDR 9 classification if these coefficients increase while all other coefficients remain stable. Conversely, fund age demonstrated a negative coefficient, implying that younger funds were likelier to attain SFDR 9 classification.

Table 2: Logit Regression Analysis of Article 9 Fund Classification – Refinitiv Data.

Table 2 illustrates the different factors influencing the likelihood of a fund being classified as an SFDR 9 fund. The dependent variable is a dummy variable for SFDR 9, regressed against two sustainability proxies based on Refinitiv ESG data: the raw ESG score (Column 1) and ESG quantiles[6] (Column 2). Both columns also incorporate additional control variables, including fund size, the presence of ESG keywords in the fund's name, and the age of the fund. The dataset used in this analysis is from March 30, 2023.

	Dependent variable:	
	sfdr_9	
	Score	Quantiles
	(1)	(2)
esg_comb_score	6.091***	
	(0.910)	
esg_comb_score_2		1.068***
		(0.186)
esg_comb_score_0		-0.672*
		(0.344)
I(log(tna))	0.313***	0.305***
	(0.055)	(0.054)
esg	0.870***	0.950***
	(0.175)	(0.175)
I(log(age))	-0.446***	-0.459***
	(0.093)	(0.093)
Constant	-4.598***	-0.499
	(0.987)	(0.734)
Observations	1,769	1,769
Akaike Inf. Crit.	1,012.275	1,024.347
Note:	*p<0.1; **p<0.05; ***p<0.01	

Comparable results are discerned when quantiles are employed in the regression model instead of the Refinitiv combined ESG score. Firstly, being classified in the top quantile - representing the top 15% funds based on the ESG combined scores - considerably boosts the probability of being classified as an Article 9 fund, a correlation statistically significant at the 1% level compared to the constant, the median quantile. Reversely, a negative coefficient for the lowest quantile suggests a decreased likelihood for funds within this classification to be designated as Article 9 fund relative to the median quantile. Again, this relationship is statistically significant, albeit only at the 10% level.

Appendix 2 demonstrates that the MSCI ESG quality score carries a significant positive impact, albeit less pronounced than the Refinitiv score. Given the normalisation of both scores mentioned in the sample construction, a comparison can be effectively made. Moreover, a significance among the quantiles is identifiable. Interestingly, the earlier

[6] The appendix Chapter I.B. describes all dummies and selected other variables.

assertion that the MSCI rating as of March 30, 2023, is not particularly meaningful is validated. Counterintuitively, the supposedly better AAA rating carries a negative coefficient compared to the A rating, and only the AA rating manifests a statistically significant coefficient.

Table 3 compares the results from both datasets using the quantiles as the primary ESG metric. Implementing the same regression model on the MSCI dataset yields similar outcomes, holding true for both ESG metrics and controls, thereby indicating the robustness of the coefficients. Contrary to the Refinitiv dataset, the top quantile of the MSCI ESG data carries only a 10% statistical significance, while the lowest quantile demonstrates a 1% level of statistical significance. Notably, the coefficient of the lowest quantile for both datasets is remarkably similar, with a divergence only occurring in the top quantile coefficient. Neither geographical investment focus in both datasets nor weighted carbon intensity in the MSCI dataset appear to have a statistically significant impact.

Table 3: Comparative Analysis of ARTICLE 9 Fund Classification Using Refinitiv and MSCI ESG Data.

Table 3 contrasts the likelihood of a fund being classified as an Article 9 fund using two different ESG data sources, Refinitiv and MSCI. The dependent variable is an SFDR 9 dummy variable regressed against specified quantiles of both ESG scores[7] (0%, 15%, 85%, and 100%). Additional control variables are included in both columns. However, they are omitted from the output. They are fund size, the presence of ESG keywords in the fund's name, and the age of the fund. The datasets employed for this analysis are sourced from March 30, 2023.

	Dependent variable:	
	sfdr_9	
	Refinitiv (1)	MSCI (2)
esg_comb_score_2	1.068***	
	(0.186)	
esg_comb_score_0	-0.672*	
	(0.344)	
msci_quality_score_2		0.388*
		(0.210)
msci_quality_score_0		-0.640**
		(0.319)
esg	0.950***	1.083***
	(0.175)	(0.178)
Constant	-0.499	-0.171
	(0.734)	(0.737)
Fund Characteristics	Yes	Yes
Observations	1,769	1,529
Note:	*p<0.1; **p<0.05; ***p<0.01	

[7] The appendix Chapter I.B. describes all dummies and selected other variables.

Finally, the application of average marginal effects, as shown in Appendix 3 and 4, reveals the actual impact on the probability of being classified as Article 9, assuming all other variables remain constant. Being ranked in the top quantile escalates the likelihood by 11% in the Refinitiv data but only by 3.9% in the MSCI data. Conversely, belonging to the lowest quantile curtails the probability by 4.6% in the Refinitiv data and by 5.0% in the MSCI data. The marginal effects of the controls are analogous in both datasets. For instance, an increase of one per cent in TNA augments the probability by approximately 0.025% based on the Refinitiv data and having an ESG keyword in the name by 9.2%. At the same time, a one per cent increase in fund age decreases the probability by 0.038%.

Given these results, the null hypothesis asserting the absence of disparate ESG metrics among SFDR classifications can be refused and thus affirm Hypothesis 1. As a result, SFDR 9 funds can indeed be deemed superior in terms of their sustainability focus according to the ESG metrics taken into account. This finding also indicates that the SFDR regulation effectively accomplishes its objective of reducing greenwashing and facilitating more robust comparisons of financial products. Finally, this study offers preliminary endorsement of the efficacy of the current regulatory tools, including the EU Taxonomy, DNSH criteria, and PAIs.

Furthermore, these findings align well with the extant literature in the field. Firstly, the results provide additional evidence supporting the notion that different ESG data streams yield divergent ratings (Berg et al., 2022; Chatterji et al., 2016; Dimson et al., 2020). The consistently positive *TNA* coefficient across all outputs concurs with previous literature indicating a large-cap bias in ESG scores (Dolvin et al., 2017; Doyle, 2018). The SFDR classification may even exacerbate the bias, as the administrative burden associated with obtaining Article 9 status, such as meeting the required documentary framework, requires a significant effort that is generally more manageable for funds with high *TNA*. On the other hand, the consistently negative *age* coefficient across all outputs indicates a trend in the fund supply to focus on more sustainable financial products (Article 9) in new funds. Finally, the positive impact of having an ESG-related keyword in the fund name echoes the findings of prior research (Ramos et al., 2023). This supports the methodology of identifying ESG funds by name before the absence of labels and, accordingly, the corresponding research results. However, the lack of significance of the geographical investment focus on the likelihood of being classified as an Article 9 fund contradicts earlier findings that pointed to a geographical bias favouring Europe due to its stringent disclosure requirements for companies (Doyle, 2018).

Generally, the use of selective ESG ratings imposes a limitation since the ratings diverge between data providers. Nevertheless, using two independent ratings is an action to countermeasure this limitation. However, the announcement by MSCI at the end of March 2023 regarding changes in its rating methodology presents an intriguing area for future exploration. This research has not accounted for these alterations, as this change's potential impacts and effectiveness have yet to be assessed comprehensively. Hence, it is essential for future research to evaluate these revisions, exploring their implications for fund classification and their potential influence on the consistency and reliability of ESG metrics. In addition, the forthcoming studies should aim to ascertain whether these methodological adjustments enhance the differentiation of funds in terms of their sustainability focus and whether they lead to any significant modifications in the ESG scores of Article 9 funds and their counterparts.

Furthermore, future academic studies should explore utilising templates concomitant with the SFDR regulation, encompassing PAI, DNSH, and EU Taxonomy across funds and their varied classifications. Through this, additional risks associated with greenwashing could be discerned and exposed. This is particularly compelling when considered in the context of Article 8 funds, which, by definition, are mandated to achieve their articulated attributes in their investments over the long term. Such a systematic investigation could bolster the existing regulatory framework, enhance investor awareness, and foster increased transparency and accountability within sustainable finance.

7. Analysis of SFDR Classifications Regarding Flow and Returns

In light of the established superior sustainability metrics of Article 9 funds, the following chapter of this paper examines the consequential investor response to that fact. Consequently, the aim is to delve into an analytical exploration of hypotheses 2, 3, and 4 regarding capital flows directed towards Article 9 funds, the investors' characteristics and the associated fund returns. First, a detailed elaboration on the sophisticated construction of the panel data dataset will be illustrated. This serves as the empirical bedrock for the subsequent analyses. Second, by presenting the descriptive statistics, the chapter will provide a succinct overview of the data. Finally, an exhaustive analysis and exposition of the result will and answer the hypotheses mentioned in the beginning and encapsulate the implications drawn from these.

7.1. Construction and Description of the Panel-Data Dataset

The panel dataset described below forms the basis for examining hypotheses 2, 3, and 4. Essential variables for this analysis are predominantly derived from monthly *TNA* and return index data, with their construction informed by existing academic research. The following paragraph elaborates on the structure of these variables and, ultimately, the final dataset for the mentioned hypotheses.

The dataset includes various time-series variables like excess return which captures the monthly return of a fund over the risk-free rate. This is academic practice when analysing returns (Hartzmark & Sussman, 2019; Leite & Cortez, 2015; Nofsinger & Varma, 2014). The risk-free rate is similar to the Fama and French 3-factor returns from the Kenneth R. French database.

Therefore, excess return, $return_{excess}$, of a fund *i* in the month *t* is calculated as

$$return_{excess_{i,t}} = \frac{RI_{i,t}}{RI_{i,t-1}} - return_{risk-free_t} - 1 \qquad (3)$$

where $RI_{i,t}$ is the return index of fund *i* in month *t*, and the $return_{risk-free_t}$ is the risk-free rate in month *t*. Respectively, the return of the last twelve months[8] is the return of a fund i in the month t over twelve months and deals in the academic sphere as a long-term return trend (Ammann et al., 2019; Capota et al., 2022). Several researchers have shown that flows are sensitive to past returns (Ammann et al., 2019; Capota et al., 2022; Goldstein et al., 2017; Hartzmark & Sussman, 2019).

Additionally, a monthly alpha is calculated as the difference of the excess return and the expected return using the factor loadings from Formula 8[9].

Secondly, the standard deviation of the returns over the last 12 months deals as a risk proxy as it is widely shown that higher volatility in returns usually results in statistically

[8] See Formula 4 in appendix Chapter I.A.
[9] See appendix Chapter I.A.

lower fund flows (Ammann et al., 2019; Capota et al., 2022; Huang et al., 2007; Sirri & Tufano, 1998). The standard deviation of the returns over the last 12 months, std_dev_{12m}, of a fund *i* in the month *t* is calculated as

$$std\_dev_{12m_{i,t}} = \sqrt{\frac{1}{12-1} \sum_{t=1}^{n=12} \left(return_{i,t} - \overline{return}\right)} \tag{5}$$

where $return_{i,t}$ is the return of a fund *i* in the month *t*.

The variable flow measures the monthly change in *TNA*, adjusted for capital inflows resulting from investment capital gains. Following (Ammann et al., 2019; Sirri & Tufano, 1998), the monthly flow, $flow$, of a fund *i* in the month *t* is calculated as

$$flow_{i,t} = \frac{tna_{i,t} - tna_{i,t-1} \times return_{i,t}}{tna_{i,t-1}} - 1 \tag{6}$$

where $tna_{i,t}$ is the total net asset value of a fund *i* in the month *t*, and $return_{i,t}$ is the return of a fund *i* in the month *t*. The twelve months flow[10], also referred to as lagged flow in the academic literature, is similar to the twelve months return of the monthly change in TNA over a 12-month period, again, adjusted for flows attributed to capital gains or losses during that time frame (Capota et al., 2022).

Alongside these time-series data, the dataset includes essential fund characteristics such as age, *TNA*, and the SFDR classification. Despite the SFDR classification data being available only as cross-sectional data, it has been incorporated into this time-series dataset. All variables delineated above are factored into the subsequent analysis, notably in the flow exploration pertinent to hypotheses 2 and 3. As indicated, the inclusion of these variables in the regressions is predicated on an expansive body of academic literature. Nevertheless, there is a potential risk of omitted variable bias relating to time-series variables, which may be obscured within the standard errors, thereby undermining the robustness of the regression outputs. A pertinent example of such a variable could be the expense ratio of the funds, a factor frequently taken into account in flow analyses (Ammann et al., 2019; Otero-Gonzalez et al., 2022). However, given that this information is not accessible as time-series data within the scope of this study, coupled with the fact that fund-fixed effects are predominantly applied, this information would ultimately be neutralised. Therefore, it is not

[10] See Formula 7 in appendix Chapter I.A.

contemplated in this study and is also coherent with other approaches in the academic sphere (Becker et al., 2022; Capota et al., 2022; Hartzmark & Sussman, 2019).

For Hypothesis 3, which explores flow relationships, separate variables[11] for positive and negative values following (Capota et al., 2022) have been included for specific variables. In other words, for example a positive excess return for a fund in a given month will carry a (positive) value for the variable pos_return_{excess} while a zero for the variable neg_return_{excess}. In these instances, negative values are presented as absolute values without the minus sign.

Based on common academic practice, the analysis is further constrained to monthly fund data that contains no missing values for the variables of interest (Alda, 2020; Barber et al., 2003; Becker et al., 2022). Additionally, to preserve historical continuity, only those funds with 12 consecutive observations for the variables of interest are retained (Capota et al., 2022). This initial subset results in a sample of 2,689 equity funds with an average of 45.5 months of data. Outliers are subsequently filtered out, removing all data with a z-score of 3 or below. This final processing stage results in a subset of 2,630 funds with an average of 40.0 months of data, amounting to 105,898 observations in the final dataset.

7.2. Descriptive Statistics

The following chapter summarises the panel data dataset. The preliminary sample contains 2,689 unique equity funds, which, after removing outliers, is reduced to 2,650 unique funds. Table 4 provides a detailed breakdown of the unique number of funds available at the end of each quarter, highlighting the dynamic nature of the fund landscape as new funds come into play. In contrast, others cease to exist within the observation period.

[11] The appendix Chapter I.B. describes all dummies and selected other variables.

Table 4: Unique Number of Funds per Month by SFDR Classification.

Table 4 presents the unique count of funds every month, categorised by SFDR classification within the final sample. This final sample accounts for all subsetting discussed in Chapter 5 covering sample construction and before controlling for outliers identified with a z-score of 3. Given the dynamic nature of the fund landscape, where funds may emerge or cease over time, the final sample consists of 2,689 unique funds, each contributing an average of 45.4 months of data, culminating in a total of 122,400 observations.

date	2018Q1	2018Q2	2018Q3	2018Q4	2019Q1	2019Q2	2019Q3	2019Q4	2020Q1	2020Q2
sfdr										
total	1809	1840	1863	1895	1927	1967	2007	2041	2063	2062
9	109	110	111	110	113	116	117	118	122	130
8	679	694	705	723	737	755	774	790	819	834
other	1021	1036	1047	1062	1077	1096	1116	1133	1122	1098

date	2020Q3	2020Q4	2021Q1	2021Q2	2021Q3	2021Q4	2022Q1	2022Q2	2022Q3	2022Q4
sfdr										
total	2060	2102	2112	2120	2145	2194	2217	2253	2278	2310
9	132	136	140	143	148	167	173	179	189	196
8	855	888	907	925	943	976	1006	1039	1066	1086
other	1073	1078	1065	1052	1054	1051	1038	1035	1023	1028

Overall, the number of funds increased from 1,809 in the initial quarter of 2018 to 2,310 by the final quarter of 2022, indicating a compound annual growth rate (CAGR) of 5%. Article 9 funds demonstrated the most considerable growth rate in fund numbers, with a CAGR of 12.5%. However, these funds constitute just 8.5% of the total funds as of the final quarter 2022, therefore remaining a minority. Article 8 funds expanded faster than other funds, with a CAGR of 9.8% versus 0.1% for other funds. Correspondingly, Article 8 funds comprised the largest segment, with 46.8%, or 1,086 funds, by the end of 2018's final quarter.

This evolution reflects the supply-side trends in funds, indicating an increased supply of sustainably oriented funds. However, whether the demand side, represented by the flow of capital, aligns with this trend and the distribution among the SFDR classifications forms an integral part of this study.

The final sample consists of 2,650 unique funds, each with an average of 40.0 months of observations, resulting in a total of 105,898 observations. The summary statistics for this dataset are presented in Table 5. Appendix 5 displays the summary statistics for each SFDR classification analysed in this study. On average, the monthly data consists of 6.5% Article 9 funds, 41.9% Article 8 funds, and 51.6% of other funds. The discrepancy with the previously stated proportions results from the weighted average calculation considering each month over the five-year period.

Table 5: Summary Statistics of Final Panel-Data Dataset.

Table 5 summarises the final panel data dataset that serves as the foundation for hypotheses 2, 3, and 4. This final dataset reflects all subsetting discussed in Chapter 5 covering sample construction, along with the management of outliers based on a z-score threshold of 3. In addition, the table features the key variables of interest without differentiation based on their SFDR classification. This final dataset comprises 2,650 equity funds, with an average observation of 40.0 months, resulting in a total of 105,898 observations.

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
flow	105,898	0.0009	0.0339	-0.2086	-0.0077	-0.0001	0.0073	0.2628	0.8012	16.0950	0
excess_return_t	105,898	0.0018	0.0402	-0.1202	-0.0221	0.0043	0.0275	0.1406	-0.2033	3.2742	0
alpha	105,898	-0.0007	0.0208	-0.0622	-0.0138	-0.0010	0.0121	0.0643	0.0727	3.1905	0
tna	105,898	187.0890	684.7338	1.0009	17.2636	48.6573	144.0834	18,918.2600	15.4432	316.4758	0
age	105,898	4,594.7630	3,080.1790	361	1,917	4,232	6,903	19,343	0.7995	3.7189	0
sfdr_9	105,898	0.0651	0.2468	0	0	0	0	1	3.5244	13.4217	0
sfdr_8	105,898	0.4192	0.4934	0	0	0	1	1	0.3274	1.1072	0
sfdr_other	105,898	0.5156	0.4998	0	0	1	1	1	-0.0626	1.0039	0

The average monthly flow among all funds is 0.09%. However, Article 9 funds display the highest monthly average inflow with 0.70%, followed by Article 8 funds with 0.23%. In comparison, other funds show a negative monthly average flow of -0.10%, which signifies an average monthly outflow. This trend in demand appears to follow supply trends initially, but other variables could influence it. The strong inflow performance of Article 9 funds, especially around the time when the SFDR regulation was published and implemented, will be discussed further in Hypothesis 2. Meanwhile, Hypothesis 3 will elaborate on the control of potential biases and other flow relationships.

The monthly average excess return is 0.18%. Article 9 and Article 8 funds show higher and similar monthly average excess returns (0.22% and 0.23%, respectively) compared to other funds, yielding a monthly average excess return of 0.14%. However, a preliminary examination of summary statistics shows a difference in the alphas. Article 9 funds have a positive monthly average alpha of 0.01%, while Article 8 and other funds exhibit negative monthly average alphas of -0.07% and -0.08%, respectively. There are preliminary indications of higher alpha for Article 9 funds at this stage, but this is not yet statistically definitive. Further on, the factor exposure and, ultimately, the monthly alpha and cumulative alpha over the entire observation period will form part of the analysis in Hypothesis 4.

None of the variables are normally distributed, as evidenced by the Jarque-Bera p-value close to zero for all variables. All flow data, including the last twelve-months' flow, *TNA*, and *age*, exhibit a positive skew and leptokurtic distribution, with positive skewness values and kurtosis values exceeding 3. The flow variables will not be transformed using the natural logarithm for interpretability and consistency with existing financial and academic literature. Moreover, applying the logarithm does not affect the results of the subsequent analysis. However, to stay consistent, adhering to common practices in the field, and Hypothesis 1, a natural logarithm is applied to *TNA* and *age* (Ammann et al., 2019; Capota et al., 2022; Hartzmark & Sussman, 2019).

7.3. Analysis and Results

In the subsequent chapter, a multifaceted analysis and presentation of results will be undertaken, examining the influence of the SFDR regulation implementation on investor capital flows (Hypothesis 2). Following this, the flow relationships of the various classifications (Hypothesis 3) will be investigated, thereby illuminating investor characteristics. Finally, the discourse will examine the investment strategy, deploying the Fama and French 3-Factor Model and risk-adjusted returns, denoted as alphas (Hypothesis 4). This presentation of results will provide a comprehensive understanding of the implications of the SFDR regulation on investor behaviour and fund performance with a focus on Article 9 funds.

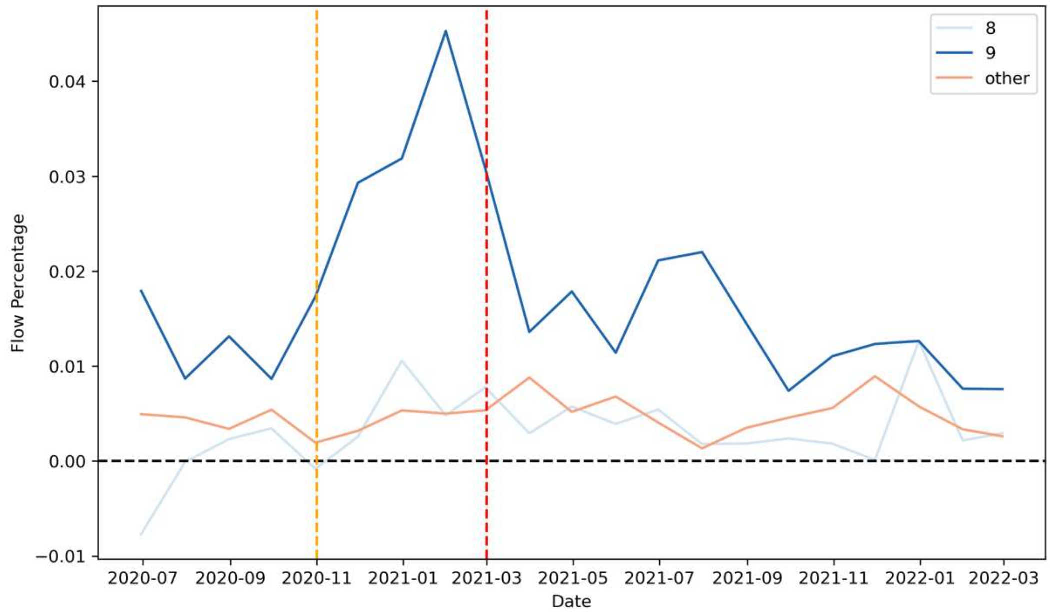
7.3.1. Impact of SFDR Publication on Investor’s Flows

The principal focus of the following paragraph is to ascertain whether the SFDR classification provokes an augmented reaction from investors, thereby exerting influence on the demand side of mutual equity funds. This query is of considerable interest given the existing body of literature substantiating the statistically significant increase in investment flows consequent to the publication of ESG ratings, such as the Morningstar Rating, as an assessment of quality (Ammann et al., 2019; Hartzmark & Sussman, 2019). The impetus for enhanced flows stemming from the SFDR classification hinges on fulfilling three requisite conditions. First, investors must harbour a predilection for sustainable products, a well-documented finding in the existing academic work (Ammann et al., 2019; Bauer et al., 2021; Becker et al., 2022; Döttling & Kim, 2022; Hartzmark & Sussman, 2019). Secondly, the SFDR classification must serve as an indicator of sustainability, a proposition substantiated by the results from the first hypothesis. As evidence, funds classified as SFDR Article 9 demonstrate superior sustainability metrics. Lastly, the SFDR classification must introduce new information to the market that market participants have not yet absorbed. This last prerequisite is the central focus of analysis in the ensuing chapter.

A review of the SFDR timeline reveals that the final decision to continue the initial timeline with its given definition has been promulgated in the end of October 2020. Accordingly to that, the regulation has become active on March 10, 2021 For the purpose of this analysis, the investigation differentiates between these two important dates: the date of (final) publication and the date of implementation. An examination of monthly flows across the SFDR publication timeline suggests a propensity for higher inflows for Article 9 funds compared to Article 8 and other funds. Figure 3 graphically represents the total monthly flows, expressed as a percentage between June 2020 and March 2022, for the various SFDR classifications. Before the publication date, flows across all classifications have been on a similar level. However, between the publication and implementation dates, Article 9 fund flows experienced a remarkable surge, while the investment flows for Article 8 and other funds remained relatively stable. After the publication date, the elevated flows for SFDR Article 9 funds returned to their pre-publication level and maintained relative stability. The factors underpinning this trend could be multifaceted, including other fund characteristics, such as returns, trends in flow or return, or risk inadvertently yielding higher flows. Moreover, amplified media coverage through the implementation of the regulation can result in such investor behaviour. Alternatively, the SFDR classification might provide additional insights to market participants regarding the sustainability focus of the funds. This could have been the case already after the final publication and not only after the implementation date if funds had already started to promote their SFDR classification with the publication date.

Figure 3: Flows per SFDR Classification during Classification Publication.

Figure 3 illustrates the total flows, expressed as a percentage, per SFDR classification quarterly within the final pre-outlier sample. Flows are computed monthly per each fund, aggregated monthly per SFDR classification, and are presented in relation to the TNA at the end of the preceding month. The sample is limited to the period between June 2020 and February 2022.



A baseline regression analysis was conducted to delve deeper into the evolution of fund flows and furnish quantitative validation for the observed patterns in Figure 3:

$$flow_{i,t} = \beta_1 \mathrm{SFDR}_{9_i} + \beta_2 \mathrm{SFDR}_{8_i} + \beta_3 flow_{12m_{i,t}} + \beta_4 return_{excess_{i,t}} + \beta_5 return_{12m_{i,t}} + \beta_6 std\_dev_{12m_{i,t}} + \beta_7 \log TNA_{i,t} + \beta_8 \log age_{i,t} + \varepsilon_{i,t} \quad (9)$$

The dependent variable of interest in this analysis is the monthly fund flow, while the independent variables constitute the different SFDR classifications. In addition, to account for potential influences from other fund characteristics, several control variables were incorporated, including fund flows in the preceding 12 months, excess return in the prior month, return over the last 12 months, the standard deviation of returns over the preceding 12 months, logarithm of the size in the current month, and the logarithm of age in the current month. The design of this regression draws from various other academic studies examining fund flow behaviour (Ammann et al., 2019; Becker et al., 2022; Capota et al., 2022; Hartzmark & Sussman, 2019). A comprehensive analysis of the impact of these control variables is presented in the flow relationship analysis section of Hypothesis 3.

The dataset was partitioned into three distinct subsets for this analysis. The first subset encompasses the entire study period, i.e., from the publication date until 12 months after the implementation date (November 2020 through March 2022). The second subset covers eight months before the implementation date (July 2020 through February 2021). Finally, the third subset extends from the implementation date until 12 months after that (March 2021 through March 2022).

Table 6 presents the output of the regression conducted on all three sub-datasets. Each regression incorporates time-fixed effects to control for any time-invariant phenomena. However, since the SFDR information remains constant over time, fund fixed effects could not be employed, thereby introducing the risk of uncontrolled fixed fund characteristics correlating with the standard errors, potentially affecting the regression's robustness.

Table 6: Mutual Fund Flows by SFDR Classification during Publication Event.

Table 6 explores how mutual fund flows, expressed as percentages, differ based on SFDR classification (Article 9, Article 8, and others). The dependent variable is fund flows. All columns incorporate additional controls, such as flows in the last 12 months, excess return in the previous month, return in the preceding 12 months, the standard deviation of returns over the past 12 months, log of size in the current month, and log of age in the current month[12]. In addition, every column includes month-fixed effects. Firstly, column 1 represents the entire study period, both before and after the SFDR classification implementation on March 10, 2021 (i.e., from November 2020 to March 2022). Secondly, column 2 depicts the period preceding the classification implementation (i.e., from July 2020 to February 2021). Lastly, column 3 covers the period following the classification (i.e., from March 2021 to March 2022).

	Dependent variable:		
	flow		
	EVENT (1)	PRE-EVENT (2)	POST-EVENT (3)
sfdr_9	0.0021*** (0.0008)	0.0042*** (0.0012)	0.0008 (0.0009)
sfdr_8	0.0002 (0.0004)	0.0002 (0.0006)	0.0003 (0.0004)
Time FE	Yes	Yes	Yes
Control	Yes	Yes	Yes
Observations	28,776	13,524	22,402
Adjusted R2	0.1618	0.1808	0.1451
Note:	*p<0.1; **p<0.05; ***p<0.01		

Column 1 of Table 6 indicates that when all other coefficients are held constant, classification as a SFDR Article 9 fund elevates the average monthly flow across the entire study period by 0.21 percentage points. Intriguingly, during the period preceding the SFDR regulation implementation, this surge in monthly flow associated with SFDR Article 9 fund

[12] Note that Appendix 6 shows the whole regression output including controls.

classification is more pronounced at 0.42 percentage points. Both coefficients demonstrate significance at the 1% significance level. Despite this, in the aftermath of the implementation date, the SFDR Article 9 classification continues to yield a positive coefficient, albeit statistically indistinguishable from zero. This offers empirical evidence that SFDR Article 9 funds attract superior flows around the time of SFDR classification publication, particularly before final implementation. However, comparing the actual differences between the periods before, during, and after still needs to be executed as the table features three independent regressions. A subsequent difference-in-difference model will evaluate these findings.

In addition, SFDR Article 8 funds emit a positive coefficient across each subsample. However, these coefficients are statistically indistinguishable from zero, suggesting that investor reactions towards SFDR Article 8 funds do not deviate significantly from those towards other funds. This observation confirms that investor reactions are predominantly heightened towards superior sustainability products (Ammann et al., 2019; Hartzmark & Sussman, 2019).

A difference-in-difference model has been employed to further elucidate the variations in monthly flows along the timeline of the SFDR classification. The foundational model remains identical to the one outlined earlier, however, covering the entire study period, which extends seven months before, and twelve months after the publication event (i.e., July 2020 to March 2022). In addition, three dummy variables have been constructed to distinguish the different stages surrounding the implementation of the SFDR classification: pre-publication (designating the months leading up to the publication date, from July 2020 to November 2020), SFDR publication (encompassing the months between the publication date and the implementation date, i.e., November 2020 to March 2021), and post-publication (capturing the periods following the implementation date, i.e., March 2021 to March 2022).

Table 7: Difference-in-Difference Regression Analysis of Mutual Fund Flows by SFDR Classification and Timing.

Table 7 performs a difference-in-difference regression to examine the variations in mutual fund flows (expressed as percentages) based on SFDR classification (Article 9, Article 8, and others) and the different time stages. The dependent variable is monthly fund flows. The regression contains additional controls such as flows in the last 12 months, excess return in the prior month, return in the previous 12 months, the standard deviation of returns over the past 12 months, log of size in the current month, and log of age in the current month. Furthermore, the regression incorporates month-fixed effects. The output encapsulates the entire study period, which spans seven months before and twelve months after the publication event (i.e., from July 2020 to March 2022), thereby highlighting the impact of SFDR classification and the different stages around the publication on mutual fund flows.

	Dependent variable: flow EVENT
sfdr_9	-0.0009
	(0.0009)
I(sfdr_9 * pre_publication)	0.0033*
	(0.0018)
I(sfdr_9 * sfdr_publication)	0.0115***
	(0.0017)
sfdr_8	-0.0002
	(0.0005)
I(sfdr_8 * pre_publication)	0.0008
	(0.0009)
I(sfdr_8 * sfdr_publication)	0.0013
	(0.0008)
Time FE	Yes
Control	Yes
Observations	35,926
Adjusted R2	0.1574
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7 presents the regression output, substantiating the findings above, namely that classification as an SFDR Article 9 fund engenders superior inflows compared to other funds. This is particularly pronounced before the final implementation date of March 10, 2021. Consequently, the coefficient of the interaction between Article 9 funds and the dummy variables pre-publication and SDFR publication yields a positive, statistically significant outcome. Specifically, in the period preceding the publication date, the average monthly flows of SFDR Article 9 funds were 0.33 percentage points higher, holding all other controls constant, compared to the average monthly flows of SFDR Article 9 across the entire study period. However, this is only statistically significantly different from zero at the 10% significance level. Furthermore, in the interval between the publication date and implementation date, these average monthly flows of SFDR Article 9 funds were elevated by 1.15 percentage points, a statistically significant finding at the 1% level.

Consistent with the above findings, the coefficients derived from applying the same analysis to SFDR Article 8 funds manifest similar behaviour. However, neither exhibits a statistical difference from zero at any significance level.

Drawing upon the empirical evidence amassed in this study, Hypothesis 2 cannot be validated. This is because the null hypothesis asserting that SFDR Article 9 funds display lower or equal fund flows in the months after the SFDR regulation's introduction cannot be refuted. Nevertheless, the findings underscore significantly heightened inflows into SFDR Article 9 funds preceding the implementation date, suggesting that the label information was processed by investors in advance. This partially contrasts with the findings of Becker et al. (2022), which demonstrated significantly increased flows into SFDR Article 8 and SFDR Article 9 funds following the implementation date.

However, this discrepancy could be attributed to differences in the month available for analysis. Whereas Becker et al. (2022) only tested differences in flows among the SFDR classifications 4 months after the implementation, i.e., March, April, May and June 2021, this study differentiates between the different periods and takes a longer time horizon after the implementation into consideration. As a result, this study provides a much more detailed view of the impact and hence increasing the quality of the findings. Based on this, the SFDR classification has an impact on capital flows, but most of the impact on the investor side takes place before the actual implementation. Additionally, the results align with the outcomes observed in the wake of the Morningstar Sustainability rating publication, affirming that investors respond to sustainability criteria and value sustainability (Aasheim et al., 2022; Ammann et al., 2019; Hartzmark & Sussman, 2019).

The results of this study are notably limited by the aforementioned static nature of the SFDR classification in this dataset and the potential for omitted variables in the final model, such as the expense ratio. In addition, the inability to apply fixed effects amplifies this issue.

Specifically, the static data concerning SFDR classification obscures a definitive causal effect of SFDR classification. Therefore, future scholars are encouraged to utilise a natural experiment to scrutinise the impact of fund upgrades and downgrades on investors' capital inflows to discern this with greater precision. A methodology like this would contribute to a more nuanced understanding of the dynamics at play, providing valuable insights for policymakers, investment professionals, and individual investors. This is of particular interest concerning the recent wave of downgrades. In addition, an area yet to be explored comprehensively in future research is whether these inflows are correlated to the heightened level of ESG integration or simply to the label itself. This issue is broached in Rzeźnik et al. (2022)'s study, indicating the need for further rigorous investigation to untangle these interconnected elements. Furthermore, researchers should examine whether the development of capital inflows remains sustainably higher in the long-term or if that outcome has been a trend. The results of this study have shown that the flows have tended to converge again with the other classifications.

7.3.2. Investor Flow Characteristics of Article 9 Funds

The ensuing paragraph is dedicated to scrutinising the flow relationship in greater detail and, in doing so, to elucidate the characteristics of the investor groups that the various SFDR fund classifications attract. As highlighted in the literature review, there is compelling evidence to suggest that investors in ESG funds exhibit greater resilience (Capota et al., 2022), an attribute partially attributable to these investors' pursuit of a particular conception of sustainable value (Bauer et al., 2021; Döttling & Kim, 2022; Hartzmark & Sussman, 2019).

The variables have been separated to examine investor behaviour in relation to positive and negative attributes, such as past returns (both negative and positive), as outlined in the data construction chapter. This applies to the variables representing the flow over the last twelve months, the return in the preceding months, and the return in the previous twelve months. Consistent with Capota et al. (2022), the dependent variable in the baseline regression are the monthly flows:

$$flow_{i,t} = \beta_1 pos\_flow_{12m_{i,t}} + \beta_2 neg\_flow_{12m_{i,t}} + \beta_3 pos\_return_{excess_{i,t}} + \beta_4 neg\_return_{excess_{i,t}} + \beta_5 pos\_return_{12m_{i,t}} + \beta_6 neg\_return_{12m_{i,t}} + \beta_7 std\_dev_{12m_{i,t}} + \beta_8 \log TNA_{i,t} + \beta_9 \log age_{i,t} + \varepsilon_{i,t} \tag{10}$$

Furthermore, the independent variables comprise the previously specified variables, including the standard deviation as a risk indicator, and other control variables, such as the natural logarithm of *TNA* and *age*. Generally, to control for time-invariant and fundinvariant effects, month fixed-effects and fund fixed-effects are employed across all regression models in this section.

Table 8 presents the regression output where the original sample is divided into three subsamples undergoing the same baseline regression. Column 2 showcases only Article 9 funds, column 3 displays the Article 8 funds, and column 4 features other funds. Most of the included variables exhibit significant effects and, when juxtaposed with previous results, exhibit similar patterns (Capota et al., 2022). This testifies the robustness of the data and model at hand.

Table 8: Flow Relationship of SFDR Classifications.

Table 8 investigates the variation of mutual fund flow relationships based on the SFDR classification. The dependent variable is fund flows, represented by monthly fund flows expressed as percentages. All columns incorporate time-series fund characteristics, such as flow in the last 12 months, excess return in the previous month, and return in the preceding 12 months. These variables are separated into positive values ("_POS") and absolute negative values ("_NEG"). Additionally, the standard deviation of returns over the past 12 months and the log of size and age in the current month are included. All columns include month and fund-fixed effects. The data is limited to the period from January 2018 to December 2022. Column 1 displays the flow relationships of all funds, regardless of their SFDR classification. Column 2 is specific to the flow relationships of Article 9 funds, column 3 focuses on the flow relationships of Article 8 funds, and column 4 presents the flow relationships of funds classified as other.

	Dependent variable:			
	flow			
	ALL	9	8	other
	(1)	(2)	(3)	(4)
flow_12m_POS	0.020***	0.023***	0.021***	0.017***
	(0.0004)	(0.001)	(0.001)	(0.001)
flow_12m_NEG	-0.049***	-0.035***	-0.050***	-0.050***
	(0.001)	(0.005)	(0.002)	(0.001)
excess_return_t.1_POS	0.038***	0.102***	0.045***	0.028***
	(0.007)	(0.030)	(0.011)	(0.008)
excess_return_t.1_NEG	-0.041***	0.0004	-0.058***	-0.035***
	(0.008)	(0.037)	(0.014)	(0.010)
return_12m_POS	0.040***	0.060***	0.050***	0.029***
	(0.002)	(0.008)	(0.003)	(0.002)
return_12m_NEG	-0.020***	-0.025*	-0.023***	-0.018***
	(0.003)	(0.013)	(0.005)	(0.004)
std_dev_12m	-0.066***	-0.140**	-0.071***	-0.063***
	(0.012)	(0.063)	(0.023)	(0.015)
log_tna	-0.005***	-0.007***	-0.005***	-0.005***
	(0.0003)	(0.001)	(0.0005)	(0.0004)
log_age	-0.001	0.006*	-0.0001	-0.003***
	(0.001)	(0.003)	(0.001)	(0.001)
Time FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	105,898	6,898	44,394	54,606
Adjusted R2	0.042	0.049	0.052	0.028
Note:	*p<0.1; **p<0.05; ***p<0.01			

Evaluating the coefficients of all funds in the sample (Column 1), a positive flow in the past 12 months, on average, increases the monthly flow, all other coefficients held constant. Conversely, a negative flow in the previous 12 months reduces the monthly flow on average. These anticipated effects are mirrored across the different classifications. However, a one percentage point increase in negative flow in the last twelve months curtails the average monthly flow for Article 9 funds by merely 0.035 percentage points, while a similar increase trims the flow of Article 8 and other funds by 0.050 percentage points. This is a preliminary indication of the higher resilience of Article 9 fund investors toward past negative flows. The statistical significance of this difference will be further elaborated later.

Scrutinising the flow performance relationship, there are also disparities between the different SFDR classifications. Firstly, the average monthly flow exhibits the highest coefficients for positive excess returns in the preceding month for Article 9 funds (0.102 percentage points), followed by Article 8 funds (0.045 percentage points) and other funds (0.028 percentage points). Furthermore, the coefficient for negative past excess returns in the prior month for Article 9 funds presents a positive coefficient, indicating that a one percentage point increase in negative excess return still results in capital inflow (i.e. 0.0004 percentage points). Again, this contrasts with Article 8 and other funds, despite the coefficient not being statistically different from zero. This adds to evidence suggesting that investors do not respond identically to past negative returns, as indicated by Capota et al. (2022). Nevertheless, the statistical significance of the difference remains to be established. Regarding the returns of the last twelve months, the coefficients among the different SFDR classifications do not present any significant differences. However, it is noteworthy that the significance level for the coefficient describing the reaction towards negative returns of the last twelve months of Article 9 funds showcases a considerably lower significance level, which could also be attributed to fewer observations available.

Regarding the standard deviation, as an indicator of risk, the coefficient of all funds denotes that a higher standard deviation in the last twelve months indicates a lower monthly flow on average. Again, this tendency is uniform for all classifications and statistically significant on a 1% significance level.

The control variables, *TNA* and *age*, yield expected outcomes. Specifically, age and TNA depress the monthly flows, aligning with other literature (Capota et al., 2022).

A difference-in-difference regression model predicated on the previously described model has been employed to evaluate the disparity between Article 9 funds and the two other classifications under analysis. As a result, Table 9 showcases only the coefficients of the interaction term of Article 9 funds with the underlying subset, with Panel A pertaining only to Article 9 and other funds and Panel B exclusively covering Article 9 and Article 8 funds. This analysis aims to delineate the differences between Article 9 funds in relation to other and to Article 8 funds.

Table 9: SFDR 9 Flow Relationships in Comparison.

Table 9 contrasts the differences in the mutual fund flow relationships of SFDR 9 funds. The dependent variable is fund flows, expressed as monthly percentages. Both Panel A and Panel B include time-series fund characteristics, such as flow in the last 12 months, excess return in the previous month, and return in the preceding 12 months, distinguished into positive values ("_POS") and absolute negative values ("_NEG"). Moreover, the standard deviation of returns over the past 12 months and the log of size and age in the current month are factored in. However, both panels exclusively display coefficients of the interaction term of each variable with the SFDR 9 dummy variable. All columns include month and fund-fixed effects. The data encompasses the period from January 2018 to December 2022. Panel A involves only SFDR 9 funds and funds classified as other (with a total of 61,504 observations), demonstrating the differential flow relationship between these two fund classifications. Conversely, Panel B includes only Article 9 funds and Article 8 funds (totalling 51,292 observations), thereby delineating the disparities between Article 9 and Article 8 funds regarding flow relationships.

Panel A: Difference SFDR 9 vs SFDR other

	Estimate	Std. Error	t-value	Pr(> | t|)
I(flow_12m_POS * sfdr_9)	0.006	0.001	4.957	0.00000
I(flow_12m_NEG * sfdr_9)	0.015	0.004	3.665	0.0002
I(excess_return_t.1_POS * sfdr_9)	0.012	0.016	0.738	0.461
I(excess_return_t.1_NEG * sfdr_9)	0.024	0.018	1.323	0.186
I(return_12m_POS * sfdr_9)	0.009	0.004	2.372	0.018
I(return_12m_NEG * sfdr_9)	-0.0001	0.008	-0.011	0.991
I(std_dev_12m * sfdr_9)	0.094	0.030	3.108	0.002
I(log_tna * sfdr_9)	-0.002	0.001	-2.604	0.009
I(log_age * sfdr_9)	0.008	0.002	3.660	0.0003

Panel B: Difference SFDR 9 versus SFDR 8

	Estimate	Std. Error	t-value	Pr(> | t|)
I(flow_12m_POS * sfdr_9)	0.001	0.001	1.003	0.316
I(flow_12m_NEG * sfdr_9)	0.015	0.005	3.010	0.003
I(excess_return_t.1_POS * sfdr_9)	0.005	0.019	0.275	0.783
I(excess_return_t.1_NEG * sfdr_9)	0.026	0.021	1.254	0.210
I(return_12m_POS * sfdr_9)	0.004	0.004	0.976	0.329
I(return_12m_NEG * sfdr_9)	0.001	0.010	0.117	0.907
I(std_dev_12m * sfdr_9)	0.067	0.035	1.901	0.057
I(log_tna * sfdr_9)	-0.002	0.001	-1.855	0.064
I(log_age * sfdr_9)	0.006	0.003	2.494	0.013

Contrary to other funds, Article 9 funds' monthly flow displays statistical differences on a 1% significance level regarding the variables' positive and negative flow in the last 12 months, the standard deviation of the previous twelve months' returns, *TNA* and *age*. Indeed, the response of monthly average flows to positive flows over the last twelve months for Article 9 funds is higher than for funds classified as other. Furthermore, the reaction to a one percentage point increase in negative flows over the last twelve months is 0.015 percentage points lower for Article 9 funds. Furthermore, the investors' response to the standard deviation of the previous twelve months' returns is statistically lower for Article 9 funds than for those classified as others in the difference-in-difference model, presenting a positive coefficient. Lastly, Article 9 funds' flow is reduced with increasing TNA and heightened with increasing age.

Looking at Article 9 funds vis-a-vis Article 8 funds, the flow relationship for Article 9 funds only differs in terms of the negative flow of the last twelve months. In fact, akin to the other funds, the monthly flow is 0.015 percentage points higher than Article 8 fund for every one percentage point increase in negative flow over the last twelve months.

According to the study's results, Hypothesis 3 cannot be confirmed, as the null hypothesis stating that there is no difference in negative excess returns, return, and flow over the last twelve months cannot be rejected. However, the hypothesis can be partially ratified. Concerning the flow relationship towards the flow trend over the past twelve months, it can be posited that SFDR 9 funds have a statistical significant more positive relationship to positive trends and a statistical significant less negative relationship to negative trends compared to funds classified as other. The latter also holds when comparing Article 9 and Article 8 funds. This constitutes preliminary evidence for swarm behaviour, where investors react to the behaviour of others due to the more positive relationship on one hand. Conversely, it suggests that once an investor has decided to invest, they do not react to other investors' fostering the financial stability (Capota et al., 2022). One possible explanation can be the intensive due diligence before investing. However, there is no further evidence in this study of a more resilient flow performance relationship as suggested by Capota et al. (2022) using the fund names to identify ESG funds. While the coefficients indicate this, they are not significant within the observation period of this study. Nevertheless, when they use Morningstar ESG rating to identify ESG funds they achieve similar results.

As elucidated in the preceding chapter, the static nature of the SFDR classification, coupled with the risk of omitted variables, poses a degree of risk to the outcomes of this analysis. However, these risks are somewhat mitigated given the ability to apply fixed effects and similar results as previous researchers.

Consequently, future researchers should focus on comprehending the investor motivations underpinning these characteristics. Additionally, subsequent studies should emphasise the analysis of capital flows and investors' satisfaction levels concerning the outcomes of their fund investments. This future research area will facilitate a more holistic understanding of the interplay between sustainable investments and investor behaviour.

7.3.3. Return Analysis of SFDR Classifications

The preceding sections have demonstrated increased investor interest in Article 9 funds, resulting in superior flows, as evidenced in the research conducted to validate Hypothesis 2, along with indications of higher investor resilience in Hypothesis 3. However, as highlighted in the literature review, investors ultimately seek higher returns in a perfect market. These could either take the form of abnormal returns or higher risk-adjusted returns. Consequently, this chapter aims to analyse the abnormal returns or alpha, of the three different fund classifications. Additionally, this chapter also compares the factor loadings, that is, the exposure to various risks in their portfolio, using the 3-Factor Model of Fama and French. Hence, this approach is widely used in academic literature (Hartzmark & Sussman, 2019; Nofsinger & Varma, 2014).

The 3-factor data from the Kenneth R. French database captures the returns of globally developed markets. This is used because over 70% of the sample demonstrate a global investment focus. However, those returns display the dollar returns of the factors, which have been transformed in euro returns by controlling for the exchange rate returns using the monthly exchange rate from Refinitiv. Hence, the funds' monthly alpha, $alpha$, is calculated as

$$return_{excess_{i,t}} = alpha_{i,t} + \beta_1 market\ premium_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t} \tag{7}$$

where $return_{excess_{i,t}}$ is the excess return of a fund i in the month t, $alpha_{i,t}$ is the alpha of a fund i in the month t, and $\beta_1$is the market premium factor, β_2 is the small-cap over large-cap factor and β_3 is the high book-to-market ratio (value) and low book-to-market ratio (growth) factor of a fund i over the time period in the dataset[13]. $Alpha_{i,t}$ in this regression is the constant, hence the difference between the expected return using the factor returns and the excess return.

Table 10 presents the different factor loadings encompassing the market, SMB, and High Minus Low (HML) factors and ultimately regresses the monthly alpha. The table illustrates the weighted average of all funds (column 1), SFDR 9 funds only (column 2), Article 8 funds only (column 3), and other funds (column 4).

Table 10: Fama and French 3-Factor Model Factor Loadings by SFDR Classification.

Table 10 examines the different factor loadings, or betas, of the Fama and French 3-Factor Model based on various SFDR classifications (Article 9, Article 8, and others). The dependent variable is excess return, defined as the difference between the month's return and the risk-free rate, expressed as a percentage. The independent variables of interest include the market premium returns, the Small Minus Big (SMB) returns, and High Minus Low (HML) returns, all converted into euro returns. All regressions control for time and fund-fixed effects by incorporating all dummy variables using the pooling method. The data covers the period from January 2018 to December 2022. Column 1 summarises the factor loadings for all funds, irrespective of their SFDR classification. Column 2 is restricted to the factor loadings of Article 9 funds, column 3 focuses on the factor loadings of Article 8 funds, and column 4 presents the factor loadings of funds classified as other.

	Dependent variable:			
	excess_return_t			
	ALL	9	8	other
	(1)	(2)	(3)	(4)
Mkt.RF_EUR	0.6190***	0.7623***	0.7201***	0.5239***
	(0.0015)	(0.0053)	(0.0022)	(0.0020)
SMB_EUR	-0.0150***	0.0486***	-0.0502***	0.0078
	(0.0046)	(0.0166)	(0.0069)	(0.0064)
HML_EUR	-0.0223***	-0.1627***	-0.0317***	0.0061**
	(0.0021)	(0.0076)	(0.0032)	(0.0029)
Constant	-0.0007***	0.0004	-0.0007***	-0.0008***
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Time FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	140,821	9,549	56,914	74,358
Adjusted R2	0.5642	0.7049	0.6592	0.4768
Note:	*p<0.1; **p<0.05; ***p<0.01			

Intriguingly, Article 9 funds display a similar market risk premium beta to Article 8 funds but a higher beta than others. All betas are statistically significant at a 1% significance level, yet are noticeably below a factor of 1. A factor of one suggests a perfectly diversified

[13] The data set considers the same funds that have been described before. However, it differs because missing data and outliers were eliminated only for the excess return variable. Therefore, the data set takes into account 140,821 observations.

portfolio and considering that this analysis is performed on a sample of funds likely to be highly diversified, a beta closer to 1 has been anticipated initially. This occurrence can be attributed to the sample selection, either implying these are accurate loadings or potentially due to a calculation error. Additionally, the models differ in comparison to their explanation power, i.e., the model covering other funds has the lowest adj. R-squared of 47.7%. However, other research outcomes show similar results (Lesser et al., 2016; Steen et al., 2020). Thus, this makes the latter possibility of a calculation error unlikely. In summary, this implies that both SFDR classifications, SFDR 9 and Article 8, exhibit tendencies to be more sensitive to market movements and concurrently demand a higher expected return. However, this chapter will further address the statistical significance of this difference using a difference-in-differences regression.

Concerning the SMB factor, only Article 9 and Article 8 funds display a beta statistically significantly different from zero. In fact, the factor is positive for SFDR 9 funds and negative for Article 8 funds. This suggests that Article 9 funds have a higher exposure to small-cap stocks in their portfolio, thereby displaying a positive relationship with the returns of small-cap stocks.

Article 9 funds exhibit the lowest HML factor, succeeded by Article 8 funds, both at a 1% significance level and other funds with a slightly positive loading at a 5% significance level. This indicates that other funds have a higher exposure to high book-to-market ratio stocks, so-called value stocks, and correspondingly, Article 9 funds have the highest exposure to low book-to-market ratio stocks, so-called growth stocks.

The constant in the regression represents the so-called alpha, i.e., the expected return not accounted for by the three factors. Thus, a positive alpha indicates outperformance, a return the model cannot explain. On the other hand, a negative alpha signifies underperformance. Theoretically, the alpha should be zero since the total expected return of a portfolio should be explained by its exposure to the three factors in the model. Analysing the monthly alpha of the different SFDR classifications in Table 10, preliminary evidence suggests that Article 8 funds and other funds have experienced underperformance, i.e., -0.07% and -0.08% on average per month, throughout the analysis period at a 1% significance level. However, on the other hand, SFDR 9 funds display a positive monthly alpha, i.e., 0.04% on average per month. Nevertheless, this is not statistically significantly different from zero.

Table 11 compares the differences in factor loadings and monthly alphas of Article 9 funds with those related to other funds (Panel A) and Article 8 funds (Panel B). The table only displays the coefficients with the interaction of the factors with the SFDR 9 dummy variable, focusing only on the differences of SFDR 9 funds. Moreover, it shows the coefficient of the SFDR 9 dummy variable, illustrating the difference of Article 9 funds to the constant, the abnormal return alpha.

Table 11: Comparative Analysis of Fama and French 3-Factor Model Factor Loadings for Article 9 Funds.

Table 11 contrasts the factor loadings, or betas, of the Fama and French 3-Factor Model for Article 9 funds. The dependent variable is excess return, computed as the difference between the month's return and the risk-free rate, expressed as a percentage. The independent variables of interest encompass the market premium returns, the Small Minus Big (SMB) returns, and High Minus Low (HML) returns, all converted into euro returns. Both Panel A and Panel B display the interaction of SFDR 9 funds with these factors and control for time and fund-fixed effects by incorporating all dummy variables using the pooling method. The data ranges from January 2018 to December 2022. However, both panels exclusively present the coefficients of the interaction term of each variable with the SFDR 9 dummy variable. Panel A includes only SFDR 9 funds and funds classified as other (comprising 83,907 observations), demonstrating the difference in factor loadings between these two fund classifications. In contrast, Panel B incorporates only SFDR 9 funds and Article 8 funds (totalling 66,463 observations), thereby outlining the differences in factor loadings between Article 9 and Article 8 funds.

Panel A: Difference SFDR 9 vs SFDR other

	Estimate	Std. Error	t-value	Pr(> | t|)
(Intercept)	-0.0008	0.0001	-7.8095	0
I(Mkt.RF_EUR * sfdr_9)	0.2366	0.0060	39.4526	0
I(SMB_EUR * sfdr_9)	0.0416	0.0187	2.2257	0.0260
I(HML_EUR * sfdr_9)	-0.1690	0.0085	-19.8167	0
sfdr_9	0.0012	0.0003	3.8837	0.0001

Panel B: Difference SFDR 9 vs SFDR 8

	Estimate	Std. Error	t-value	Pr(> | t|)
(Intercept)	-0.0007	0.0001	-6.5371	0
I(Mkt.RF_EUR * sfdr_9)	0.0422	0.0058	7.2906	0
I(SMB_EUR * sfdr_9)	0.0991	0.0180	5.4940	0.000000
I(HML_EUR * sfdr_9)	-0.1307	0.0082	-15.8669	0
sfdr_9	0.0011	0.0003	3.7725	0.0002

The market factor for Article 9 funds is higher for both other funds by 0.24 and for Article 8 funds by 0.04. These differences are statistically significant at a 1% level. As outlined earlier, this suggests that Article 9 funds are more sensitive to market returns and simultaneously exhibit a higher risk profile than their counterparts. These findings are analogous to those of Lesser et al. (2016), which found a market factor loading of 0.81 for high sustainable funds, resulting in a difference of 0.22 by their low sustainable counterparts when analysing Norwegian mutual funds.

Furthermore, the SMB factor for Article 9 funds is higher than both counterparts, although it's only significant at a 5% level compared to other funds. However, this contrasts with the size bias of ESG metrics, which suggests that larger firms have higher ESG metrics and hence more sustainable funds should have a lower SMB factor than their counterparts.

As indicated previously, Article 9 funds have a higher exposure to growth stocks in their portfolios since their beta is significantly lower than that of their counterparts. A plausible explanation could be that technology companies generally have higher ESG metrics and concurrently lower book-to-market ratios than their peers with traditional business models. Additionally, modern business models often have a sustainability focus, implying that the value stocks of tomorrow naturally feature higher ESG metrics. This opens new research opportunities.

Lastly, even though the monthly alpha is not statistically significantly different from zero, it is statistically higher than that of other funds, which is 0.12 percentage points on average per month, and than that of Article 8 funds, with 0.11 percentage points on average per month.

In summary, Article 9 funds do not display overperformance but perform statistically higher than their counterparts in this analysis. Possible reasons for this could be that during the observation period, two major crises occurred, namely the Covid-19 crisis in 2020 and the turmoil following the invasion of Ukraine, alongside high inflation in the main markets and simultaneous drastic interest increases by the central bank. However, the differentiated analysis of these periods in crisis and non-crisis times are left for future researchers, as there is substantial evidence that highly sustainable funds behave differently in both types of periods.

8. Conclusion and Future Research

This work contributes to the literature in a threefold way. First, this study scrutinises the influence of the SFDR regulation on its capacity to effectively add value to the markets by identifying sustainable investments, consequently reducing the potential risk of greenwashing, as highlighted by the ESG scandal involving Deutsche Bank's mutual fund division DWS. In addition, the study examines investors' responses to the SFDR regulation by measuring capital flows before and after the regulation's publication and contributing a comprehensive analysis to earlier findings. This is supplemented by the assessment of flow relationships, consequently revealing investor characteristics. In doing so, it complements existing literature that has previously addressed this phenom only in the context of ESG ratings adoption and not in the context of the SFDR regulation. Lastly, the study uncovers investment strategies of the different classifications and measures risk-adjusted performance utilising the Fama and French 3-Factor Model. Until today, an analysis of factor exposures has not yet been conducted in the context of the new SFDR regulation, but this has only been studied in relation to other sustainability criteria.

Overall, the empirical analysis of this research has been bifurcated into two parts regarding their underlying datasets. The first segment reveals that a position within the top 15% of ESG scores has a statistically significant positive effect on the classification as an Article 9 fund. Conversely, being within the bottom 15% of ESG scores has a statistically significant negative impact on this classification. These results remain robust when employing data from two independent ESG data providers, thereby indicating the superior sustainability metrics of Article 9 funds. Consequently, this regulation mitigates greenwashing risks, enhancing financial market efficacy. Nevertheless, the divergence of different ESG ratings imposes a limit on these findings as only two providers were takin into account, inviting further exploration by future researchers. In particular, the recently introduced MSCI ratings methodology could provide an intriguing basis for further research. Additionally, the efficacy of associated regulatory frameworks is worthy of further investigation.

The second segment concentrates on investors' reactions to the SFDR regulation, investor characteristics, and performance analysis through a comprehensive empirical study of 2,630 mutual equity funds domiciled in the Eurozone. Regarding investors' responses, this study contributes to the academic field by revealing that SFDR 9 funds have statistically significant higher inflows between the final date of publication and the implementation date. This aligns with previous findings, indicating that investors value sustainability in equity funds. Nonetheless, the static SFDR classification in this study constrains the causal effect. Thus, future researchers should analyse the impact of downgrades and upgrades in the wake of the final RTS publication. Moreover, researchers should explore whether investors are merely interested in the label itself or the level of ESG integration in funds.

Investors in Article 9 funds demonstrate signs of higher resilience, particularly concerning positive and negative past flows, negative returns, and higher risk levels, aligning with other findings. Future research should focus on identifying the motivations underlying these investor characteristics.

Finally, the analysis of factor exposure across different SFDR classifications reveals that Article 9 funds exhibit higher exposure to growth investments. However, they do not show a statistically positive risk-adjusted return, although there a positive statistical difference is observable compared to their counterparts. Future researchers should investigate the impact of events such as the Covid-19 pandemic, the war in Ukraine and the consequent inflation since existing literature has proffered various interpretations during times of crisis.

I. Data Preparation

The following information covers the formulas computed and variables added in the empirical analysis.

A. Formulas

The following information lists all formulas computed and implemented in the datasets.

The age, age, of a fund *i* in the month *t* is calculated as

$$age_{i,t} = date_t - date_{launch_i} \tag{1}$$

where $date_t$ is the date of the last day in month *t*[14], and $date_{launch_i}$ is the launch date of fund *i*.

Excess return, $return_{excess}$, of a fund *i* in the month *t* is calculated as

$$return_{excess_{i,t}} = \frac{RI_{i,t}}{RI_{i,t-1}} - return_{risk-free_t} - 1 \tag{3}$$

where $RI_{i,t}$ is the return index of fund *i* in month *t*, and the $return_{risk-free_t}$ is the risk-free rate in month *t*.

The return of the last twelve months, $return_{12m}$, of a fund *i* in the month *t* is calculated as

$$return_{12m_{i,t}} = \frac{RI_{i,t}}{RI_{i,t-12}} - 1 \tag{4}$$

where $RI_{i,t}$ is the return index of fund *i* in month *t*.

The standard deviation of the last twelve months returns, std_dev_{12m}, of a fund *i* in the month *t* is calculated as

$$std\_dev_{12m_t} = \sqrt{\frac{1}{12-1} \sum_{i=1}^{n=12} (return_i - \overline{return})} \tag{5}$$

where $return_{i,t}$ is the return of a fund *i* in the month *t*.

[14] Note, that $date_t$ is the 30.03.2023 for the cross-section dataset and the last day of each month in the panel-data dataset.

The monthly flow, $flow$, of a fund *i* in the month *t* is calculated as

$$flow_{i,t} = \frac{tna_{i,t} - tna_{i,t-1} \times return_{i,t}}{tna_{i,t-1}} - 1 \tag{6}$$

where $tna_{i,t}$ is the total net asset value of a fund *i* in the month *t*, and $return_{i,t}$ is the return of a fund *i* in the month *t*.

The twelve months flow, $flow_{12m}$, of a fund *i* in the month *t* is calculated as

$$flow_{12m_{i,t}} = \frac{tna_{i,t} - tna_{i,t-12} \times return_{12m_{i,t}}}{tna_{i,t-12}} - 1 \tag{7}$$

where $tna_{i,t}$ is the total net asset value of a fund *i* in the month *t*, and $return_{12m_{i,t}}$ is the return of a fund *i* in the month *t*.

Alpha, $alpha$, of a fund *i* in the month *t* is calculated as

$$return_{excess_{i,t}} = alpha_{i,t} + \beta_1 market\ premium_t + \beta_2 SMB_t + \ \beta_3 HML_t + \varepsilon_{i,t} \tag{8}$$

where $return_{excess_{i,t}}$ is the excess return of a fund I in the month t, $alpha_{i,t}$ is the alpha of a fund I in the month t, and $\beta_1$is the market premium factor, β_2 is the small-cap over large-cap factor and β_3 is the high book-to-market ratio (value) and low book-to-market ratio (growth) factor of a fund *i* over the time period in the dataset.

B. Variables

The following information lists selected dummies and other variables used in the empirical analysis.

VARIABLE	DESCRIPTION
SFDR_9	1, if the fund is classified as Article 9 fund.
SFDR_8	1, if the fund is classified as Article 8 fund.
SFDR_OTHER	1, if the fund is classified as Article 6 und or fund has no classification at all.
GLOBAL	1, if the fund pursues a Global geographical focus.
EUROZONE	1, if the fund pursues geographical focus in the Eurozone.
EMERGINGMARKETS	1, if the fund pursues geographical focus in Emerging Markets.
ESG	1, if the fund name contains one of the ESG keywords in either English, German, Italian, Spanish or French. Keywords are such as *ESG, SRI, Social, Environment, Climate, Sustainable, Green, Governance, Transition, Ecology, Responsible, Durable, Ethical, and SDG*.
MSCI_RATING_SUFFIX	1, if the fund is classified in the corresponding MSCI rating category.

PREFIX_0	1, if the fund’s score is classified in the lower quantile (threshold below 15%)
PREFIX_1	1, if the fund's score is classified in the middle quantile (threshold between 15% and 85%)
PREFIX_2	1, if the fund's score is classified in the upper quantile (threshold above 85%)
PRE_PUBLICATION	1, if the month is before November 2020.
SFDR_PUBLICATION	1, if the month is within November 2020 until (including) March 2021
POST PUBLICATION	1, if the month is after March 2021.
PREFIX_POS	Prefix value, if value of prefix variable is positive
PREFIX_NEG	Absolute prefix value, if value of prefix variable is negative

II. Appendix

List of Appendices

Appendix 1: Summary Statistics of MSCI Dataset.

Appendix 1 presents summary statistics derived from the MSCI ESG data. These statistics showcase the key fund characteristics which form the foundation for the subsequent regression analysis investigating the ESG alignment of SFDR 9 funds, as stipulated in Hypothesis 1.

Panel A: MSCI ESG Data

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
sfdr_9	1,529	0.11	0.32	0	0	0	0	1	2.44	6.97	0
sfdr_8	1,529	0.52	0.50	0	0	1	1	1	-0.08	1.01	0
sfdr_other	1,529	0.37	0.48	0	0	0	1	1	0.55	1.30	0
msci_quality_score	1,529	0.63	0.14	0	0.57	0.64	0.73	1	-0.72	4.07	0
esg	1,529	0.20	0.40	0	0	0	0	1	1.48	3.20	0
msci_rating_AAA	1,529	0.01	0.09	0	0	0	0	1	10.71	115.62	0
msci_rating_AA	1,529	0.56	0.50	0	0	1	1	1	-0.23	1.05	0
msci_rating_A	1,529	0.40	0.49	0	0	0	1	1	0.42	1.18	0
msci_rating_BBB	1,529	0.04	0.19	0	0	0	0	1	4.93	25.34	0
msci_rating_BB	1,529	0.001	0.04	0	0	0	0	1	27.60	762.50	0
msci_quality_score_2	1,529	0.15	0.36	0	0	0	0	1	1.96	4.82	0
msci_quality_score_1	1,529	0.70	0.46	0	0	1	1	1	-0.87	1.75	0
msci_quality_score_0	1,529	0.15	0.36	0	0	0	0	1	1.96	4.82	0
msci_carbon	1,529	128.36	105.44	1.99	68.86	108.90	148.85	1,128.06	3.17	19.88	0
tna	1,529	441.20	1,171.58	5.01	39.33	118.75	386.40	20,236.95	8.61	105.49	0
age	1,529	4,617.91	3,344.78	374	1,650	3,848	7,339	19,343	0.82	3.54	0
EuroZone	1,529	0.20	0.40	0	0	0	0	1	1.52	3.32	0
Global	1,529	0.74	0.44	0	0	1	1	1	-1.08	2.17	0
EmergingMarkets	1,529	0.07	0.25	0	0	0	0	1	3.52	13.36	0

Appendix 2: Logit Regression Analysis of Article 9 Fund Classification – MSCI ESG Data.

Appendix 2 illustrates the different factors influencing the likelihood of a fund being classified as an SFDR 9 fund. The dependent variable is a dummy variable for SFDR 9, regressed against three sustainability proxies based on MSCI ESG data: the raw ESG score (Column 1), ESG quantiles (Column 2) and the MSCI rating (Column 3). All columns also incorporate additional control variables, including fund size, the presence of ESG keywords in the fund's name, and the age of the fund. The dataset used in this analysis is from March 30, 2023.

	Dependent variable:		
	sfdr_9		
	Score	Quantiles	Ratings
	(1)	(2)	(3)
msci_quality_score	2.595***		
	(0.718)		
msci_quality_score_2		0.388*	
		(0.210)	
msci_quality_score_0		-0.640**	
		(0.319)	
msci_rating_AAA			-1.010
			(1.081)
msci_rating_AA			0.766***
			(0.200)
msci_rating_BB			-10.628
			(375.505)
msci_rating_BBB			-1.173
			(1.033)
I(log(tna))	0.264***	0.262***	0.269***
	(0.055)	(0.055)	(0.056)
esg	0.998***	1.083***	1.053***
	(0.180)	(0.178)	(0.178)
I(log(age))	-0.434***	-0.443***	-0.437***
	(0.094)	(0.095)	(0.095)
Constant	-1.940**	-0.171	-0.726
	(0.874)	(0.737)	(0.753)
Observations	1,529	1,529	1,529
Akaike Inf. Crit.	978.370	985.008	974.063
Note:	*p<0.1; **p<0.05; ***p<0.01		

Appendix 3: Marginal Effects in Response to Fund Characteristics on SFDR 9 Classification – Refinitiv ESG Data.

Appendix 3 illustrates the marginal effects of a fund being classified as an Article 9 fund using logit average marginal effects. The dependent variable is a dummy variable for SFDR 9, regressed against specified quantiles of the Refinitiv combined ESG score (0%, 15%, 85%, and 100%) including additional control variables. Those are fund size, the presence of ESG keywords in the fund's name, and the age of the fund. The dataset used in this analysis is from March 30, 2023.

```
Call:
logitmfx(formula = sfdr_9 ~ esg_comb_score_2 + esg_comb_score_0 +
    I(log(tna)) + esg + I(log(age)), data = data_refinitiv, atmean = FALSE)

Marginal Effects:
                      dF/dx  Std. Err.       z     P>|z|
esg_comb_score_2  0.1100953  0.0232806  4.7291 2.256e-06 ***
esg_comb_score_0 -0.0460268  0.0193141 -2.3831   0.01717 *
I(log(tna))       0.0249304  0.0048839  5.1046 3.315e-07 ***
esg               0.0917344  0.0195173  4.7002 2.599e-06 ***
I(log(age))      -0.0375069  0.0082078 -4.5697 4.885e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

dF/dx is for discrete change for the following variables:

[1] "esg_comb_score_2" "esg_comb_score_0" "esg"
```

Appendix 4: Marginal Effects in Response to Fund Characteristics on SFDR 9 Classification – MSCI ESG Data.

Appendix 4 illustrates the marginal effects of a fund being classified as an Article 9 fund using logit average marginal effects. The dependent variable is a dummy variable for SFDR 9, against specified quantiles of the MSCI ESG quality score (0%, 15%, 85%, and 100%) including additional control variables. Those are fund size, the presence of ESG keywords in the fund's name, and the age of the fund. The dataset used in this analysis is from March 30, 2023.

```
Call:
logitmfx(formula = sfdr_9 ~ msci_quality_score_2 + msci_quality_score_0 +
    I(log(tna)) + esg + I(log(age)), data = data_msci, atmean = FALSE)

Marginal Effects:
                          dF/dx  Std. Err.       z     P>|z|
msci_quality_score_2  0.0389251  0.0228762  1.7016   0.08884 .
msci_quality_score_0 -0.0498922  0.0206677 -2.4140   0.01578 *
I(log(tna))           0.0241020  0.0054737  4.4032 1.067e-05 ***
esg                   0.1218225  0.0234382  5.1976 2.019e-07 ***
I(log(age))          -0.0408358  0.0093840 -4.3516 1.351e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

dF/dx is for discrete change for the following variables:

[1] "msci_quality_score_2" "msci_quality_score_0" "esg"
```

Appendix 5: Summary Statistics of Final Panel-Data Dataset.

Appendix 5 summarises the final panel data dataset that serves as the foundation for hypotheses 2, 3, and 4. This final dataset reflects all subsetting discussed in Chapter 5 covering sample construction, along with the management of outliers based on a z-score threshold of 3. The table features the key variables of interest with differentiation based on their SFDR classification. Panel A shows the summary statistics for SFDR 9 funds, Panel B displays the statistics for Article 8 fund and, ultimately, Panel C illustrates the summary statistics for other funds. The total dataset comprises 2,650 equity funds, with an average observation of 40.0 months, resulting in a total of 105,898 observations.

Panel A: SFDR 9 Funds: Summary Statistics

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
flow	6,898	0.0070	0.0376	-0.2005	-0.0066	0.0020	0.0165	0.2622	1.2037	13.4123	0
excess_return_t	6,898	0.0022	0.0456	-0.1200	-0.0275	0.0080	0.0328	0.1394	-0.1909	2.9119	0
alpha	6,898	0.0001	0.0218	-0.0616	-0.0139	-0.0003	0.0137	0.0642	0.1212	3.0602	0.0001
tna	6,898	222.4936	457.3456	1.0284	30.9884	70.1175	207.2826	4,597.8590	4.7094	29.9168	0
age	6,898	4,360.1860	2,863.1770	365	1,791.7500	4,200.5000	6,366.7500	14,488	0.5965	2.8870	0

Panel B: SFDR 8 Funds: Summary Statistics

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
flow	44,394	0.0023	0.0369	-0.2085	-0.0086	-0.00004	0.0107	0.2625	0.7996	13.5899	0
excess_return_t	44,394	0.0021	0.0423	-0.1202	-0.0251	0.0064	0.0301	0.1406	-0.1879	3.0020	0
alpha	44,394	-0.0007	0.0212	-0.0622	-0.0145	-0.0009	0.0127	0.0643	0.0686	3.0474	0
tna	44,394	225.6746	781.4879	1.0009	20.4512	64.4605	192.5150	18,918.2600	15.5500	305.8560	0
age	44,394	4,672.1720	3,198.3190	361	1,874	4,293	6,969	19,343	0.8525	3.8787	0

Panel C: SFDR Other Funds: Summary Statistics

	Count	Mean	Std	Min	1st Q	Median	3rd Q	Max	Skewness	Kurtosis	Jarque-Bera p-value
flow	54,606	-0.0010	0.0305	-0.2086	-0.0072	-0.0004	0.0035	0.2628	0.5995	19.5539	0
excess_return_t	54,606	0.0014	0.0376	-0.1202	-0.0192	0.0025	0.0247	0.1406	-0.2283	3.5777	0
alpha	54,606	-0.0008	0.0203	-0.0622	-0.0133	-0.0012	0.0115	0.0643	0.0670	3.3330	0
tna	54,606	151.2469	619.4297	1.0011	14.4020	38.2789	103.5906	17,103.9500	14.7499	282.3540	0
age	54,606	4,561.4630	3,005.7940	362	1,957	4,192	6,913	18,796	0.7573	3.5699	0

Appendix 6: Mutual Fund Flows by SFDR Classification during Publication Event.

Appendix 6 explores how mutual fund flows, expressed as percentages, differ based on SFDR classification (Article 9, Article 8, and others). The dependent variable is fund flows. All columns incorporate additional controls, such as flows in the last 12 months, excess return in the previous month, return in the preceding 12 months, the standard deviation of returns over the past 12 months, log of size in the current month, and log of age in the current month. In addition, every column includes month-fixed effects. Firstly, column 1 represents the entire study period, both before and after the SFDR classification publication on March 10, 2021 (i.e., from November 2020 to March 2022). Secondly, column 2 depicts the period preceding the classification release (i.e., from July 2020 to February 2021). Lastly, column 3 covers the period following the classification (i.e., from March 2021 to March 2022).

	Dependent variable:		
	flow		
	EVENT	PRE-EVENT	POST-EVENT
	(1)	(2)	(3)
flow_12m	0.0292***	0.0310***	0.0269***
	(0.0004)	(0.0007)	(0.0005)
excess_return_t.1	0.0661***	0.0454***	0.0570***
	(0.0086)	(0.0134)	(0.0097)
return_12m	0.0255***	0.0443***	0.0166***
	(0.0020)	(0.0029)	(0.0022)
std_dev_12m	-0.0755***	-0.0248	-0.0729***
	(0.0152)	(0.0175)	(0.0188)
log_tna	-0.0004***	-0.0002	-0.0003*
	(0.0001)	(0.0002)	(0.0001)
log_age	-0.0007***	-0.0002	-0.0008***
	(0.0002)	(0.0004)	(0.0003)
sfdr_9	0.0021***	0.0042***	0.0008
	(0.0008)	(0.0012)	(0.0009)
sfdr_8	0.0002	0.0002	0.0003
	(0.0004)	(0.0006)	(0.0004)
Time FE	Yes	Yes	Yes
Observations	28,776	13,524	22,402
Adjusted R2	0.1618	0.1808	0.1451
Note:	*p<0.1; **p<0.05; ***p<0.01		

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