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The Role of Intangible Assets and ESG Factors in Modern Portfolio Strategies.

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Abstract

This thesis explores the influence of intangible assets and environmental, social, and governance (ESG) factors on the financial performance of companies and the effectiveness of investment strategies, through three distinct studies that examine different dimensions of these interactions. In the first study of this thesis, we examine how the integration of intangible assets influences risk-adjusted investment performance within the context of value investing, focusing specifically on the Sparkline Intangible Value ETF. For this analysis, we compared the risk-adjusted performance of the Sparkline Intangible Value ETF with that of well-established benchmarks, namely the Russell 1000 Value index and the S&P 500 index, over a 36-month period. We used measures such as Sharpe and Sortino ratios, as well as Jensen's alpha and Fama-French alpha to evaluate these performances. Our results show that, although the Sparkline Intangible Value ETF offers superior risk-adjusted returns compared to the Russell 1000 Value index, it does not reach the performance of the S&P 500 over the studied period. This observation suggests that, while intangible assets can enhance performance relative to certain traditional value measures, their integration does not systematically guarantee outperformance over broader market indices. Our analysis also shows that intangible assets contribute significantly to the added value of companies, particularly during phases of economic recovery. The results suggest that integrating intangible assets into valuation models could uncover previously unidentified investment opportunities, thus offering significant implications for financial market participants.

In the second study, we examine the impact of flexible work arrangements (FWAs) on risk-adjusted investment performance. We analyzed a comprehensive sample of companies in Europe and the United States over nine years, categorizing these firms into portfolios based on whether they had high or low FWAs scores, with monthly rebalancing. Comparative evaluation shows that portfolios with high FWAs scores consistently outperform those with low scores. This superiority is evidenced by metrics such as adjusted Sharpe and Sortino ratios, Jensen's alpha, and Fama-French alpha. The results reveal that companies integrating flexible work practices not only tend to attract more investments but also generate superior financial performance, particularly in terms of risk-adjusted returns. This finding supports the idea that FWAs, by improving the work environment and human capital management, act as strategic intangible assets that increase the overall value of the company on financial markets. Companies in the United States, where flexible work practices are more commonly integrated, show notable outperformance compared to their European counterparts. This regional difference highlights the influence of work cultures and market dynamics in the valuation and impact of FWAs. These discoveries encourage further integration of FWAs into sustainable development and risk management strategies, underlining their potential role in enhancing risk-adjusted returns and promoting innovative and responsible corporate management.

Finally, in the third chapter of this thesis, we explore the integration of environmental, social, and governance (ESG) factors into the traditional Fama-French five-factor model (FF5) to create an enhanced model (FFESG). This new model aims to assess the risk-adjusted performance of sectoral portfolios over an extended period of sixteen years, based on the ability of ESG factors to provide an alpha more representative of market realities. To evaluate the effectiveness of the enhanced FFESG model, we developed investment strategies based on the alphas generated by this model. Two main approaches were tested : a long-only strategy, which involves buying portfolios with positive alphas, and a long-short strategy, where portfolios with positive alphas are bought (long) while those with negative alphas are sold (short). These portfolios were rebalanced monthly over rolling periods of 12, 36, and 60 months and compared to the S&P 500 benchmark. Subsequently, we employed Sharpe and Sortino ratios to measure the performance of these portfolios. Analyses reveal that the FFESG model more effectively explains the variability of returns in sectoral portfolios compared to the traditional FF5 model, as evidenced by a higher R^2. This indicates that the integration of ESG criteria not only enhances the accuracy of the model but also its ability to capture the complex dynamics of sectoral markets. Portfolios based on the alpha derived from the FFESG model have consistently outperformed those based on the alpha generated by the FF5 model. This demonstrates that sector rotation strategies using alphas enriched by ESG criteria can generate superior returns, highlighting the effectiveness of integrating ESG factors into financial valuation models. These results underscore the added value of ESG criteria in constructing sectoral portfolios and improving predictions of risk-adjusted returns. They encourage broader adoption of ESG criteria by investors and portfolio managers, who can use this information to refine their investment strategies and better respond to the challenges and opportunities of the contemporary market.

Keywords : Intangible assets, ESG factors, human capital, portfolio choice, portfolio performance, underreaction, mispricing, value investing, flexible work arrangements, sector rotation, multi-factor models

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Chapitre 1

Introduction

1.1 Context

In this thesis, I examine how intangible assets and ESG criteria influence modern portfolio strategies. The reason I have chosen this topic is rather idealistic. What would happen if fund managers consciously valued intangible assets and ESG practices in their investment decisions ? Could it be that this approach not only improves risk-adjusted financial returns but also promotes a more sustainable and equitable business environment ? Thus, the conscious integration of these elements by fund managers could transform investment practices into a profit maximization strategy that is both rational and responsible. The purpose of this thesis is to analyze how the integration of intangible assets and environmental, social, and governance (ESG) performances by fund managers impacts portfolio returns and risk management. In other words, I investigate to what extent fund managers consider intangible assets and ESG factors to optimize investment strategies while positively contributing to society and the environment.

Historically, portfolio management has relied on two sets of information to develop investment strategies. Fundamental information, which heavily depends on a company's financial statements,

provides insights into a company's intrinsic value and growth prospects (Verheyden et al., 2016). Technical information, which can be derived from a company's past performance on the stock market, offers indicators of current momentum or trends in stock prices and to what extent these trends might continue into the future.

While these two sets of information have helped investors make solid investment decisions for decades, the widespread availability of such data and the technology to process it have increasingly made it difficult to create superior performance in the form of market-beating returns (Verheyden et al., 2016). Beyond fundamental and technical information, which primarily represent a company's past performance, intangible assets and ESG factors present an additional set of information that can also provide insight into future performance (Wu et al., 2022). For example, Warren Buffett shared how, under the influence of his partner Charlie Munger, he transitioned from an investment strategy focused on buying mediocre companies at low prices to investing in quality companies at fair prices. A striking example of this evolution is his investment in Coca-Cola, chosen not for its tangible assets, which are limited, but for the strength of its brand and the quality of its management, illustrating the value of intangible assets and human capital. Moreover, Buffett's investment in Apple in 2016 reinforced this view, marking a decisive turning point. He evaluated Apple as "the best company I know in the world", highlighting not only its technological superiority but also the value of its ecosystem and network effects. These elements underscore the crucial importance of intangible assets in evaluating modern companies.

Echoing these strategic transitions towards investments focused on intangible assets, environmental, social, and governance considerations are also becoming increasingly prominent in business eva-

luations. Effective carbon emission management, for instance, responds to growing regulatory and social pressure in the face of climate change. Concurrently, companies that invest in employee well-being and maintain rigorous governance practices, such as a well-structured board of directors and incentive compensation systems, are better positioned to maintain quality customer service and execute long-term strategies that create sustainable value.

Moreover, according to Morningstar, inflows into U.S. sustainable funds amounted to about 55 billion dollars annually between 2014 and 2018, while they increased to more than 20 and 50 billion dollars in 2019 and 2020, respectively (Naffa and Fain, 2022). The assets under management of U.S. sustainable funds grew from 30 billion dollars in 2010 to 240 billion dollars in 2020. Investors, whether individual or institutional, have expressed, directly or indirectly, a preference for companies with good ratings in environmental, social, and governance aspects (Naffa and Fain, 2022). Thus, these approaches explicitly acknowledge the importance of intangible assets and ESG criteria, serving as tangible proof that these factors are essential for understanding the intrinsic value and future prospects of companies in our current economy.

The literature on the performance of investments in intangible assets and ESG factors covers three main arguments. Firstly, the neutral relationship, supported by Fama (1970), asserts that markets are efficient in terms of information, which makes it impossible to achieve superior risk-adjusted returns. This neutrality is also supported by the studies of Hartmark and Sussman (2019) and Managi et al. (2012). Conversely, some authors argue that these investments lead to potential underperformance. From the perspective of intangible assets, a growing concern among investors, due to the high risk associated with these assets, can make

investors hesitant to increase investments despite potential benefits (Lin et al., 2014; Qureshi and Siddiqui, 2021; Maharani and Narsa, 2023). As for ESG investments, they are often perceived as a restricted subset of the market, which limits their diversification capacity. Moreover, it is sometimes suggested that these investments prioritize sustainability at the expense of short-term returns (Adler and Kritzman, 2008; Bauer et al., 2005; Berlinger and Lovas, 2015). Finally, other studies highlight superior returns by emphasizing the valuation of skills and innovations (Gamayuni, 2015; Zhang, 2017; Kaymaz et al., 2019) and the principle of "doing well by doing good" (Renneboog et al., 2008; Consolandi et al., 2009).

Furthermore, studies on investments in intangible assets and those that integrate ESG criteria adopt two distinct approaches to evaluating these investments. The first approach compares the performance of investments that consider these criteria to those that do not, as demonstrated by Lesser et al. (2016), Nofsinger and Varma (2014), and Pástor and Vorsatz (2020). Another approach considers these criteria as new risk factors, similar to the Fama-French factors (Jin, 2018; Maiti, 2020; Maharani and Narsa, 2023; Gulen et al., 2024). While such performance comparisons are interesting, the goal of this thesis is to explore the possibility that integrating information related to intangible assets and ESG factors may offer opportunities for all investment approaches, including for fund managers who do not primarily focus on non-physical resources.

1.2 Research problem and objectives

Based on the above discussion, we have narrowed the study of intangible assets and ESG factors to the following fundamental dimensions :

According to the International Accounting Standards 38[1], an intangible asset is defined as non-monetary assets that do not have physical substance and are identifiable (being either separable or arising from contractual or other legal rights). Furthermore, Lev and Radhakrishnan (2005) defined intangible assets as claims to future earnings that possess neither physical substance nor financial embodiment. The importance of non-physical assets in business valuation was already recognized by John Stuart, chairman of Quaker Oats in the twentieth century, who valued trademarks and reputation more than physical assets, thus highlighting the superior value of intangible assets (Intara and Suwansin, 2024).

Over time, the recognition of the importance of intangible assets has strengthened in the business world. In 2020, the intangible assets of the S&P 500 constituted 90% of their total value, up from only 17% in 1975, illustrating their growing role in value creation and competitiveness (Tomo, 2020). This trend illustrates how intangible assets have become a broad and complex concept, evolving with changes in the real economy as well as in management practices and economic theory (Castelli et al., 2024).

In 2021, the World Intellectual Property Organization noted that the total value of intangible assets held by listed companies had reached 74 trillion dollars, marking an increase of over 25% since 2019 (World Intellectual Property Organization, 2022). This underscores the strategic importance of intangible assets, such as research and development, computerized databases, and know-how (CFI Team, 2023; Castelli et al., 2024).

According to Augier and Teece (2005) and Wyatt (2005), these intangible assets, which include patents, copyrights, trademarks,

1. https://www.ifrs.org/issued-standards/list-of-standards/ias-38-intangible-assets/

software, and capitalized research and development, are often predominant in high technology and service sectors. They are distinctly different from tangible assets such as information and communication technology (ICT), real estate, and machinery, and illustrate the importance of innovations and specific skills for business competitiveness (Haskel and Westlake, 2018; Kumari and Mishra, 2020).

In the literature, intangible assets are classified into two categories. The first includes clearly identifiable assets such as brand value (Belo et al., 2020; Ertz et al., 2024) and intellectual property (Albuquerque et al., 2020; Huang et al., 2021). The second contains elements related to other assets of the company, such as network effects (McIntyre et al., 2020; Gregory et al., 2021) and human capital (Lopez-Cabrales et al., 2006; Edmans, 2011; Gehrels, 2019; Chokki et al., 2024).

Furthermore, the decline in the effectiveness of traditional investment strategies has been attributed to profound changes in the nature of businesses and the assets they hold, which affects their intrinsic value (Ohlson, 1995; Angelopoulos et al., 2012; Ashraf, 2020; Dugar and Pozharny, 2021). Dukes et al. (1980) and Lev and Aboody (1998) also highlighted that the evolution of accounting standards and the rise of intangible assets, often unrecognized in financial statements, have begun to make traditional valuation methods less effective.

This trend has been confirmed by more recent research by Falato et al. (2020), Lev and Srivastava (2019), Belo et al. (2020), and Israel et al. (2021), who noted that the increasing importance of these intangible assets and changes in modern accounting have complicated the successful application of value investment strate-

gies in an economic environment increasingly valuing innovation and intangible assets.

These observations have led to the hypothesis that value investment strategies are facing difficulties due to the increasing importance of intangible assets. If intrinsic value is redefined to include these tangible and intangible assets, it is likely that value investing will once again outperform (Ahmed and Nanda, 2000; Eisfeldt and Papanikolaou, 2014; Bezuidenhout and van Vuuren, 2021; Eisfeldt et al., 2022; Ewens et al., 2023).

In response to this evolution of market conditions, the Sparkline Intangible Value ETF (ITAN) was launched in 2021 (Sparkline, 2024; Refinitiv, 2024). This fund uses advanced natural language processing (NLP) techniques to quantify the value of intangible assets (brand value, intellectual property, network effect, human capital) introducing an AI-based method for targeting investments in companies with high intangible value. The use of NLP for assessing intangible assets is also explored in academic works such as those by Mori (2016), Ranjan and Read (2016), Argyris et al. (2020), Ezenwafor et al. (2021), Cui et al. (2021), Ozheya (2021), and Xu et al. (2022).

This situation leads to our first research question : Is it profitable to invest in the enhanced intrinsic value of intangible assets through the Sparkline Intangible Value ETF ? We address this question by comparing the financial performance of the Sparkline Intangible Value ETF with that of its conventional counterpart, the Russell 1000 Value index, and the S&P 500, over the period from 2021 to 2024.

Alongside the growing recognition of the value of intangible assets, the COVID-19 pandemic has highlighted the importance of

flexible work arrangements (FWAs), which directly influence key aspects of an organization's human capital such as satisfaction, motivation, and employee loyalty (Akuoko et al., 2021; Craig and Churchill, 2021). These arrangements have been crucial in maintaining operational effectiveness during periods of lockdown and health restrictions (Parlak et al., 2021; Bin et al., 2021; Kähkönen, 2023). Lambert et al. (2008) define flexible work arrangements as a set of benefits offered by the employer that allow employees to choose when and where they work, outside of normal working hours. This includes full-time flexible schedules, part-time work options, and teleworking (Blake-Beard et al., 2010).

The existing literature emphasizes that flexible work arrangements significantly contribute to the increase in employee satisfaction and engagement, as well as to the reduction of turnover rates (Posthuma et al., 2013; Cegarra-Leiva et al., 2012; Wang et al., 2011). These practices are also associated with an improvement in organizational performance (Kotey and Sharma, 2019) and play a crucial role in attracting exceptional talent and developing strategic skills, enhancing business competitiveness (Kotey, 2017). Furthermore, several studies have highlighted a positive impact of FWAs on the financial performance of companies (Bal and Dorenbosch, 2015; Been et al., 2016a).

However, the efficient market hypothesis proposes that any beneficial characteristic of a company should be quickly integrated into its stock valuation, reducing the possibility of realizing abnormal gains (Edmans, 2011). Despite this, a substantial body of research indicates that the market tends to undervalue certain essential aspects of companies, particularly intangible assets (Lev and Sougiannis, 1996; Chan et al., 2001; Gompers et al., 2003; Yermack, 2006). Therefore, given that FWAs contribute to the

creation of these intangible assets, it can be inferred that they are also undervalued by the market. Thus, the research question guiding our second chapter is as follows : Do the benefits of flexible work arrangements lead to superior returns on the stock market ?

To answer this question, we constructed two portfolios : the Q5 portfolio, consisting of companies with the top 20% of FWA scores, and the Q1 portfolio, comprising those with the lowest 20% of scores. We also evaluated a long-short portfolio (Q5-Q1) to isolate the impact of FWAs from general market trends. The effectiveness of these portfolios was measured through risk-adjusted performance indicators such as the Sharpe and Sortino ratios, value-at-risk adjusted returns, and the alphas from Jensen's and the Fama-French five-factor model.

In the extension of transformations in management practices, particularly the emphasis on intangible assets and flexible work arrangements, commitment to sustainability principles has also gained momentum. The launch of the Sustainable Development Goals by the United Nations in 2015 marked a global commitment to a more sustainable future, demanding active involvement from all sectors of society (Naffa and Fain, 2020). Stakeholder and societal pressure has prompted the investment community to direct its resources towards more sustainable initiatives, significantly increasing the appeal for environmentally, socially, and governance (ESG) responsible investments (Nagy et al., 2016; Giese et al., 2021). Capital flows into socially responsible funds have reached historical highs, with assets under management in sustainable funds in the United States climbing from 30 billion dollars in 2010 to 240 billion dollars in 2020, reflecting a transition towards non-financial motivations in investment decisions (Dinh, 2023; Nsibande and Sebastian, 2023).

Concurrently, the five-factor model (FF5) has shown its limitations in fully explaining the cross-sections of industry returns (Chava et al., 2019; Nsibande and Sebastian, 2023). Faced with this shortcoming and the growing interest in ESG factors, it has become essential to enhance portfolio return forecasts by integrating ESG factors (FFESG) into traditional models (FF5) (Jin, 2018; Maiti, 2020; Naffa and Fain, 2022; Nsibande and Sebastian, 2023).

It is therefore reasonable to ask why we choose ESG factors to enhance the model. Our answer is that : companies with high ESG scores attract additional investments due to their compliance with these practices, which can lead to a short-term rise in their stock prices. This increase, often perceived as a boost, is the result of the influx of capital from investors attracted by social and environmental responsibility (Hartmark and Sussman, 2019; Statman, 2020). The market also tends to react positively to good ESG evaluations by anticipating a reduction in future risks, such as costs related to new environmental regulations or the consequences of social scandals (Clark et al., 2015; Friede et al., 2015; Díaz et al., 2024). These anticipations translate into more favorable stock valuations (Maiti, 2021; Dinh, 2023). Particularly in sectors heavily impacted by environmental issues, such as energy, clean technologies, or healthcare, companies well-rated on the ESG scale may benefit from a specific sectoral advantage (Miralles-Quirós et al., 2020). Innovations and advancements in these areas can position these companies ahead of their competitors, reflecting a premium on their shares. Thus, the ESG factor, by measuring the difference in performance between companies with the highest and lowest scores, captures these market dynamics (Nsibande and Sebastian, 2023). This differential not only demonstrates traditional financial strength but also the momentum generated by a commitment to ESG practices (Giese et al., 2021). This momentum allows for an alpha that is more re-

presentative of the current and future opportunities and risks of companies (Nsibande and Sebastian, 2023).

Consequently, the enhanced alpha that takes into account both financial performance and sustainability offers a more comprehensive approach, enhancing the appeal of companies with high ESG ratings and confirming the effectiveness of integrating ESG criteria into investment strategies. This approach also addresses the concerns of investors who increasingly prioritize social and environmental responsibility. This leads us to the question : Can ESG factors enhance the Fama and French five-factor model (FF5) by providing a better explanation of sectoral portfolio returns ? This inquiry allows us to examine the risk-adjusted performance (alpha) of sectoral portfolios through the new FFESG model.

If the FFESG alpha of a sector is truly the genuine alpha (i.e., an accurate indicator of stock-picking talent), then applying a sectoral investment strategy based on such an alpha should yield superior returns. This observation leads us to pose the following question : What is the effectiveness of using the alpha generated by the FFESG model in constructing sector rotation strategies ?

To evaluate the effectiveness of the FFESG model compared to the FF5 model, we use an OLS regression to compare their ability to explain the variance in sectoral portfolio returns. A higher R^2 for the FFESG model would indicate better predictive performance, thus confirming the utility of ESG factors in forecasting returns. Next, to test the practical viability of the alphas generated, we have developed four investment strategies : two "long only" and "long-short" strategies, based on the alphas from the FFESG and FF5 models. These strategies are tested over rolling periods of 12, 36, and 60 months to examine their performance under different

market conditions. The results are compared to the returns of the S&P 500 index to assess whether investing based on FFESG alphas leads to outperformance.

1.3 Choice of data

In this thesis, we have used data provided by Refinitiv, which is now part of the data and analytics activities of the London Stock Exchange Group (LSEG).

The selection of this database was based on its reputation, breadth, and availability. Refinitiv is one of the global leaders in providing financial data. Its ESG database, one of the most comprehensive, covers over 90% of global market capitalization with more than 720 different ESG metrics. It is recognized as a benchmark in the field, also offering extensive coverage of emerging markets. Despite the criticisms often directed at ESG data providers concerning the divergence of their ratings, based on sets of customized metrics, Refinitiv displays correlation coefficients of 0.75 and 0.752 with Bloomberg and Sustainalytics, respectively (Gibson et al., 2021). These scores are therefore considered robust and reliable for the needs of this thesis.

The factor data, including regression factors, comes from the data library of Kenneth R. French [2], which is based on the complete universe of public equities.

1.4 Contribution

In this thesis, we propose to deeply explore how the integration of non-traditional metrics such as intangible assets and ESG factors

2. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

can potentially lead to better investment strategies and superior financial outcomes.

The integration of Environmental, Social, and Governance (ESG) factors, along with intangible assets, is becoming crucial in the development of modern investment strategies. These ESG factors, representative of the principles of sustainable finance, include ecological initiatives, fair labor policies, and transparent governance, and are considered key indicators of the viability and long-term performance of companies. Intangible assets, such as intellectual property, human capital, and brand reputation, also play an increasingly strategic role. As environmental challenges intensify pressure on companies to adopt more sustainable practices, the effective management of these assets becomes essential. Companies that manage to integrate ESG factors and intangible assets into their investment strategies judiciously do not only meet the heightened expectations of regulators, investors, and the public in terms of responsibility. They also position themselves to benefit from superior and sustainable financial performance, while contributing to environmental protection and the promotion of a more equitable society. This synergy between intangible assets and ESG criteria constitutes a fundamental pillar for modern investors, who seek not only financial returns but also a positive impact on society.

Consequently, the question remains open as to the ability of investors to profit from companies that value their intangible assets, as demonstrated in the analysis of the Sparkline Intangible Value ETF (Chapter 2). Similarly, it is pertinent to ask whether companies that broadly adopt flexible work arrangements (Chapter 3) present a favorable investment opportunity. Finally, the effectiveness of the alphas generated by the Fama-French model enhanced with the integration of ESG factors, in the context of sector ro-

tation strategies in the United States (Chapter 4), also raises a major inquiry. These crucial aspects prompt significant reflections on modern investment strategies and the valuation of companies within current financial markets.

We enrich the existing literature by testing these hypotheses on various samples and employing different methodologies, including a wide range of measures such as the adjusted Sharpe ratio, return on value at risk, and the alphas from factor models, among others. These contributions are intended to have a significant impact in the field in the short term and will contribute to deepening the academic exploration of the dynamics surrounding the integration of intangible assets and ESG factors. This innovative approach not only illuminates the practical implications of these strategies but also enriches the academic debate on the effectiveness of integrating ESG factors and intangible assets into financial models.

Our research addresses existing gaps by exploring less studied aspects in the context of value investing, flexible work arrangements, and sector rotation strategies. This study enriches our understanding of the benefits that companies, fund managers, and financial institutions can achieve by focusing on enhancing the impact of intangible assets and ESG factors. It underscores the importance of redirecting their investment strategy to integrate supplementary financial information. This research offers new perspectives on the influence of intangible assets and ESG factors in traditional financial decision-making, providing valuable insights for policymakers and industry professionals.

This thesis sheds new light on the added value of asset diversification, with a particular focus on intangible assets. The originality of the research lies in its demonstration of how the effective exploi-

tation of these resources can improve the risk-adjusted financial performance of companies from various economic sectors.

This thesis also enriches several areas of academic literature, highlighting the importance of corporate social and environmental information in evaluating their overall performance. Our work supports a view of performance that integrates financial, economic, social, environmental, and societal objectives, affecting both companies and their stakeholders. This finding reinforces the theories presented by Lin et al. (2014) and Naffa and Fain (2022), who emphasize the importance of integrating environmental and social information in extra-financial communications.

Our results also support the argument for a broader view of shareholder value, which includes stakeholders in value creation. They highlight the diversity of performance dimensions and the heterogeneity of their nature, echoing the contributions of Chava et al. (2019), Chan et al. (2001), and Lev and Zarowin (1999). These authors propose an expanded analysis of the value created, including non-financial factors such as human capital, relational capital, and communities.

Finally, our work shows that recent financial and health crises have catalyzed a change in the discourse of leaders. Environmental, societal, ethical, and financial concerns now coexist, marking the beginning of an era where communication is more centered on overall performance.

Chapitre 2

Does It Pay to Incorporate Tangible and Intangible Value in Value Investing ? Evidence from the Sparkline Intangible Value ETF

Abstract

Value investing has seen its effectiveness decrease in recent years, primarily due to the increase in intangible assets that are not accounted for in financial statements. Adjusting book values to integrate intangible assets has become a significant topic of debate. In this context, the Sparkline Intangible Value ETF (ITAN) has modernized value investing by incorporating four pillars of intangible value. However, evaluating the performance of this fund, particularly in terms of risk-adjusted returns, remains an open question. This paper analyzes the financial performance of ITAN compared to its conventional counterpart, the Russell 1000 Value index, and the S&P 500, to assess the impact of this modern approach on returns. Our analyses reveal that although ITAN often offers risk-adjusted returns superior to those of the Value index, it has shown inferior performance during economic recovery phases and in comparison with the S&P 500 throughout the studied period. These results illustrate that, despite the potential of intangible assets to enhance performance relative to traditional investment strategies, their integration does not guarantee consistent outperformance against the broader market.

Keywords : Value investing, intangible assets, portfolio choice, performance

JEL Classification : E32, E52, G11

2.1 Introduction

Value investing, one of the earliest structured investment strategies in the world, has become essential in the investment universe since its introduction to the general public by by Graham et al. (1934). In recent years, one of the most discussed debates from the perspective of academic research is the differentiation of returns in value versus growth portfolios, known as the value premium debate (see e.g., De Bondt and Thaler, 1985; Fama and French, 1992, 1993; Fama, 1996; Lakonishok et al., 1994; Daniel and Titman, 1997; Cronqvist et al., 2015).

The value premium is the result of cheaper stocks outperforming more expensive stocks on average. It is achieved by buying cheap stocks and short-selling expensive ones (Asness et al., 2015). The intuition behind the value premium suggests that investors earn a risk-adjusted return by buying cheaper stocks because there has been a net overreaction by market participants associated with the specific stock. The value investor's gain is realized when the market recognizes that the stocks are undervalued, and subsequently, the price returns to its intrinsic value (Lev and Srivastava, 2019). Lev2019, Bezuidenhout2021. The value premium has been sought by investors for centuries, as the strategy has produced risk-adjusted returns (Zhang, 2005).

In recent years, particularly before the health crisis, investments in growth stocks have significantly outperformed those in value stocks. Although value investments have occasionally outperformed the growth category, the Russell 1000 Growth index recorded an increase of 264%, compared to only 91% for the Russell 1000 Value index (Monge et al., 2023).

Historically, the Fama-French value strategy experienced a no-

table period of success from 1970 to 1990, with impressive returns of $2.02 and $1.75 for every dollar invested in 1970 and 1980, respectively. However, starting in 1989, the effectiveness of this strategy declined due to the tech bubble of the 1990s, which overvalued fast-growing companies and made shorting these "glamour stocks" unprofitable (Lev and Srivastava, 2022). After the bubble burst in 2000, there was a brief recovery thanks to effective shorting of overvalued stocks, but since 2007, the value strategy has again faced difficulties, signaling the end of its previous prosperity (Bogdanova, 2020).

This decline in the effectiveness of the value strategy can also be explained by profound changes in the nature of companies and the assets they hold, thereby affecting their intrinsic value (Ohlson, 1995; Angelopoulos et al., 2012; Ashraf, 2020; Dugar and Pozharny, 2021). Studies conducted by Dukes et al. (1980) and Lev and Sougiannis (1996), highlighted how the evolution of accounting standards and the rise of intangible assets, often unrecognized in financial statements, began to make traditional valuation methods less effective. More recently, Falato et al. (2020), Lev and Srivastava (2019), Belo et al. (2020) and Israel et al. (2021) have confirmed that the increased importance of these intangible assets and changes in modern accounting have contributed to the obsolescence of financial information, further complicating the successful application of value investment strategies in an economic environment that increasingly values innovation and intangible assets.

In light of these observations, we hypothesize that value investment strategies have encountered difficulties due to the growing importance of intangible assets. Consequently, if intrinsic value is redefined to include both tangible and intangible values, it is likely that value investing will once again outperform (Ahmed and

Nanda, 2000; Eisfeldt and Papanikolaou, 2014; Bezuidenhout and van Vuuren, 2021; Eisfeldt et al., 2022; Ewens et al., 2023).

In response to this evolution of market conditions, which underscores the need to more precisely integrate intangible assets into business valuations, the Sparkline Intangible Value ETF (ITAN) [1] was launched in 2021 (Sparkline, 2024; Refinitiv, 2024). This fund employs advanced natural language processing (NLP) techniques to quantify the value of intangible assets, introducing an AI-based method to target investments in companies with high intangible value. The use of NLP for the evaluation of intangible assets is also explored in academic works such as those by Mori (2016), Ranjan and Read (2016), Argyris et al. (2020), Ezenwafor et al. (2021), Cui et al. (2021),Ozheya (2021), and Xu et al. (2022), although the specific algorithms used by the fund are not disclosed.

This leads to the central research question of this paper : Is it profitable to invest in the intangible-augmented intrinsic value through the Sparkline Intangible Value ETF ? We address this question by comparing the financial performance of the Sparkline Intangible Value ETF with that of its conventional counterpart, the Russell 1000 Value index, and the S&P 500 index, which serves as a general market benchmark, over the period from 2021 to 2024. This analysis will allow us to determine whether investing in intangible assets, as targeted by ITAN, offers a competitive advantage over the general market and specifically compared to value-focused investment strategies. Examining the performance of ITAN is essential for investors interested in intangible assets. These investors want to ensure that the risk-adjusted returns of this fund are competitive before deciding to invest, particularly if these returns can rival

1. https://etf.sparklinecapital.com/itan/. To our knowledge, ITAN is the only fund that uses natural language processing to quantify intangible assets and integrate them into the intrinsic value of companies, thus offering a value investing approach adapted to the modern intangible economy.

those of more traditional investment vehicles. Strong performance of ITAN could positively influence investment decisions towards companies that highly value their intangible assets.

By examining the risk-adjusted returns of the Sparkline Intangible Value ETF, this study contributes to the literature in several ways. First, it expands the debate on the impact of integrating intangible values into the evaluation of intrinsic value and their effect on the financial performance of portfolios. Although many studies have explored the financial consequences of integrating intangible assets (Core et al., 2003; Corrado, 2005; Ciftci et al., 2014; Crouzet and Eberly, 2019; Peters and Taylor, 2017; Amenc et al., 2020; Arnott et al., 2021) from a portfolio perspective, very few have examined the specific effects of using advanced techniques like natural language processing (NLP) to quantify these assets before their integration into valuations.

Furthermore, it is important to note that our study does not create portfolios based on a new evaluation of intrinsic value (Peillex et al., 2021). Instead, we directly use the Sparkline Intangible Value ETF, an existing and actively managed financial product, accessible via platforms such as Refinitiv. This allows us to more accurately assess the gains or losses that investors may experience by allocating their wealth to a real financial product that encourages companies to implement strategies focused on intangible values, such as R&D (Lim et al., 2020; Huang et al., 2021), brand development (Keller, 1993; Belo et al., 2020; Ertz et al., 2024), human capital (Hitt et al., 2001; Edmans, 2011; Kotey and Koomson, 2021; Yarovaya et al., 2021), and network effects (Hagiu and Wright, 2015; McIntyre et al., 2020; Gregory et al., 2021). Indeed, analyzing the Sparkline Intangible Value ETF, an existing and actively managed financial product, can provide directly useful ap-

plications for investors looking to refine their investment strategies. This product, which focuses on the valuation of intangible assets, allows investors to better align their portfolios with emerging intangible trends in the market. Moreover, the study of ITAN offers an in-depth understanding of market mechanisms and the effectiveness of investment strategies based on intangible values, thus providing valuable insights for researchers, financial practitioners, and policymakers.

Finally, we enrich the literature on value investing by exploring how, in an economic context where intangible assets predominate, our study can redefine and update traditional value investing methods. By focusing on the integration of intangible assets, we propose a new perspective that adapts value investing to current market dynamics.

Our results show that ITAN outperformed the Value index in terms of risk-adjusted returns, except during the economic recovery period from July 2021 to December 2022. However, compared to the broader market S&P 500, neither ITAN nor the Value index offer superior risk-adjusted performance.

The rest of this paper is organized as follows. Section 2.2 presents a review of the existing literature on value investing and its adaptations to intangible assets. Section 2.3 details the database used and methodology employed. Section 2.4 examines the descriptive statistics and details the empirical results of the proposed investment strategies. Finally, Section 2.5 provides the main conclusions.

2.2 Literature review

2.2.1 Value Investing

Value investing is an approach where one selects stocks trading at prices that appear to be below their true value, whether it be book or intrinsic value (Chee et al., 2013; Calandro, 2014; Duong et al., 2014; Asness et al., 2015; Chen, 2017). This method involves targeting assets deemed undervalued by the market, assuming an exaggerated reaction to news, whether good or bad, thus creating opportunities to make a profit (Gray and Carlisle, 2013). Graham et al. (1934) introduced this approach, emphasizing the importance of thorough analysis, both qualitative and quantitative.

According to Lakonishok et al. (1994), value stocks tend to outperform during periods of economic stability but have lower returns during recessions, thus challenging the traditional hypothesis that higher risk leads to higher returns. Chopra et al. (1992) and Zhang (2005) confirmed this observation by studying the historical effect of what is known as the value premium, concluding that this strategy does not expose investors to additional risk. Over time, and despite the economic fluctuations of the 20th century, value investing has maintained solid performance (Asness et al., 2015; Israel et al., 2021).

However, since the early 2010s, value stocks have tended to underperform compared to growth stocks in the United States, with brief periods where they outperform the latter. This situation is likely due to the significant outperformance of technology stocks and the underperformance of the energy and finance sectors (Lev and Srivastava, 2022; Monge et al., 2023).

2.2.2 Accounting Failures

Book value, crucial for the price-to-book ratio, is often marred by substantial errors due to the failure to update balance sheet assets to reflect their current value (Eisfeldt et al., 2022). This inaccuracy is exacerbated by the immediate expensing of intangible investments such as R&D (Donadelli et al., 2017; Albuquerque et al., 2020; Hochberg et al., 2018; Li and Hou, 2019; Lim et al., 2020; Huang et al., 2021), brand development(Pillai, 2012; Belo et al., 2020; Keller, 1993; Yoo et al., 2000; Moorman and Day, 2016) , human capital (Edmans, 2011; Gehrels, 2019), and network effects (Afuah, 2013; Parker et al., 2017; Hagiu and Wright, 2015; McIntyre et al., 2020; Gregory et al., 2021), which, although drivers of future value creation, are not reflected in book values.

Historically, since the late 1980s, the omission of these intangible investments in balance sheets has profoundly altered companies' financial data (Lev and Sougiannis, 1996; Li, 2020; Israel et al., 2021). In the era of Graham et al. (1934), tangible assets were fully represented in book values. However, with the increase in intangible investments, a major transformation in business models has taken place, marking the shift from tangible asset predominance to intangible dominance (Upton, 2001; Perez and Famá, 2006; Corrado and Hulten, 2010; Mooncraft, 2020). For example, two similar companies, one developing patents internally and the other acquiring patents, will show very different price-to-book ratios, with the former having a lower book value. The same phenomenon is observed with the price-to-earnings ratio. Companies investing in intangibles have understated earnings due to the immediate expensing of these assets, leading to inflated PE ratios (Lev and Srivastava, 2022).

Intangible assets now represent a significant portion of companies' capital. In 2003, they accounted for about one-third of the

non-residential capital stock in the United States (Corrado et al., 2009), and more recent studies indicate that this share could be nearly half (Falato et al., 2020; Belo et al., 2020; Eisfeldt et al., 2022; Ewens et al., 2023). These investments are primarily generated by spending on personnel and knowledge capital development, which, although essential, remain invisible in balance sheets, thus contributing to the undervaluation of assets in companies' financial statements (Lev and Srivastava, 2019; Arnott et al., 2021).

2.2.3 Adapting Value Investing to Intangible Assets

Penman and Reggiani (2018) highlight the limitations of accounting ratios, even when combined with the earnings yield (E/P), in predicting future growth rates, revealing that investments classified as "value" can, in reality, target growth. This observation is reinforced by Lettau et al. (2019), who find that many funds labeled as "value funds" do not rely exclusively on the book-to-price ratio, often resulting in portfolios that combine growth and value. They also note that some funds have outperformed during periods of value strategy underperformance, thanks to a timely redefinition of what constitutes "value." Similarly, Arnott et al. (2021) emphasize the importance of capitalizing intangible assets for a more accurate evaluation of companies' capital, an approach that, according to their analyses, would have increased the annual average return of the Fama-French HML factor by 2.2% over the past 13.5 years.

Recent studies, including those by Amenc et al. (2020) and Lev and Srivastava (2019), examine how the ascendancy of intangible assets over physical assets affects value strategies in the United States. They adjust price-to-book ratios to mitigate biases induced by unaccounted intangible capital and agree that the decline in the effectiveness of valuation strategies in the United States cannot be fully explained by structural economic changes related to intan-

gible assets or by the inadequacy of current accounting standards to these changes. Li (2020) extends this research to other countries, including the United Kingdom, Japan, continental Europe, and Asia excluding Japan. Dugar and Pozharny (2021) also explore the adaptation of traditional equity investment analysis to incorporate the impact of varying intensity of intangible assets among companies and industries. Extending this analysis to the fourteen major world economies, they demonstrate a notable decrease in the correlation between financial variables and stock prices, observable both in the United States and internationally for high-intangible intensity companies.

The previously discussed studies have focused on the necessary accounting and financial adjustments to properly evaluate intangible assets, highlighting the transition to an information-dominated economy. This awareness has paved the way for innovative approaches such as the use of natural language processing (NLP) to analyze and quantify these intangible assets, a crucial approach for modern financial instruments such as the Sparkline Intangible Value ETF (ITAN).

2.2.4 An Overview of the Sparkline Intangible Value ETF (ITAN)

The Sparkline Intangible Value ETF, launched on June 29, 2021, modernizes value investing by emphasizing intangible assets. As the economy evolves from industrial sectors to information-dominated domains, the valuation of intangible assets becomes crucial for determining the intrinsic value of companies (Ashraf, 2020). ITAN capitalizes on this trend by leveraging advanced technologies, including natural language processing (NLP), to analyze unstructured data and quantify the value of these intangible assets.

As of May 31, 2024, ITAN trades on the NYSE with net as-

sets of $35.49 million spread across 153 holdings (Refinitiv, 2024). The fund focuses on the equity securities of the 1,000 largest U.S. companies by market capitalization, seeking to achieve long-term capital appreciation by investing in companies that significantly value their intangible assets (Sparkline, 2024).

ITAN employs a proprietary quantitative methodology to evaluate companies across several key dimensions (Sparkline, 2024). Human capital pertains to the evaluation of a company's workforce, including its ability to attract and retain talent (Edmans, 2011; Chokki et al., 2024). Brand value is measured by the brand's recognition and influence on sales and customer loyalty (Belo et al., 2020; Ertz et al., 2024). Intellectual property is assessed by the value of patents and trade secrets, which are crucial for innovative companies (Huang et al., 2021; Albuquerque et al., 2020). Network effects consider the added value from an increasing number of users, strengthening the company's market position (McIntyre et al., 2020; Gregory et al., 2021). Finally, while the emphasis is on intangibles, tangible assets are also considered to provide a comprehensive company evaluation (Lev and Srivastava, 2019; Bezuidenhout and van Vuuren, 2021).

By combining scores from these five pillars, ITAN creates a composite score for each company, highlighting those with the best evaluations (Sparkline, 2024). This strategy allows ITAN to target companies with high growth potential and outperform traditional value-focused approaches.

Table 2.1 displays the top 10 companies and their respective weights in the ITAN as well as in the Value and SPY indices. Table 2.2 compares the sector weights of ITAN with those in the Value and SPY indices. ITAN shows a strong concentration in the

technology and consumer discretionary sectors, with 40.17% and 14.46% respectively, compared to the Value index, which shows only 9.93% and 6.89% in these same sectors. This overrepresentation highlights the importance of intangible assets such as intellectual property, patents, network effects, and advanced technologies, which are frequently valued in technology companies. Similarly, consumer discretionary companies, such as Amazon, benefit from strong brands and efficient distribution networks, crucial elements of their intangible value. On the other hand, ITAN exhibits a notable underrepresentation in the financial sector, with only 5.15% compared to 22.05% in the Value index. Financial companies, despite possessing intangible assets such as fintech and loyal customer networks, are less prominent in ITAN due to the predominance of more tangible assets in this sector. Regarding the SPY, the sector compositions are similar. However, ITAN shows a higher concentration in the industrial sector compared to the SPY, with 16.37% versus 10.27%.

Table 2.1. Top 10 constituents of the ITAN, Value, and SPY indices as of May 31, 2024. *Source : Refinitiv*

ITAN			**Value**			**SPY**		
Company	Sector	Weight	Company	Sector	Weight	Company	Sector	Weight
AMZN	Cons. Cycl.	4.01	BERKSH.	Cons. Non-Cyc.	3.52	MSFT	Tech	6.95
META	Tech	3.08	JPMORG.	Fin.	2.71	AAPL	Tech	6.29
ORCL	Tech	2.19	EXXON	Energy	2.47	NVDA	Tech	6.10
GOOGL A	Tech	2.14	J&J	Health	1.64	AMZN	Cons. Cycl.	3.63
GOOGL C	Tech	2.13	P&G	Cons. Non-Cyc.	1.46	META	Tech	2.31
QCOM	Tech	2.00	WALMART	Cons. Non-Cyc.	1.30	GOOGL C	Tech	2.29
CRM	Tech	1.73	CHEVRON	Energy	1.29	GOOGL A	Tech	1.93
CSCO	Tech	1.68	BOA	Fin.	1.28	BERKSH.	Cons. Non-Cyc.	1.70
IBM	Tech	1.61	MERCK	Health	1.21	LLY	Health	1.47
AT&T	Tech	1.53	WELLS FARGO	Fin.	1.00	JPMORG.	Fin.	1.32

Table 2.2. Sector weights for ITAN, Value, and SPY indices as of May 31, 2024. *Source : Refinitiv*

Sector	ITAN	Value	SPY
Technology	40.17	9.93	39.83
Industrials	16.37	17.85	10.27
Consumer Cyclicals	14.64	6.89	11.47
Healthcare	11.28	13.52	11.73
Telecom	5.98	2.57	1.31
Financials	5.15	22.05	10.78
Non Classified Equity	1.75	-	-
Consumer Non-Cyclicals	1.72	7.99	4.97
Basic Materials	1.59	4.68	2.26
Energy	0.89	8.18	3.96
Utilities	-	5.45	2.58

2.3 Data and methodology

The Sparkline Intangible Value ETF was launched on June 29, 2021 (Refinitiv, 2024; Sparkline, 2024). Therefore, our study spans from July 2021 to May 2024, encompassing nearly three years of monthly data, totaling 35 observations. Following the methodology of Gil-Bazo et al. (2010), Erragragui et al. (2018), and Peillex et al. (2021), we also analyze two sub-periods : from July 2021 to December 2022 and from January 2023 to May 2024. This allows us to assess the persistence of comparative performance between ITAN and its conventional counterparts. Monthly prices for ITAN, Value Index, and the S&P 500 Index are sourced from the Thomson Reuters Eikon database (Hawn and Ioannou, 2016; Chokki et al., 2024). All prices are denominated in U.S. dollars (Mirza et al., 2020). All risk factors are also expressed in U.S. dollars and gathered from the Kenneth R. French data library. [2]

Building on the methodologies established by Peillex et al. (2021) and **?**, the monthly returns of ITAN, Value, and SPY are calculated

2. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

using the following formula :

$$R_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{2.1}$$

where R_t represents the monthly return of index i at time t, and $P_{i,t}$ is its closing price at the end of the month.

To assess the financial performance of ITAN relative to the Value and SPY, several traditional performance indicators are used, including Sharpe ratios (Sharpe, 1966), adjusted Sharpe ratios (Pezier and White, 2006), Sortino ratios (Sortino and Price, 1994), value-at-risk adjusted returns (Jorion, 2001), Jensen's alphas (Jensen, 1968), the three-factor models of Fama-French (Fama and French, 1993), and the five-factor models of Fama-French (Fama and French, 2015).

Given ITAN's focus on both tangible and intangible assets, it is crucial that it effectively manages both diversifiable and non-diversifiable risks. The Sharpe ratio, an indicator of risk-adjusted performance for portfolios, is particularly suited for this analysis :

$$\text{Sharpe Ratio} = \frac{R_i - R_f}{\sigma_i} \tag{2.2}$$

In this formula, R_i represents the average monthly return of the index, R_f is the risk-free rate, and σ_i is the standard deviation of the index's monthly returns over the study period. This approach ensures that ITAN's performance analysis is directly comparable to that of traditional indices over the same monthly periods, providing a clear view of how ITAN manages investment risks associated with tangible and intangible assets. In addition to the Sharpe ratio, we also use the Adjusted Sharpe Ratio (ASR) for a more accurate assessment of risk-adjusted performance. The ASR accounts not only for volatility but also for skewness and kurtosis of returns,

thus providing a more comprehensive and realistic measure of the risks associated with a portfolio. Indeed, stock portfolios are often subject to asymmetric return distributions and high kurtosis, which can distort performance evaluation if based solely on volatility (Ángel León and Niguez, 2021; Vinzelberg and Auer, 2022). The Adjusted Sharpe Ratio is calculated as follows, following the methodology of Rizvi et al. (2020) :

$$\mathrm{ASR}_{pt} = \mathrm{SR}_{pt}\left(1 + \frac{\mathrm{sk}}{6} \times \mathrm{SR}_{pt} - \left(\frac{\mathrm{kr}-3}{24}\right)\right) \times \mathrm{SR}_{pt}^2 \tag{2.3}$$

where SR_{pt} is the Sharpe Ratio, sk is the skewness of the returns, and kr refers to kurtosis. This adjustment better accounts for the specific characteristics of the return distributions of portfolios, thus providing a more faithful evaluation of their risk-adjusted performance. The Sortino Ratio is also a measure of risk-adjusted performance. Unlike the Sharpe Ratio, it compares excess returns to the downside deviation of portfolio returns. This comparison is relevant because a typical investor is concerned about adverse shocks and wishes to evaluate returns relative to downside risk. Therefore, the Sortino Ratio is a popular metric for estimating risk-adjusted performance across various asset classes (Damianov and Elsayed, 2020; Sanford, 2021). In the presence of negative volatility σ_d, for a portfolio with returns R_p and the risk-free rate r_f, we estimate the Sortino Ratio (ST) as follows :

$$\mathrm{ST}_{pt} = \frac{R_p - R_f}{\sigma_d} \tag{2.4}$$

Previous studies on stock returns (Liu and Lei, 2021; Galakis et al., 2022) have indicated the non-linearity and plausibility of higher-order moments. Therefore, in addition to the ASR, we also use Value-at-Risk adjusted returns (Chokki et al., 2024). VaR is the maximum possible investment loss incurred over a fixed time

horizon under a certain confidence interval. For this paper, we estimate the VaR for portfolio p based on the returns R, volatility σ, and z_α at 95% as follows :

$$\text{VaR}_{pt} = R_{pt} - z_\alpha \sigma_{pt} \tag{2.5}$$

Once the VaR is estimated, we calculate the risk-adjusted returns as follows :

$$\text{RAR}_{pt} = \frac{R_p - R_f}{\text{VaR}_{pt}} \tag{2.6}$$

The models used to estimate Jensen's alpha, the three-factor model by Fama-French, and the five-factor model by Fama-French are as follows : For Jensen's alpha :

$$R_{i,t} - R_{f,t} = \alpha_{\text{Jensen}} + \beta^{\text{MKT}}(R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \tag{2.7}$$

For the three-factor model by Fama-French :

$$R_{i,t} - R_{f,t} = \alpha_{\text{FF3F}} + \beta^{\text{MKT}}(R_{m,t} - R_{f,t}) + \beta^{\text{SMB}}\text{SMB} + \beta^{\text{HML}}\text{HML} + \varepsilon_{i,t} \tag{2.8}$$

For the five-factor model by Fama-French :

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i^{\text{FF5F}} &+ \beta_i^{\text{MKT}}(R_{m,t} - R_{f,t}) + \beta_i^{\text{SMB}}\text{SMB} \\ &+ \beta_i^{\text{HML}}\text{HML} + \beta_i^{\text{RMW}}\text{RMW} + \beta_i^{\text{CMA}}\text{CMA} + \epsilon_{i,t} \end{aligned} \tag{2.9}$$

In each model, $R_{i,t}$ and $R_{f,t}$ respectively represent the returns of the index and the risk-free rate for month t, with $R_{m,t}$ being the return of the market portfolio during the same period. The SMB and HML factors represent size and value factors as defined by Fama and French (1993), while RMW and CMA, introduced by Fama and French (2015), represent robust operating profitability and conservative investment, respectively. These models are designed to explain variations in returns, capturing the effects of market, size, value, profitability, and investment styles. The significance of the alphas, representing excess returns after accounting

for these factors, is estimated using ordinary least squares (OLS), with statistical tests to assess their significance and to control for autocorrelation and heteroscedasticity in the residuals (Newey and West, 1987; Xiao et al., 2017).

2.4 Results

Table 2.3 presents the descriptive statistics of the monthly returns for the ITAN, as well as the Value and SPY indices and risk factors.

The average monthly returns of ITAN are not lower than those of its conventional counterpart (Value), regardless of the period considered (full period or different sub-periods). These results are in line with existing literature (Ahmed and Nanda, 2000; Penman and Reggiani, 2018; Lettau et al., 2019; Li, 2020; Arnott et al., 2021) which indicates that incorporating growth characteristics, such as intangible assets, into value stocks can enhance returns. The results show that the average monthly returns of the ITAN are between those of the Value index and SPY. ITAN generated an average monthly return of 0.26% (3.16% annualized), which is higher than the Value index with an average return of 0.23% (2.76% annualized), but lower than the SPY with a return of 0.47% (5.76% annualized).

This superior performance compared to the Value index is attributed to the integration of intangible values into the investment criteria of the ITAN. Indeed, companies included in ITAN invest heavily in intangible assets such as research and development (R&D), patents, strong brand development, and network effects. These investments can lead to significant competitive advantages, such as technological innovations, increased customer loyalty, and

higher profit margins. For example, a company with a robust patent portfolio can benefit from licensing revenues and protections against competition ; or a company with strong human capital can benefit from increased motivation and retention (Edmans, 2011; Kotey and Koomson, 2021; Yarovaya et al., 2021).

On the other hand, companies in the Value index, although solid and often undervalued (Akinde et al., 2019), do not invest as much in intangible assets. They generally focus on more mature sectors with stable revenue streams but less potential for rapid growth (Penman and Reggiani, 2018). This explains why ITAN can generate superior returns by capturing the value created by intangible investments. From a financial market perspective, clear and targeted investment strategies, like those of the SPY index, which show high and rapid returns, are often more valued, particularly in a favorable economic environment. The mixed approach of ITAN may therefore be less attractive to investors seeking immediate returns, which can negatively influence its valuation in the stock market. Additionally, the years 2021 to 2024 (the period of our analysis) have been marked by market reactions to monetary policies, geopolitical uncertainties, and post-pandemic economic recoveries. The SPY, encompassing a broad range of major American companies, offers some stability and benefits from a generalized market rebound. In comparison, a fund like ITAN, which balances tangible and intangible assets, may not react as quickly or favorably to short-term and volatile economic impulses.

In analyzing the standard deviations of the different panels of our study on ITAN, we find that this fund exhibits a higher level of risk than its conventional counterparts, such as the Value index and SPY. For example, the average monthly standard deviation for ITAN was 6.46% (22.40% when annualized) over the entire period.

This result seems to confirm a key hypothesis of modern portfolio theory, which posits that reducing the investment universe due to specific criteria, such as the inclusion of intangible assets, can increase total risk.

From a company perspective, this increase in risk could be explained by the nature of intangible assets themselves, which are often less liquid and more difficult to precisely value than tangible assets. Companies included in ITAN, which invest heavily in elements like R&D, patents, or brands, may experience more pronounced value fluctuations due to rapid technological advancements or changes in regulations that directly affect the perceived value of these assets. Additionally, these companies may be more exposed to specific sector shocks that disproportionately affect innovation-focused industries (Petkova and Zhang, 2005).

From the perspective of financial markets and investors, the characteristics of intangible assets can make ITAN more sensitive to market sentiment variations. Investors, attempting to anticipate technological trends and regulatory changes, can cause greater volatility in the stock prices of companies focused on intangible assets. Furthermore, since intangible assets are difficult to value, they are often the first to be affected in the event of market disruption, which can lead to rapid devaluation during crises (Monge et al., 2023). Thus, while ITAN's investment approach offers opportunities for outperformance by exploiting often undervalued market niches, it also entails a higher level of risk.

Nevertheless, these initial results should be interpreted with caution, as they provide only a basic overview of the financial performance of ITAN, Value index and SPY by examining returns and risks independently. Future analyses will explore risk-adjusted per-

formance measures.

Table 2.3. Descriptive statistics of monthly returns of ITAN, Value and SPY

	ITAN	**Value**	**SPY**	**Mkt-RF**	**SMB**	**HML**	**RMW**	**CMA**	**RF**
Panel A : July 2021 – May 2024									
Mean	0.0026	0.0022	0.0046	0.003171	-0.0069	-0.0066	0.0091	0.0035	0.0023
STD	0.0598	0.0493	0.0524	0.0529	0.0291	0.0444	0.0284	0.0351	0.0019
Max	0.1064	0.0963	0.0872	0.0957	0.0732	0.1275	0.0720	0.0772	0.0047
Min	-0.1126	-0.0977	-0.0980	-0.0946	-0.0694	-0.0885	-0.0475	-0.0772	0.0000
Skewness	-0.2265	-0.1201	-0.2955	-0.1469	0.3038	0.3315	0.1410	-0.0409	-0.1766
Kurtosis	-0.7129	-0.8609	-0.9273	-0.9166	0.5232	0.5447	-0.3598	-0.1971	-1.6899
Observations	35	35	35	35	35	35	35	35	35
Panel B : July 2021 – Dec. 2022									
Mean	-0.0123	-0.0024	-0.0062	-0.0073	0.0058	0.0195	0.0142	0.0173	0.0007
STD	0.0646	0.0558	0.0604	0.0597	0.0213	0.0469	0.0234	0.0383	0.0011
Max	0.0843	0.0963	0.0872	0.0957	0.0461	0.1275	0.0720	0.0772	0.0033
Min	-0.1126	-0.0977	-0.0980	-0.0946	-0.0461	-0.0597	-0.0475	-0.0683	0.0000
Skewness	-0.1466	-0.0627	-0.0336	0.0725	-0.2379	0.5773	0.1124	-0.5813	1.1238
Kurtosis	-1.1413	-0.9081	-1.3025	-1.1372	-0.8230	-0.0844	-2.7166	-0.2133	-0.2631
Observations	18	18	18	18	18	18	18	18	18
Panel C : Jan. 2023 – May 2024									
Mean	0.0194	0.0076	0.0169	0.0150	-0.0082	-0.0078	0.0034	-0.0120	0.0041
STD	0.0506	0.0420	0.0399	0.0379	0.0366	0.0317	0.0229	0.0236	0.0004
Max	0.1064	0.0728	0.0854	0.0884	0.0732	0.0829	0.0343	0.0286	0.0047
Min	-0.0569	-0.0460	-0.0499	-0.0509	-0.0694	-0.0597	-0.0319	-0.0722	0.0034
Skewness	0.1641	0.0409	-0.1446	0.0254	0.4610	0.5351	-0.5317	-0.7958	-0.3786
Kurtosis	-0.9079	-1.5517	-1.0873	-1.0885	-0.0437	-0.1779	-1.1198	1.0698	-1.3496
Observations	17	17	17	17	17	17	17	17	17

This table presents the descriptive statistics for the various variables used to calculate risk-adjusted performance indicators. The Mean corresponds to the average monthly returns. STD measures the volatility of monthly returns. ITAN, Value, and SPY represent respectively the Sparkline Intangible Value ETF, the Russell 1000 Value Index, and the S&P 500 index. The monthly stock prices are extracted from the Thomson Reuters Eikon database. The monthly returns are calculated using equation (eq. 2.1). Mkt-RF represents the excess return of the overall stock market over the risk-free rate, represented by U.S. Treasury bills. SMB is the difference in returns between a portfolio of small and a portfolio of large U.S. stocks ; HML is the difference in returns between a value portfolio and a growth stock portfolio in the U.S., using the price-to-book ratio as a discriminating factor. RMW is the difference in returns between a portfolio of robust operational profitability and a portfolio of low operational profitability of U.S. stocks ; CMA is the return of a conservative investment portfolio minus the return of an aggressive investment portfolio of U.S. stocks. These risk factors are collected from the Kenneth R. French data library.

The risk-adjusted performance measures presented in Table 2.4

convincingly show that the ITAN offers a significantly higher average risk premium per unit of total risk compared to the Value index but lower than that of the SPY. For example, for the period from July 2021 to May 2024, ITAN's Sharpe ratio is 0.0045, indicating that its returns substantially exceed those of the Value index, which has a Sharpe ratio of -0.0014. This suggests that an investor who favored ITAN would have achieved above-average returns for each unit of risk taken compared to the Value index. This finding aligns with the results of Park (2022), which demonstrated that value strategies incorporating intangible assets exhibit a higher Sharpe ratio than strategies focusing solely on tangible assets throughout their study period. The analysis of Sharpe ratios during the sub-period, Panel C (January 2023 to May 2024), reinforces this conclusion. With a Sharpe Ratio of 0.3030 for ITAN versus only 0.0844 for the Value index, it is evident that ITAN funds better manage risk-adjusted returns, thereby maximizing the reward for risk taken by investors.

Regarding the Sortino ratio, which focuses on the volatility of negative returns, ITAN also shows superior results compared to the Value index. For the full period (Panel A), the Sortino ratio for ITAN is 0.0041 compared to -0.0014 for the Value index. This measure indicates that ITAN not only reduces downside risk but does so in a way that significantly improves returns for investors focused on minimizing losses. For the analyzed period, the excess returns over the Value at Risk for ITAN are 0.0028, significantly surpassing the -0.0009 for the Value index. This result underscores ITAN's ability to offer superior risk-adjusted returns while providing robust protection against extreme risks compared to the Value index. The results from January 2022 to May 2024 (Panel C) confirm ITAN's robustness in terms of risk-adjusted performance relative to the Value index.

In Panel B, all Sharpe Ratios are negative, indicating that risk-adjusted returns were low relative to market volatility. This period could be characterized as one of market turbulence, although it also coincides with a phase of economic recovery, reflecting the complexity of market conditions during this time (Zhou and Liu, 2021). Compared to the Value index with a Sharpe ratio of -0.0589, ITAN, with a Sharpe ratio of -0.2031, shows inferior risk-adjusted performance during this period. The SPY index, with a Sharpe ratio of -0.1167, also outperforms ITAN in terms of the Sharpe ratio. This weak performance of ITAN can be attributed to the negative impact of its significant proportion of intangible assets. These assets, while advantageous in terms of growth and innovation, are susceptible to adverse impacts during economic or financial crises, where markets and investors prioritize the safety and liquidity of tangible assets. The analysis of other ratios reinforces this conclusion during this turbulent period.

Furthermore, compared to the SPY index, ITAN exhibited a lower Sharpe Ratio during the period from June 2021 to May 2024, with a ratio of 0.0045 for ITAN versus 0.0438 for SPY. This trend of inferior risk-adjusted performance is also confirmed through other ratios : ITAN has a Sortino Ratio of 0.0041 compared to 0.0397 for SPY, and the Excess Returns to VaR are 0.0028 for ITAN versus 0.0281 for SPY. This indicates that, while ITAN outperformed Value in terms of risk-adjusted returns, it did not achieve the efficiency of SPY in converting risk taken into excess returns.

This detailed analysis uses the Sharpe Ratio, Sortino Ratio, and Excess Returns to VaR to provide a comprehensive view of the value added by the ITAN in terms of risk-adjusted returns and risk management. The results show that investors would have benefited from above-average returns for each unit of risk with ITAN, compa-

red to the Value index, but did not reach the performance levels of SPY. This consistency across different risk-adjusted measures highlights the advantages of an investment strategy that leverages the strengths of both tangible and intangible assets, offering adequate compensation for risk and opportunities for outperformance in certain market environments. However, the results also highlight the challenges ITAN faces in highly volatile market conditions where the Value index, with its potentially more stable assets, tends to prevail. The results of these risk-adjusted performance measures show that, in line with the analysis of averages and standard deviations, investing in ITAN surpasses the Value index, particularly in stable market conditions, while underperforming compared to the SPY index.

Table 2.4. Risk-adjusted performance metrics for ITAN, Value and SPY

	Sharpe Ratio	**Adj. Sharpe Ratio**	**Sortino Ratio**	**Excess Returns to VaR**
Panel A : July 2021 – May 2024				
ITAN	0.0045	0.0000	0.0041	0.0028
Value	-0.0014	-0.0000	-0.0014	-0.0009
SPY	0.0438	0.0001	0.0397	0.0281
Panel B : July 2021 – Dec. 2022				
ITAN	-0.2031	-0.0099	-0.1727	-0.1107
Value	-0.0589	-0.0020	-0.0572	-0.0349
SPY	-0.1167	-0.0019	-0.1078	-0.0668
Panel C : Jan. 2023 – May 2024				
ITAN	0.3030	0.0326	0.3749	0.2405
Value	0.0844	0.0007	0.0890	0.0578
SPY	0.3204	0.0381	0.3373	0.2625

Sharpe Ratio measures the excess return per unit of risk above the risk-free rate(eq. 3.2). Adjusted Sharpe Ratio accounts for skewness and kurtosis in returns(eq. 3.3). Sortino Ratio focuses on downside risk by comparing returns above a minimum target to the downside deviation(eq. 3.4). Excess Returns to VaR quantifies how much the portfolio's returns exceed the Value at Risk (VaR), calculated as the maximum potential loss over a set period at a 95% confidence level(eq. 3.6). ITAN, Value, and SPY represent respectively the Sparkline Intangible Value ETF, the Russell 1000 Value Index, and the S&P 500 index.

The results reported in Table 2.5 show that, regardless of the

period examined, the Jensen alphas for ITAN and the Value index are not significantly different from zero in most cases. For example, ITAN, with its strategy of integrating intangible assets in addition to tangible assets, and the Value index, which traditionally focuses on tangible assets, do not offer a risk-adjusted performance that is significantly different from that of the market portfolio during 2021 to 2024. However, ITAN and the Value index underperform the market during the periods 2021 to 2022 and 2023 to 2024, respectively. Furthermore, ITAN underperformed compared to the Value index during the first two periods. ITAN's alphas are lower than those of the Value index by 4 and 85 basis points for Panels A and B, respectively. However, in Panel C, ITAN outperformed the Value index, with an alpha exceeding that of Value by 83 basis points, which is consistent with our findings from descriptive statistics and performance ratios during the period from 2023 to 2024. Regarding systematic risk measured by betas, ITAN's betas are consistently higher than those of the Value index across all panels, indicating that ITAN's strategy, although following market direction, is more volatile than that of the Value index. The incorporation of intangible assets could explain this greater exposure of ITAN to the market, suggesting a more pronounced responsiveness to market fluctuations compared to the Value index (Goodwin and Ahmed, 2006; Amenc et al., 2020).

Table 2.5. Jensen's alphas and betas for ITAN and Value

	Jensen's alphas	**Mkt-RF**	**Adj. R^2**
Panel A : July 2021 – May 2024			
ITAN	−0.0032	1.1023***	0.961
	(0.002)	(0.039)	
Value	−0.0028	0.8681***	0.866
	(0.003)	(0.059)	
Difference	−0.0004	0.2342	
Panel B : July 2021 – Dec 2022			
ITAN	−0.0053**	1.0694***	0.974
	(0.002)	(0.043)	
Value	0.0032	0.8842***	0.888
	(0.004)	(0.076)	
Difference	−0.0085	0.1852	
Panel C : Jan. 2023 – May 2024			
ITAN	−0.0019	1.1486***	0.933
	(0.003)	(0.079)	
Value	−0.0102**	0.9190***	0.865
	(0.004)	(0.093)	
Difference	0.0083	0.2296	

This table presents the Jensen's alphas and betas (eq. 3.7) for ITAN and Value. ITAN and Value represent respectively the Sparkline Intangible Value ETF and the Russell 1000 Value Index. The monthly stock prices are extracted from the Thomson Reuters Eikon database. The "difference" is constructed by subtracting the results on the ITAN from the Value, i.e., its conventional peer. The coefficients are estimated using standard OLS regression with Mkt-RF as the explanatory variable. The intercept, α_i^{Jensen}, indicates the excess return of the respective portfolio. Standard errors are shown in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

The Jensen model is based on the idea that the return of a portfolio can be explained by the return of a market portfolio (Mkt-RF), the portfolio's sensitivity to the market (β_i^{MKT}), and an alpha term (α_i^{Jensen}). Bauer et al. (2007) suggested that excess returns cannot be fully explained by a single risk factor. Fama and French (1993) extended this approach by demonstrating that expected return also depends on the portfolio's exposure to differences in returns between small and large capitalizations (SMB) and between stocks

with high book-to-market ratios and those with low ratios (HML). Adding these two risk factors to the Jensen model should improve alpha estimates and the explanatory power of the asset pricing model. To illustrate this, Table 2.6 summarizes the results of the Fama-French three-factor model estimation for the ITAN fund and the Value index over different sub-periods. These results confirm that market returns explain a significant but not exhaustive part of the excess returns, justifying the inclusion of SMB and HML factors for a more comprehensive analysis.

The ITAN and the Value index are not significantly exposed to the SMB factor, except during the period from 2023 to 2024. Indeed, in Panel C, ITAN shows significant exposure to small-cap companies with an SMB coefficient of 0.2116, indicating a favorable orientation towards these companies. Furthermore, during the period from 2021 to 2022, ITAN exhibits a preference for value stocks, as evidenced by a positive HML coefficient of 0.1118. The Value index, on the other hand, indicates a consistent and positive exposure to value stocks throughout the entire analysis period.

In terms of risk-adjusted performance, ITAN underperformed the market between 2021 and 2022, while the Value index underperformed the market both during the period from 2021 to 2024 and from 2023 to 2024. However, the addition of the two risk factors (SMB and HML) leads to conclusions that are consistent with the results of descriptive analyses and performance ratios : ITAN does not underperform the Value index in Panels A and C, posting alphas of +24 and +88 basis points, respectively. These results support the findings of previous studies such as Arnott et al. (2021) and Park (2022), which suggest that the integration of intangible assets into value strategies outperforms traditional strategies focused on tangible assets. Conversely, in Panel B, ITAN underper-

forms relative to the Value index, with a negative alpha of -51 basis points. This observation suggests that investors might favor intangible assets during calm market periods without compromising their financial performance, but this strategy might not be as effective at the beginning of an economic recovery (Fallahgoul et al., 2021; Monge et al., 2023).

It is therefore relevant to use the Fama-French three-factor model, rather than the Jensen model, to estimate the risk-adjusted performance of ITAN and the Value index. The examination of the adjusted R^2 shows that the Fama-French model offers superior predictive power compared to the Jensen model.

Table 2.6. Fama-French three-factor alphas for ITAN and Value

	Three-factor alphas	Mkt-RF	SMB	HML	Adj. R^2
Panel A : July 2021 – May 2024					
ITAN	−0.0033	1.1038***	0.0405	0.0454	0.960
	(0.002)	(0.041)	(0.075)	(0.048)	
Value	−0.0057***	0.9193***	−0.0569	0.3526***	0.964
	(0.002)	(0.032)	(0.059)	(0.038)	
Difference	0.0024	0.1845	0.0974	−0.3072	
Panel B : July 2021 – Dec. 2022					
ITAN	−0.0082***	1.0810***	−0.1495	0.1118**	0.981
	(0.002)	(0.036)	(0.101)	(0.046)	
Value	−0.0031	0.9240***	−0.0338	0.3272***	0.962
	(0.003)	(0.045)	(0.124)	(0.057)	
Difference	−0.0051	0.1570	−0.1157	−0.2154	
Panel C : Jan. 2023 – May 2024					
ITAN	0.0003	1.0650***	0.2116*	−0.0996	0.939
	(0.004)	(0.088)	(0.115)	(0.096)	
Value	−0.0085***	0.9464***	−0.0939	0.3691***	0.965
	(0.002)	(0.056)	(0.073)	(0.060)	
Difference	0.0088	0.1186	0.3055	−0.4687	

This table presents the three-factor regressions (eq. 2.8) for ITAN and Value. ITAN and Value represent respectively the Sparkline Intangible Value ETF and the Russell 1000 Value Index. The monthly stock prices are extracted from the Thomson Reuters Eikon database. The "difference" is constructed by subtracting the results on the ITAN from the Value, i.e., its conventional peer. Coefficients are estimated using a standard OLS regression. Explanatory variables are Mkt-RF, SMB, HML, RMW. The effect of the intercept (α_i^{FF3F}) shows the excess return of the respective portfolio. Standard errors are reported in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

More recently, Fama and French (2015) asserted that adding two new risk factors — RMW (robust minus weak) and CMA (conservative minus aggressive) — to the Fama-French three-factor model improves the predictability of stock excess returns.Table 2.7 provides the factor loadings for the Fama-French five-factor model for ITAN and the Value index. ITAN is not exposed to the RMW and CMA factors, while the Value index is not exposed to RMW but shows a preference for less conservative companies (positive CMA) during the periods 2021-2024 and 2021-2022. The five-factor alphas presented in the first column confirm our observations. In-

deed, ITAN underperformed the market from 2021 to 2022, while the Value index underperformed the market during the periods 2021-2024 and 2023-2024. Additionally, ITAN does not underperform the Value index in Panels A and C, posting alphas of +18 and +40 basis points, respectively. Conversely, it underperforms in Panel B, with a negative alpha of -51 basis points.

Table 2.7. Fama-French five-factor alphas for ITAN and Value portfolio returns over different periods

	Five-factor alphas	**Mkt-RF**	**SMB**	**HML**	**RMW**	**CMA**	**Adj. R^2**
Panel A : July 2021 – May 2024							
ITAN	−0.0036	1.0989***	0.0320	0.1026	0.0260	−0.0899	0.958
	(0.002)	(0.042)	(0.091)	(0.091)	(0.088)	(0.116)	
Value	−0.0054***	0.9269***	0.0434	0.1771	0.0732	0.2499***	0.975
	(0.001)	(0.027)	(0.059)	(0.059)	(0.056)	(0.075)	
Difference	0.0018	0.1720	−0.0114	−0.0745	−0.0472	−0.3398	
Panel B : July 2021 – Dec. 2022							
ITAN	−0.0093***	1.0705***	0.0825	0.0867	0.0282	0.0351	0.981
	(0.003)	(0.039)	(0.116)	(0.086)	(0.082)	(0.108)	
Value	−0.0042	0.9316***	0.0417	0.1531	0.0351	0.2597**	0.970
	(0.003)	(0.042)	(0.067)	(0.059)	(0.061)	(0.117)	
Difference	−0.0051	0.1389	0.0408	−0.0664	−0.0069	−0.2246	
Panel C : Jan. 2023 – May 2024							
ITAN	−0.0035	1.0809***	0.1387	0.1187	−0.0417	−0.3685	0.941
	(0.005)	(0.102)	(0.152)	(0.170)	(0.225)	(0.252)	
Value	−0.0075**	0.9809***	0.0368	0.2338**	0.2214	0.1867	0.975
	(0.003)	(0.056)	(0.079)	(0.092)	(0.121)	(0.136)	
Difference	0.0040	0.1000	0.1019	−0.1151	−0.2631	−0.5552	

This table presents the five-factor regressions (eq. 3.8) for ITAN and Value. ITAN and Value represent respectively the Sparkline Intangible Value ETF and the Russell 1000 Value Index. The monthly stock prices are extracted from the Thomson Reuters Eikon database. The "difference" is constructed by subtracting the results on the ITAN from the Value, i.e., its conventional peer. Coefficients are estimated using a standard OLS regression. Explanatory variables are Mkt-RF, SMB, HML, RMW. The effect of the intercept (α_i^{FF5F}) shows the excess return of the respective portfolio. Standard errors are reported in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

2.5 Conclusion

In recent years, the effectiveness of value investment strategies has significantly declined, partly due to the uneven increase in expenditures on activities generating intangible capital without a corresponding adaptation of financial reporting standards.

In this context, inspired by the works of Amenc et al. (2020), Li (2020) and Arnott et al. (2021) on adjusting book values for unaccounted intangible capital, the Sparkline Intangible Value ETF (ITAN) was launched in 2021 on the NYSE. This fund uses natural language processing to evaluate intangible assets, thus adapting value investing to the current economy dominated by intangible assets. However, the assessment of the fund's performance, particularly in terms of risk-adjusted returns, remains an open question.

To this end, we analyze the financial performance of the Sparkline Intangible Value ETF compared to its conventional counterpart, the Russell 1000 Value index, and the S&P 500. Performance is evaluated using traditional risk-adjusted return indicators such as the Sharpe ratio, adjusted Sharpe ratio, Sortino ratio, Value at Risk-adjusted return, Jensen's alpha, the Fama-French three-factor and five-factor models. The analysis is conducted over two distinct periods : a full period from 2021 to 2024, as well as two sub-periods from 2021 to 2022 and from 2023 to 2024.

Our analyses reveal that, despite superior risk-adjusted returns compared to the Value index in most cases, ITAN underperformed during the economic recovery period from July 2021 to December 2022, and compared to the S&P 500 over the entire study period. This demonstrates that while integrating intangible assets can improve performance relative to traditional strategies, it does not consistently outperform the broader market.

This study, covering approximately three years, raises unresolved questions about the long-term performance of ITAN. Further analysis with longer-term data is needed to more conclusively evaluate the impact of intangible assets on risk-adjusted returns. Future results could provide more precise insights into the effectiveness of modernized value investment strategies.

Chapitre 3

Do Investors Gain when Companies Implement Flexible Work Practices ?

Abstract

Flexible Work Arrangements (FWAs) are widely considered to enhance corporate performance. But whether these benefits fully reflected in stock prices and whether investors can earn higher risk-adjusted returns remain open questions. In this paper, we analyze the performance of investment portfolios sorted by FWAs scores in the United-States and Europe. Our results indicate that portfolios of companies with high FWAs scores are associated with higher risk-adjusted performance indicators. They also exceed the returns predicted by standard factor models, though only significantly so in the United-States. This study deepens our understanding of unconventional factors in investment strategies and underscores the importance of considering flexible work practices in investment decision-making, while highlighting regional differences in the valuation of intangible assets.

Keywords : Flexible Work Arrangements, performance, underreaction, mispricing

JEL Classification : G10, G11, J24, J81

3.1 Introduction

Family structures and labor markets have evolved, with an increase in dual-income couples and working mothers (Bond et al., 1998). This evolution has heightened the need for employees, both men and women, to manage both family and professional responsibilities (Gilbert et al., 1994). Moreover, the simultaneous management of various life spheres, combined with increasing stress levels and demographic shifts towards an aging population in developed countries, intensifies these challenges (Bal and Dorenbosch, 2015). Additionally, unforeseen societal crises, including recent pandemics like COVID-19, have rapidly disrupted organizational routines, forcing many employees to shift to an exclusively home-based work mode (Akuoko et al., 2021; Craig and Churchill, 2021; Parlak et al., 2021; Bin et al., 2021; Kähkönen, 2023). These obstacles highlight the crucial role of human resources(HR) in organizational performance (Jiang et al., 2012; Bierema, 2020; Shirmohammadi et al., 2022).

However, motivating staff is complex as direct leadership alone is no longer sufficient to influence behavior. It is therefore crucial to design all aspects of work and the professional environment to enhance performance (Becker and Huselid, 1998; Gerhart, 2007). Globalization, increased competition, cultural diversity, legislative changes, technological advancements, and a focus on customer satisfaction further complicate the management of HR, prompting leaders to identify effective strategies to foster high performance among employees (Delaney and Goddard, 2001). Among these strategies are Flexible Work Arrangements.

Lambert et al. (2008) define Flexible Work Arrangements as a set of benefits provided by the employer that allows employees to choose when and where they work, outside of standard hours. This

includes full-time flexible schedules, part-time work options, and remote work (Blake-Beard et al., 2010). Morgan (2014) states that work flexibility encompasses the freedom for employees to work anytime and anywhere, focusing more on outcomes than on processes. Providing remote work arrangements could symbolize an employer's willingness to modify the work environment in response to employee needs (Shockley and Allen, 2012). This may also be perceived by employees as reflecting or enabling a better match between themselves and their work, which is an aspect of positive role adjustment (Shockley and Allen, 2010). Moreover, flexibility policies provide employees with the freedom and ability to manage professional and personal demands, thus promoting a more balanced work-life dynamic in the current global economic environment, which operates 24/7 (Possenriede, 2014). These measures are considered to enhance the work-life balance of employees (Kelliher and Anderson, 2010). The flexibility of work arrangements is also an important aspect of the United Nations Sustainable Development Goal 8, considered as a crucial factor for decent work and inclusive and sustainable economic growth (United Nations Development Programme (UNDP), 2023).

Research has highlighted the positive link between the policy of FWAs and various organizational indicators. These include an increase in job satisfaction, greater employee engagement, and reduced turnover rates (Posthuma et al., 2013; Cegarra-Leiva et al., 2012; Wang et al., 2011; Lott and Abendroth, 2020; Peters and Blomme, 2019; Ipsen et al., 2021). Furthermore, an improvement in job performance has been noted, according to Kotey and Sharma (2019). Kotey (2017) also found that FWAs are among the key strategies for attracting exceptional talent and developing strategic skills, thus enhancing a company's competitive edge. These observations suggest that FWAs can substantially improve a com-

pany's financial performance (Bal and Dorenbosch, 2015; Been et al., 2016a; Kotey and Koomson, 2021; Belzunegui-Eraso and Erro-Garcés, 2020; Karaniakas and Cauchi, 2020; García-Buades et al., 2020).

The goal of this paper is to examine whether the competitive advantages conferred by FWAs are quickly reflected in the stock market valuation of companies. This is a relevant question for both traditional investors and those favoring flexible work arrangements. These latter investors seek to evaluate whether the risk-adjusted returns of investments focused on FWAs are competitive, which could deter them from investing in these products if the returns are lower. Conversely, strong financial performance of portfolios incorporating significant work flexibility might encourage traditional investors to allocate their resources towards these new investment products.

In accordance with the efficient market theory, as discussed by Edmans (2011), one might expect that any clearly beneficial characteristic of a company would be quickly reflected in its stock market valuation, thus eliminating the potential for abnormal gains. The speed at which financial markets adjust their valuations to reflect the benefits of FWAs is therefore a key point. A delay in this integration could offer investors a window of opportunity to capitalize on benefits that are not yet accounted for.

A significant body of research highlights the market's tendency to undervalue certain fundamental characteristics of companies, particularly intangible assets. Lev and Sougiannis (1996) discovered an abnormal return of 4.6% related to R&D expenditures, and Chan et al. (2001) observed that companies investing heavily in R&D outperform standard returns by an additional 6.1%. Invest-

ments in advertising, patents, and software development are also identified as drivers of superior returns (Deng et al., 1999; Aboody and Lev, 1998; Chan et al., 2001). Beyond intangible assets, other studies such as those by Gompers et al. (2003) have revealed abnormal returns of 8.5% associated with good governance practices. Yermack (2006) documented a negative alpha of 3.8% for companies whose CEOs use private jets. Liu and Yermack (2007) report negative abnormal returns of up to 20% for CEOs acquiring ostentatiously large homes.

The application of these ideas to FWAs suggests that while they are beneficial to the company, FWAs contribute to the creation of intangible assets such as employee motivation and loyalty, which are not always immediately or fully valued by the market. This undervaluation could create opportunities for long-term excess returns, similar to those observed in other areas such as R&D investments and strategic corporate decisions. The ability of FWAs to generate intangible assets implies that the benefits they bring to a company are not always fully recognized or capitalized by the market. This deferred recognition could, in turn, offer opportunities for excess returns, strengthening the argument for integrating FWAs into corporate strategies to enhance long-term financial performance.

By analyzing the performance of portfolios based on FWAs scores, this research aims to identify and address this gap in the existing literature, assessing whether FWAs can also contribute to excess returns similar to those observed in other intangible investments. To do this, we constructed two distinct portfolios to thoroughly examine the effects of FWAs on risk-adjusted returns. The first, the Q5 portfolio, groups companies with the top 20% of scores, demonstrating strong adoption of FWAs. The second, the Q1 port-

folio, includes companies with the bottom 20% of scores, reflecting low adoption of FWAs. Additionally, we analyze a long-short portfolio (Q5-Q1) that measures relative performance by taking long positions in Q5 companies and short positions in Q1 companies. This strategy allows us to isolate the specific effect of FWAs by neutralizing general market movements. These portfolios are tested using a series of risk-adjusted performance indicators, such as Sharpe ratios, adjusted Sharpe ratios, Sortino ratios, adjusted returns to value at risk, as well as Jensen's alphas and the alphas from Fama-French five-factor model. This approach enables an in-depth assessment of whether FWAs contribute to financial outperformance, while adjusting for the risk associated with different portfolio strategies. The monthly data used for this study comes from Thomson Reuters Eikon database and covers the period from January 2014 to December 2022. Our approach also distinguishes companies located in the United-States and Europe, creating a heterogeneous sample and refining our understanding of the impacts of FWAs in different jurisdictions. This regional structure and portfolio analysis strategy significantly enrich our study by offering a detailed perspective on how legal environments and corporate policies influence the financial outcomes associated with FWAs (Bannier et al., 2019).

By examining the effects of FWAs on risk-adjusted returns, this study enriches the literature by contributing to four research areas : the stock market's inability to fully integrate the value of intangible assets ; the growing importance of human capital in the modern enterprise ; the effect of socially responsible investment (SRI) screens on investment performance ; and exploring the financial impact of FWAs through a multidimensional approach.

First, this study enriches the debate on intangible assets and

their influence on portfolio performance. While much research has been devoted to intangible assets, Serpeninova et al. (2022) observed that Slovak software companies increased their profitability upon the acquisition of intangible assets. Skhvediani et al. (2022), analyzing 1,044 Russian IT companies, showed a positive relationship between intangible assets and ROA. Pechlivanidis et al. (2022) demonstrated that including intangible assets in a deep learning model enhances the performance of models predicting profitability. Cardozo-Torres et al. (2021) and Chiarelo et al. (2015) reported negative effects of certain intangible assets, such as brand value, on financial performance. Méndez-Morales and Yanes-Guerra (2021) highlighted methodological divergences in measuring intangible assets. De Nicola et al. (2021) and Xiong et al. (2020) shed light on the increased importance of intangible assets during the COVID-19 pandemic, enabling companies to maintain their flexibility. Barker et al. (2021) and Haji and Ghazali (2018) discussed the challenges associated with the valuation of intangible assets and their influence on market volatility. Wahyuni et al. (2023) identified a positive relationship between intangible assets and ROA in Sharia-listed banks in Indonesia. Despite this abundance of research, very little attention has been specifically paid to FWAs. Although FWAs are not intangible assets per se, they promote the creation of intangible assets such as employee motivation and retention, factors that positively influence the long-term financial outcomes of companies. Thus, this study aims to fill this gap by demonstrating how FWAs, as a crucial component of human resources, contribute to the overall financial performance of portfolios.

Next, this research addresses the strategic importance of investing in human capital, recognized for its ability to create value (Hitt et al., 2001; Lopez-Cabrales et al., 2006; Yarovaya et al., 2021). By highlighting the role of FWAs, the study suggests that

enhancing FWAs can directly influence employee motivation and loyalty, which in turn can improve the long-term financial outcomes of companies. This approach not only recognizes FWAs as a crucial element of human capital but also their direct impact on the risk-adjusted performance of investment portfolios.

Furthermore, this research deepens the discussion on the integration of SRI filters and their impact on the financial performance of portfolios. Indeed, traditional portfolio theory, illustrated by Markowitz (1952), posits that socially responsible investment filters, such as employee welfare, limit investment options and could therefore decrease returns, assuming that a constrained optimization is inferior to an unconstrained optimization (Geczy et al., 2005; Hong and Kacperczyk, 2009). However, conflicting research has shown that certain SRI filters might improve returns (see, for example, Bajic and Yurtoglu (2018); Dimson et al. (2012); Deng et al. (2013); Eccles et al. (2014); Edmans (2011); El Ghoul et al. (2017); Flammer (2015); In et al. (2017); Flammer (2021); Krüger (2015); Malik (2015); Margolis et al. (2011); Tang and Zhang (2020); Gillan et al. (2021); Barker et al. (2021)). This study explores a filter based on FWAs, suggesting that, contrary to Markowitz's opinion, such a filter can concentrate investment choices on quality assets in scenarios where investors have limited knowledge, enabling them to focus on potentially undervalued investments by the market due to their intangibility, such as stakeholder capital.

Finally, we complement the literature on FWAs by assessing their financial impact through a multidimensional approach, rather than merely examining the impact of their implementation. Adopting an investor's perspective rather than a corporate one (Peillex et al., 2021), our study investigates whether companies that effectively implement FWAs offer more advantageous risk-adjusted

returns. In doing so, our research contributes to expanding discussions on the economic benefits of FWAs, adding a new dimension to the argument in favor of their adoption in modern management practices.

Our results demonstrate that in the United-States, regardless of the performance measurement method used or the period examined, both the Q5 portfolio and the Long Short strategy (Q5-Q1) exhibit superior risk-adjusted returns compared to the Q1 portfolio. In Europe, our observations show that, similar to the United-States, the Q5 portfolio and the Long Short strategy (Q5-Q1) display superior risk-adjusted returns compared to the Q1 portfolio when measured by performance ratios. However, unlike the results in the United-States, neither Jensen's alphas nor the alphas from the Fama-French five-factor model are statistically significant in Europe.

The rest of this paper is organized as follows. Section 3.2 presents a review of the existing literature on FWAs. Section 3.3 details the database used and examines the descriptive statistics. In Section 3.4, the methodology employed to construct FWAs Strategy is described. Section 3.5 details the empirical results of the proposed investment strategies. Finally, Section 3.6 provides the main conclusions.

3.2 Literature review

3.2.1 Flexible Work Arrangements and Balancing Work-Life Dynamics

Contemporary scholarly discourse emphasizes the burgeoning necessity for FWAs as a strategy to mitigate the intensifying demands of professional duties and their intrusion into familial and

personal spheres (Shirom, 2005). A notable body of research underscores the potential of FWAs in ameliorating the adverse repercussions of occupational stress on individuals' health and personal lives Lewis et al. (2007); Wang and Verma (2012). Institutional endorsements for FWAs have been pronounced, with international entities such as the International Labour Organization (ILO) Messenger (2006), the European Union (EU), and the Organisation for Economic Co-operation and Development (OECD) advocating for their adoption (Goetschy, 2006; Zeytinoglu et al., 2009). These organizations highlight the dual benefits of FWAs : augmenting workplace productivity and contributing positively to the broader socio-economic landscape (Croucher et al., 2013).

3.2.2 Statutory Entitlement to Flexible Working Arrangements

Recent scholarly examinations, such as those by Eurofound (2016) and the Australian Institute of Family Studies (AIFS) (2015), have observed an evolution in the process of employee requests for FWAs. Whereas such requests were traditionally granted at the discretion of employers, legislative developments in various countries have empowered workers to formally seek adjustments to their work schedules and locations. Specifically, legislation in nations like the United Kingdom and Australia, has been analyzed by authors such as those of The Flexible Working Legislation (2014), providing workers with the right to request FWAs.

3.2.3 Impact and Theoretical Underpinnings of Flexible Work Arrangements

A consolidated body of research underscores the multifaceted benefits of FWAs, particularly highlighting the enhancement of employee performance indicators (Wang et al., 2011; Posthuma et al., 2013; Cegarra-Leiva et al., 2012). While Kelliher and Anderson

(2010) found a positive correlation between FWAs and overall job satisfaction and organisational commitment, some studies, including that of Lee and Hong (2011), identified no direct link between working from home (WFH) and improvements in staff turnover and experienced well-being. Further investigation into the dynamics of FWAs by McNall et al. (2010) revealed that flexible schedules and compressed work weeks might enrich the work-family interface. O'Neill et al. (2009) noted the significant impact of managerial response to FWAs requests in the hospitality sector. The theoretical framework is grounded in social exchange theory, as explained by Blau (1964), and is complemented by notions of organisational support, as Takeuchi et al. (2009) and Casper and Harris (2008) suggest. The leader-member exchange theory, discussed by Lee and Hong (2011) and Bal and Dorenbosch (2015), also provides insight into the success of FWAs. Collectively, these theoretical perspectives highlight how FWAs can foster a more responsive and adaptive organisational culture, leading to improved performance and competitiveness. However, the literature also acknowledges that without proper consideration of the sociological and psychological aspects involved in FWAs implementation, the potential benefits may not be fully actualised, indicating a need for more comprehensive research in this area.

3.2.4 Flexible Work Arrangements and Company Value

Been et al. (2016b) indicates that Dutch decision-makers incorporate institutional considerations and a cost-benefit assessment to guide their FWAs strategies. Similarly, Maxwell et al. (2007) highlight a similar approach in Scottish SMEs, where each FWAs decision is made by evaluating its impact on both employer and employee. The indirect benefits of FWAs, such as increased employee satisfaction, engagement, reduced turnover, and absen-

teeism (Cegarra-Leiva et al., 2012; Kelliher and Anderson, 2010). These factors contribute to improved overall employee health, positively affecting productivity (Haar et al., 2014; Beauregard and Henry, 2009). At the organizational level, these benefits translate into better organizational behavior and increased customer satisfaction, leading to productivity gains and enhancing the company's reputation, which aids in attracting top-tier talent (Lewis et al., 2007; Abid and Barech, 2017). The culture of flexibility encouraged within companies also promotes collaboration and team spirit, key elements in boosting productivity (Dex and Scheibl, 2001; Golden, 2001). Kotey and Sharma (2019) differentiate between direct and indirect impacts of FWAs, noting that increased employee engagement and reduced absenteeism result from recognizing the added value of FWAs. This dynamic, based on social exchange theory, leads to reduced turnover intentions and, by extension, recruitment costs. However, FWAs can also incur additional costs, especially when compensating for employee absences, as indicated by Kotey and Sharma (2016), or facing implementation challenges Dickens (2006). Conflicts and poor communication among employees sharing the same positions can diminish the perceived benefits of FWAs Williamson et al. (2015). Similarly, the isolation felt by teleworkers can reduce the effectiveness of these arrangements, as Lee and Hong (2011) observe, and certain sectors requiring physical presence might not efficiently accommodate telework (Kotey and Sharma, 2016). Employees engaged in long-term FWAs may face barriers to professional advancement, affecting their motivation and performance, as shown in the studies by Blankenship et al. (2006) and Frank and Lowe (2003). Emphasizing physical presence over achievements can also negatively impact the perception of FWAs within the company (Atkinson and Sandiford, 2016). Although FWAs offer numerous benefits, both direct and indirect, their implementation requires a thorough cost-benefit analysis to

maximize their positive impact on company value. Balancing benefits and costs must be meticulously managed to ensure FWAs effectively enhance the company's performance value.

3.3 Data

The goal of this study is to compare the financial performance of portfolios based on the FWAs score. We analyze the top quintile portfolios (Q5, comprising the companies most active in FWAs) and the bottom quintile portfolios (Q1, comprising the companies least active in FWAs). We also add the long-short strategy (Q5-Q1) to diversify investment strategies and minimize market risk. This approach allows for generating returns independent of the fluctuations of the overall market, thereby providing better management of risk-adjusted returns (Bannier et al., 2019). The comparison is made with conventional benchmark indices, namely the S&P 500 in the United-States and the Stoxx600 in Europe. These indices were chosen because they represent the most commonly used market benchmarks by investors (Amon et al., 2021).

Superior financial performance of portfolios based on the FWAs score could encourage conventional investors to incorporate SRI criteria into portfolio selection based on financial motives. Indeed, this would demonstrate that integrating FWAs criteria could be a source of financial wealth. Competitive financial performance of these portfolios might also encourage pro-FWAs investors with a financial objective to strengthen their SRI practices. In this regard, the incorporation of FWAs filters would thus be cost-free and facilitate SRI decision-making, confirming that the market does not always fully integrate intangibles, such as investments in R&D (Lev and Sougiannis, 1996), advertising (Chan et al., 2001), and patents (Deng et al., 1999).

We focus on the period from January 2014 to December 2022. As FWAs scores only began to be available for some listed companies in the early 2000s, we chose this period to ensure a sufficiently large sample of data from the respective indices (Monti et al., 2018). Thus, the analysis covers nine (09) years of monthly data, for a total of 108 observations. We also delineated a sub-period, from January 2014 to January 2020, excluding the COVID-19 pandemic crisis (Ouchen, 2022). This pre-COVID period is essential as it includes stable and representative economic data before the market disruptions related to the health crisis. This temporal segmentation allows us to observe trends and financial performance without the disturbances induced by the global pandemic, thus providing a clear and distinct comparative perspective (Ouchen, 2022). Monthly data including FWAs scores and historical pricing are extracted from the Thomson Reuters Eikon database (Ioannou and Serafeim, 2012; Cheng et al., 2013; Hawn and Ioannou, 2016). All prices are denominated in U.S. dollars and adjusted according to monthly average exchange rates (Mirza et al., 2020). Monthly regression factors for the United-States and Europe are obtained from the data library of Kenneth R. French, based on the complete universe of public equities in their respective regions. [1]

After eliminating companies with incomplete price histories or FWAs scores (Amon et al., 2021), the sample comprises 22,521 observations in the United-States and 36,218 in Europe (see, Table 3.1). The average FWAs scores for companies in the U.S. is 84.08, slightly higher than that for companies in the EU, which is 83.96, suggesting a slightly higher or more effective adoption of flexible work practices in the United-States. The standard deviation, indicating the variability of scores, is 4.46 for the United-States and 4.66 for Europe, showing that scores are more dispersed in Europe, which

1. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

may reflect more marked differences in the implementation of these policies among European companies. The median FWAs scores are very close in both regions, with 84.92 for the United-States and 84.81 for Europe, indicating that half of the companies in each region have flexible work practices at comparable levels, reinforcing the idea that these policies have become a common norm among large companies in developed markets (Kotey, 2017).

Table 3.1. Descriptive statistics of FWAs scores for U.S and Europe

Statistic	U.S (S&P500)	Europe (STOXX600)
Count	22,521	36,218
Mean	84.0847	83.9604
Standard Deviation	4.4633	4.6608
Minimum	60.0000	58.3333
25% Percentile	81.2888	81.1111
50% Percentile (Median)	84.9265	84.8178
75% Percentile	87.1429	86.9159
Maximum	97.2973	96.3320

3.4 Methodology

We use a portfolio construction methodology inspired by the work of Gompers et al. (2003), which studied the impact of governance-related risks on stock returns. More specifically, our process involves the monthly ranking of companies in our samples in the United-States and Europe based on their FWAs scores from the previous month, in descending order. For month t, we use the FWAs scores from month $t-1$ to create two quintiles, Q1 (lowest scores) and Q5 (highest scores). These quintiles serve as the basis for the monthly reallocation of portfolios according to the updated FWAs scores of the companies. All portfolios are structured so that all stocks within the portfolios have equal weight (Ferguson and Schofield, 2010). Indeed, Plyakha et al. (2012) found that equally weighted portfolios exhibit higher risk and generate higher returns than price-weighted and value-weighted portfolios.

Next, we calculate the returns of the two stock indices, S&P500 and STOXX600, following Schröder (2007) and Jaballah et al. (2018) as follows :

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{3.1}$$

where $R_{i,t}$ denotes the return of index i for month t, and $P_{i,t}$ is its monthly closing value.

The risk-adjusted performance of the FWAs portfolios is examined using several traditional performance indicators, namely, Sharpe ratios (Sharpe, 1966), adjusted Sharpe ratios (Pezier and White, 2006), Sortino ratios (Sortino and Price, 1994), adjusted returns to value at risk (Jorion, 2001), Jensen's alphas (Jensen, 1968), and the alphas from the Fama-French five-factor model (Fama and French, 2015). The use of FWAs scores in portfolio selection can restrict the investment universe and expose these portfolios to diversifiable and non-diversifiable risks (Peillex et al., 2021). The Sharpe ratio, a well-known measure of risk-adjusted performance, is particularly useful for assessing portfolios that do not benefit from optimal diversification, such as those based on FWAs scores (Nainggolan et al., 2016). This ratio measures the excess returns of a portfolio per unit of total risk :

$$\text{Sharpe Ratio} = \frac{R_i - R_f}{\sigma_i}, \tag{3.2}$$

where R_i represents the average monthly return of the portfolio based on FWAs scores, and R_f is the risk-free rate, approximated by the one-month Treasury bill rate for the United-States and an equivalent for Europe, according to Fama-French data. σ_i is the standard deviation of the portfolio's monthly returns over the analyzed period.

In addition to the Sharpe ratio, we also use the Adjusted Sharpe Ratio (ASR) for a more precise evaluation of risk-adjusted performance. The ASR takes into account not only volatility but also skewness and kurtosis of returns, thereby providing a more comprehensive and realistic measure of the risks associated with a portfolio. Indeed, stock portfolios are often subject to asymmetric return distributions and high kurtosis, which can distort performance evaluation if based solely on volatility (Ángel León and Niguez, 2021; Vinzelberg and Auer, 2022). The Adjusted Sharpe Ratio is calculated as follows, following the methodology of Brière et al. (2015) and Rizvi et al. (2020) :

$$\mathrm{ASR}_{pt} = \mathrm{SR}_{pt}\left(1 + \frac{\mathrm{sk}}{6} \times \mathrm{SR}_{pt} - \left(\frac{\mathrm{kr}-3}{24}\right) \times \mathrm{SR}_{pt}^2\right) \tag{3.3}$$

where SR_{pt} corresponds to the Sharpe Ratio, sk is the skewness of the returns, and kr refers to the kurtosis. This adjustment allows for better consideration of the specific characteristics of portfolio return distributions, thus providing a more accurate assessment of their risk-adjusted performance. The Sortino ratio is also a measure of risk-adjusted performance. Unlike the Sharpe ratio, it compares excess returns to the downside deviation of portfolio returns. This comparison is relevant because a typical investor is concerned about adverse shocks and prefers to assess returns relative to downside risk. Therefore, the Sortino ratio is a popular metric for estimating risk-adjusted performance across various asset classes (Damianov and Elsayed, 2020; Sanford, 2021). In the presence of negative volatility σ_d, for a portfolio with returns R_p and the risk-free rate r_f, we estimate the Sortino ratio (ST) as follows :

$$\mathrm{ST}_{pt} = \frac{R_p - R_f}{\sigma_d} \tag{3.4}$$

Previous studies on stock returns by Liu and Lei (2021); Chen et al. (2021); Galakis et al. (2022) have indicated the non-linearity and

the plausibility of higher order moments. Consequently, in addition to the ASR, we also use adjusted returns to value at risk (Rahat and Nguyen, 2022). VaR represents the maximum possible investment loss incurred over a fixed time horizon under a certain confidence interval. For this paper, we estimate the VaR for portfolio p based on the returns R, volatility σ, and z_α at 95% as follows :

$$\text{VaR}_{pt} = R_{pt} - z_\alpha \sigma_{pt} \tag{3.5}$$

Once the VaR is estimated, we calculate the risk-adjusted returns as follows :

$$\text{RAR}_{pt} = \frac{R_p - R_f}{\text{VaR}_{pt}} \tag{3.6}$$

The Jensen's alpha and the Fama-French Five-Factor alpha are estimated using the following models respectively :

$$R_{i,t} - R_{f,t} = \alpha_i^{\text{Jensen}} + \beta_i^{\text{MKT}}(R_{m,t} - R_{f,t}) + \epsilon_{i,t}, \tag{3.7}$$

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i^{\text{FF5F}} + \beta_i^{\text{MKT}}(R_{m,t} - R_{f,t}) + \beta_i^{\text{SMB}}\text{SMB} \\ + \beta_i^{\text{HML}}\text{HML} + \beta_i^{\text{RMW}}\text{RMW} + \beta_i^{\text{CMA}}\text{CMA} + \epsilon_{i,t} \end{aligned} \tag{3.8}$$

where $R_{i,t}$ and $R_{f,t}$ denote the portfolio return i in month t and the risk-free rate in month t, respectively. Following Jensen (1968), $R_{m,t}$ is the market portfolio return in month t. In line with Fama and French (1993), SMB is the difference in returns between small and large stock portfolios in month t, while HML is the difference in returns between value and growth stock portfolios using the book-to-market ratio as a discriminating factor. As defined by Fama and French (2015), RMW is the difference in returns between a portfolio with high operating profitability and one with low operating profitability of stocks, while CMA is the return on a conservative

investment portfolio minus the return on an aggressive investment portfolio of stocks in month t. All these risk factors are well known for explaining the cross-sectional variation in stock returns. α_i^{Jensen} and α_i^{FF5F} are the Jensen's alpha and the Fama-French five-factor alphas, respectively. They are defined by the excess returns of portfolio i not explained by the systematic risk to the factors described above. Positive (negative) and significant alphas indicate that the index outperforms (underperforms) the market portfolio. These equations are estimated using the Ordinary Least Squares (OLS) method. Following Xiao et al. (2017) and Trinks and Scholtens (2017), we test the statistical significance of the coefficients using a t-test where the variance-covariance matrix of the residuals is corrected for autocorrelation and heteroscedasticity (Newey and West, 1987). Finally, $\epsilon_{i,t}$ is the error term.

3.5 Results

Tables 3.2 and 3.3 show the descriptive statistics of the monthly returns of the portfolios based on FWAs, their respective benchmarks, and the risk factors.

In the U.S, Table 3.2, the results clearly demonstrate the benefits of FWAs. The Q5 portfolio, which groups companies with the highest FWA scores, generated an average monthly return of 1.28% (15.36% annualized). This surpasses the Q1 portfolio, with a monthly return of 0.69% (8.28% annualized) and even the SPY at 0.68% monthly (8.16% annualized) over the period from January 2014 to December 2022. For the sub-period (January 2014 to January 2020), Q5 achieved 1.28% monthly (15.36% annualized) compared to 0.75% monthly (9% annualized) for Q1 and 0.76% monthly (9.12% annualized) for the SPY.

These results demonstrate the positive impact of FWAs not only on financial performance but also on the creation of intangible assets. Assets such as employee motivation and retention significantly boost performance (Edmans, 2011). FWAs, by improving morale and motivation, contribute directly to these assets. This translates into improved customer satisfaction and increased productivity (Shockley and Allen, 2012; Lewis et al., 2007). FWAs go beyond simple benefits for employees, enhancing financial performance and enriching human capital, making them essential strategies for companies. From a financial market perspective, the growing appeal of FWAs in the United-States explains the superior performance of Q5. Investors favor companies promoting FWAs, perceived as better investment opportunities. This increases the demand for their shares, thereby strengthening their market performance. This interaction between HR practices and market valuation highlights the potential of FWAs to increase corporate competitiveness. The analysis of the standard deviations of returns for the Q5, Q1 portfolios, and the SPY reveals that the risk level for portfolios focused on FWAs is actually lower than that of the SPY, used as a benchmark in the United-States. For instance, for the period from January 2014 to December 2022, the average monthly standard deviation for Q5 is 4.18% (14.49% annualized) and for Q1 is 3.99% (13.82% annualized), while the SPY, which includes a wide range of companies from various sectors, has a standard deviation of 4.41% (15.28% annualized). These observations demonstrate that the risk of the Q5 and Q1 portfolios, although focused on specific criteria such as FWAs, is very close to that of the SPY, a highly diversified portfolio.

These observations challenge the traditional assumption of modern portfolio theory (Markowitz, 1952) that increased concentration on specific criteria, such as high or low FWAs scores, would

necessarily increase risk relative to more diversified investments. This confirms the empirical findings provided by Schröder (2007), Cortez et al. (2009), and Peillex et al. (2021), who documented very small differences in standard deviation between socially responsible indices and their unrestricted benchmarks.

From a corporate perspective, the observed risk reduction in the Q5 and Q1 portfolios compared to the SPY can be attributed to the effectiveness of FWAs. These practices enhance employee satisfaction and productivity, leading to reduced turnover and increased operational stability. A stable workforce minimizes fluctuations in operations and maintains consistent performance (Kotey and Sharma, 2019; Kotey and Koomson, 2021). From the perspective of financial markets and investors, the lower risk level observed in the Q5 and Q1 portfolios compared to the SPY can be explained by the valuation of intangible assets generated by FWAs. FWAs contribute to creating a favorable work environment, thereby improving motivation, commitment, and employee loyalty. These elements, although intangible, are valuable assets for companies because they strengthen organizational culture and enhance overall performance (Alarussi and Gao, 2021; Qureshi and Siddiqui, 2021; Hartsema et al., 2021; Pechlivanidis et al., 2022; Wahyuni et al., 2023). This enhancement of intangible assets makes companies less risky and more attractive to investors who value long-term stability and sustainability of business practices. The analysis of the return distributions of the Q5 and Q1 portfolios, based on FWAs, as well as the SPY, reveals that these portfolios are platykurtic and skewed to the left over both periods studied, from January 2014 to December 2022 and from January 2014 to January 2020. This analysis demonstrates that the return distributions are characterized by lower risks of extreme returns but an increased propensity for significant losses.

Table 3.2. Descriptive statistics of monthly returns on the FWAs portfolios and risk factors in the U.S.

	Q5	Q1	(Q5-Q1)	SPY	Mkt-RF	SMB	HML	RMW	CMA
Panel A : Jan 2014 – Dec 2022									
Mean	0.0128	0.0069	0.0059	0.0068	0.0083	-0.0012	-0.0006	0.0037	0.0013
STD	0.0418	0.0399	0.0199	0.0441	0.0457	0.0278	0.0368	0.0210	0.0230
Max	0.1442	0.1085	0.0600	0.1194	0.1356	0.0711	0.1275	0.0720	0.0772
Min	-0.0943	-0.1370	-0.0411	-0.1337	-0.1339	-0.0828	-0.1387	-0.0475	-0.0863
Skewness	-0.3141	-0.4782	-0.1111	-0.5336	-0.3405	0.2215	0.3347	0.6624	0.5995
Kurtosis	0.6695	1.2062	0.1111	0.7542	0.8804	0.2113	2.2458	1.2169	1.1950
Observations	108	108	108	108	108	108	108	108	108
Panel B : Jan 2014 – Jan 2020									
Mean	0.0128	0.0075	0.0053	0.0076	0.0089	-0.0030	-0.0039	0.0013	-0.0023
STD	0.0322	0.0304	0.0192	0.0327	0.0340	0.0255	0.0260	0.0148	0.0155
Max	0.0774	0.0780	0.0493	0.0798	0.0840	0.0707	0.0821	0.0348	0.0370
Min	-0.0744	-0.0779	-0.0411	-0.0963	-0.0957	-0.0455	-0.0625	-0.0389	-0.0325
Skewness	-0.3884	-0.2163	-0.0078	-0.6293	-0.5606	0.3387	0.7512	-0.2234	0.5429
Kurtosis	0.2255	0.4094	0.2082	1.1255	0.9417	-0.2963	1.0533	0.0996	-0.0361
Observations	73	73	73	73	73	73	73	73	73

This table presents the descriptive statistics for the various variables used to calculate risk-adjusted performance indicators in United-States. The Mean corresponds to the average monthly returns. STD measures the volatility of monthly returns. Q5 represents companies with the highest FWAs scores (top 20%) and Q1 includes companies with the lowest FWAs scores (bottom 20%). The difference portfolio (Q5-Q1) represents a portfolio that buys companies from Q5 and short sells companies from Q1.The portfolios are reallocated monthly. SPY represents the monthly return (eq. 3.1)of the S&P500 index. Monthly stock prices are extracted from the Thomson Reuters Eikon database. Mkt-RF represents the excess return of the overall stock market over the risk-free rate, represented by U.S. Treasury bills. SMB is the difference in returns between a small and a large U.S. stock portfolio ; HML is the difference in returns between a value portfolio and a growth stock portfolio in the U.S., using the price-to-book ratio as a discriminating factor. RMW is the difference in returns between a portfolio of robust operational profitability and a portfolio of low operational profitability of U.S. stocks ; CMA is the return of a conservative investment portfolio minus the return of an aggressive investment portfolio of U.S. stocks. These risk factors are collected from the Kenneth R. French data library.

After reviewing the returns and standard deviations of portfolios based on FWAs in the United-States, our analysis turns to Europe (Table 3.3). Data from January 2014 to December 2022 show that the Q5 portfolio, which includes companies with the highest FWAs scores, achieved higher average returns than those

of the Q1 portfolio and the STOXX benchmark. During this period, the Q5 portfolio exhibited an average monthly return of 0.37% (4.44% annualized), compared to 0.12% (1.44% annualized) for the Q1 portfolio and 0.01% (0.12% annualized) for the STOXX. This trend also continues in the sub-period ending in January 2020, where Q5 achieved a return of 0.41% monthly (4.92% annualized), higher than the 0.20% (2.4% annualized) for Q1 and 0.01% (0.12% annualized) for the STOXX. These results highlight the ability of companies with flexible work practices to generate superior returns, even in a different market context. Regarding risk, measured by the standard deviation of returns, the Q5 and Q1 portfolios exhibit levels comparable to those of the STOXX, corroborating the notion that FWAs do not necessarily increase risk for investors. For the complete period analyzed, the average monthly standard deviation is 4.97% (17.42% annualized) for Q5, 4.41% (15.27% annualized) for Q1, and 4.72% (16.34% annualized) for the STOXX. In the sub-period, these figures are 3.86% (13.37% annualized) for Q5, 3.49% (12.09% annualized) for Q1, and 3.62% (12.54% annualized) for the STOXX600. These observations in Europe validate the conclusions drawn from the US data, demonstrating that FWAs can offer both solid financial performance and effective risk management, without increasing risk compared to traditional benchmarks. These findings coincide with the conclusions of Amon et al. (2021), who also note an absence of significant differences between the returns and risks of portfolios in Europe and the United-States.

Nevertheless, these initial results should be interpreted with caution, as they provide only a basic overview of the financial performance of portfolios by examining returns and risks independently. Future analyses will explore risk-adjusted performance measures.

Table 3.3. Descriptive statistics of monthly returns on the FWAs portfolio and risk factors in the E.U

	Q5	Q1	(Q5-Q1)	STOXX	Mkt-RF	SMB	HML	RMW	CMA
Panel A : Jan 2014 – Dec 2022									
Mean	0.0037	0.0012	0.0026	0.0001	0.0033	0.0013	-0.0015	0.0033	-0.0019
STD	0.0497	0.0441	0.0241	0.0472	0.0478	0.0167	0.0300	0.0162	0.0160
Max	0.1756	0.1685	0.0668	0.1525	0.1620	0.0472	0.1290	0.0345	0.0521
Min	-0.1413	-0.1211	-0.0518	-0.1598	-0.1544	-0.0560	-0.1130	-0.0540	-0.0439
Skewness	-0.0755	0.1205	0.0429	-0.1954	-0.0736	0.1426	0.7040	-0.6332	0.2296
Kurtosis	1.1346	1.7514	0.3440	1.0034	1.5940	4.4989	4.1810	0.8786	1.5153
Observations	108	108	108	108	108	108	108	108	108
Panel B : Jan 2014 – Jan 2020									
Mean	0.0041	0.0020	0.0030	0.0001	0.0030	0.0017	-0.0033	0.0037	-0.0015
STD	0.0386	0.0349	0.0200	0.0362	0.0360	0.0150	0.0193	0.0140	0.0110
Max	0.0899	0.0786	0.0668	0.0702	0.0742	0.0374	0.0636	0.0325	0.0296
Min	-0.0912	-0.0855	-0.0459	-0.0839	-0.0854	-0.0294	-0.0498	-0.0385	-0.0242
Skewness	-0.5636	-0.1532	0.2205	-0.1135	-0.0603	0.2649	0.4404	-0.2793	2.5344
Kurtosis	-0.1809	-0.1604	0.7298	-0.7353	-0.6564	-0.4097	0.8353	0.1589	0.4715
Observations	73	73	73	73	73	73	73	73	73

This table presents the descriptive statistics for the various variables used to calculate risk-adjusted performance indicators in Europe. The Mean corresponds to the average monthly returns. STD measures the volatility of monthly returns. Q5 represents companies with the highest FWAs scores (top 20%) and Q1 includes companies with the lowest FWAs scores (bottom 20%). The difference portfolio (Q5-Q1) represents a portfolio that buys companies from Q5 and short sells companies from Q1. The portfolios are reallocated monthly. STOXX represents the monthly return (eq. 3.1) of the EuroSTOXX600 index. Monthly stock prices are extracted from the Thomson Reuters Eikon database in U.S. dollars. Mkt-RF represents the excess return of the overall stock market over the risk-free rate, represented by the one-month European government bond rate. SMB is the difference in returns between a small and a large E.U stock portfolio ; HML is the difference in returns between a value portfolio and a growth stock portfolio in the E.U., using the price-to-book ratio as a discriminating factor. RMW is the difference in returns between a portfolio of robust operational profitability and a portfolio of low operational profitability of E.U. stocks ; CMA is the return of a conservative investment portfolio minus the return of an aggressive investment portfolio of E.U. stocks. These risk factors are collected from the Kenneth R. French data library.

The risk-adjusted performance measures provided in Table 3.4 convincingly demonstrate that investment in FWAs portfolios in the United-States, particularly the top quintile (Q5), offers a significantly higher average risk premium per unit of total risk compared to SPY (benchmark).

For example, over the period from January 2014 to December 2022, the Sharpe ratio of Q5 is 0.2916, indicating that returns substantially exceed those of the SPY, which has a ratio of 0.1390. This suggests that an investor favoring Q5 would have achieved superior returns for each unit of risk taken. Analysis of the adjusted Sharpe ratios reinforces this conclusion. With an ASR of 0.0272 for Q5 versus only 0.0029 for the SPY during the same period, it is evident that FWAs portfolios manage risk-adjusted performance better, thereby maximizing risk compensation for investors. Additionally, the long-short strategy (Q5-Q1) displays an ASR of 0.0212, proving that even an elaborate investment approach can offer significantly attractive risk-adjusted returns. Regarding the Sortino ratio, which emphasizes the volatility of negative returns, Q5 also shows superior results. The Sortino ratio for Q5 is 0.2893 compared to 0.1172 for the SPY. This measure indicates that Q5 not only reduces downside risk but does so in a manner that substantially improves returns for investors focused on minimizing losses. For the analyzed period, the excess returns relative to VaR for Q5 are 0.2179, significantly surpassing the 0.0932 of the SPY. This result underscores not only the ability of Q5 to offer superior risk-adjusted returns but also to provide robust protection against extreme risks. Similarly, the long-short strategy (Q5-Q1) presents Excess Returns relative to VaR of 0.1974 for the same period. This indicates that the strategy effectively exploited performance gaps between the upper and lower quintiles to generate returns that far exceed the maximum risk expectations estimated by the VaR. This shows that investors employing complex strategies can enhance their compensation for risk while limiting their exposure to severe losses. The results over the period from January 2014 to January 2020 confirm the robustness of the FWA portfolios, particularly the top quintile (Q5) and the bottom quintile (Q1), in terms of risk-adjusted performance. The Sharpe ratio for

Q5 reaches 0.3758, demonstrating significant outperformance compared to the SPY, which has a ratio of 0.2123. In comparison, Q1 shows a Sharpe ratio of 0.2231, indicating respectable but lower risk-adjusted performance than Q5. The adjusted Sharpe ratio for Q5 is 0.0579, in contrast to 0.0122 for Q1, highlighting superior risk-adjusted management for the top quintile. The Sortino ratio of 0.3662 for Q5, compared to 0.2356 for Q1, illustrates better minimization of downside risks by Q5. Finally, the excess returns relative to VaR for Q5, at 0.3012, also exceed those of Q1 at 0.1594, providing better protection against extreme risks.

This comprehensive analysis combines Sharpe ratios, adjusted and Sortino ratios with Excess Returns relative to VaR to offer an exhaustive perspective on the added value of FWAs portfolios in terms of risk-adjusted return and risk management. Essentially, the data reveal that investors could have achieved above-average returns for each unit of risk taken on their investment if they had invested in FWAs stocks. The consistency of performances across different measures of risk-adjusted performance underscores the benefits of an investment strategy centered on assets valued by FWAs, offering not only adequate compensation for risk but also an opportunity for outperformance in diverse market environments.

Table 3.4. Risk-adjusted performance metrics for the FWAs portfolios and S&P500 in the U.S.

	Sharpe Ratio	Adj. Sharpe Ratio	Sortino Ratio	Excess Returns to VaR
Panel A : Jan 2014 – Dec 2022				
Q5	0.2916	0.0272	0.2893	0.2179
Q1	0.1569	0.0041	0.1525	0.1006
(Q5-Q1)	0.2659	0.0212	0.2981	0.1974
SPY	0.1390	0.0029	0.1172	0.0932
Panel B : Jan 2014 – Jan 2020				
Q5	0.3758	0.0579	0.3662	0.3012
Q1	0.2231	0.0122	0.2356	0.1594
(Q5-Q1)	0.2407	0.0156	0.2564	0.1760
SPY	0.2123	0.0101	0.1789	0.1504

Sharpe Ratio measures the excess return per unit of risk above the risk-free rate(eq. 3.2). Adjusted Sharpe Ratio accounts for skewness and kurtosis in returns(eq. 3.3). Sortino Ratio focuses on downside risk by comparing returns above a minimum target to the downside deviation(eq. 3.4). Excess Returns to VaR quantifies how much the portfolio's returns exceed the Value at Risk (VaR), calculated as the maximum potential loss over a set period at a 95% confidence level(eq. 3.6). SPY, representing the S&P 500 index, serves as the benchmark.

The results from Table 3.5 compare the performances of FWAs portfolios against the STOXX600, the European benchmark. For the period from January 2014 to December 2022, FWAs, particularly Q5 and Q1, display better risk-adjusted performances compared to the STOXX600. Q5 exhibits a Sharpe ratio of 0.0626 and an adjusted Sharpe ratio of 0.0003, surpassing the STOXX600 which shows a negative Sharpe ratio of -0.0118 and an adjusted Sharpe ratio of 0.0000. Q1, although less performant than Q5, still has a Sharpe ratio of 0.0123 and an adjusted Sharpe ratio of 0.0000, also outperforming the STOXX600. The Sortino ratio for Q5 is 0.0615, compared to -0.0112 for the STOXX600, highlighting better downside risk management for Q5. Q1 has a Sortino ratio of 0.0123, also showing more effective downside risk management than the STOXX600. The excess returns relative to VaR for Q5 and Q1 are respectively 0.0399 and 0.0076, indicating better protection against extreme risks compared to -0.0072 for the

STOXX600. From January 2014 to January 2020, Q5 displays a Sharpe ratio of 0.0886 and an adjusted Sharpe ratio of 0.0008, with a Sortino ratio of 0.0904, all superior to the indicators of the STOXX600. Q1, with a Sharpe ratio of 0.0378 and an adjusted Sharpe ratio of 0.0001, as well as a Sortino ratio of 0.0391, continues to surpass the STOXX600 in risk management and adjusted performances. The excess returns relative to VaR of 0.0576 for Q5 and 0.0238 for Q1 during this period are well above -0.0094 for the STOXX600. These observations demonstrate that, both over long and short periods, FWAs portfolios not only outperform European benchmarks in terms of risk-adjusted returns but also offer more robust downside risk management and better protection against market disruptions. In Europe, investing in FWAs could thus represent an advantageous strategy for those looking to maximize their returns while controlling risks.

The results of these risk-adjusted performance measures show that, as already indicated by the analysis of means and standard deviations, investing in FWAs portfolios does not underperform relative to their benchmarks. This second set of results leads us to conclude that investors do not pay any premium for allocating their capital to the best companies in terms of FWAs.

Table 3.5. Risk-adjusted performance metrics for the FWAs portfolios and STOXX600 in EU

	Sharpe Ratio	Adj. Sharpe Ratio	Sortino Ratio	Excess Returns to VaR
Panel A : Jan 2014 – Dec 2022				
Q5	0.0626	0.0003	0.0615	0.0399
Q1	0.0123	0.0000	0.0123	0.0076
(Q5-Q1)	0.0908	0.0008	0.0949	0.0596
STOXX	-0.0118	0.0000	-0.0112	-0.0072
Panel B : Jan 2014 – Jan 2020				
Q5	0.0886	0.0008	0.0904	0.0576
Q1	0.0378	0.0001	0.0391	0.0238
(Q5-Q1)	0.0703	0.0004	0.0756	0.0456
STOXX	-0.0154	0.0000	-0.0151	-0.0094

Sharpe Ratio measures the excess return per unit of risk above the risk-free rate(eq. 3.2). Adjusted Sharpe Ratio accounts for skewness and kurtosis in returns(eq. 3.3). Sortino Ratio focuses on downside risk by comparing returns above a minimum target to the downside deviation(eq. 3.4). Excess Returns to VaR quantifies how much the portfolio's returns exceed the Value at Risk (VaR), calculated as the maximum potential loss over a set period at a 95% confidence level(eq. 3.6). STOXX, representing the STOXX600 index, serves as the benchmark.

Jensen's single-factor model alphas reflect the average risk-adjusted performance of FWAs portfolios. They show the excess returns of these portfolios relative to a theoretical benchmark index. According to the results reported in Table 3.6, in the United-States, Jensen's alphas for the Q5 and (Q5-Q1) portfolios significantly differ from zero during the periods studied. For example, from January 2014 to December 2022, the alpha for the Q5 portfolio is 0.52% monthly (6.24% annually). For the Q1 portfolio, the alpha is negative, at -0.05% per month (-0.6% annually). The long-short strategy (Q5-Q1) displays an alpha of 0.57% monthly (6.84% annually). The results are slightly lower for the period from January 2014 to January 2020, where the alpha for Q5 is 0.46% per month (5.52% annually). The alpha for Q1 remains negative at -0.03% per month (-0.36% annually), and that of the strategy (Q5-Q1) is 0.49% per month (5.88% annually). These alphas, all above the

risk-free rate, indicate excess returns. The magnitude of these alphas, reflecting the mispricing of assets, is corroborated by previous studies on similar portfolios, especially those based on human capital (Yarovaya et al., 2021) and intangible assets (Xiong et al., 2020; De Nicola et al., 2021). Regarding the betas, analyses show that for both periods, the betas of the Q5 and Q1 portfolios, although close to 1, reveal differences. The Q5 portfolio has slightly higher betas than Q1, indicating a somewhat higher market sensitivity. However, the difference between the betas of Q5 and Q1 is not statistically significant, suggesting a similar overall market sensitivity for both portfolios. The limited number of stocks in the Q5 portfolio and specific characteristics such as better risk management and stable work practices might explain this slight difference in market sensitivity. These results are in line with our previous conclusions based on descriptive statistics and performance ratios.

Table 3.6. Jensen's alphas and betas for FWAs portfolios (U.S.)

	Jensen's alphas	Mkt-RF	Adj. R^2
Panel A : Jan 2014 – Dec 2022			
Q5	0.0052***	0.8371***	0.833
	(0.0017)	(0.0361)	
Q1	−0.0005	0.8094***	0.856
	(0.0015)	(0.0321)	
(Q5-Q1)	0.0057***	0.0277	−0.005
	(0.0020)	(0.0422)	
Panel B : Jan 2014 – Jan 2020			
Q5	0.0046**	0.8511***	0.805
	(0.002)	(0.049)	
Q1	−0.0003	0.7990***	0.796
	(0.002)	(0.048)	
(Q5-Q1)	0.0049**	0.0521	−0.005
	(0.002)	(0.067)	

This table presents the Jensen's alphas and betas (eq. 3.7) for FWAs portfolios in the U.S. Q5 represents companies with the highest FWAs scores (top 20%), while Q1 comprises companies with the lowest FWAs scores (bottom 20%). Portfolios are reallocated monthly. The difference portfolio (Q5-Q1) buys Q5 companies and short sells Q1 companies. The coefficients are estimated using standard OLS regression with Mkt-RF as the explanatory variable. The intercept, α_i^{Jensen}, indicates the excess return of the respective portfolio. Standard errors are shown in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

In Europe, the results from Table 3.7 offer a marked contrast to those observed in the United-States. We find that, regardless of the period studied, the alphas of the Q5 and Q1 portfolios do not show a significant difference from zero. This indicates that whether for a portfolio with a high FWAs score (Q5) or a low score (Q1), the average risk-adjusted performance does not stand out from that of the market portfolio. These observations are consistent with the works of Statman and Glushkov (2009), Schröder (2007), and Peillex et al. (2021), who found that Jensen's alphas for socially responsible portfolios do not significantly deviate from zero. Furthermore, the difference between the Q5 and Q1 portfolios remains

positive during the analyzed periods. The alphas of the long-short strategy for panels A and B are +21 and +17 basis points per month, respectively. These results highlight that although the individual performances of Q5 and Q1 relative to the market are not remarkable, the combined long-short strategy provides a slight excess return, albeit modest. Regarding betas, for the first period analyzed, the Q5 portfolio presents a beta of 1.0077, indicating a volatility slightly higher than that of the overall market. In comparison, the Q1 portfolio displays a lower beta at 0.8663, indicating reduced sensitivity to market movements. The long-short strategy (Q5-Q1) has a beta of 0.1414, which is significant, reflecting a moderate but notable reactivity to market fluctuations. During the second period, the beta of Q5 increases to 1.0190, confirming its heightened sensitivity relative to the market. The beta of Q1 is 0.8822, remaining below unity but closer to that of Q5 compared to the first period. The long-short strategy (Q5-Q1) maintains a similar reactivity with a beta of 0.1368, demonstrating a moderate but consistent exposure to market variations. These results indicate that the Q5 portfolio reacts more strongly to market conditions compared to Q1. The long-short strategy between Q5 and Q1 shows effective risk management by providing relative stability against market fluctuations. This analysis highlights the utility of the long-short strategy as a tool for diversification and hedging against market movements.

Table 3.7. Jensen's alphas and betas for FWAs portfolios (E.U.)

	Jensen's alphas	**Mkt-RF**	**Adj. R^2**
Panel A : Jan 2014 – Dec 2022			
Q5	−0.0002	1.0077***	0.937
	(0.0010)	(0.0252)	
Q1	−0.0023	0.8663***	0.878
	(0.0015)	(0.0312)	
(Q5-Q1)	0.0021	0.1414***	0.091
	(0.0019)	(0.0413)	
Panel B : Jan 2014 – Jan 2020			
Q5	0.0004	1.0190***	0.902
	(0.0015)	(0.040)	
Q1	−0.0013	0.8822***	0.823
	(0.0017)	(0.048)	
(Q5-Q1)	0.0017	0.1368**	0.047
	(0.0023)	(0.064)	

This table presents the Jensen's alphas and betas(eq. 3.7)for FWAs portfolios in Europe. Q5 represents companies with the highest FWAs scores (top 20%), while Q1 comprises companies with the lowest FWAs scores (bottom 20%). Portfolios are reallocated monthly. The difference portfolio (Q5-Q1) buys Q5 companies and short sells Q1 companies. The coefficients are estimated using standard OLS regression with Mkt-RF as the explanatory variable. The intercept, α_i^{Jensen}, indicates the excess return of the respective portfolio. Standard errors are shown in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

The Jensen model is based on the idea that the return of a portfolio can be explained by the return of a market portfolio (MKT), the portfolio's market sensitivity (β_i^{MKT}), and alpha (α_i^{Jensen}). In fact, the excess return of a portfolio cannot be fully explained by a single risk factor (Bauer et al., 2007). Fama and French (1993) showed that the expected return also depends on the portfolio's exposure to the difference in returns between large and small capitalization stocks (SMB) and between stocks with a high book-to-market ratio and those with a low book-to-market ratio (HML). More recently, Fama and French (2015) argued that adding two new risk factors — RMW (robust-minus-weak profitability) and

CMA (conservative-minus-aggressive investment) — to the three-factor Fama-French model can improve the predictability of excess stock returns. Adding these risk factors to the Jensen model should enhance the alpha estimates and the explanatory power of the asset pricing model.

Table 3.8 shows that market returns are not the sole determinants of the excess returns of FWA portfolios in US. The coefficients related to the book-to-market ratio (HML) and investment levels (CMA) are also significant. Across both periods, we observe that the Q5 portfolio (high FWAs scores), and the long-short strategy (Q5-Q1) favor companies with low book-to-market ratios (growth stocks), and those with prudent investment strategies (conservative). This orientation can be explained by the fact that investors recognize the superior potential of companies that effectively utilize FWAs. These companies are often seen as more capable of innovating and adapting to market changes while prudently managing their financial resources in the face of economic uncertainties. In terms of risk-adjusted performance, the incorporation of risk factors confirms the outperformance of the Q5 portfolio compared to the Q1 portfolio, as well as that of the long-short strategy (Q5-Q1). The alphas for the Q5 portfolio and the (Q5-Q1) strategy are positive in all cases examined. Specifically, the Q5 portfolio displays an alpha of +40 basis points for both the complete period and the sub-period, while the Q5-Q1 strategy records an alpha of +49 basis points for the complete period and +42 basis points for the sub-period from January 2014 to January 2020.

Table 3.8. Fama-French five-factor for FWAs portfolios (U.S.)

	Five-factor alphas	Mkt-RF	SMB	HML	RMW	CMA	Adj. R^2
Panel A : Jan 2014 – Dec 2022							
Q5	0.0040**	0.8853***	−0.0224	−0.1002*	0.0563	0.4098***	0.862
	(0.002)	(0.037)	(0.068)	(0.059)	(0.085)	(0.091)	
Q1	−0.0009	0.8137***	−0.0217	0.1324**	0.0820	0.0726	0.879
	(0.001)	(0.034)	(0.061)	(0.052)	(0.076)	(0.081)	
(Q5-Q1)	0.0049**	0.0717	−0.0008	−0.2326***	0.0258	0.3372***	0.073
	(0.002)	(0.046)	(0.084)	(0.072)	(0.105)	(0.112)	
Panel B : Jan 2014 – Jan 2020							
Q5	0.0040**	0.9048***	0.0335	−0.2560***	0.1847	0.4288***	0.832
	(0.002)	(0.052)	(0.075)	(0.082)	(0.122)	(0.142)	
Q1	−0.0002	0.8179***	−0.0038	0.0276	0.1173	0.1067	0.794
	(0.002)	(0.054)	(0.079)	(0.085)	(0.128)	(0.148)	
(Q5-Q1)	0.0042*	0.0869	0.0373	−0.2835**	0.0674	0.3221	0.022
	(0.0024)	(0.074)	(0.108)	(0.117)	(0.176)	(0.204)	

This table presents the five-factor regressions (eq. 3.8) for FWAs portfolios in U.S. Q5 represents the companies with the highest FWAs scores (top 20%) while Q1 comprises the companies with the lowest FWAs scores (lowest 20%). Portfolios are reallocated monthly. The difference portfolio represents a portfolio that buys Q5 companies and sells short Q1 companies. Coefficients are estimated using a standard OLS regression. Explanatory variables are Mkt-RF, SMB, HML, RMW, and CMA. The effect of the intercept (α_i^{FF5F}) shows the excess return of the respective portfolio. Standard errors are reported in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Contrary to the United-States, in Europe, for the entire period, the Q5 portfolio and the (Q5-Q1) strategy show significant exposure to small-cap companies, as indicated by the SMB column in Table 3.9. This trend, aligned with the research by Peillex et al. (2021), suggests a preference of non-US SRI portfolios (Japan) for small capitalizations, likely due to their ability to quickly integrate practices SRI, making them attractive for flexible and sustainable investments. During the sub-period from January 2014 to January 2020, the Q5 and (Q5-Q1) portfolios exhibit varied levels of investment, as indicated by the CMA column. Q5 shows a trend towards more conservative investments, signaled by a significant negative coefficient, suggesting a cautious strategy in the face of market uncertainties. In contrast, the (Q5-Q1) does not display a

clear investment trend, as evidenced by the lack of statistical significance of its CMA coefficient, indicating a less defined or balanced investment strategy between conservatism and aggressiveness. In terms of risk-adjusted performance, the incorporation of risk factors confirms that the alphas of the FWAs portfolios do not show a significant difference from zero.

The use of the Fama-French five-factor model, rather than Jensen's model, is justified for estimating the risk-adjusted performance of FWAs portfolios, as it provides better predictive power. This is particularly evident in the adjusted R^2. The analysis also reveals that the adjusted R^2 is higher for the entire period than for the sub-period. This difference could be explained by investment movements during the pandemic, where flows were directed towards responsible investments (Harjoto et al., 2021).

Table 3.9. Fama-French five-factor for FWAs portfolios (E.U.)

	Five-factor alphas	Mkt-RF	SMB	HML	RMW	CMA	Adj. R^2
Panel A : Jan 2014 – Dec 2022							
Q5	−0.0007	0.9768***	0.1637**	0.0243	−0.0134	−0.2200	0.943
	(0.0011)	(0.0297)	(0.0763)	(0.0925)	(0.1218)	(0.1404)	
Q1	−0.0020	0.8355***	−0.1660*	0.2261*	−0.0807	−0.2769	0.888
	(0.0015)	(0.0368)	(0.0947)	(0.1147)	(0.1508)	(0.1731)	
(Q5-Q1)	0.0013	0.1413***	0.3297***	−0.2018	0.0673	0.0569	0.262
	(0.0020)	(0.0474)	(0.1217)	(0.1476)	(0.1950)	(0.2228)	
Panel B : Jan 2014 – Jan 2020							
Q5	−0.0006	0.9879***	0.1085	0.0848	0.0779	−0.5864***	0.926
	(0.0013)	(0.038)	(0.088)	(0.133)	(0.150)	(0.169)	
Q1	−0.0002	0.8154***	−0.1626	0.4658**	0.0620	−0.4332*	0.843
	(0.0017)	(0.051)	(0.116)	(0.175)	(0.197)	(0.223)	
(Q5-Q1)	−0.0004	0.1726***	0.2711	−0.3810	0.0160	−0.1532	0.235
	(0.0023)	(0.064)	(0.146)	(0.221)	(0.249)	(0.282)	

This table presents the five-factor regressions(eq. 3.8) for FWAs portfolios in Europe. Q5 represents the companies with the highest FWAs scores (top 20%) while Q1 comprises the companies with the lowest FWAs scores (lowest 20%). Portfolios are reallocated monthly. The difference portfolio represents a portfolio that buys Q5 companies and sells short Q1 companies. Coefficients are estimated using a standard OLS regression. Explanatory variables are Mkt-RF, SMB, HML, RMW, and CMA. The effect of the intercept (α_i^{FF5F}) shows the excess return of the respective portfolio. Standard errors are reported in parentheses. Significance levels : $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

3.6 Conclusion

Traditional management theories consider FWAs as superfluous expenses that do not necessarily enhance productivity (Taylor, 1911). In contrast, more modern perspectives from human relations (Maslow, 1943; Hertzberg, 1959; McGregor, 1960) and human capital theory (Bloom et al., 2015) suggest that FWAs can significantly enhance corporate performance. According to the efficient market hypothesis, one might expect that any distinctly beneficial characteristic of a company would be quickly integrated into its stock valuation, thus eliminating the potential for abnormal gains.

However, research conducted by (Alarussi and Gao, 2021; Balzer

et al., 2020; Haji and Ghazali, 2018; Hartsema et al., 2021; Pechlivanidis et al., 2022; Qureshi and Siddiqui, 2021; Wahyuni et al., 2023) highlights a persistent undervaluation of intangible assets in financial markets. Applying these ideas to FWAs reveals that, while beneficial for the company, FWAs generate intangible assets such as employee motivation, loyalty, and improved customer satisfaction (Lewis et al., 2007; Kotey and Koomson, 2021), which are not always immediately or fully valued by the market.

The goal of this paper is thus to examine whether the competitive advantages conferred by FWAs are quickly reflected in the stock valuations of companies. Hence, we test the theory of efficient markets in the context of FWAs.

To this end, we analyze the financial performance of portfolios based on FWAs scores from 2014 to 2022 in the United-States and Europe. We specifically seek to determine whether the Q5 portfolios, which group the top 20% of companies in terms of FWAs performance, exhibit financial results different from those of the Q1 portfolios, which include the bottom 20% in FWAs performance. Additionally, we analyze a long-short portfolio (Q5-Q1) that measures relative performance by adopting long positions in Q5 companies and short positions in Q1 companies. Performance is evaluated using traditional risk-adjusted return indicators such as the Sharpe ratio, adjusted Sharpe ratio, Sortino ratio, adjusted returns to value at risk, Jensen's alpha, and the Fama-French five-factor model. The analysis is conducted over two distinct periods : a complete period from 2014 to 2022, and a shorter period from 2014 to 2020.

Our results reveal that in the United-States, regardless of the performance measurement method used or the period examined,

both the Q5 portfolio and the Long-Short strategy (Q5-Q1) display higher risk-adjusted returns compared to the Q1 portfolio. In Europe, our observations show that, just like in the United-States, the Q5 portfolio and the Long-Short strategy (Q5-Q1) exhibit superior risk-adjusted returns relative to the Q1 portfolio, when measured by performance ratios. However, unlike the results in the United-States, neither Jensen's alphas nor the alphas derived from the Fama-French five-factor model are statistically significant in Europe.

Thus, based on these results, we conclude that investing in FWAs is particularly beneficial in the United-States, where the Q5 portfolios and the Long-Short strategy (Q5-Q1) demonstrate superior risk-adjusted returns and abnormal gains, as indicated by Jensen's alphas and the Fama-French five-factor model. On the other hand, while FWAs also offer financial benefits in Europe, the lack of significance of the alphas suggests that these advantages are already integrated into stock prices. Therefore, for investors aiming to achieve abnormal gains, FWAs seem to offer opportunities primarily in the United States and not in Europe, where markets appear to anticipate and appropriately value these flexible work arrangements.

The divergence in these results between the United-States and Europe regarding financial performance related to FWAs can be attributed to several key factors. In the United-States, the S&P 500, rich in high technology and service companies, benefits from the intangible assets generated by FWAs, such as employee motivation and retention. These assets are particularly valuable in sectors where commercial value does not primarily rest on fixed physical assets and can therefore create high value. In contrast, in Europe, the STOXX 600 includes a greater proportion of tradi-

tional industries where the benefits of FWAs are quickly integrated into company valuations, limiting observable abnormal gains. Furthermore, Europe, as a global leader in ESG investment (Alastair, 2021), enforces strict and transparent regulations on FWAs. These practices, well standardized and anticipated by the markets, also limit abnormal gains on European exchanges. Finally, in the United-States, the use of traditional valuation methodologies designed for 20th-century businesses and primarily based on physical assets does not readily incorporate the value of intangible assets.

These results are encouraging and offer strategic perspectives for both fund managers and companies. Fund managers should consider developing or integrating investment strategies that value companies effectively implementing FWAs. By featuring these companies in their portfolios, they can attract investors interested in progressive and ethical work practices, while encouraging less-performing companies to improve their practices to access new capital. On the other hand, companies that have not yet effectively implemented FWAs or are seeking to enhance their existing practices should recognize the significant benefits of these arrangements. By adopting or strengthening FWAs, they can not only improve their financial performance but also increase their attractiveness to investors, which could open the door to their inclusion in thematic investment portfolios and thus benefit from substantial financial inflows. These initiatives can play a key role in enhancing corporate social responsibility and financial performance, aligning investment objectives with modern and sustainable work practices.

Chapitre 4

Can US Sector Rotation Strategies Benefit from FFESG Alphas ?

Abstract

Environmental, Social, and Governance (ESG) factors are crucial for performance in sectors that depend on resources or have a significant social impact, attracting more capital and enhancing risk resilience. Consequently, a plausible link exists between ESG factors and sector performance. In this paper, we attempt to validate this link by first integrating ESG factors into the five-factor Fama-French model (FFESG) to better explain the performances of American sector portfolios. We observe that the FFESG model better adjusts the returns of these portfolios than the traditional FF5 model. Furthermore, by exploiting the alpha derived from this enhanced model (FFESG alpha), we test whether it indicates true outperformance or underperformance, applying long-only and long-short sector rotation strategies. This approach allows us to test the efficacy of FFESG alpha in dynamic portfolio management, compared to strategies based on the FF5 model. Our long-only sector rotation strategy, which buys sectors showing a positive FFESG alpha, generates performance superior to that of the S&P 500. All strategies based on FFESG alpha outperform those founded on FF5 alpha. These results demonstrate the utility of integrating ESG criteria into traditional financial models to improve long-term performance, thus highlighting the crucial role of responsible investment in modern markets.

Keywords : Sector rotation, multi-factor models, ESG factors, portfolio performance.

JEL Classification : G10, G11, G12

4.1 Introduction

Sector rotation, recognized as a tactical investment strategy, exploits cyclical economic variations to generate profits by shifting investments between different sectors (Beber et al., 2010; Chong and Phillips, 2015; Zhu, 2022; Bock and Maewal, 2023; Sebayang and Soekarno, 2023; Chen et al., 2023). As each sector reacts distinctly to changes in economic policies, macroeconomic factors, and news events (Lamponi, 2014), committing to specific sectors is often seen as an optimal approach to balance risk and return (Baiocchi and Britt, 2012). This characteristic explains the marked interest in sector rotation not only within the financial community but also more broadly in society (Conover et al., 2008; Held, 2009; Vashakmadze, 2012; Chong and Phillips, 2015; Chava et al., 2019; Jain, 2022; Molchanov and Stangl, 2023; Chen et al., 2023).

According to Chisholm et al. (2013), the appeal of sector rotation is closely associated with the past performances of the American stock market. From December 1990 to December 2012, Chisholm et al. (2013) identified that factors specific to each company were the primary source of variation in stock returns, accounting for an average of 61% of historical returns. The influence of sector exposure emerged as the second most significant factor, explaining 22% of the returns, followed by investment style at 12% and market capitalization at 5%.

Research on sector rotation differs, among other things, in the indicators used to signal a sector change. The signals vary from economic indicators (Greetham and Hartnett, 2004; Conover et al., 2008; Shang and Xu, 2020; Bock and Maewal, 2023), to technical indicators (Jegadeesh and Titman, 1993; Sassetti and Tani, 2006; Newsome and Turner, 2007), and performance indicators such as the alpha of factor models (Sassetti and Tani, 2006; Sarwar et al.,

2017; Alexiou and Tyagi, 2020; Miralles-Quirós et al., 2020; Nsibande and Sebastian, 2023; Miralles-Quirós and Miralles-Quirós, 2024).

These models, particularly those developed by Fama and French (1992, 1993, 2015, 2016), have evolved to better capture market dynamics. For example, the Fama-French five-factor model (Fama and French, 2015), widely recognized as an enhancement over earlier versions including the CAPM and the three-factor model (Fama and French, 1993), has been featured in numerous international studies (Charters et al., 2018; Cox and Britten, 2019; Fama and French, 2016). These studies illustrate that incorporating additional dimensions into traditional factors leads to better estimations of expected returns by integrating aspects such as firm profitability and investment, thus enhancing understanding of return variations across different markets.

However, despite these advances, research by Alrabadi and Alrabadi (2018), Chava et al. (2019), and Nsibande and Sebastian (2023) suggests that these models do not fully account for the expected returns observed in various industries. Given the shortcomings of the Fama-French five-factor model (FF5) in fully explaining sectoral performance, there exists a potential for improvement by adding an additional risk factor (Chiah et al., 2016).

In the current context where the importance of environmental, social, and governance (ESG) criteria is gaining ground among investors and academics (see e.g., Naffa and Fain, 2022; Alda, 2020; Capelle-Blancard and Petit, 2019; Clark et al., 2015; Friede et al., 2015; Nagy et al., 2016; Verheyden et al., 2016; Giese et al., 2019; Kaiser, 2020; Maiti, 2021; Consolandi et al., 2022; Dinh, 2023; Kumar, 2023), some authors propose a FFESG model which adds

the ESG factor, measured by ESG performance scores, to the FF5 model. They find that for portfolios formed on ESG, the FFESG model provides a better fit than their original FF5 model (Hübel and Scholz, 2020; Jin, 2018; Maiti, 2020; Nsibande and Sebastian, 2023). In this vein, we also choose to integrate ESG factors into our model in order to enhance the accuracy of return forecasts.

It is therefore reasonable to ask why we choose ESG factors to enhance the model. Our answer is that : companies with high ESG scores attract additional investments due to their compliance with these practices, which can lead to a short-term rise in their stock prices. This increase, often perceived as a boost, is the result of the influx of capital from investors attracted by social and environmental responsibility (Hartmark and Sussman, 2019; Statman, 2020). The market also tends to react positively to good ESG evaluations by anticipating a reduction in future risks, such as costs related to new environmental regulations or the consequences of social scandals (Clark et al., 2015; Friede et al., 2015; Díaz et al., 2024). These anticipations translate into more favorable stock valuations (Maiti, 2021; Dinh, 2023). Particularly in sectors heavily impacted by environmental issues, such as energy, clean technologies, or healthcare, companies well-rated on the ESG scale may benefit from a specific sectoral advantage (Miralles-Quirós et al., 2020). Innovations and advancements in these areas can position these companies ahead of their competitors, reflecting a premium on their shares. Thus, the ESG factor, by measuring the difference in performance between companies with the highest and lowest scores, captures these market dynamics (Nsibande and Sebastian, 2023). This differential not only demonstrates traditional financial strength but also the momentum generated by a commitment to ESG practices (Giese et al., 2021). This momentum allows for an alpha that is more representative of the current and future opportunities and risks of

companies (Nsibande and Sebastian, 2023). Consequently, the enhanced alpha that takes into account both financial performance and sustainability offers a more comprehensive approach, enhancing the appeal of companies with high ESG ratings and confirming the effectiveness of integrating ESG criteria into investment strategies. This approach also addresses the concerns of investors who increasingly prioritize social and environmental responsibility.

In this study, we examine the risk-adjusted performance of sector portfolios in the United States and the strategy of sector rotation using the alphas from the FFESG model. We hypothesize that adopting a sectoral investment strategy based on the alpha generated by the FFESG model should lead to higher returns.

Following the methodology of Sarwal (Sarwar et al., 2017), we propose a sector rotation strategy that includes both long-only and long-short approaches, where a tipping signal is the alpha from the FFESG model. If the alpha of the FFESG for a sector at time t is positive (negative), we will buy (sell) that sector in period $t + 1$. Our sector rotation strategies are demonstrated on Fama-French US sector portfolios. These portfolios are evaluated using risk-adjusted performance indicators, such as Sharpe and Sortino ratios. To ensure the robustness of the results, different rolling periods have been used : 12 months (Miralles-Quirós and Miralles-Quirós, 2024), 36 months (Sarwar et al., 2017), and 60 months (Miralles-Quirós et al., 2020). Throughout the paper, we compare the effectiveness of the FF5 and FFESG models for this sector rotation strategy in the United States.

Our results show that the FFESG model better explains sector returns than the FF5 model, providing more detailed information and a higher R-squared. Furthermore, strategies based on the

FFESG model consistently outperform those using the FF5 model. Our analyses demonstrate that only long-only strategies were able to outperform the S&P 500 index, generating an average annual excess return of 6.49% over a 12 months rolling period, 3.86% over 36 months, and 2.38% over 60 months. These strategies also stand out for their superior performance in terms of Sharpe and Sortino ratios. The long-short strategy based on the FFESG model demonstrated outperformance.

The contribution of this paper is twofold. Firstly, it enriches the literature on performance evaluation by analyzing sectoral performance in the United States through the integration of Environmental, Social, and Governance (ESG) factors into the traditional Fama-French five-factor model (FF5). This extension, which leads to the FFESG model, enhances the understanding of asset valuation by incorporating sustainable factors, thus offering a more comprehensive perspective on the determinants of sectoral returns. Secondly, this paper contributes to the still limited literature on sectoral investment by focusing on a dynamic market timing strategy : sector rotation. This strategy involves adjusting the composition of portfolios based on performance forecasts for different sectors, thereby capitalizing on sectoral cycles. Although the predictability of sectoral returns is well-documented, sector rotation as a strategic approach remains underexplored in academic research. By examining this method, the study aims to fill this gap by demonstrating how the use of alphas generated by the FFESG model can optimize risk-adjusted returns in the context of dynamic portfolio management.

The rest of this paper is organized as follows. Section 4.2 presents a review of the existing literature on sector rotation and factors models. Section 4.3 details the database and analyzes the descriptive

statistics. Section 4.4 describes methodology employed to construct portfolios. Section 4.5 list the empirical results of the proposed portfolios. Finally, Section 4.6 provides the main conclusions.

4.2 Literature review

4.2.1 Sector Rotation

The strategy of sector rotation was first documented by Sorensen and Burke (1986) and Grauer et al. (1990). This approach was popularized by Fidelity Investments with the launch of the "Select" series of mutual funds during the 1980s (Sarwar et al., 2017). The modern era of sector investing truly began in December 1998 with the introduction of the first sector-based exchange-traded funds (ETFs), marking a turning point in sector-based portfolio management.

Exploring the effectiveness of this strategy, Dellva et al. (2001) analyzed the timing and selection ability of 35 sector mutual funds from Fidelity, observing underperformance of 35% relative to market indices between 1994 and 1998, a period where Jensen's alphas were negative. Concurrently, Chordia and Shivakumar (2002) examined trading strategies based on momentum, which proved effective during periods of economic expansion but were less robust during recessions. This observation highlights the importance of considering economic cycles to predict the relative performance of different market sectors(Luk, 2012). Faff (2004) observed the performance of 24 Australian industrial portfolios, noting a tendency for mining industries to generate a negative FF3 alpha, while industrial sectors tended to produce a positive alpha. In contrast, Kacperczyk et al. (2005) found that mutual funds with a specific industrial concentration, deviating from the passive market portfolio, tend to outperform.

Research by Stangl et al. (2009) suggests that sector rotation could yield returns superior to those of traditional buy-and-hold strategies. Doeswijk and van Vliet (2010) applied seasonal factors to predict future returns, developing a sector rotation strategy from 1970 to 2008 that achieved an average annual return of 12.9%. Rapach et al. (2015) reported annual return increases of 7.82% and 12.28% from 1985 to 2012 thanks to this strategy. Dou et al. (2014) explored asset allocation across different economic regimes through sectors, noting a positive alpha for the Energy, High Technology, and Health sectors, against a negative alpha for the Durable Goods, Telecommunications, and Manufacturing sectors, both in bull and bear markets. Chava et al. (2019) examined the impact of economic cycles on sector returns with a strategy based on Sharpe ratios, discovering that this approach generated an annualized alpha of 14.02% between 1985 and 2014. This finding suggests that investors do not fully integrate cyclical variations into their decisions.

Recent studies continue to validate the effectiveness of sector rotation. Croce et al. (2022) found that firms in leading industries had higher average returns than those in lagging industries. McMillan (2021) found that a sector rotation strategy based on forecasting defaults and the variance of stock returns generated superior performance. Kinlaw et al. (2019) showed that their rotation strategy based on identifying bubbles was particularly effective during recessions. Karatas and Hirsa (2021) demonstrated the superiority of a rotation strategy based on machine learning, while Sarwar et al. (2017) and Noble et al. (2021) documented outperformance of SPDR ETFs based on sector rotation, supporting the idea that this strategy can be founded on a five-factor Fama-French alpha. These studies show that sector rotation, when applied judiciously and informed by thorough analyses, can significantly enhance investment performance by accounting for economic cycles and sector-specific

characteristics.

4.2.2 Factor Models

Traditional Factor Models

In empirical finance, the three-factor Fama-French model (FF3) and Carhart's four-factor model have become standards for assessing asset performance and pricing models. However, these models have been criticized for their inability to capture all variations in stock returns. The FF3, which extends the CAPM, includes factors aimed at explaining the outperformance observed by the CAPM, including profitability and investment factors. This inadequacy is confirmed by the research of Novy-Marx (2013), Walkshäusl and Lobe (2014), and Titman et al. (2004), who identified anomalies such as the positive correlation between average returns and earnings surprises, or the negative correlation with financial distress and other variables such as idiosyncratic volatility, net share issuance, and asset growth. These issues were further explored by Spiess and Affleck-Graves (1995) and Chan et al. (1995). In response, Fama and French (2015) introduced a five-factor model (FF5), which adds two new factors : profitability and investment. This FF5 model provides a better basis for analyzing portfolios according to size, book-to-market ratio (B/M), profitability, and investment, thus enhancing the model's ability to explain expected stock returns.

Nevertheless, despite the increased number of risk factors in the FF5, recent empirical tests such as those conducted by Walkshäusl and Lobe (2014), Alrabadi and Alrabadi (2018), Mosoeu and Kodongo (2020), and Nsibande and Sebastian (2023) indicate that the model still has gaps in explaining the returns of listed stocks. These authors therefore use the FF5 as a base model while exploring whether the model's predictability can be improved by including

additional factors.

ESG factors

Investors are increasingly attentive to the impact of environmental, social, and governance (ESG) factors on corporate performance. Social aspects encompass employee diversity and gender equity, governance issues deal with corruption, and environmental stakes include carbon emissions and waste management. These factors, which signal long-term sustainability risks, are crucial for evaluating corporate performance, as recognized by researchers and investors (Pástor et al., 2022; Zerbib, 2022; Dimson et al., 2015; Nath, 2021; Statman, 2020; Kumar, 2023; Dinh, 2023; Díaz et al., 2024).

Studies have demonstrated that environmental, social, and governance (ESG) criteria are essential for stock market performance, according to various authors (Clark et al., 2015; Friede et al., 2015; Nagy et al., 2016; Verheyden et al., 2016; Heinsz and McGlinch, 2019; Giese et al., 2019; Kaiser, 2020; Maiti, 2021; Consolandi et al., 2022). Additionally, Jin (2018) explored the integration of an ESG factor into the Fama and French model by analyzing 1,425 U.S. equity funds from 2009 to 2016. The results show that portfolios with high ESG scores act as an effective hedge against systematic ESG risks and that market prices reflect these risks. The study also indicates that sustainable investment strategies can provide additional protection against risks, beyond what traditional diversification offers. Pollard and Sherwood (2018) demonstrated that integrating ESG factors can serve as a risk premium in equity portfolios, thereby enriching risk assessment. Maiti (2021) identified a link between ESG factors and expected stock returns, while Giese et al. (2019) observed that ESG data influence corporate valuations and performance through systemic and idiosyncratic risk

profiles. They emphasize that variations in ESG attributes can serve as significant financial indicators and that ESG scores can be valuable for financial analysis. Kaiser (2020) demonstrated that improving ESG levels in portfolios can also enhance risk-adjusted performance. Díaz et al. (2024) confirmed that ESG ratings (Environmental, Social, and Governance) play a crucial role in the performance of industries during the COVID-19 period. They established an ESG factor by measuring the difference in returns between companies with the highest and lowest ESG scores. This ESG factor, integrated into the traditional Fama-French factors, significantly contributed to explaining return variations among industries. Shanaev and Ghimire (2021) enriched the Fama-French five-factor model by adding a sustainability element and the momentum factor. Their approach, which integrates principles of microeconomics and ecological economics, demonstrated that sustainable management practices can reduce the cost of equity by 1.6% to 2.9% annually, contributing to an increase in global GDP of 1.3 to 2.3 trillion dollars in 2018.

However, some research indicates that ESG criteria do not systematically benefit corporate performance(see e.g., Van Beurden and Gossling, 2008; Reilly and Visciani, 2015; Capelle-Blancard and Petit, 2019; Breedt et al., 2019; La Torre et al., 2020; Demers et al., 2021). Capelle-Blancard and Petit (2019) examined investors' reactions to ESG news released in the media versus that issued directly by companies, concluding that shareholder reactions are primarily driven by negative ESG-related news. Naffa and Fain (2022) show that from 2015 to 2019, ESG portfolios did not generate significant alphas with the Fama-MacBeth model, indicating that ESG factors do not enhance the Fama-French five-factor model. However, pure factor portfolios might be useful for assessing the sustainability risks of ESG investments.

The main conclusions indicate that, once rated, ESG portfolios tend to exhibit short-term performance comparable to non-ESG portfolios, while displaying reduced risk levels. These results suggest that ESG criteria have a more pronounced influence on risks than on returns, and that this influence varies across sectors (Dinh, 2023).

4.3 Data

We utilize monthly return data covering the period from January 2007 to December 2022 (16 years) extracted from the website of Kenneth French [1]. These data include returns from the Fama-French five-factor model, returns from 10 U.S. sector portfolios and 1-month US Treasury bill. The 10 sectors include non-durable consumer goods (NoDur), durable consumer goods (Durbl), manufacturing (Manuf), energy (Enrgy), advanced technology equipment (HiTec), telecommunications (Telcm), retail (Shops), health care (Hlth), utilities (Utils), and Other sectors.

Additionally, we have integrated ESG scores from Thomson Reuters EIKON (Berg et al., 2021; Gutsche et al., 2017; Nsibande and Sebastian, 2023). The ESG factor is defined by the performance differential between quintiles of portfolios, distinguishing companies with high ESG scores (leaders) from those with lower scores (laggards). The portfolios are equally weighted and rebalanced monthly. Our analysis includes all publicly listed companies in the U.S. that are indexed in the S&P 500 based on their market capitalization (Giese et al., 2019; Bali et al., 2016; Menchero and Ji, 2017; Naffa and Fain, 2022; Sahin et al., 2022; Ciciretti et al., 2023).

1. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 4.1 presents the descriptive statistics for the risk factors. The average monthly market premium (0.73%) proves to be higher than other risk premiums related to size, value, earnings quality, investment, and ESG criteria. This aligns with findings by Maiti (2020), who also noted that the monthly market premium is higher than other premiums. Table 4.2 shows the correlation among different risk factors. It is observed that the ESG factors are uncorrelated with the market over the studied period, thereby offering an interesting diversification opportunity for investors looking to reduce their exposure to general market fluctuations.

Monthly price data for the S&P 500 index [2], which serves as a benchmark, also come from Thomson Reuters EIKON.

Table 4.1. Descriptive statistics.

Factors	N	Mean	Standard Deviation	Skewness	Kurtosis
Mkt-RF	192	0.0073	0.0476	-0.5357	1.0528
SMB	192	0.0003	0.0257	0.2225	0.3959
HML	192	-0.0013	0.0333	0.1834	2.7642
RMW	192	0.0037	0.0191	0.5675	1.2401
CMA	192	0.0014	0.0195	0.5675	1.8582
ESG	192	-0.0084	0.0261	-1.6532	12.7689

This table presents the descriptive statistics (Mean, Standard Deviation, Skewness, Kurtosis) for the monthly return series of risk factors (Fama-French five-factor model and ESG factors) over the period from January 2007 to December 2022. Skewness and Kurtosis refer to the series' skewness and kurtosis coefficients. N represents the number of observations for each factor. The risk-free rate used is the yield of a one-month U.S. Treasury Bill.

2. The monthly return of the S&P 500 index is calculated using the following formula : $R_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, where $P_{i,t}$ represents the closing price for the current month and $P_{i,t-1}$ the closing price for the previous month (Chokki et al., 2024).

Table 4.2. Correlation matrix.

Factors	Mkt-RF	SMB	HML	RMW	CMA	ESG
Mkt-RF	1					
SMB	0.372	1				
HML	0.184	0.310	1			
RMW	−0.151	−0.349	0.002	1		
CMA	−0.135	0.043	0.592	0.114	1	
ESG	−0.074	−0.212	0.375	0.275	0.347	1

This table provides the correlation matrix of risk factors. Each cell shows the correlation coefficient between the returns of two factors, where a value of 1 indicates a perfect positive correlation and values closer to 0 indicate little to no linear relationship.

4.4 Methodology

In this study, we employed two regression models to analyze returns. The first model is the Fama and French five-factor model (FF5), which is an extension of the FF3. In this model, Fama and French (2015) added an investment factor and a profitability factor to address the empirical shortcomings of the FF3. The FF5 is specified as follows :

$$\begin{aligned} R_{it} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t \\ + r_i\text{RMW}_t + c_i\text{CMA}_t + e_{it} \end{aligned} \tag{4.1}$$

where R_{it} is the excess return of sector i over the risk-free rate R_{ft} (proxied by 1-month US Treasury bill), α_i represents the intercept (alpha)[3] for asset i, $R_{mt} - R_{ft}$ is the excess return of the market over the risk-free rate, s_i, h_i, r_i, and c_i represent the loadings on the respective factors of size, value, profitability, and investment ; SMB (Small Minus Big) is the size factor, HML (High

3. Alphas are defined by the excess returns of portfolio i not explained by the systematic risk to the factors described above. Positive (negative) and significant alphas indicate that the index outperforms (underperforms) the market portfolio. These equations are estimated using the Ordinary Least Squares (OLS) method.

Minus Low) is the value factor, RMW (Robust Minus Weak) is the profitability factor, and CMA (Conservative Minus Aggressive) is the investment factor. The second model, similar to the first, incorporates an additional factor : ESG scores. The regression formula for this model is :

$$R_{it} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + r_i\text{RMW}_t + c_i\text{CMA}_t + l_i\text{ESG}_t + e_{it} \tag{4.2}$$

where l_i represents the loading on the new ESG factor. In this equation, all factors except for the new ESG factor are consistent with those defined in the original FF5 model. The ESG factor represents the return differential between companies with high ESG scores (leaders) and those with low scores (laggards). We evaluate the effectiveness of these models using the R-squared (R^2), which measures the proportion of variation in returns explained by the model factors. A higher R^2 for the model including ESG would indicate that the addition of this factor improves the accuracy of return predictions. This improvement could justify extending the FF5 model to incorporate ESG scores, enabling the exploitation of alphas to develop a profitable sector rotation strategy.

Alpha trading strategy

We estimate the FFESG model for the period from January 2007 to December 2022, using rolling windows of 12 months (Miralles-Quirós and Miralles-Quirós, 2024), 36 months (Sarwar et al., 2017), and 60 months (Miralles-Quirós et al., 2020). We develop both Long-only and Long-Short investment strategies, where alpha, representing the returns not explained by the factors of the FFESG model, serves as the signal. For example, consider the 36-month

window : the first 36 months of this sample period are used to estimate the first set of alphas with the FFESG model, over a total of 192 months of trading. Our Long-only strategy takes a long position in month $t+1$ in all sector portfolios that have a positive FFESG alpha for the 36 months of the rolling window ending in month t. The Long-Short strategy buys sector portfolios in month $t+1$ that have a positive alpha in month t and sells short those that have a negative alpha in month t. These positions are rebalanced each month, based on the alpha from the previous 36 months' rolling window.

We then evaluate the performance of our strategies using the Sharpe and Sortino, which measure the effectiveness of risk-adjusted returns. The Sharpe ratio, following the method of Bessler and Wolff (2015), is calculated as the average of excess returns over the risk-free rate, here represented by the return of a one-month U.S. Treasury bill, divided by the standard deviation of returns :

$$\text{Sharpe} = \frac{\mu - r_f}{\sigma} \tag{4.3}$$

The Sortino ratio, recommended by Sortino and Satchell (2001) and further explored by Sortino (2009), modifies this approach by using the downside deviation instead of the total standard deviation, focusing the analysis only on negative returns :

$$\text{Sortino} = \frac{\mu - r_f}{\text{Downside Deviation}} \tag{4.4}$$

These indicators are crucial for assessing whether investment strategies generate superior returns in light of the risk taken, by providing a detailed comparison of risk-adjusted performances.

4.5 Results

Table 4.3 presents the descriptive statistics of average monthly returns, standard deviations, skewness, and kurtosis for ten sector portfolios over the period from January 2007 to December 2022 (192 months) in the United States. The average excess returns vary from a minimum of 0.52% per month (6.42% annually) in the telecommunications sector to a maximum of 1.05% per month (13.35% annually) in the technology sector. The durable goods sector displayed a high average return of 1.03% per month (13.08% annually) and a higher standard deviation of 9.94% per month (34.43% annually), while the non-durable goods sector showed less volatility, with a standard deviation of 3.85% per month (13.34% annually). Most of the sector portfolios exhibit negative skewness and a kurtosis less than 3, indicating that the return distributions for these portfolios were negatively skewed and platykurtic. Only the sectors of durable goods and energy display positive skewness and a kurtosis greater than 3, suggesting that investors might expect higher potential gains while managing a higher risk of extreme outcomes. These observations on the durable goods sector are consistent with the findings of Sarwar et al. (2017), who identified similar characteristics.

Table 4.3. Descriptive statistics.

Sector	N	Mean	Standard Deviation	Skewness	Kurtosis
NoDur	192	0.0075	0.0385	-0.5982	1.0642
Durbl	192	0.0103	0.0994	0.9017	4.4812
Manuf	192	0.0081	0.0547	-0.5711	1.7647
Energy	192	0.0070	0.0793	0.0786	3.4712
HiTec	192	0.0105	0.0553	-0.4729	0.4700
Telcm	192	0.0052	0.0488	-0.4940	0.7716
Shops	192	0.0089	0.0468	-0.0699	1.2767
Hlth	192	0.0088	0.0427	-0.3143	0.1378
Utils	192	0.0064	0.0411	-0.7958	1.2135
Other	192	0.0055	0.0585	-0.5842	1.5169

This table presents the descriptive statistics (Mean, Standard Deviation, Skewness, Kurtosis) for the monthly return series of 10 sector portfolios (monthly excess returns) over the period from January 2007 to December 2022. Skewness and Kurtosis refer to the series' skewness and kurtosis coefficients. N represents the number of observations for each sector. The risk-free rate used is the yield of a one-month U.S. Treasury Bill.

Table 4.4 presents the average rolling alphas over 12, 36, and 60 months according to the FFESG model, along with their standard deviations. The total number of alphas for each sector is 181, 157, and 133, respectively. Overall, the health, technology, and utilities sectors exhibit the highest average alphas. Conversely, the sectors of energy, telecommunications, and manufacturing show the lowest average alphas. For instance, for the 12-month rolling period, the average monthly alphas for the health, technology, and utilities sectors are 0.50% (6.17% annually), 0.28% (3.41% annually), and 0.20% (2.43% annually), respectively. The lowest are found in the energy (-11.58% annually), telecommunications (-2.37% annually), and manufacturing (-1.79% annually) sectors. These results corroborate the studies by Dou et al. (2014); Sarwar et al. (2017); Alexiou and Tyagi (2020), which noted positive alphas in the health, technology, and utilities sectors, and negative alphas in telecommunications and manufacturing. However, unlike these studies which reported a positive alpha for the energy sector, our findings show a negative alpha for this sector. This can be attributed

to the significant impact of the COVID-19 pandemic which heavily affected the energy sector Federal Reserve Bank of St. Louis (2021). Finally, among the 10 sectors analyzed, the average net monthly alpha is -0.014% (-0.17% annually) for the 12-month rolling, -0.017% (-0.20% annually) for the 36-month rolling, and -0.036% (-0.43% annually) for the 60-month rolling. These results are in line with the studies by Alexiou and Tyagi (2020), which also identified negative net average alphas for sector portfolios in the United States.

Table 4.4. Mean of rolling FFESG alphas

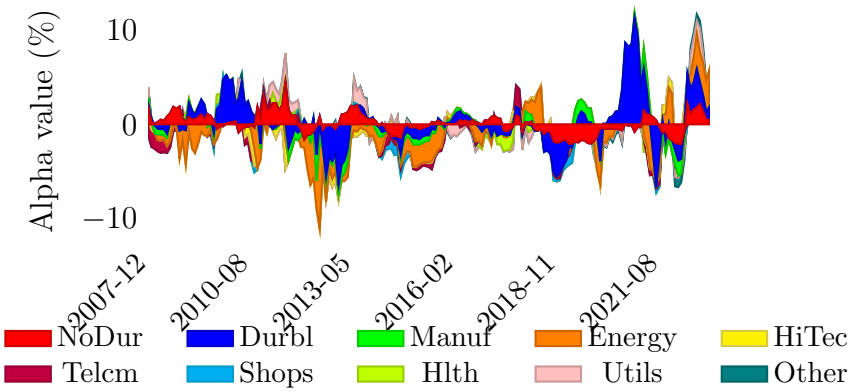
Sector	12-month rolling		36-month rolling		60-month rolling	
	Mean alpha (%)	SD (%)	Mean alpha (%)	SD (%)	Mean alpha (%)	SD (%)
NoDur	0.07	11.14	0.18	4.71	0.16	4.14
Durbl	0.09	26.53	-0.23	6.76	-0.42	2.88
Manuf	-0.15	8.10	-0.11	2.51	-0.14	2.07
Energy	-1.02	24.23	-0.81	7.78	-0.87	6.60
HiTec	0.28	8.02	0.18	2.72	0.14	2.33
Telcm	-0.20	14.94	-0.28	4.75	-0.26	2.88
Hlth	0.50	11.17	0.52	6.00	0.54	5.63
Shops	-0.01	9.66	0.01	3.20	0.06	2.43
Utils	0.20	12.45	0.26	5.60	0.29	4.48
Other	0.10	5.43	0.11	1.69	0.14	1.24
Net	-0.014	13.167	-0.017	4.572	-0.036	3.468

Ten sector portfolios are regressed with FFESG factors over the sample period January 2007 to December 2022 on a 12, 36, and 60 months rolling window basis. Total number of alphas estimated for each sector is respectively 181, 157, and 133. The FFESG model is given in (eq. 4.2). Alpha is the performance unexplained by exposures to the given factors. Table reports the monthly mean of rolling FFESG alphas and standard deviation (SD) of FFESG rolling alpha series (in percentages) for each sector. The 'Net' row represents the average performance across all sectors.

To better understand and illustrate the performance of the analyzed sectors over time, several charts (Figures 4.1, 4.2, and 4.3) have been created, depicting the rolling alphas according to the FFESG factors for the United States over the sampling period. In particular, Figure 4.3 shows that the energy and telecommunications sectors displayed poor performance throughout the analyzed period, except for the year 2022. The technology sector experienced a decline during the period from 2013 to 2016 but subsequently re-

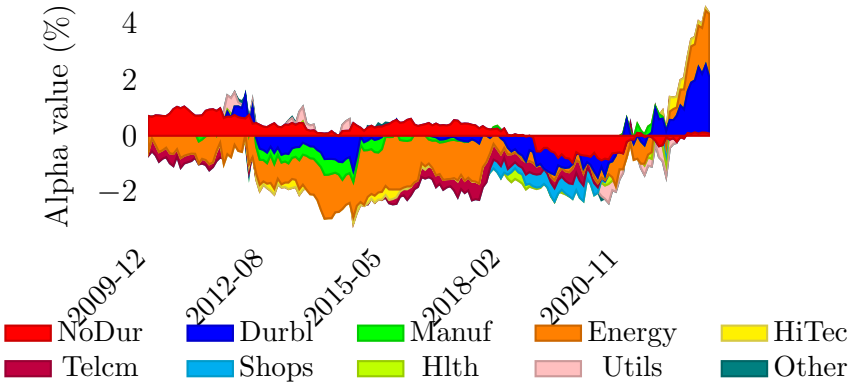
corded the highest alphas from the end of 2021 to December 2022. The utilities sector exhibited alternating periods of positive and negative alphas. As for the health sector, it has generally performed well over the sampling period, marked only by brief periods of negative alphas.

Figure 4.1. – 12-month rolling alpha trend



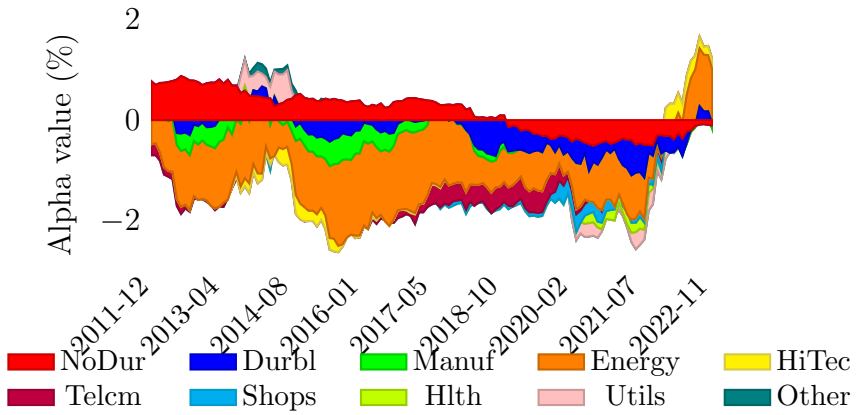
This figure presents the time series of alphas derived from regressing sector portfolios on the FFESG factors. The data spans from January 2007 to December 2022 and is analyzed using a 12-month rolling window.

Figure 4.2. – 36-month rolling alpha trend



This figure presents the time series of alphas derived from regressing sector portfolios on the FFESG factors. The data spans from January 2007 to December 2022 and is analyzed using a 36-month rolling window.

Figure 4.3. – 60-month rolling alpha trend



This figure presents the time series of alphas derived from regressing sector portfolios on the FFESG factors. The data spans from January 2007 to December 2022 and is analyzed using a 60-month rolling window.

Table 4.5 show that the FFESG model exhibits a higher rate of positive alphas than the FF5 model across all rolling periods. This performance underscores its ability to more effectively capture overperformance opportunities, particularly in the sectors of non-durable goods, healthcare, and others. This observation aligns with the findings of Betti et al. (2018) and Miralles-Quirós et al. (2020), who also notes significant positive performance in the healthcare sector, highlighting potential investment opportunities in this area. Furthermore, the overall positive alpha increased for 5 out of 10 sector portfolios when transitioning from the FF5 model to the FFESG model, during all rolling periods. This increase in positive alpha for half of the sector portfolios when switching from the FF5 to the FFESG indicates a significant improvement in performance, suggesting that the FFESG model better captures key factors influencing sector returns. The average R^2 for each sector, as shown in Table 4.5, is consistently higher with the FFESG model. This demonstrates that the integration of additional ESG factors into the FFESG model has enhanced its ability to explain sector returns. The more precise alphas of the FFESG model compared to those of the FF5 open opportunities for trading, particularly

in portfolio construction, which we will explore in the section on sector rotation strategies.

Table 4.5. Positive and negative alphas over the rolling window

Sector	Model	12-month rolling		36-month rolling		60-month rolling	
		Pos.(%)	**Avg. R2 (%)**	**Pos.(%)**	**Avg. R2 (%)**	**Pos. (%)**	**Avg. R2 (%)**
NoDur	FFESG	51.93	88.32	71.97	79.47	63.16	76.19
	FF5	49.17	85.39	55.41	78.65	58.65	75.50
Durbl	FFESG	46.41	87.48	19.11	77.04	8.27	74.25
	FF5	45.86	84.04	34.39	76.13	23.31	73.86
Manuf	FFESG	38.12	95.74	39.49	93.24	33.08	92.56
	FF5	39.78	94.27	19.11	92.76	9.77	92.23
Enrgy	FFESG	27.62	89.34	8.28	77.38	9.02	73.50
	FF5	26.52	87.16	5.73	75.99	6.02	72.15
HiTec	FFESG	71.82	95.82	71.97	91.82	66.92	90.51
	FF5	75.14	95.24	83.44	91.68	78.95	90.37
Telcm	FFESG	33.15	87.43	30.57	79.07	22.56	75.69
	FF5	46.96	82.52	40.76	76.85	39.85	73.91
Hlth	FFESG	67.96	87.48	71.97	79.13	77.44	76.84
	FF5	51.38	84.04	61.15	76.85	68.42	74.83
Shops	FFESG	44.75	93.15	58.60	86.01	53.38	84.68
	FF5	61.33	92.11	72.61	85.35	79.70	84.29
Utils	FFESG	54.70	73.15	65.61	45.27	60.15	38.01
	FF5	56.35	67.35	73.89	42.86	75.19	36.20
Other	FFESG	55.80	97.61	73.25	95.97	85.71	95.47
	FF5	45.30	96.91	53.50	95.70	63.16	95.25

This table presents the count of positive (Pos.) alphas and their percentages of the total from rolling regressions of both the FFESG (eq. 4.2) and FF5(eq. 4.1). factor models for each sector. It also notes that a negative (Neg.) alpha is calculated as $1 -$ positive alpha. The average (Avg.) R^2 values for each sector portfolio and model are reported in the final column.

Table 4.6 presents a summary of the performances of long-only and long-short trading strategies, based on the alphas from the FFESG and FF5 models for sector rotation, as well as those of the

S&P 500 index. The tables show the average monthly return, standard deviation, Sharpe ratio, and Sortino ratio for each strategy. They allow for comparisons between different strategies as well as between the same strategies across various rolling periods. Furthermore, the results indicate that the long-only strategies based on the FFESG and FF5 models have managed to outperform the benchmark. For example, for the 12-month period : These performances translate into superior performance ratios, with a Sharpe ratio of 0.20 for the FFESG and 0.19 for the FF5, compared to 0.10 for the S&P 500. The Sortino ratio is 0.19 for the FFESG and 0.18 for the FF5, compared to 0.08 for the S&P 500. These results are in line with those reported by Alexiou and Tyagi (2020), Miralles-Quirós et al. (2020) and Sarwar et al. (2017), who also observed that the best performances in the United States were achieved through this strategy. It is observed that the alphas from the FFESG model function more effectively as indicators for sector rotation in long-short strategies, compared to the FF5 model. For instance, over a 36-month period, the average return of the long-short strategy based on the FFESG model is 0.05% per month (0.605% annually), whereas for the FF5 model, it is -0.02% per month (-0.24% annually). Furthermore, the volatility of the long-short strategies is lower compared to other strategies, which contrasts with the findings of Alexiou and Tyagi (2020), who reported very high volatility for long-short strategies. This discrepancy can be explained by our market-neutral long-short approach, which aims to reduce risks. Regardless of the strategy or rolling period considered, alphas based on the FFESG model consistently outperform those based on the FF model. For example, over a 60-month period, the average monthly return generated by the FFESG alphas is 1.04% (13.33% annually) compared to 1.02% (12.91% annually) for long-only strategies based on the FF. In terms of performance ratios, the Sharpe ratio is 0.24 for the FFESG alpha compared to 0.22 for

the FF alpha, and the Sortino ratio is 0.20 for the FFESG alpha versus 0.19 for the FF alpha. This trend is also confirmed for the long-short strategies, where the FFESG alpha regularly exceeds the FF alpha. These results demonstrate that the FFESG model, by incorporating ESG factors, offers a more robust and potentially more profitable method for sectoral investment analysis compared to the traditional FF model. However, it is interesting to note that the returns of the strategies based on the FFESG and FF5 models do not show a significant difference in profitability, despite the higher explanatory power of the FFESG model in explaining sectoral returns. This finding is similar to that of Alexiou and Tyagi (2020) and Sarwar et al. (2017), who, in working with the FF5 and FF3 models, also observed no significant difference in profitability, despite the higher explanatory power of the five-factor model.

Table 4.6. Trading strategy performance

12-month rolling				
Trading Strategy	**Mean (%)**	**SD (%)**	**Sharpe**	**Sortino**
Long only FFESG alpha	1.06	5.07	0.2012	0.1926
Long only FF5 alpha	1.03	5.24	0.1877	0.1807
Long-Short FFESG alpha	0.39	2.65	0.1308	0.1424
Long-Short FF5 alpha	0.29	3.12	0.0793	0.0897
S&P 500	0.53	4.75	0.1013	0.0839
36-month rolling				
Trading Strategy	**Mean (%)**	**SD (%)**	**Sharpe**	**Sortino**
Long only FFESG alpha	1.09	4.26	0.2452	0.2234
Long only FF5 alpha	1.01	4.63	0.2091	0.1933
Long-Short FFESG alpha	0.05	2.41	0.0041	0.0038
Long-Short FF5 alpha	-0.02	3.01	-0.0228	-0.0206
S&P 500	0.80	4.28	0.1762	0.1528
60-month rolling				
Trading Strategy	**Mean (%)**	**SD (%)**	**Sharpe**	**Sortino**
Long only FFESG alpha	1.05	4.14	0.2421	0.2019
Long only FF5 alpha	1.02	4.38	0.2218	0.1918
Long-Short FFESG alpha	0.02	2.00	-0.0124	-0.0117
Long-Short FF5 alpha	-0.03	2.68	-0.0301	-0.0296
S&P 500	0.85	4.15	0.1928	0.1588

This table reports the results of long-only and long-short trading strategies based on the FFESG and FF5 factor models. It includes monthly mean returns, standard deviation (SD), Sharpe ratio (eq. 4.3), and Sortino ratio (eq. 4.4). for all strategies. The risk-free rate used is the yield of a one-month U.S. Treasury Bill. Rotation strategies take long positions in sector portfolios demonstrating positive alpha over 12, 36, and 60-month rolling window regressions. The long-short strategies buy sector portfolios with positive alpha and sell those with negative alpha. The sector portfolio is rebalanced monthly and is equally weighted. The S&P 500 index serves as the benchmark.

4.6 Conclusion

Traditional pricing models reveal their limitations, prompting the integration of new risk factors, particularly Environmental, Social, and Governance (ESG) criteria. These criteria are increasingly important in the evaluation of sectoral performance, especially in sectors like energy, utilities, and finance, which are heavily impacted by social and environmental issues. In response to this evolution, our study enriches the Fama-French five-factor model (FF5)

by integrating ESG scores, thus forming the FFESG model to improve return forecasts for sectoral portfolios. We then implemented sector rotation based on rolling alphas to evaluate whether the FFESG model produces alphas that investors can exploit.

When comparing the FF5 and FFESG models, Ordinary Least Squares (OLS) analyses show that the FFESG model better explains the variability of sector portfolio returns than the FF5, generating a higher R^2. This improvement is attributed to the inclusion of ESG scores that enrich the analysis by integrating environmental, social, and governance factors in addition to financial criteria.

We developed four strategies : two long-only and two long-short strategies, based on the alphas from the FFESG and FF5 models, applied over rolling periods of 12, 36, and 60 months.

It turned out that strategies using the FFESG model consistently outperform those based on the FF5 model, thanks to the integration of ESG factors. Furthermore, the results indicate that only the long-only strategies managed to outperform the benchmark (S&P500), in line with existing research. The long-short strategy based on the FFESG model demonstrated outperformance combined with low volatility.

This study lays the groundwork for future research that should examine in detail the interactions between different ESG factors, a crucial aspect for companies with limited resources. It is recommended to deepen the analysis of ESG scores by integrating quantitative data from sustainability reports and third-party assessments to reduce the current subjectivity of analyses. Furthermore, the use of SPDR ETFs from the S&P sector for sector rotation strategies would allow for a precise quantification of the impact of ESG criteria on investment performance. This would provide concrete

indications of the actual effectiveness of ESG criteria in investment management and help formulate more effective resource allocation strategies for companies.

Chapitre 5

Conclusion

In this thesis, we address three interrelated research questions on the impacts of intangible assets and ESG factors on financial performance. These questions have significant implications for investors, financial institutions, and policymakers, offering them essential perspectives for navigating sustainability challenges in promising economies.

The first research question examines how the integration of intangible assets affects stock market performance in the context of value investing, focusing on the valuation of the Sparkline Intangible Value ETF. This analysis is based on a comparative study with major financial indices in the United States, such as the Russell 1000 Value index and the S&P500.

The observed decline in the effectiveness of traditional investment strategies can largely be attributed to structural changes in modern enterprises and the evolving nature of the assets they possess. Historically, valuation methods focused on tangible assets such as real estate and physical equipment, which are easily quantifiable and transparently represented in financial statements. However, with the advent of the knowledge economy, intangible assets such as patents, trademarks, and technological expertise have become

essential components of value creation within companies, although their quantification remains complex and often omitted in balance sheets.

This shift has revealed the limitations of traditional accounting standards that struggle to capture the real value of intangible assets, despite their significant impact on the financial performance of companies. As a result, investors relying on conventional valuation approaches may find themselves underestimating or overvaluing companies whose true economic value is heavily influenced by non-physical assets.

In response to these challenges, it is imperative to revisit and modernize valuation methods and accounting standards to more faithfully reflect the economic value of companies in the contemporary era. Such an adjustment would allow for better integration of intangible assets in evaluations, providing a more complete and accurate picture of the financial health of companies.

By redefining intrinsic value to encompass both tangible and intangible assets, it is plausible that value investing strategies could experience a renaissance, allowing investors to better identify undervalued companies and capitalize on market opportunities previously unrecognized by traditional models. This repositioning would require an evolution of investment criteria to adopt a more holistic view of "value," which could revitalize value investing strategies by aligning them more closely with current economic realities. In response to this evolution of market conditions, the Sparkline Intangible Value ETF was launched in 2021, embodying a major innovation in the field of value investing. This fund employs advanced natural language processing (NLP) techniques to quantify the value of intangible assets such as brand value, intellectual pro-

perty, network effect, and human capital. This AI-based approach aims to strategically target investments in companies that possess strong intangible value, thus introducing a new dimension in asset evaluation. The use of NLP to evaluate these types of assets is not only practical but also supported by various academic works, highlighting its potential and relevance in modern investment strategies.

Despite the relevance and innovation represented by the Sparkline Intangible Value ETF, the question of its profitability remains. This leads to our first research question : Is it profitable to invest in the enhanced intrinsic value of intangible assets through the Sparkline Intangible Value ETF ? This question serves as the main axis for our study, aiming to determine whether integrating intangible value into value investment strategies can indeed generate superior returns. Therefore, the main objective of this study is to evaluate the effectiveness of this investment method in the current context, where intangible assets play an increasingly central role in the valuation of companies. This analysis will contribute to a better understanding of the mechanisms through which intangible assets influence financial performance, thereby offering crucial insights for investors, financial analysts, and policymakers.

The results of this research were very interesting. We found that, although the Sparkline Intangible Value ETF offers superior risk-adjusted returns during economic recovery phases, it underperforms compared to the Russell 1000 Value index and the S&P 500 over the entire period studied. This indicates that, despite the potential of intangible assets to enhance performance, their integration into value investment strategies does not guarantee consistent outperformance against the broader market.

We suggest that the divergence in performance could be attributed to initially overvalued assessments of intangible assets or to more pronounced fluctuations in the valuations of these assets during periods of economic volatility. In terms of portfolio management, this implies that investors should be cautious when incorporating a significant proportion of intangible assets into their investment strategies, taking into account their complex and sometimes speculative valuation potential.

Overall, these findings have significant implications for fund managers, policy formulation, and regulatory frameworks. We advocate that policymakers and regulators consider revisions to accounting standards to better integrate and reflect the value of intangible assets in financial evaluations. Moreover, it is crucial that fund managers adapt their valuation methods to account for the volatility and specificity of intangible assets, thereby enhancing the accuracy of investment decisions and the robustness of portfolio strategies.

Furthermore, this research highlights the need for educators and trainers in the financial field to update educational programs to include a comprehensive understanding of intangible assets and their impact on financial performance. This would prepare the next generation of financial professionals to better navigate an economic landscape where intangible assets play an increasing role.

In conclusion, while recognizing the challenges associated with integrating intangible assets into traditional investment strategies, our study paves the way for enriching discussions on best practices for valuing and managing these types of assets in an evolving financial context. These discussions are essential to ensure that regulatory frameworks and market practices remain relevant and effective in the face of contemporary economic dynamics.

The second research question of this study focuses on the impact of flexible work arrangements (FWAs) on the performance of investment portfolios in major stock markets, including the United States and Europe. This analysis deepens our understanding of the impact of intangible assets on company valuation by examining how flexible work practices can be integrated and valued as intangible assets, thereby directly influencing investment performance.

Existing research highlights that FWAs not only improve employee satisfaction and engagement but also reduce turnover rates while enhancing organizational performance. These practices are crucial for attracting top-tier talent and developing strategic skills, thereby increasing a company's competitiveness. Additionally, FWAs have been associated with improvements in corporate financial performance.

However, the efficient market theory suggests that all beneficial characteristics of a company, such as FWAs, should be quickly reflected in its stock valuation, which could limit opportunities for above-average gains. Nevertheless, it has been observed that the market sometimes undervalues certain aspects of companies, particularly those related to intangible assets generated by practices such as FWAs.

Therefore, our second research question explores whether the benefits of flexible work arrangements lead to superior returns in the stock markets, shedding light on whether these practices, as components of intangible assets, are undervalued by the market and whether they can represent profitable investment opportunities. This question is essential for understanding whether innovative and flexible work practices can effectively create measurable added value for investors in a globalized economic context.

To analyze the effect of FWAs on portfolio performance, we structured our study around two types of portfolios : portfolios with high FWA scores and portfolios with low FWA scores. The comparative performance of these portfolios was assessed based on risk-adjusted measures of the Sharpe and Treynor ratios, as well as Jensen's alpha and the Fama-French five-factor alpha.

Our results suggest that portfolios with high FWA scores outperform their counterparts with low FWA scores. We find that investments in companies with robust flexible work practices not only yield higher gross returns but also superior risk-adjusted returns. This indicates that portfolios with high FWA scores offer a more attractive return profile, particularly appealing to risk-averse investors looking for ethical and sustainable investment opportunities.

Moreover, this outperformance can be explained by a suboptimal market valuation of the intangible benefits that FWAs provide. These benefits, although difficult to quantify precisely, appear to offer a sustainable source of added value, potentially overlooked by conventional valuation models. Investors who identify and exploit these inefficiencies can thus benefit from significant return premiums.

Furthermore, flexible work practices are often associated with improvements in employee well-being and corporate culture, which can in turn positively influence the overall performance of the company. Companies with robust FWA policies may also attract and retain high-quality talent, which is crucial in industries where competition for human capital is intense.

However, it is essential to note that the superior risk-adjusted performance of portfolios with high FWA scores is primarily visible

in the United States, while in Europe, this advantage is less evident. This disparity between the American and European markets can be explained by several fundamental differences.

Firstly, regulatory frameworks and work cultures vary significantly between these two regions. In the United States, the labor market is generally perceived as more dynamic and quick to adopt human resource management innovations, including FWAs. This rapid adoption is often positively valued by investors, reflected in a better risk-adjusted performance of companies that integrate these practices.

Secondly, in the United States, the focus on performance and results-oriented approaches may facilitate a deeper and more strategic integration of FWAs into business objectives, which could lead to more immediate recognition and valuation by financial markets.

In contrast, in Europe, more regulated work systems and strong employee protections may result in a slower and more rigid adoption of flexible work practices. Additionally, the regulatory diversity across European countries can lead to uneven implementation of FWAs, which may dilute their observable impact on stock market performance across the region.

These factors not only highlight the importance of regional and cultural context in evaluating the impact of flexible work practices but also show that the valuation of these practices by markets can vary significantly depending on local specifics and market conditions. This analysis suggests that while FWAs can be beneficial, their effect on risk-adjusted stock market performance may be strongly influenced by the regional context.

These findings offer several important policy implications for

fund managers, investors, policymakers, and regulators, which deserve special attention in their strategic approach. For fund managers and investors, integrating Flexible Work Arrangements (FWAs) as an evaluation criterion could prove beneficial. FWAs, as indicators of innovative corporate culture and progressive human resource management, may signal forward-thinking corporate management likely to generate superior performance. Recognizing these practices as a potential factor for outperformance would allow managers to better position their portfolios, focusing on companies that adopt modern talent management practices, which is particularly relevant in a volatile and competitive market environment.

For policymakers and regulators, the results suggest the need to promote and perhaps standardize reporting on flexible work practices in corporate communications. This could include developing regulatory frameworks that encourage or require transparent disclosures about FWAs, enabling investors to more effectively assess their potential impact on company performance. Such transparency would not only benefit investors but also employees, fostering a more flexible and responsive work environment that can attract and retain talent.

Moreover, the results highlight the importance of contextualizing investment analyses by considering regional variations in the valuation of FWAs. Policymakers might consider policies that support flexible work practices according to the cultural and economic specificities of each region, which could in turn enhance the global competitiveness of companies on international markets.

In conclusion, while FWAs may still be undervalued by some market segments, their potential as a driver of sustainable growth and financial performance should not be underestimated. By ad-

justing investment strategies and regulatory frameworks to better reflect the growing importance of these practices, market participants can enhance their ability to generate risk-adjusted returns while contributing to the creation of a more dynamic and adaptive work environment.

The last research topic we explored in this thesis was the link between sector rotation strategies in the United States and the integration of alphas derived from enhanced ESG models, particularly the Fama-French five-factor model extended to include environmental, social, and governance (ESG) criteria. This analysis led to the development and testing of the FFESG model, an enriched version of the Fama-French model that incorporates these ESG aspects, aiming to better explain the variability of sectoral portfolio returns compared to the traditional five-factor model (FF5).

The growing interest in environmentally, socially, and governance (ESG) respectful investments marks a significant evolution in investor priorities, eager to synchronize their financial strategies with sustainable development goals. This trend has led to an influx of capital into socially responsible funds, resulting in a notable increase in assets under management in sustainable funds.

Nevertheless, it appeared that the traditional five-factor (FF5) model has limitations in fully explaining the cross-sections of industry returns. These limitations have underscored the need to integrate additional criteria that could enrich portfolio return forecasts.

To address these gaps, we opted to enhance this model by integrating ESG factors. Why ? Firstly, because companies that display high ESG scores tend to attract additional investments. These companies, in compliance with environmental, social, and governance

standards, often experience a short-term increase in their stock prices, perceived as a "boost" resulting from the influx of capital from investors who value corporate responsibility. Indeed, adherence to ESG practices can serve as a signal to markets that a company is less risky and more sustainable in the long term.

Secondly, the market often reacts positively to good ESG evaluations, anticipating a reduction in future risks. For example, a company well-rated for its environmental practices may be perceived as less likely to incur high costs related to new environmental regulations or suffer the negative repercussions of ecological or social scandals. These anticipations can lead to higher stock valuations, especially in sectors vulnerable to specific regulatory or ethical issues.

Thirdly, companies operating in sectors particularly sensitive to ESG issues, such as energy, clean technologies, and healthcare, can gain significant competitive advantages if they are perceived as leaders in sustainable practices. These advantages manifest not only in their ability to attract investments but also to innovate and strategically position themselves against competitors.

Fourthly, by integrating ESG factors, the enhanced model (FFESG) is better able to capture market dynamics that favor companies with strong ESG ratings. This allows for the identification of companies that not only demonstrate traditional financial robustness but also benefit from the momentum created by their commitment to sustainable practices.

Finally, by measuring the performance differential between companies with high and low ESG scores, the ESG factor provides a more representative alpha of current and future opportunities and risks for companies. This offers a more comprehensive perspective,

thus enhancing the attractiveness of investments in high ESG-rated companies and confirming the effectiveness of integrating ESG criteria into investment strategies.

This approach leads us to our main hypothesis : the integration of ESG factors should allow for a better explanation of return variations between industries and provide a more accurate measure of risk-adjusted performance.

The goal of this study is twofold. Firstly, to validate the hypothesis that the model enriched with ESG criteria (FFESG) offers a better understanding of sectoral portfolio returns than the traditional FF5 model. Secondly, to examine whether the alpha generated by this new FFESG model can effectively serve as a basis for developing sector rotation strategies that outperform traditional approaches, taking into account the specificities and risks associated with each sector.

The study compared the Fama-French five-factor (FF5) model and the ESG-enriched model (FFESG) to assess their ability to explain sectoral portfolio returns. It used ordinary least squares (OLS) regression analyses to determine that the FFESG model better explains the variability of returns through the integration of ESG scores, producing a higher R^2.

To test the practical application of the alphas generated by these models, the study developed four investment strategies : two long-only and two long-short strategies, applied over rotation periods of 12, 36, and 60 months. The results showed that strategies using the FFESG model outperform those based on the FF5.

The findings of this study on integrating ESG factors into traditional financial models offer profound implications for various

aspects of the financial world and business. These implications are crucial for understanding how ESG criteria can influence corporate strategy, investor behavior, market dynamics, and portfolio management.

Firstly, from a corporate strategy perspective, companies that strongly adopt ESG practices might see their stock valuation improve. This is particularly relevant for companies in sectors sensitive to environmental regulations or societal expectations. By adopting robust ESG practices, these companies can gain a significant competitive advantage, potentially prompting other companies to follow suit to remain competitive.

Regarding investor behavior, the results suggest that investors might benefit from reevaluating their investment methodology to include ESG assessments. Investments that account for high ESG scores tend to outperform, indicating that integrating ESG criteria could lead to better risk-adjusted returns.

In terms of market dynamics, financial markets might gradually place more importance on ESG factors in the evaluation of companies. This evolution could influence the structure of stock indices and favor companies with robust ESG practices, thereby redefining the distribution of capital in the markets.

For portfolio management, managers might consider adjusting their strategies to capitalize on the benefits of integrating ESG criteria. Long-only strategies that use alphas derived from models including ESG have proven particularly effective, suggesting a beneficial potential for funds seeking to maximize returns while reducing risks.

Finally, the implications for policy and regulation are also signifi-

cant. Regulators and policymakers could be encouraged to impose stricter standards regarding the disclosure of ESG practices by companies to ensure greater transparency, thus helping investors make better-informed decisions and promoting a more sustainable economy. These implications demonstrate the growing importance of ESG criteria, not only for enhancing profitability and minimizing risks but also for contributing to the long-term sustainability of the global economy.

We believe that the implications of the three in-depth issues addressed in this thesis are profound, prompting policymakers, financial institutions, and investors to reconsider their strategies and frameworks to more effectively integrate intangible assets and ESG factors. In doing so, they can not only enhance the resilience and financial performance of their portfolios but also play an active role in promoting sustainability and social responsibility within the global market.

The first research question demonstrated that intangible assets, such as technological know-how and brands, have a direct impact on the financial performance of companies. This suggests that financial institutions and investors should refine their valuation methods to better capture and value these types of assets, which are often underestimated by traditional financial models.

The second question explored how flexible work practices (FWAs) influence investment performance, revealing that companies that adopt these practices attract more substantial investments and display superior risk-adjusted returns. This discovery encourages organizations to integrate FWAs into their corporate culture, recognizing their potential to enhance employee satisfaction and productivity, which translates into better financial outcomes.

Finally, the third question addressed the integration of ESG criteria into financial models, showing that ESG-enhanced models more accurately capture the risks and opportunities associated with sustainable practices. Financial institutions and investors can use this information to develop investment strategies that not only meet financial criteria but also contribute to sustainable development goals.

Although this thesis addressed important issues concerning the integration of intangible assets and ESG factors into financial models, it is essential to recognize certain limitations that could influence the interpretation and application of the obtained results.

Firstly, our results are presented gross, without accounting for transaction costs that can be significant, especially in sector rotation strategies that require frequent transactions. The omission of these costs could therefore overestimate the actual performance of strategies based on the FFESG and FF5 models. It is crucial for investors and fund managers to consider these costs when assessing the viability and profitability of the proposed strategies.

Secondly, the analyses presented in the last two chapters of this thesis rely on FWAs and ESG scores provided by Refinitiv. Although Refinitiv is a reputable and widely used source for this type of data, ESG scores can vary significantly among different providers. Studies have shown that ESG scores from different providers often exhibit low correlations with each other, which can lead to divergences in evaluations of companies based on these scores.

In this regard, it would be beneficial for future research to examine the impact of using ESG scores from other sources, such as Bloomberg, to see if the conclusions remain robust or if they vary depending on the source of the ESG data. This approach would

further validate the stability and reliability of models based on ESG scores and enhance the understanding of the underlying dynamics that influence company performance according to different sustainability criteria.

In summary, while providing valuable insights and opening up interesting research avenues, this thesis also underscores the importance of critical analysis and cautious evaluation of the tools and methods used in sustainable finance. These limitations must be taken into account by practitioners and researchers to continually improve investment practices and financial evaluations in an ESG context.

Résumé de la Thèse

Cette thèse explore l'influence des actifs intangibles et des facteurs environnementaux, sociaux et de gouvernance (ESG) sur la performance financière des entreprises et l'efficacité des stratégies d'investissement, à travers trois études distinctes qui examinent différentes dimensions de ces interactions. Dans la première étude de cette thèse, nous examinons comment l'intégration des actifs intangibles influence la performance d'investissement ajustée au risque dans le cadre du value investing, en se concentrant spécifiquement sur le Sparkline Intangible Value ETF. Pour cette analyse, nous avons comparé la performance ajustée au risque du Sparkline Intangible Value ETF avec celle de benchmarks bien établis, à savoir le Russell 1000 Value index et le S&P 500 index, sur une période de 36 mois. Nous avons utilisé des mesures telles que les ratios de Sharpe et de Sortino, ainsi que l'alpha de Jensen et l'alpha de Fama-French pour évaluer ces performances. Nos résultats montrent que, bien que l'ETF Sparkline Intangible Value offre des rendements ajustés au risque supérieurs par rapport au Russell 1000 Value index, il n'atteint pas les performances du S&P 500 sur la période étudiée. Cette observation suggère que, bien que les actifs intangibles puissent améliorer les performances par rapport à certaines mesures de valeur traditionnelle, leur intégration ne garantit pas systématiquement une surperformance par rapport aux indices de marché plus larges. Notre analyse montre également que les actifs intangibles contribuent de manière significative à la valeur ajoutée des entreprises, en particulier durant les phases de reprise économique. Les résultats suggèrent que l'intégration des actifs intangibles dans les modèles d'évaluation pourrait révéler des opportunités d'investissement précédemment non identifiées, offrant ainsi des implications importantes pour les acteurs du marché financier.

Dans la deuxième étude, nous étudions l'impact des arrangements de travail flexibles (FWAs) sur la performance d'investissement ajustée au risque. Nous avons analysé un échantillon complet d'entreprises en Europe et aux États-Unis sur neuf ans, classant ces sociétés dans des portefeuilles selon qu'elles avaient des scores élevés ou faibles de FWAs, avec un rééquilibrage mensuel. L'évaluation comparative montre que les portefeuilles avec des scores élevés de FWAs dominent régulièrement ceux avec des scores faibles. Cette supériorité est mise en évidence par des mesures telles que les ratios de Sharpe et de Sortino ajustés, l'alpha de Jensen et l'alpha de Fama-French. Les résultats révèlent que les entreprises intégrant des pratiques de travail flexibles tendent non seulement à attirer plus d'investissements mais aussi à générer des performances financières supérieures, en particulier en termes de rendements ajustés au risque. Cette constatation soutient l'idée que les FWAs, en améliorant l'environnement de travail et la gestion du capital humain, agissent comme des actifs intangibles stratégiques qui augmentent la valeur globale de l'entreprise sur les marchés financiers. Les entreprises aux États-Unis, où les pratiques de travail flexibles sont plus couramment intégrées, montrent une surperformance notable

par rapport à leurs homologues européennes. Cette différence régionale souligne l'influence des cultures de travail et des dynamiques de marché dans l'évaluation et l'impact des FWAs. Ces découvertes encouragent une intégration plus poussée des FWAs dans les stratégies de développement durable et de gestion des risques, soulignant leur rôle potentiel dans l'amélioration des rendements ajustés au risque et dans la promotion d'une gestion d'entreprise innovante et responsable.

Enfin, dans le troisième chapitre de cette thèse, nous explorons l'intégration des facteurs environnementaux, sociaux et de gouvernance (ESG) dans le modèle financier traditionnel Fama-French à cinq facteurs (FF5) pour créer un modèle amélioré (FFESG). Ce nouveau modèle vise à évaluer la performance ajustée au risque des portefeuilles sectoriels sur une période étendue de seize ans, en se basant sur la capacité des facteurs ESG à fournir un alpha plus représentatif des réalités du marché. Pour évaluer l'efficacité du modèle FFESG amélioré, nous avons élaboré des stratégies d'investissement basées sur les alphas générés par ce modèle. Deux approches principales ont été testées : une stratégie long-only, qui consiste à acheter des portefeuilles présentant des alphas positifs, et une stratégie long-short, où les portefeuilles avec des alphas positifs sont achetés (long) tandis que ceux avec des alphas négatifs sont vendus (short). Ces portefeuilles ont été rééquilibrés mensuellement sur différentes périodes roulantes de 12, 36 et 60 mois, et comparés au benchmark S&P 500. Ensuite nous avons employé les ratios de Sharpe et de Sortino pour mesurer la performance de ces portefeuilles. Les analyses révèlent que le modèle FFESG explique plus efficacement la variabilité des rendements des portefeuilles sectoriels par rapport au modèle FF5 traditionnel, comme en témoigne un R^2 supérieur. Cela indique que l'intégration des critères ESG améliore non seulement la précision du modèle, mais aussi sa capacité à capter les dynamiques complexes des marchés sectoriels. Les portefeuilles basés sur l'alpha dérivé du modèle FFESG ont systématiquement surperformé ceux basés sur l'alpha généré par le modèle FF5. Cela démontre que les stratégies de rotation sectorielle utilisant des alphas enrichis par les critères ESG peuvent générer des rendements supérieurs, soulignant l'efficacité de l'intégration des facteurs ESG dans les modèles d'évaluation financière. Ces résultats mettent en évidence la valeur ajoutée des critères ESG dans la construction de portefeuilles sectoriels et l'amélioration des prévisions de rendements ajustés au risque. Ils encouragent l'adoption plus large des critères ESG par les investisseurs et les gestionnaires de portefeuille, qui peuvent utiliser ces informations pour affiner leurs stratégies d'investissement et mieux répondre aux défis et opportunités du marché contemporain.

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