Empirical Studies on Sustainable Finance and Alternative Assets

Von der Fakultät für Wirtschaftswissenschaften der Rheinisch-Westfälischen Technischen Hochschule Aachen zur Erlangung des akademischen Grades eines Doktors der Wirtschafts- und Sozialwissenschaften genehmigte Dissertation

vorgelegt von

Arthur Friedrich Enders

Berichter: Univ.-Prof. Dr. sc. pol. Thomas S. Lontzek
Berichter: Prof. Karl Schmedders, PhD — IMD Lausanne

Tag der mündlichen Prüfung: 07.02.2025

The study *Carbon Risk and Equity Prices* was published in February 2025 in The Financial Review, Volume 60, Issue 1, by Wiley.

The study *How to Attract ESG Funds* is forthcoming in 2025 in The Journal of Impact and ESG Investing by Portfolio Management Research.

The study *Predicting Returns of Listed Private Equity* is currently submitted and under revision.

Acknowledgements

I would like to thank my supervisors, Thomas Lontzek and Karl Schmedders, for their guidance and support throughout this dissertation. Their expertise and constructive feedback have significantly shaped my research. I am also grateful to my coauthors, Marco Thalhammer, Maximilian Werner, and Michel Degosciu for their valuable collaboration. I extend my thanks to my colleagues at RWTH Aachen for their thoughtful comments on early drafts and for their ongoing encouragement. Finally, I owe a special debt of gratitude to my parents, whose unwavering belief in my goals and ambitions has been a constant source of motivation. Without their support, this dissertation would not have been possible.

Contents

Preamble

Publications

Preamble

1. Introduction

1.1 Motivation

Empirical and econometric analyses of financial markets have become increasingly popular due to the substantial availability of financial data and advancements in computational capabilities. As this trend continues, with even greater computational power and larger data sets, new computational methods and models based on machine learning are gaining significant traction and being applied across various financial disciplines. These new models hold great promise for enhancing efficiency and offering potential applications in finance. However, they still face numerous challenges and often fall short when compared to more established statistical techniques.

Traditional financial models and theories are predominantly based on linear algebraic frameworks (Giot, 2003). The key advantages of these models for academics, practitioners, and students are their accessibility, ease of understanding, and practical application in capturing linear relationships (Dixon et al., 2020). Machine learning models, in contrast, offer the potential to analyze non-linear or non-monotonic dynamics, which naturally arise in real-world financial time series data. Nonetheless, these models are often viewed as "black boxes" and, being rooted in engineering fields, their applicability to financial analysis remains poorly understood, potentially leading to misconceptions and misinterpretations (Burkart & Huber, 2020). Furthermore, the complexity of newer machine learning models does not always translate into better performance or outcomes (Gerlein et al., 2016).

Econometric analyses and traditional empirical finance continue to be indispensable tools for understanding financial market behavior and asset pricing. As the economy evolves and new market dynamics and effects emerge, investors increasingly depend on rigorous academic research to identify and manage the associated risks and opportunities.

This thesis conducts empirical analyses, employing a variety of econometric techniques, to explore contemporary financial market concepts that remain underexplored and not yet fully understood.

This thesis investigates several emerging phenomena in financial markets, specifically the effects of carbon transition risks on equity prices, the influence of Environmental, Social, and Governance (ESG) practices on institutional ESG fund holdings, and the return predictability of net asset values in listed private equity (LPE) indices. The first two publications relate to the broader theme of sustainable finance, which has gained significant traction over the past decade and requires new approaches and heightened awareness from investors. The final publication focuses on an alternative asset class, private equity, with a focus on listed private equity assets. This underexplored market may present mispricings, offering potential excess returns to attentive investors.

This thesis proceeds by expanding on the motivations behind the examined financial concepts. The next Section 1.2 provides an overview and summaries of all the articles included in this dissertation, before Section 1.3 concludes the introduction. The remainder of the thesis, from Chapters I to III, consists of the individual articles.

1.1.1 Carbon Transition Risk

Anthropogenic climate change is widely regarded as one of the greatest threats to humanity (UN, 2021). According to the Intergovernmental Panel on Climate Change, human activities are responsible for nearly all greenhouse gas emissions, the majority of which arise from the production and consumption of goods and services by companies, governments, and households. Policymakers in many regions have recognized the environmental and societal risks posed by these emissions and have implemented increasingly stringent environmental regulations. The goal of these regulations is to accelerate the "green transition"—a shift toward a sustainable, low-emission, and environmentally friendly economy. Figure 1.1 shows that current policies are not yet sufficient to reach our climate goals, and we can expect more and stricter policies and regulations to be implemented in the near future. Such regulations significantly influence the behavior and competitiveness of companies, with both positive and negative impacts on their operations.

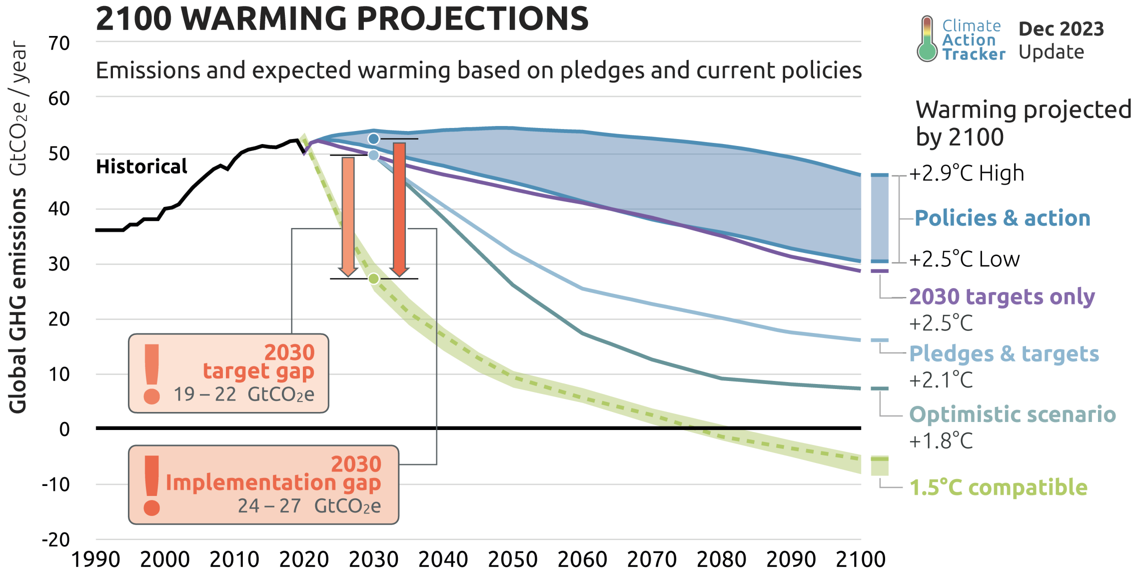


Figure 1.1
Warming projections based on different policies. Source: Climate Action Tracker (2023) with copyright 2023 by Climate Analytics and NewClimate Institute.

Environmental regulations can impact companies in various ways. They may incur significant compliance costs, as they are required to invest in new technologies, processes, or equipment to meet regulatory standards. Additionally, companies may be obligated to pay carbon taxes or participate in cap-and-trade systems, directly affecting their profitability. These emission-related expenses lead to increased energy costs and higher supplier prices, further impacting a company's earnings.

Regulation can also reshape the competitive landscape. Companies that adapt cost-effectively—for example, by developing cleaner, more efficient technologies—may gain a competitive edge over less innovative peers. On the other hand, companies that fail to meet environmental standards risk fines, legal action, and reputational damage, which can result in significant financial costs. Conversely, companies perceived as environmentally responsible may enhance their reputations and attract environmentally conscious customers.

In summary, companies may face considerable financial risks as they transition to a low-carbon economy, depending on factors such as their greenhouse gas emissions, operations, business models, and R&D capabilities. In the literature, this transition risk is commonly referred to as "carbon risk".[1] Naturally, this raises the question of whether carbon risk has been priced in financial markets. The paper "Carbon Risk and Equity Prices" in Chapter I studies the effects of carbon risk on equity prices in global financial markets.

1.1.2 ESG Funds

The increasing prominence of Environmental, Social, and Governance (ESG) factors in financial markets reflects a transformative shift in how investors approach their investment decisions. As sustainability concerns grow, both institutional and retail investors are becoming increasingly aware of the long-term risks and opportunities associated with ESG practices. This trend is evident from the rising inflows into ESG funds and the resulting market pressure these funds exert on stock prices. In the first six months of 2024, approximately 170 new sustainable funds were launched globally, increasing global ESG fund assets to USD 3.1 trillion (Morningstar, 2024). Similarly, Figure 1.2 illustrates the consistent growth of investment managers who have signed the Principles for Responsible Investment (PRI) from 2006 to 2021. As of March 2024, there were 5,345 PRI signatories, representing total assets under management of USD 128.4 trillion (Principles of Responsible Investment, 2024).

A PRI signature signals an asset manager's emphasis on ESG-focused investments. This substantial volume of investment can exert significant price pressure on stocks. In his empirical analysis, van der Beck (2021) demonstrates that the flows toward ESG funds exert substantial price pressure on stocks, driving up the realized returns of so-called "green" or sustainable stocks. ESG investors, in particular, tend to exhibit greater price inelasticity in their portfolio rebalancing, meaning they are more likely to hold onto stocks even after significant price inflation. As a result, ESG funds generally place more upward pressure on stock prices compared to traditional institutional funds.

[1] Global warming also increases the likelihood of extreme weather events, known as physical risks, but the focus of this thesis remains on transition risk, as carbon-intensive businesses are, idiosyncratically, more likely to be impacted by transitional than by physical climate risks.

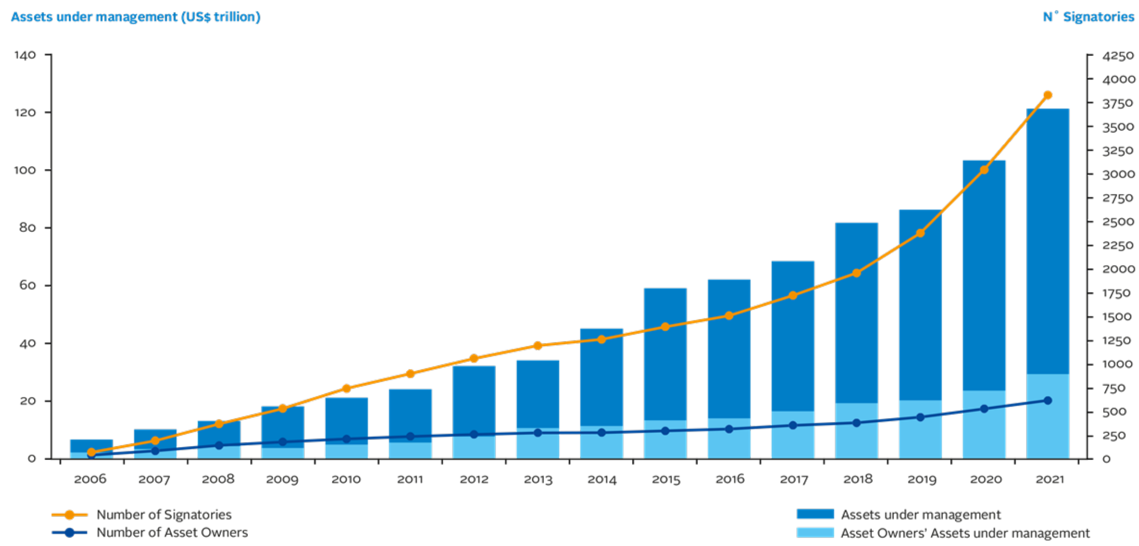


Figure 1.2
Principles for Responsible Investment signatories and assets under management growth. Source: Principles of Responsible Investment (2021).

Given that institutional investors are key drivers of market value and growth, it becomes crucial for firms to understand the specific ESG factors that resonate most with these investors. Despite the increasing research on ESG and institutional investment, there is still a major gap in understanding the specific relationships between individual ESG practices and fund holdings, especially for ESG-focused funds.

The paper "How to Attract ESG Funds" in Chapter II addresses this gap by offering a more detailed examination of the mechanisms through which various ESG practices attract institutional and ESG-specific investors. It seeks to move beyond the limitations of broad ESG scores and ratings, which are often inconsistent and vary across providers (Berg et al., 2022), by focusing on concrete ESG practices that companies adopt. In doing so, this research not only clarifies how ESG factors influence investment decisions but also offers practical insights for companies aiming to enhance their ESG performance and, in turn, attract a broader and more engaged investor base.

1.1.3 Listed Private Equity

Private equity (PE) is an alternative asset class where investment funds acquire stakes in private companies or buy out public ones. Managed by specialized firms, PE funds create value through operational improvements, restructuring, and industry expertise. Historically, they offer higher returns, diversification, and active management, with access to undervalued companies and long-term growth potential.

The performance of PE investments can be compared to public market benchmarks by using the "Public Market Equivalent" (PME) method introduced by Kaplan and Schoar (2005). PME measures the relative performance of a PE fund by calculating the ratio of the present value of its cash flows to what those cash flows would have generated if invested in a public market index over the same time frame:

$$PME = \frac{\sum_t \left(\frac{D_t}{I_t}\right)}{\sum_t \left(\frac{C_t}{I_t}\right)}, \tag{1.1}$$

where D_t denotes the distributions from the PE fund at time t, and C_t refers the contributions made to the PE fund at time t. I_t represents the value of the public market index at time t. A PME greater than 1 indicates that the PE fund outperformed the public market index, while a PME below 1 suggests that the public market index outperformed the PE fund.

Figure 1.3, sourced from Kaplan (2024), presents the average and median PME values for U.S. buyout funds compared to the S&P 500, categorized by vintage year—the year in which each private equity (PE) fund made its first investment. The figure demonstrates that the buyout industry consistently outperformed the public market benchmark, with PME values typically ranging from just above 1 to over 1.50. This indicates that private equity investments have historically generated excess returns for investors willing and able to participate in the private markets.

However, the potential for high returns in traditional PE investments comes with several challenges. PE typically demands substantial capital commitments, limiting access primarily to institutional investors and high-net-worth individuals. These investments are also highly illiquid, often locking investors into long-term commitments that can span 7 to 10 years or more, with little to no flexibility to exit early. Moreover, PE deals often involve complex structures, leading to reduced transparency and making it difficult for

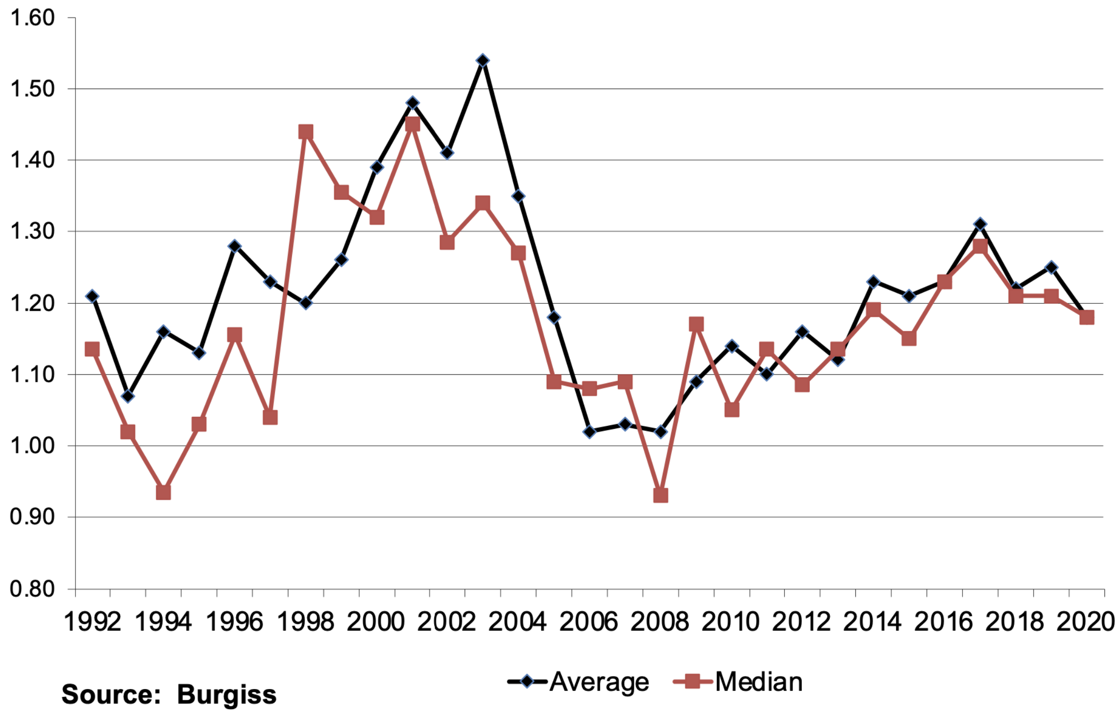


Figure 1.3
U.S. buyout PMEs by vintage year. This figure shows U.S. buyout funds performance by vintage year from 1992 to 2020 measured by PME compared to the S&P 500. Source: Kaplan (2024) with data from Burgiss.

investors to fully assess the risks and potential returns.

Listed private equity (LPE) has emerged as a more accessible alternative to traditional private equity (PE). LPE firms are publicly traded, allowing investors to engage in private equity strategies—such as buyouts and venture capital—through publicly available shares. This provides access to PE returns without the typical high entry barriers or long-term capital commitments. Unlike traditional PE, LPE offers greater liquidity and transparency, as these firms must comply with stock exchange regulations, including regular financial reporting. As a result, LPE combines the potential rewards of private equity with the liquidity, oversight, and transparency of public markets.

In the paper "Predicting Returns of Listed Private Equity" in Chapter III, we utilize data from LPE indices and underlying net asset values to develop forecasting models aimed at predicting future returns. By identifying undervalued periods in the market, we seek to achieve excess returns through strategic timing of investments.

1.2 Summaries of the Publications

The following sections provide summaries of the three main publications that constitute this dissertation. Each paper delves into a distinct area of financial economics, offering insights into carbon risk in equity markets, strategies for firms to attract ESG funds, and methodologies for predicting returns in listed private equity. These summaries highlight our key findings, methodologies, and contributions to the field.

1.2.1 Carbon Risk and Equity Prices

We investigate the effects of carbon transition risk on U.S. and European equity prices from 2009 to 2019, using disclosed carbon intensity data—measured as the ratio of a firm's carbon emissions to its annual revenues—from publicly traded companies. Our primary objective is to understand how carbon emissions influence stock returns and to quantify the carbon risk exposure of individual assets.

Univariate portfolio analyses, sorting firms into quintiles based on carbon intensity, reveal that portfolios of low-carbon-intensity ("green") firms significantly outperform those of high-carbon-intensity ("brown") firms. This indicates a negative carbon premium during the sample period, suggesting that investors were not compensated for bearing carbon risk.

Using Fama–MacBeth cross-sectional regressions, we find that carbon intensity has a statistically significant negative effect on stock returns, even after controlling for other factors. This effect is more pronounced in European markets compared to the U.S. and is particularly strong before the Paris Agreement of December 2015. After the Agreement, the negative impact of carbon intensity on returns diminishes, implying a potential shift in market perception of carbon risk.

Analyzing institutional ownership data, we find that institutional investors have systematically reduced their holdings in carbon-intensive firms, demonstrating an aversion to carbon risk. This divestment from brown stocks and increased investment in green stocks could partly explain the superior performance of green firms during the study period.

We develop an asset-pricing model incorporating a novel risk factor, Brown-minus-Green (BMG), representing the return differential between portfolios of brown and green stocks. Including BMG in a multifactor model alongside traditional risk factors allows us to calculate a "carbon beta" for each stock, indicating its sensitivity to carbon risk. This method enables the assessment of carbon risk exposure even for firms that do not disclose emissions data.

Our findings highlight significant variations in carbon betas across industries and countries. Sectors like energy and utilities exhibit high positive carbon betas, indicating substantial exposure to carbon risk. In contrast, sectors such as technology and consumer cyclicals have negative carbon betas, suggesting they may serve as a hedge against carbon risk. At the country level, nations like Russia and Norway show high average carbon betas due to their reliance on carbon-intensive industries, while Germany and France display negative average carbon betas.

We conclude that carbon risk was not adequately priced into equity valuations during the sample period, resulting in a negative carbon premium. However, as investors fully integrate carbon risk into valuation models, a positive carbon premium may emerge, meaning brown assets will offer higher expected returns to compensate for elevated risk exposure. Our carbon beta metric serves as a valuable tool for investors, firms, and policymakers to assess and manage carbon risk within portfolios, facilitating informed decision-making in a transitioning global economy.

This study contributes to the literature on carbon risk and asset pricing by providing empirical evidence of a negative carbon premium in U.S. and European equity markets during 2009–2019. By utilizing disclosed carbon emissions scaled by revenue, we offer a more precise measure of firms' carbon exposure compared to prior studies that often rely on environmental scores or estimated emissions. Our findings challenge earlier research suggesting a positive carbon premium, thereby enriching the debate on how carbon risk is priced in financial markets. Additionally, the introduction of our carbon beta, derived from the Brown-minus-Green factor added to standard multifactor models, presents a novel methodology for quantifying carbon risk exposure even for firms that do not disclose emissions data.

1.2.2 How to Attract ESG Funds

In this paper, I investigate how specific Environmental, Social, and Governance (ESG) practices influence institutional fund holdings, focusing on distinguishing between ESG-focused funds and general institutional funds. Recognizing the rise of ESG investments, my objective is to identify key ESG measures that attract ESG funds, offering actionable insights for companies aiming to enhance their appeal to these investors.

Avoiding the inconsistencies of conventional ESG ratings, I concentrate on foundational ESG factors such as carbon emissions, emission reduction targets, board diversity, political and lobbying contributions, and corporate governance structures. Using data from S&P 500 companies between 2010 and 2021, I analyze how these ESG practices affect both the depth (percentage ownership) and breadth (number of funds) of institutional holdings.

To differentiate ESG funds from general institutional funds, I employ ESG-related keywords to categorize funds based on their investment focus. This approach allows me to examine ESG fund holdings and understand the fund market's view on companies' sustainability practices.

My study contributes to the literature by directly examining the impact of specific ESG practices on institutional fund holdings, rather than relying on aggregated ESG scores. This addresses challenges posed by inconsistencies in ESG ratings across different agencies and offers novel insights into how companies can tailor their ESG practices to appeal to distinct investor groups.

My findings reveal that environmental measures are crucial in attracting ESG funds. Companies that disclose carbon emissions and have lower carbon intensity tend to have higher ESG fund ownership. Setting emission reduction targets also positively influences ESG fund holdings, especially when targets are more immediate; simply having a target increases ESG fund ownership, with target proximity being more significant than magnitude.

In social measures, ESG funds are sensitive to companies' political and lobbying contributions. Higher expenditures in these areas are associated with lower ESG fund ownership, suggesting ESG investors view such activities unfavorably. Conversely, companies that comply with fundamental human rights standards attract more ESG funds, highlighting the importance of ethical considerations in investment decisions.

Regarding governance, corporate structures significantly impact fund holdings. Both ESG and general institutional funds show an aversion to CEO duality, where the CEO also serves as board chairman. A higher percentage of independent board members positively affects fund ownership, emphasizing the value placed on unbiased oversight and accountability. Additionally, board gender diversity increases the number of both institutional and ESG funds invested in the company, indicating that diversity at the board level is valued by investors.

I conclude that as sustainable investing grows, companies that proactively adopt and disclose meaningful ESG practices are better positioned to attract both ESG-focused and general institutional investors. By concentrating on specific ESG practices rather than aggregated ESG scores, my study provides clear guidance for companies seeking to attract ESG investments and offers valuable insights for corporate managers aiming to align with responsible investment imperatives and improve their market valuation.

1.2.3 Predicting Returns of Listed Private Equity

In this last paper, we investigate the predictive power of the net asset value (NAV)/price ratio for the LPX50 index, which is a key benchmark in the field of listed private equity (LPE). Using monthly data spanning from December 2002 to February 2024, our study aims to fill a gap in the understanding of the factors driving returns in the LPE market.

Our research employs a structured approach consisting of three main analyses. First, we apply the Fama–French six-factor model to the LPX50 index to understand its underlying risk exposures. The results reveal significant exposure to the size and value factors. This is consistent with the typical private equity strategy of investing in smaller and undervalued companies, suggesting that part of the index's return is derived from these common risk factors.

Second, we examine the market efficiency of the LPX50 index by analyzing autocorrelations in its return series. We find significant autocorrelations, indicating that the index returns are not fully efficient and may exhibit predictability based on past price information. This suggests potential opportunities for investors to forecast future returns using historical data.

Third, we assess the predictive power of the lagged NAV/price ratio through both in-sample and out-of-sample regressions across various investment horizons, ranging from 1 to 24 months ahead. The findings demonstrate that the NAV/price ratio is a significant predictor of future returns, especially over longer horizons. The predictive power is particularly pronounced when periods of financial instability, such as the COVID-19 pandemic, are excluded from the analysis.

Our key findings include the significant predictive power of the NAV/price ratio for the LPX50 index returns. Investors can leverage this ratio to identify undervalued periods and adjust their investment strategies accordingly. The index's returns are partly driven by its exposure to value and size risk factors, aligning with private equity's focus on smaller and undervalued firms. The presence of significant autocorrelations suggests market inefficiencies in the LPE sector, providing potential opportunities for return predictability based on past performance.

The implications for investors are substantial. By monitoring the NAV/price ratio, investors can enhance returns by increasing exposure during periods when the index's NAV is low relative to its market price. The predictability of returns strengthens over longer investment horizons, making this strategy more suitable for long-term investors. Additionally, the predictive model's effectiveness is influenced by broader economic conditions, emphasizing the need to consider periods of financial stability in investment decisions.

In conclusion, the study contributes to the literature on return predictability in the LPE market and offers practical insights for institutional investors. By demonstrating the significant predictive power of the NAV/price ratio, particularly over longer horizons and during stable financial periods, the research provides a valuable tool for investors seeking to enhance returns in an otherwise illiquid and opaque market. This aligns with the growing interest in LPE as a more accessible alternative to traditional private equity investments.

1.3 Conclusion

This introduction outlines the motivations and objectives of this dissertation, focusing on empirical analyses in the realms of sustainable asset pricing and alternative asset classes. Key areas of interest are identified: the impact of carbon transition risks on equity prices, strategies for companies to attract ESG-focused institutional funds, and the return predictability of listed private equity investments. Each of these topics addresses significant and contemporary challenges in financial markets, offering insights into how emerging risks and investor preferences shape asset pricing and investment strategies.

The subsequent chapters present the individual studies that comprise this dissertation. Through rigorous empirical methods and advanced econometric techniques, these papers contribute to the existing literature by providing novel findings and practical implications for investors, firms, and policymakers. By exploring underexamined phenomena—such as the pricing of carbon risk, the specific ESG practices that influence institutional investment, and the dynamics of return predictability in listed private equity—this thesis aims to enhance the understanding of how sustainability considerations and alternative investments are reshaping financial markets.

Each paper contributes a unique perspective, ranging from asset pricing under carbon risk to the specific ESG factors that attract institutional funds, and finally, to predictive methods for alternative asset classes. Together, these studies provide not only empirical evidence but also actionable insights that can inform future research and practice. The cumulative contributions of this thesis bridge gaps in sustainable finance literature, paving the way for deeper exploration into how emerging risks and investor preferences shape asset pricing and investment strategies. Ultimately, this dissertation provides a cohesive framework for understanding the evolving role of sustainability in financial markets and lays a foundation for future research in sustainable asset pricing and investment strategies.

Bibliography

Berg, F., Koelbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, *26*(6), 1315–1344.

Burkart, N., & Huber, M. F. (2020). A survey on the explainability of supervised machine learning. *ArXiv*.

Climate Action Tracker. (2023). Warming projections: Emissions and expected warming based on pledges and current policies. climateactiontracker.org/global/temperatures/

Dixon, M. F., Halperin, I., & Bilokon, P. (2020). *Machine learning in finance* (Vol. 1170). Springer.

Gerlein, E., McGinnity, T., Belatreche, A., & Coleman, S. (2016). Evaluating machine learning classification for financial trading: An empirical approach. *Expert Syst. Appl.*, *54*, 193–207.

Giot, P. (2003). Market models: A guide to financial data analysis. *Journal of Financial Econometrics*, *1*, 471–473.

Kaplan, S. N. (2024). Private equity: Past, present and future. *Financial Management Association International.* www.fmaconferences.org/DA/Kaplan%20RSiFEB.pdf

Kaplan, S. N., & Schoar, A. (2005). Private equity performance: Returns, persistence, and capital flows. *The Journal of Finance*, *60*(4), 1791–1823.

Morningstar. (2024). Global Sustainable Fund Flows: Q2 2024 in Review. *Morningstar Manager Research.*

Principles of Responsible Investment. (2021). Annual report 2021. www.unpri.org/annual-report-2021/how-we-work/building-our-effectiveness/enhance-our-global-footprint

Principles of Responsible Investment. (2024). Annual report 2024. www.unpri.org/about-us/about-the-pri/annual-report

UN. (2021). Climate Change 'Biggest Threat Modern Humans Have Ever Faced', World-Renowned Naturalist Tells Security Council, Calls for Greater Global Cooperation. press.un.org/en/2021/sc14445.doc.htm

van der Beck, P. (2021). Flow-driven ESG returns. *SSRN Electronic Journal*.

Publications

I. Carbon Risk and Equity Prices

by Arthur Enders[a], Thomas Lontzek[a], Karl Schmedders[b], Marco Thalhammer[a]

published in *The Financial Review*

Abstract: We study the effects of carbon transition risk on equity prices in the US and Europe using disclosed carbon intensity data and find a negative effect on the cross section of returns and a negative carbon premium for the period 2009–2019. Examining fund flows, we find that institutional investors had an aversion to carbon-intensive stocks, which could help explain the outperformance of green stocks. We find that after the Paris Agreement this negative carbon premium disappears, and expect a positive premium in the future. We apply an asset-pricing approach to quantify the carbon risk exposure of any given asset.

Keywords: Carbon emissions, carbon risk, climate change, equity returns, factor model, institutional investors.

JEL Classification: G11, G12, Q51, Q54.

Acknowledgements: We thank Nicole Branger, Eugene Fama, Caroline Flammer, Andrea Flori, Stefano Giglio, Elise Gourier, Paul Meyerhof, Lubos Pastor, David Ririmasse, and seminar participants at the ESSEC Business School Paris, Finance Center Münster, Maastricht University School of Business and Economics, FMA European Conference 2023, EEA-ESEM Congress 2023, RWTH Aachen University School of Business and Economics, and the EAERE Green Bonds and Environmental Finance workshop for their helpful comments. We are grateful to Dave Brooks for editorial support. We also thank the anonymous reviewers and the editors Tina Yang and Mike Pagano for their invaluable contributions. All errors are those of the authors.

Citation: Enders, A., Lontzek, T., Schmedders, K., Thalhammer, M. (2025). Carbon Risk and Equity Prices. *The Financial Review*, 60, 13–32. The Eastern Finance Association. doi: 10.1111/fire.12414.

[a]RWTH Aachen University
[b]International Institute for Management Development Lausanne

I.1 Introduction

We examine the effects of the disclosed carbon emissions[1] of publicly traded companies in the US and Europe on their stock returns from 2009 to 2019. We characterize companies by their "carbon intensity," the ratio of their disclosed (scope 1 and 2) carbon emissions to their annual revenues. Using this metric, we document several noteworthy results. Low-carbon portfolios outperform high-carbon portfolios, which is statistically significant even after controlling for common risk factor exposures. Carbon intensity has statistically significant explanatory power and, on average, a negative effect on the cross section of returns. In our time frame and sample, the carbon premium is negative, and investors are not compensated for carbon risk[2] exposure. The effects become more nuanced when we examine US and European stocks separately or when we distinguish between the periods before and after the Paris Agreement of December 2015. While the negative effect of carbon intensity is statistically highly significant in Europe, it is not in the US. Before the Paris Agreement the effect is negative and highly significant, but vanishes afterward.

Considering the increasing relevance of climate change in public discourse and the emergence of carbon risk on financial markets, we would expect investors to be aware of the risks associated with investments in carbon-intensive companies. Policy responses to climate change significantly influence the current and future profitability of companies. For instance, policies such as the European Union Emissions Trading System (EU ETS) in Europe or the Clean Power Plan in the US have significantly influenced corporate behavior, especially in the energy sector.[3]

Our analysis of the link between carbon emissions and fund flows reveals a fourth noteworthy result: carbon intensity has a significant negative effect on institutional ownership. Professional investors actively reduced their holdings in carbon-intensive compa-

[1] In the present paper the term "carbon emissions" always refers to total CO_2 equivalent emissions of all relevant greenhouse gases.

[2] In this paper, "carbon risk" refers to carbon transition risk. We acknowledge that global warming also increases the likelihood of extreme weather events, so-called physical risks. We restrict our focus to transition risk as, idiosyncratically, carbon-intensive business models are more likely to be affected by transitional than by physical climate risks.

[3] Table A5 in the online appendix provides a more comprehensive overview of key climate regulations and initiatives between 2009 and 2019. The online appendix is available in the supporting materials section online.

nies to avoid carbon risk exposure. We consequently develop a measure of carbon risk by constructing a carbon premium portfolio that is long in high CO_2 intensity portfolios ("brown" stocks) and short in low CO_2 intensity portfolios ("green" stocks). We include this portfolio as an additional factor, "Brown-minus-Green," in standard multi-factor models. We call the loading on this new factor the "carbon beta." Notably, we can estimate the factor loading for every stock using only publicly available returns data—that is, even for stocks that do not publicly disclose their greenhouse gas emissions.

We complete our analysis by reporting average carbon betas for different sectors and countries. We detect large variations between as well as within both. Carbon betas are high for Energy and Utilities but low or negative for Technology and Consumer Cyclicals. Carbon risk exposure is high for Russia and Norway, and low (negative) for many EU countries, including Greece, Germany, and France.

Furthermore, there are remarkable discrepancies between the average levels of carbon intensity and the average carbon betas. We calculate carbon intensities based on scope 1 and 2 emissions, as scope 3 data are limited. Investors, however, likely understand the impact of indirect (scope 3) emissions on carbon risk, and so we should observe the effect of these emissions on carbon betas. For example, the Energy sector has a carbon beta more than three times higher than that of the Utilities sector, despite having a lower average carbon intensity. This disparity arises from significantly higher average scope 3 carbon emissions in the Energy sector. This anecdotal evidence suggests that our Brown-minus-Green factor extracts valuable additional information on carbon risk from financial market data, despite the absence of scope 3 emissions data. A thorough analysis is challenging, however, due to the lack of reliable scope 3 data.

The literature provides much evidence that investors care about carbon risk. According to an extensive survey by Krueger et al. (2020), institutional investors are also aware of climate-related risks and believe they have an impact on their portfolios' financial performance that has already started to materialize. Bolton and Kacperczyk (2021) suggest that investors care about carbon risk, by showing a negative relationship between company emissions and institutional ownership. In their sample, this effect is only significant with regard to the level and growth rate of total emissions. However, Aswani et al. (2024) show that using unscaled emissions data can disturb and bias the effect. We agree with this criticism and therefore use scaled emissions. As Bauer et al. (2022) emphasize, emission intensity has for some time been the industry standard for determining the carbon exposure of stock indices (e.g., MSCI, 2022; S&P Global, 2020). Contrary to Bolton and Kacperczyk (2021), by using emission intensities instead of simple emissions we find a statistically significant negative effect of carbon intensity on institutional ownership. Investors care about carbon risk and have developed a general aversion to carbon-intensive stocks.

Unlike Pástor et al. (2022) or many other studies in this field, we deliberately decide against using environmental scores since they are very noisy and highly dependent on the rating agency that provides them. Berg et al. (2022) show low correlations for the environmental, social, and governance (ESG) ratings of different ESG rating agencies. This high divergence has its roots mainly in differences in measurement and scope, and there are fundamental disagreements about the underlying data. Furthermore, Alves et al. (2023) find little evidence that ESG ratings significantly impacted global stock returns in 2001–2020. We therefore only use the raw data from companies' disclosed carbon intensities.

While there is a broad consensus that carbon risk affects asset valuations, recent studies have yielded different results as to the way in which returns are affected. From a theoretical standpoint, green assets offer lower expected returns in equilibrium, hinting at a so-called negative "greenium" (e.g., Pástor et al., 2021). This greenium may arise from the non-monetary utility derived by green investors holding green stocks or the potential for these stocks to serve as a more effective hedge against specific types of climate risks. Bolton and Kacperczyk (2021) study the effects of carbon emissions on the cross section of returns in the US stock market, finding that stocks with a higher total level of (and change in) carbon emissions earn higher returns. They extend this analysis to global markets and find similar results (Bolton & Kacperczyk, 2023). Oestreich and Tsiakas (2015) report a positive carbon risk premium in the German market by investigating the effects of carbon emissions allowances in the EU ETS. Mo et al. (2012) analyze the different phases of the EU ETS, revealing a positive relationship between the EU emissions allowance price and company value in phase I but a negative relationship in phase II. Other studies could not find such a carbon premium. In et al. (2017) show that a carbon-efficient (low–carbon intensity) portfolio generates a positive alpha. Garvey et al. (2018) link lower carbon intensities with higher future profitability. All this research though remains inconclusive. In our time frame and sample, using carbon intensity, we find a negative carbon premium.

Measuring carbon risk is important for investors but also for firms and policymakers. Using such a measurement, investors can evaluate and optimize their portfolios' exposure levels, and firms can review their own exposure and compare it to peers. Policymakers, meanwhile, could use it to assess a new regulation's impact on specific companies, sectors, and countries.

Various methods of measuring carbon risk, often called carbon beta, have been proposed. Görgen et al. (2020) construct a carbon premium portfolio by categorizing companies into brown and green portfolios according to their "Brown-Green-Score," which incorporates a range of measures relevant to the carbon transition process. They compute carbon betas for equities across 43 countries, providing a detailed analysis of carbon risk exposures for different companies, sectors, and countries through their carbon betas. Sautner, Van Lent, et al. (2023) measure companies' climate exposure through a textual analysis of earnings conference call transcripts. They show explanatory power to predict green job creation and green technology. They also estimate climate risk premiums, and find a positive expected risk premium for firms with higher exposures (Sautner, van Lent, et al., 2023). Huij et al. (2021) build a carbon premium portfolio by sorting US companies by total emissions, using reported and estimated emissions data. We extend this research with our own approach, which uses only reported emissions intensity data for US and European stocks.

Another strand of the literature explores the implications of climate risk from an asset-pricing perspective. Hong et al. (2019) study the effect of droughts on food companies' cash flows and find a significant negative impact on profitability ratios. Pástor et al.

(2021) develop an equilibrium model that considers ESG criteria to explore the effects of climate risk on returns. They assume that green assets have lower expected returns because investors enjoy holding them and because green assets hedge climate risk. Green assets can, however, still outperform brown assets because of a shift in customer and investor tastes. Pástor et al. (2022) also provide empirical evidence that a greenium exists, with data from German green bonds as well as US stocks.

In summary, our study suggests that carbon intensity has a significant effect on returns and that carbon risk is prevalent. We show that from 2009 until 2019 this effect was significantly negative and that green stocks notably outperformed brown stocks in our sample. We demonstrate that institutional investors actively decarbonized their portfolio holdings and sought to lower their carbon risk exposure. Once such rebalancing is complete, we expect that carbon risk will be priced and that brown assets will have higher returns in the future. Our capital market approach effectively quantifies carbon risk through a carbon beta measure. All countries and industries are exposed to carbon risk to various degrees, and we demonstrate large variations.

I.2 Data

All firm-level data are collected from Refinitiv. Monthly risk factors and risk-free rates are retrieved from the website of Kenneth R. French. We restrict the data collection to common stocks with a country of issuance either as the United States or in Europe. Our time frame ranges from the beginning of 2009 to the end of 2019 for a total of 11 years of data. We believe that awareness of carbon risk has only recently gained attention from investors and that the carbon transition is particularly being demanded by the public in the US and Europe. The time frame also excludes large non-linear effects from the financial crisis of 2007–2008 as well as from the COVID-19 pandemic of 2020–2021 and the Russian invasion of Ukraine in 2022. Our final sample only includes companies that disclosed their greenhouse gas (GHG) emissions at some point during our time frame. Similar to Fama and French (1993), we exclude firms with a negative book value and require at least six months of return data if a firm is to be included in a portfolio. We also follow prior literature by excluding companies that are marked as "Financials" under the Refinitiv Business Classification because financial firms are not directly exposed to carbon risks.[4] The final data sample consists of 1,883 unique firms from across 25 countries, with 668 from the US and 1,215 from Europe.

I.2.1 Emissions Data

To separate green from brown stocks we use solely companies' disclosed carbon emissions data. We exclude companies without disclosed emissions even if estimated emissions are available. Aswani et al. (2024) show that these estimates can be biased and disturb analysis. Bolton and Kacperczyk (2023) argue that the level of carbon emissions is the most appropriate proxy for a company's carbon risk exposure because it relates to a firm's distance from carbon neutrality. Aswani et al. (2024) counter, however, that unscaled emissions are primarily influenced by the volume of goods produced. They elaborate that any correlation observed between unscaled emissions and stock returns should be interpreted as indicative of a connection between a company's productivity and its stock's performance. To avoid this disturbance in the effect, we scale the emissions by revenue, the result of which is commonly known as the carbon intensity.

The carbon (CO_2) intensity of a company measures the total CO_2 equivalent (CO_2e) emissions in a year (in tonnes) divided by the total revenue in that year (in millions of US dollars (USD)). Total CO_2 equivalent emissions is the aggregated total CO_2 equivalent output in scope 1 and scope 2 emissions. Figure I.1 shows the number of firms that reported the necessary emissions data (left) as well as the average CO_2 intensity of the firms in our sample (right). The sample is unbalanced and rather small at the beginning of our time frame with only 505 firms at the beginning of 2009. We see that over time more firms started to report their emissions. At the end of our time frame, in 2019, 1,557 unique firms reported emissions data.[5]

[4]Financial firms remain indirectly exposed to carbon risks via their loan and investment portfolios, but our carbon intensity measure does not capture these indirect risks.

[5]This number differs from the total of 1,883 unique companies during the total time frame since some companies stopped reporting their emissions or their stocks were delisted.

In the panel on the right of Figure I.1, we see that the average CO_2 intensity drops over time. Carbon-intensive firms are often obliged to disclose their emissions and were among the first to have such an obligation imposed. This led to a high carbon intensity to begin with, with an average CO_2 intensity of 546 tonnes of CO_2e/million USD. Many other companies, particularly more sustainable ones, then started to disclose their emissions, which decreased the average CO_2 intensity to 373 tonnes of CO_2e/million USD in 2019. We also observe this trend being more pronounced among the US firms in our sample. This suggests a potential selection bias over time, as brown firms were required to report before green firms were. This selection issue, however, is less evident among European firms. Where applicable, we additionally conduct separate analyses for US and European firms to account for and mitigate the impact of this potential selection bias.

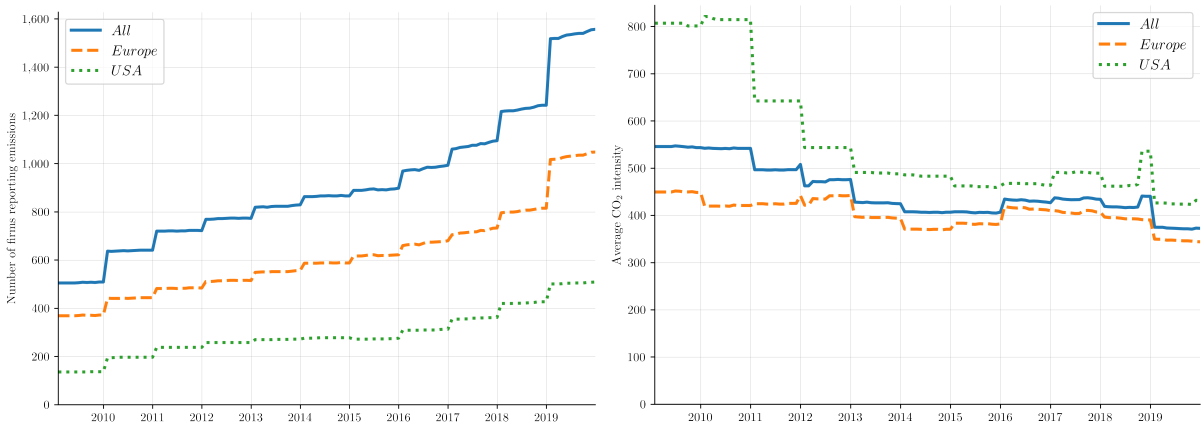


Figure I.1
Carbon emissions sample over time. The graph on the left shows the number of unique firms with valid emissions data included in our data sample over the time frame of 2009 to the end of 2019. The graph on the right shows the resulting average CO_2 intensity of all the firms in the sample in the same time frame.

Table I.1 provides summary statistics for carbon intensity for all firms over the whole time frame. An average firm in our sample has a carbon intensity of 438 tonnes of CO_2e/million USD. The deviation between the firms is very high, with a standard deviation of 1,805, and the median in our sample—with only 45 tonnes of CO_2e/million USD—is much lower than the mean.

Table I.1

Data Statistics

This table reports general statistics (mean, median, and standard deviation) for all variables used in the analyses in this paper. The sample period is 2009–2019. All firm-level variables are retrieved from Refinitiv Datastream. The CO_2 Intensity is the yearly CO_2 equivalent (CO_2e) emissions output (scope 1 and 2, in tonnes of CO_2e) divided by the yearly sales (in USD M). Market Beta is the CAPM beta computed over a 5-year rolling horizon using monthly returns. Institutional Ownership is the fraction of the shares held by major institutions. Major institutions are defined as firms or individuals that exercise investment discretion, over the assets of others, in excess of USD 100 million. Mkt-RF is the monthly excess returns of a value-weighted stock portfolio over the risk-free rate. SMB is the returns of a portfolio that is long in small stocks and short in large stocks. HML is the returns of a portfolio that is long in value stocks and short in growth stocks. WML is the returns of a portfolio that is long in winner stocks and short in loser stocks. RMW is the returns of a portfolio that is long in robust stocks, with high operating profitability, and short in weak stocks. CMA is the returns of a portfolio that is long in conservative investment stocks and short in aggressive investment stocks. Table A1 in the online appendix additionally reports quartiles for some key variables and also separate results for US and European firms.

Variable	Mean	Median	SD
Firm-Level Variables			
Monthly Stock Returns (%)	1.20	1.04	8.89
Log CO_2 Intensity (tonnes CO_2e/USD M)	4.05	3.82	1.96
Log Market Capitalization (USD M)	8.67	8.76	1.72
Log Book-to-Market Ratio	-0.85	-0.81	0.86
Log Property, Plant, and Equipment (USD M)	6.96	7.12	2.33
Yearly Revenue Growth (%)	7.20	3.11	196.80
Return on Equity (%)	19.71	13.20	121.64
Institutional Ownership (%)	55.64	57.53	32.02
Market Beta	0.85	0.77	0.57
Monthly Risk Factors			
Mkt-RF (%)	1.20	1.48	4.02
SMB (%)	0.04	0.26	2.44
HML (%)	-0.20	-0.32	2.67
WML (%)	-0.24	0.17	4.66
RMW (%)	0.12	0.18	1.52
CMA (%)	-0.01	0.00	1.47

I.2.2 Firm-Level Data

Our return and market capitalization data are always measured monthly. All other company financial data are collected yearly. Table I.1 presents all the firm-level data that are used in the following analyses.

An average company in our sample has a monthly return of 1.2% with a market capitalization of USD 20.9 billion. It has a book-to-market ratio of 0.64 and USD 6.9 billion worth of property, plant, and equipment. It has a yearly revenue growth of 7.2% and a return on equity of 19.71%. The average estimated market beta is below the general market beta at 0.85, and 55.64% of the company's shares are held by major institutions.

I.2.3 Risk Factor Data

Risk factor data and risk-free rates are retrieved from the data library of the website of Kenneth R. French (French, 2021). Griffin (2002) suggests that domestic Fama and French factors work better than global factors. We therefore use monthly factor data from the US and Europe separately wherever possible to better explain the time-series variations in our returns.

In our time frame of 2009–2019, the average monthly market return is 1.2%. The SMB and RMW factors also return positive average monthly returns premiums while the HML, WML, and CMA factors each have an average negative returns premium. The medians are still positive for all factors except for the HML factor. Pástor et al. (2022) explain the poor performance of value stocks in the 2010s by the recent outperformance of green stocks, as value stocks are, on average, more brown than green.

I.3 Results

We first examine general determinants of a company's carbon emissions. We then form univariate portfolios based on the carbon intensity and compare their performance over time. We continue to analyze the effect of carbon intensity on the cross section of returns with cross-sectional Fama–MacBeth regressions. We next study the behavior of institutional investors with regard to emissions output and carbon risk by looking at Institutional Ownership in relation to carbon intensity. Finally, we create a multi-factor model to measure an asset's carbon risk by looking at its sensitivity to a carbon premium portfolio. We report carbon risk distributions for all sectors and countries in our sample.

I.3.1 Analysis of the Carbon Intensity

We first investigate the relation of a company's carbon intensity to other firm-level variables to assess occurrences of possible pseudo causalities in our analyses. Table I.2 provides the coefficients of the pooled regression. Model (2) additionally includes year and industry fixed effects. In both models we cluster standard errors at the firm and year levels as carbon intensity is likely to be very persistent.

Table I.2

Determinants of the Carbon Intensity

The sample period is 2009–2019. The dependent variable is the natural logarithm of the carbon intensity (further explained in Table I.1). This table reports the results of the pooled regression with standard errors clustered at the firm and year levels. All variables are winsorized at the 2.5% and 97.5% levels. *Size* is the market capitalization, *BM* is the book-to-market ratio, *Sales Growth* is the yearly revenue growth, *PPE* is the property, plant, and equipment value, and *ROE* is the return on equity. The regression in the right column also includes year and industry fixed effects. ***1% significance, **5% significance, *10% significance.

Variable	(1) $log(CO_2\ Intensity)$	(2) $log(CO_2\ Intensity)$
Intercept	3.22***	3.21***
$log(Size)$	-0.43***	-0.34***
BM	0.53***	0.06
Sales Growth	-0.28	-0.25
$log(PPE)$	0.61***	0.46***
ROE	-0.02	0.01
Year F.E.	No	Yes
Industry F.E.	No	Yes
Adj. R^2	0.33	0.54

We see in regression (2) that the size of a company has a negative coefficient that is significant at the 1% level. Larger companies have, on average, a lower carbon intensity. Larger companies might be more efficient in their production because of economies of scale. We also see a strong positive effect of property, plant, and equipment (PPE) on the carbon intensity. Unsurprisingly, companies with higher levels of equipment, such as machinery, produce, on average, more emissions. Finally, industry fixed effects notably increase the explanatory power of the model. This finding shows that the carbon intensity differs significantly across industries.

I.3.2 Univariate Portfolio Returns

We construct quintile portfolios based on the carbon intensity. Each year at the end of June, all valid stocks are sorted by their carbon intensity. A stock is eligible for inclusion in a portfolio if the company has reported its carbon emissions for the last year, if at least six months of valid returns data are available, and if the company has a market capitalization larger than USD 100 million and a positive book value. The univariate sorting constructs five quintile portfolios from Q_1 to Q_5. Quintiles are rebalanced yearly at the end of June and include all stocks with valid data in the given year.

The lower quintile portfolios, Q_1 and Q_2, include the stocks with the lowest carbon intensities. Stocks in these portfolios thus result in fewer emissions per unit of revenue earned, so we consider them "green" firms. The higher quintile portfolios, Q_4 and Q_5, are comprised of stocks with the highest carbon intensities. The stocks in these portfolios are more carbon intensive so we consider them "brown" stocks. All portfolios are value-weighted by the stocks' market capitalizations.

We also build a difference portfolio called Brown-minus-Green (BMG), following the nomenclature of Görgen et al. (2020). The BMG portfolio is equally long in the brown portfolios, Q_5 and Q_4, and equally short in the green portfolios, Q_1 and Q_2. The resulting returns are thus

$$BMG = \frac{1}{2}\left(Q_5 + Q_4\right) - \frac{1}{2}\left(Q_1 + Q_2\right). \tag{I.1}$$

The BMG portfolio gives the returns difference between brown and green firms. The returns represent the average carbon premium in a given month.

Figure I.2 shows the cumulative performance of the portfolios during the time frame 2009–2019. We see a monotonic decrease in performance from Q_1 to Q_5. The green portfolios have significantly higher total returns during our time frame than those of their brown counterparts. From January 2009 to December 2019, the lowest quintile portfolio—Q_1, the greenest portfolio—has total cumulative returns of 997% over 11 years. The most carbon-intensive portfolio, Q_5, meanwhile, has cumulative returns of 317%. This represents a very notable returns difference between green and brown stocks.[6] The carbon premium portfolio, BMG, therefore has negative cumulative returns of -50% from 2009 to 2019.

Table I.3 reports returns statistics for the sorted portfolios. We see the same pattern of monotonic decreasing mean and median returns from green to brown. Q_1 has a monthly mean return of 1.87% and an even higher monthly median return of 2.19%. Q_5 has a far lower monthly mean return of 1.12% and a monthly median return of 1.10%. The pattern persists on a risk-adjusted scale such as the Sharpe ratio. The green portfolio Q_1 has a fairly large Sharpe ratio of 0.46 whereas the brown portfolio Q_5 has a relatively low Sharpe ratio of 0.28. Because of these returns differences, the carbon premium portfolio, BMG, has a negative average monthly return of -0.51% and a negative Sharpe ratio of -0.29.

We also present alpha statistics, which control for risk exposures. We still see the same decreasing pattern in alpha performance from green to brown. The greenest portfolio, Q_1, produces a positive four-factor alpha of 0.64%, which is significant at the 1% level even after accounting for the portfolio's risk exposures. The brownest portfolio, Q_5, has a monthly alpha of 0.13%, which is not significantly different from 0. The six-factor alpha additionally includes two more risk factors: profitability and robustness. The effect does

[6] The substantial gap in returns between the Q_1 and Q_5 portfolios may be influenced by factors beyond carbon risk alone. To mitigate sample selection biases, we conduct separate analyses for US and European markets, and simulations with fixed quintiles set in 2009 and 2019. These checks consistently reveal similar trends. Notably, the performance gap between Q_1 and Q_5 is least pronounced in the European sample. A significant portion of the superior performance of the greenest portfolio, Q_1, can be attributed to the strong performance of US technology firms during this period. Nonetheless, the trend of decreasing returns from the greenest to the brownest portfolios remains robust; see the additional results reported in Figure A1 in the online appendix.

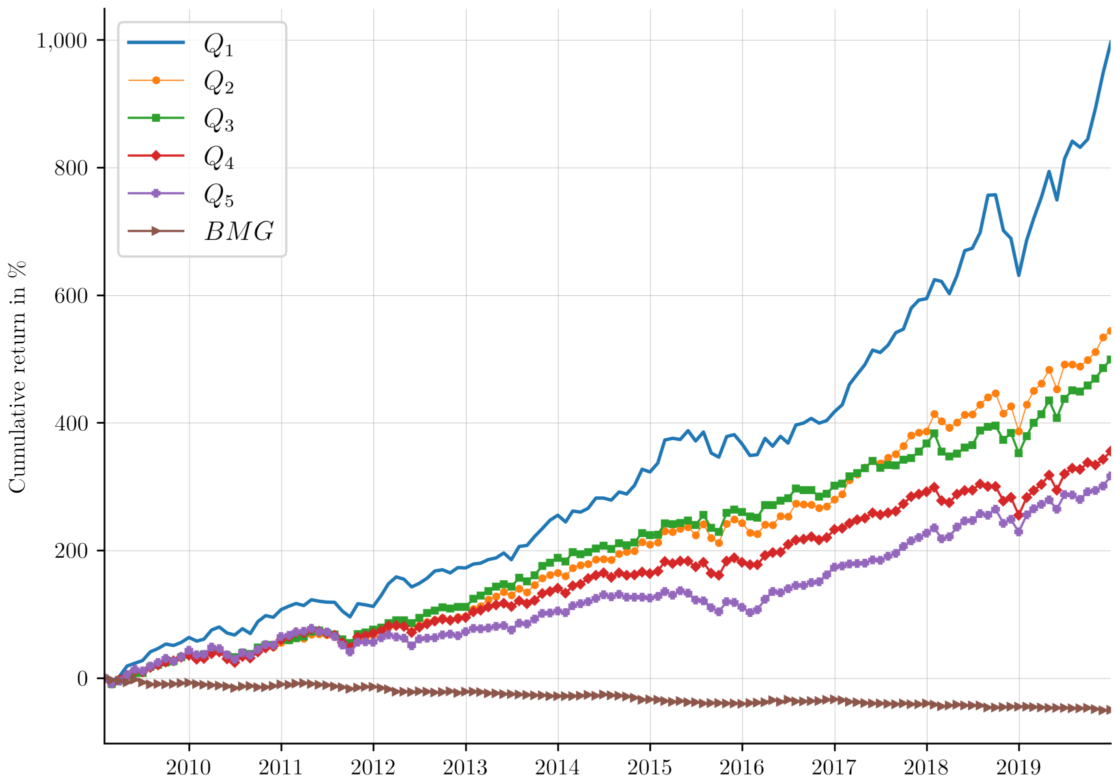


Figure I.2
Performance of univariate portfolios sorted by carbon intensity. This figure shows the cumulative performance of the quintile portfolios sorted by carbon intensity, as well as that of the difference portfolio, BMG. The sample period is January 2009 to December 2019.

not change even after accounting for all six risk factor exposures. The alpha of Q_1 even increases to 0.66%. The alpha of Q_5 further decreases, to 0.09%.

The significant differences in performance between the sorted portfolios show that the carbon intensity of a stock may have an impact on its returns. We observe that green stocks outperformed brown stocks during our time frame, which leads to an average negative carbon premium in our sample. Next, we investigate the effect of carbon intensity on the cross section of returns.

I.3.3 The Effect on the Cross Section

We analyze the effect of carbon intensity on the cross section of returns by running Fama–MacBeth regressions (Fama & MacBeth, 1973). For each month t, we regress a

Table I.3

Return and Risk Statistics of Univariate Portfolio Sorts Based on the CO_2 Intensity

This table presents monthly returns statistics for the quintile portfolios, sorted by the CO_2 intensity, and for the difference portfolio, BMG. The sample period is 2009–2019. The values are presented in percentages (except for the Sharpe ratio). The Sharpe ratio is the mean monthly returns in excess of the risk-free rate divided by the standard deviation of the excess returns. 4F Alpha is the four-factor alpha from the time-series regression of monthly excess returns on the four risk factors Mkt-RF, SMB, HML, and WML. 6F Alpha is the six-factor alpha, which additionally includes the risk factors RMW and CMA. ***1% significance, **5% significance, *10% significance.

	Portfolio	Mean (%)	Median (%)	Std Dev (%)	Sharpe Ratio	4F Alpha (%)	6F Alpha (%)
Green	Q1	1.87	2.19	4.03	0.46	0.64***	0.66***
	Q2	1.45	1.83	3.27	0.43	0.40***	0.39***
	Q3	1.35	1.49	3.26	0.40	0.34**	0.26**
	Q4	1.18	1.45	3.47	0.33	0.16	0.08
Brown	Q5	1.12	1.10	3.89	0.28	0.13	0.09
Difference	BMG	-0.51	-0.38	1.91	-0.29	-0.41**	-0.48***

company's returns on the lagged logarithm of carbon intensity and other controls:

$$r_{nt} = \gamma_{0t} + \gamma_{1t}\,\log(\mathrm{CO}_2)_{nt-1} + \gamma_{2t}\,Controls_{nt-1} + \epsilon_{nt}\,. \tag{I.2}$$

We control for a variety of firm-specific variables that could have an impact on the returns or are correlated with the carbon output, such as $Market\,Beta$, BM, $Size$, Mom, PPE, ROE, $Vola$, $Sales\,Growth$, and r_{t-1}. The time-series averages of the regression coefficients γ_{1t} over the 132-month period give us the average effect of carbon intensity on the cross section of returns. Table I.4 provides the average coefficients of the cross-sectional regressions, with t-statistics based on Newey–West adjusted standard errors in parentheses below.

Table I.4

Average Coefficients of Fama–MacBeth Regressions

This table reports the average coefficients of cross-sectional Fama–MacBeth regressions. The dependent variables are monthly returns. In Table A2 in the online appendix, we present the results of the same regression using different returns as dependent variables for robustness checks. The effects remain similar and significant. The sample period is 2009–2019. The t-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. All independent variables are winsorized monthly at the 2.5% and 97.5% levels. CO_2 is the carbon intensity, $Market\,Beta$ is the 5-year rolling CAPM beta, BM is the book-to-market ratio, $Size$ is the market capitalization, Mom is the cumulative returns for the trailing 12 months, PPE is the property, plant, and equipment value, ROE is the return on equity, $Vola$ is the standard deviation of the trailing 12 months' returns, $Sales\,Growth$ is the yearly revenue growth, and r_{t-1} is the last month's return.***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)
$Intercept$	1.64*** (4.51)	1.76*** (3.71)	1.71*** (3.43)
$log(CO_2)$	-0.08** (-2.28)	-0.07** (-2.47)	-0.07** (-2.42)
$Market\,Beta$		0.23 (0.61)	0.47 (0.91)
$log(BM)$		-0.07 (-0.89)	0.06 (0.74)
$log(Size)$		-0.09** (-2.22)	-0.07 (-1.09)
$log(1 + Mom)$		0.58 (1.32)	0.94** (2.51)
$log(PPE)$			-0.02 (-0.66)
ROE			0.76** (2.36)
$Vola$			-0.24 (-0.08)
$Sales\,Growth$			-1.02*** (-3.04)
r_{t-1}			-4.42*** (-4.83)

Model (3) shows that the logarithm of carbon intensity has a negative effect on the cross section of returns that is significant at the 5% level even when controlling for all other firm-specific variables. The average of the regression coefficients is -0.07, with a Fama–MacBeth t-statistic of -2.42. Momentum ($log(1 + Mom)$) has a positive average coefficient of 0.94 that is significant at the 5% level, Return on Equity (ROE) also has a positive average coefficient of 0.76 that is significant at the 5% level, and Yearly Revenue Growth ($Sales\,Growth$) has a significantly negative average effect of -1.02. Finally, last month's return (r_{t-1}) to account for short-term return reversal has a significantly negative average effect of -4.42, significant at the 1% level. The effect of carbon intensity is consistent across the model specifications from Models (1) to (3), whereas the control variables differ. Only the magnitude of the effect changes slightly, which can be attributed to the weak multicollinearity of the independent variables. A significant coefficient of the CO_2 intensity provides empirical evidence that investors associate risk with companies' greenhouse gas emissions. This carbon risk stems from a company's possible exposure to the impact of climate transition actions. Investors should thus incorporate emissions data into their investing process and adjust their valuations according to this risk. If we can assume this behavior in market participants, carbon risk should be priced. Contrary to our expectation and to a popular contribution to the literature by Bolton and Kacperczyk (2021), in our data and time frame we find a negative relation between carbon emissions and stock returns. This result implies that carbon-intensive stocks do not offer higher returns. Instead, low-carbon companies realize higher returns on average.

This reversed risk–reward relationship means that investors are not sufficiently compensated for carbon risk exposure. Attention to climate change has only recently gained a lot of traction, and there are more and stricter carbon actions to come. Many large investors have possibly tried to reduce their exposure to these events and developed a general aversion to carbon-intensive stocks. A consequence of this aversion could be the selling of brown stocks, which would result in lower or even negative realized returns for brown firms and in higher returns for green firms. We investigate this hypothesis in the next subsection by examining companies' Institutional Ownership. In the long term, this reverse effect can lead to lower prices for brown firms that offer higher expected returns in the future. We further explore the relationship between carbon intensity and the cross section of returns across different regions and time horizons. Table I.5 compares the effects between the US and Europe as well as before and after the Paris Agreement.[7]

Table I.5

Comparison of the Average Cross-Sectional Effects

This table reports the average coefficients of cross-sectional Fama–MacBeth regressions with different samples. The dependent variables are monthly returns. The full regression model is specified as in Model (3) in Table I.4. The t-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. *All* includes the complete sample from the period 2009–2019. *US* includes only stocks with the country of issuance as the United States. *Europe* restricts the sample to European stocks. *Pre-Paris* concerns the time frame between January 2009 and November 2015. *Post-Paris* concerns the time frame after the Paris Agreement, from December 2015 to December 2019. CO_2 is the carbon intensity. ***1% significance, **5% significance, *10% significance.

	All	US	Europe	Pre-Paris	Post-Paris
$log(CO_2)$	-0.07**	-0.06	-0.08***	-0.11***	0.00
	(-2.42)	(-1.36)	(-2.75)	(-3.05)	(-0.09)

We observe that the effect is much stronger in Europe than in the US. The average coefficient of the US sample is -0.06 and is not statistically significant. The average effect of carbon intensity on the cross section of returns in Europe is -0.08 and significant at the 1% level. Carbon risk could be more prevalent in Europe as the carbon transition is progressing faster there.[8] Climate policies are thus implemented more quickly and to a larger extent than in the US, leaving European companies more exposed to carbon transition risks.

The cross-sectional effect of carbon intensity is also much stronger before the adoption of the Paris Agreement on December 12, 2015. In the part of our time frame before

[7]Table A3 in the online appendix additionally reports the cross splits of the European and US samples before and after the Paris Agreement. There is no notable difference in these effects.

[8]For example, the world's first international emissions trading system, the EU ETS, was launched in 2005, and has become the largest multi-sector ETS in the world. To this day, the US does not have a carbon tax at the national level. The first mandatory cap-and-trade program in the US, the Regional Greenhouse Gas Initiative (RGGI), began to auction off emissions allowances in 2008. In 2021, eleven states participated in the RGGI. California started a cap-and-trade program in 2013. Since 2019, utilities in Massachusetts have been regulated under an additional cap-and-trade system.

the Agreement, the effect is negative and highly significant, with an average coefficient of -0.11. After the Paris Agreement, this effect completely vanishes, with an average coefficient of 0.00. A possible reason for this could be a revaluation of green and brown stocks leading up to the Agreement. As the likelihood of climate policy implementation grew, brown stocks, which are exposed to the impacts of such policies, decreased in value, whereas the value of green stocks, which can benefit from the carbon transition, increased. In the long term, this effect may reverse, the cheaper brown stocks offering higher returns in the future to compensate for their carbon risk exposure.

Figure I.3 shows the cumulative returns of the brown (average of Q_4 and Q_5) and the green (average of Q_1 and Q_2) portfolios one year before and after the Paris Agreement. The performance of the portfolios switches significantly around the month of the Agreement, December 2015. Before the Agreement, the green portfolio strongly outperforms the brown portfolio, with a cumulative return of 12.03%. The brown portfolio, in contrast, has a cumulative yearly return of only 2.21%. After the Agreement, in 2016 the brown portfolio considerably outperforms the green portfolio, delivering a total cumulative return of 24.06%, while the green portfolio only returns 10.75%.

The Paris Agreement may have been a turning point for the carbon premium in stock returns. Investors possibly needed time to evaluate and incorporate carbon risks into equity-price valuations because of the many uncertainties revolving around the carbon transition. The Agreement solidifies the existence of carbon risk and may have reduced some of the uncertainties surrounding the future implementation of climate policies. In the years leading up to the Agreement, investors' anticipation may have adjusted valuations accordingly. In line with the concept of the pollution premium discovered by Hsu et al., 2023, we expect to see a positive carbon premium in the future once carbon risk is fully priced into stock price valuations.

I.3.4 The Behavior of Institutional Investors

Once aware of carbon transition risks, market participants might choose to actively divest carbon-intensive stocks and industries to lower their exposure. Rohleder et al.

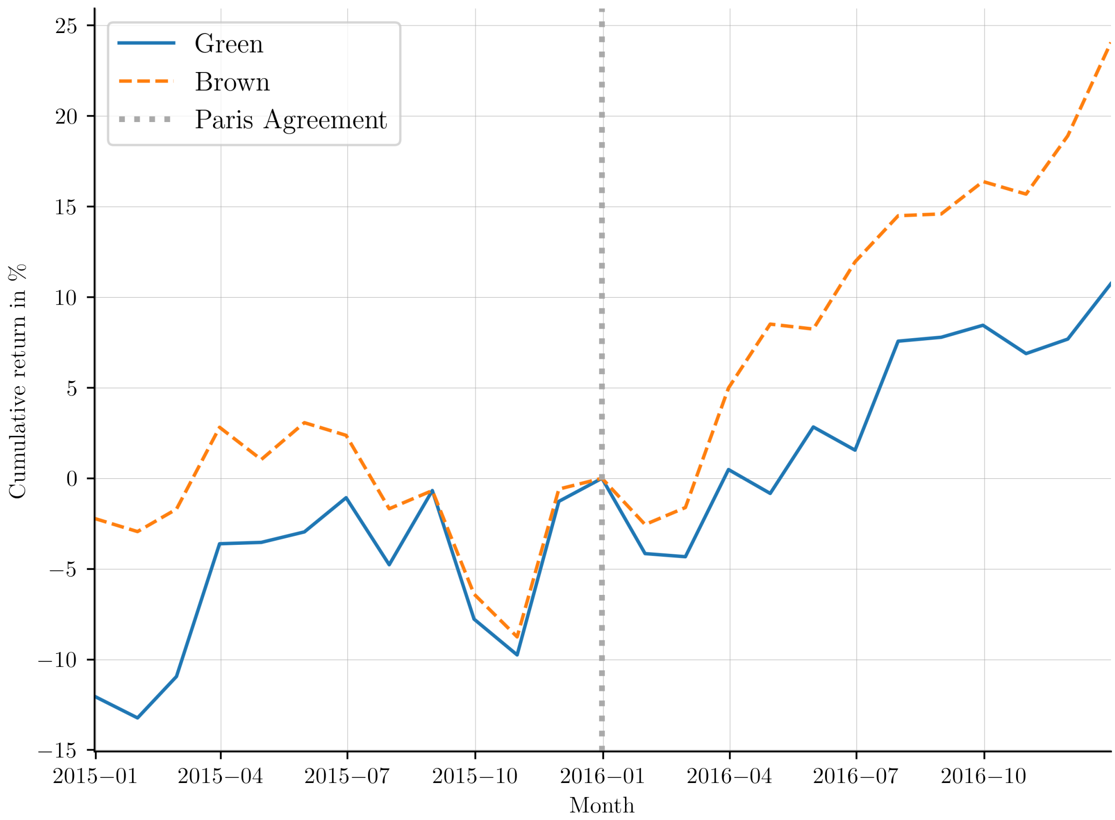


Figure I.3
Comparison of returns around the Paris Agreement. This figure shows the raw cumulative returns of the green portfolio (average of Q_1 and Q_2) and the brown portfolio (average of Q_4 and Q_5), respectively, one year before and one year after the Paris Agreement. The cumulative returns series are re-leveled to 0 at the point of the Paris Agreement, which was reached in December 2015.

(2022) show that the decarbonization of mutual funds puts pressure on the prices of the stocks they divest. This rebalancing by investors could lead to price declines in carbon-intensive stocks. We investigate this by examining institutional investors' behavior using their portfolio holdings.

Institutional Ownership (IO) is the share of a stock held by major institutions. We first regress Institutional Ownership on the carbon intensity and other firm-specific control variables:

$$IO_{it} = \delta_0 + \delta_1 \log(CO_2)_{it} + \delta_2 \, Controls_{it} + \epsilon_{it}. \tag{I.3}$$

Table I.6 reports the results, with standard errors clustered at the industry level. The variable of interest is the estimated coefficient (δ_1) of the logarithm of the carbon intensity.

We observe a significant relationship between carbon intensity and the Institutional

Table I.6

The Effect of Carbon Risk on Institutional Ownership

The sample period is 2009–2019. The dependent variable IO is the share of the stock held by major institutions (in %). This table reports the results of the pooled regression with standard errors clustered at the industry level. All independent variables are winsorized at the 2.5% and 97.5% levels. CO_2 is the carbon intensity, $Market\,Beta$ is the 5-year rolling CAPM beta, BM is the book-to-market ratio, $Size$ is the market capitalization, Mom is the cumulative returns for the trailing 12 months, ROE is the return on equity, $Vola$ is the standard deviation of the trailing 12 months' returns, and $Sales\,Growth$ is the yearly revenue growth. The regression in the first column includes country fixed effects. The second column additionally includes year fixed effects. ***1% significance, **5% significance, *10% significance.

	(1)	(2)
Variable	IO (%)	IO (%)
$Intercept$	80.86***	75.98***
$log(CO_2)$	-0.97***	-0.91***
$Market\,Beta$	6.43***	6.50***
BM	-6.33***	-5.48***
$log(Size)$	-0.68*	-0.54
$log(1+Mom)$	-1.31	0.18
ROE	-0.13***	-0.12***
$Vola$	-36.50**	-31.17*
$Sales\,Growth$	0.02	0.02
Country F.E.	Yes	Yes
Year F.E.	No	Yes
Adj. R^2	0.66	0.67

Ownership of a stock. A stock with a higher carbon intensity is generally held by fewer institutional investors and—in an aggregate sense—in smaller amounts. On average, Model (2) states that an increase in carbon intensity of 1% decreases the Institutional Ownership of a stock by 0.91 percentage points, which is significant at the 1% level.

We subsequently analyze the change in Institutional Ownership of green (bottom quintiles Q_1 and Q_2) and of brown (top quintiles Q_4 and Q_5) stocks over time to explore the asset managers' fund flows.[9] For each month, we calculate the weighted change in Institutional Ownership for the green and the brown stocks. The change in Institutional Ownership ($\Delta\, IO_{it}$) of a stock i in month t is defined as

$$\Delta\, IO_{i\,t} = IO_{i\,t} - IO_{i\,t-1}\ . \tag{I.4}$$

The total weighted (by market capitalization) change in Institutional Ownership ($\Delta^w IO_{Pt}$) for a portfolio P in month t is then given by

$$\Delta^w IO_{Pt} = \frac{\sum_{i\in P}(\Delta\, IO_{it} \cdot Market\, Cap_{it})}{\sum_{i\in P} Market\, Cap_{it}}\ , \tag{I.5}$$

where $Market\, Cap_{it}$ is the market capitalization of stock i in month t. Figure I.4 shows the cumulative weighted delta in Institutional Ownership over time.

We see that Institutional Ownership of brown stocks decreases from 2009 to the end of 2012 despite an overall increase in assets under management (Heredia et al., 2021). The cumulative delta for brown stocks remains lower than for green stocks until December 2015, coinciding with the Paris Agreement. Afterward, Institutional Ownership of brown stocks increases more than that of green stocks.[10]

Large fund flows out of brown stocks can put pressure on these stocks and result in lower prices. Similarly, higher inflows into green stocks raise the demand for them and can result in higher prices. This difference in fund flows could be one of the reasons for the difference in returns between green and brown stocks during our time frame. We see a strong outperformance of green stocks, with a higher fund inflow until 2016. Afterward, the negative carbon premium disappears and brown stocks start to outperform green stocks and also experience higher inflows. This aligns with the work of Nofsinger and Sias (1999), who find a strong correlation between changes in Institutional Ownership and returns measured over the same period. More closely related to the present paper, van der Beck (2021) analyzes the flows of sustainable funds and finds that their price pressure leads to higher returns for sustainable investing.

[9] Fund flows refer to changes in all types of institutional fund holdings, including but not limited to hedge funds, pension funds, mutual funds, and ETFs.

[10] To check for potential sample selection issues, we also run this analysis with fixed portfolios (using the original sample from the beginning of our time frame), and find similar results.

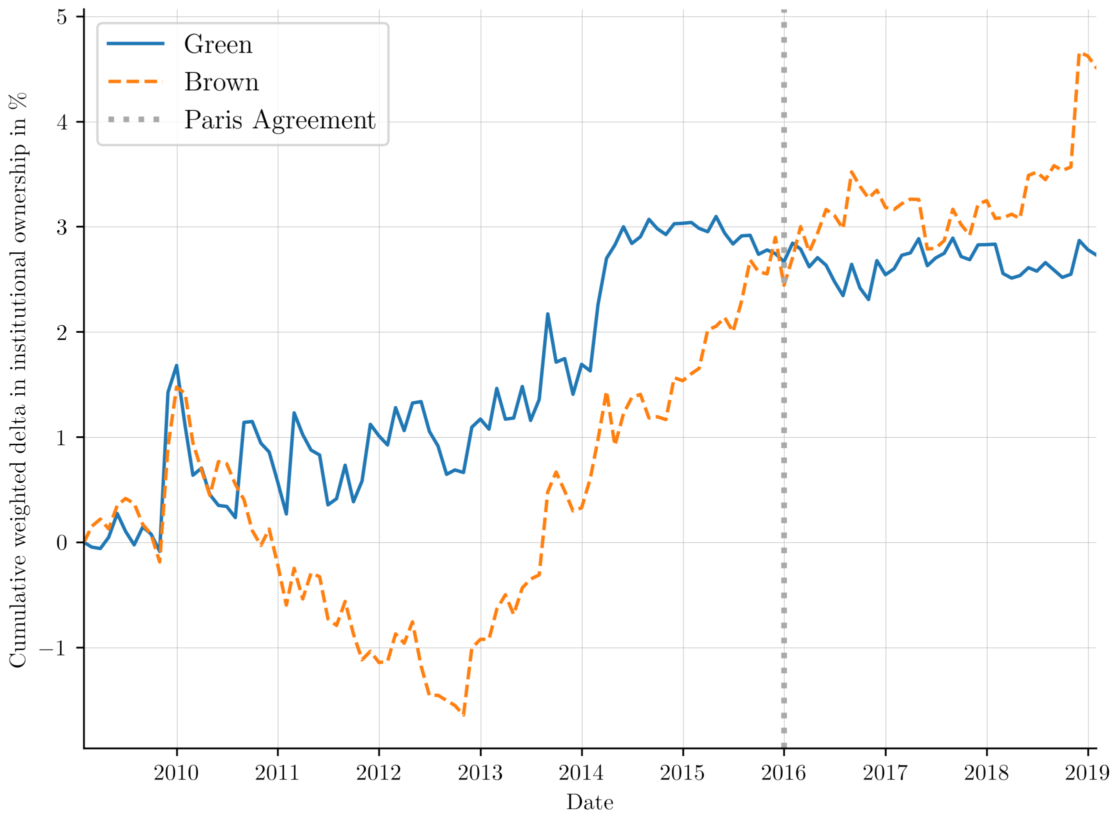


Figure I.4
Cumulative weighted change in Institutional Ownership over time. This figure shows the cumulative weighted change in Institutional Ownership of the green portfolio (consisting of all stocks of the portfolios Q_1 and Q_2) and the brown portfolio (consisting of all stocks of Q_4 and Q_5) from 2009 to the end of 2019. The dotted grey line marks the Paris Agreement, reached in December 2015.

Our analysis indicates that institutional investors consider carbon emission information in their investment decisions—an indication supported by Krueger et al. (2020) and Bolton and Kacperczyk (2021). Major investment institutions generally avoided carbon-intensive companies, particularly from 2009 to the end of 2015. This divestment can be driven by social or moral pressure, as investment firms and fundholders push for greener portfolios. The high inflows to sustainable funds confirm this fundholder demand (BlackRock, 2021). Financial motives could also play a role, as managers divest to reduce carbon transition risks and improve performance. These motives are also the most common ones provided by the investors in the survey by Krueger et al. (2020). Institutional investors account for a large portion of market capital and can significantly impact asset prices. Their behavior could be one possible explaination for the negative carbon premium during our observed time frame.

I.3.5 A Measure of Carbon Risk

Carbon intensity is a systemic risk factor if uniform climate policies are implemented that affect all companies that emit greenhouse gas emissions. Such policies might include an international carbon price. However, if interventions are introduced incrementally or selectively target specific operations or sectors, carbon intensity might be an industry-specific risk instead. We argue that carbon risk is systemic, supported by its interconnectedness through general equilibrium effects (Pástor et al., 2021), potential for widespread regulation, and financial exposure. Its effects span sectors and regions, posing a significant threat to the stability of the economy and financial system. If carbon risk is substantiated, forward-looking market participants should price it as a systemic risk factor already today.

We show that carbon risk indeed exists and that investors are aware of it. We analyze the effect on equity prices and to what extent it had already materialized in our time frame, of 2009 to 2019. Based on these results using the carbon intensity, we build a model to quantitatively measure the carbon risk exposure of an asset. Along the lines of Görgen et al. (2020), we use the popular Fama–French multi-factor model and extend it with an additional factor, carbon risk. The carbon premium portfolio, BMG, given by Equation (I.1), serves to mimic the carbon risk factor returns. This allows us to measure an asset's sensitivity to changes in the carbon premium portfolio while controlling for other common risk factor exposures of Fama and French (1993) and Carhart (1997).[11] We compute the coefficient of carbon risk with a time-series regression of an asset's excess returns:

$$r_{nt} - rf_t = \alpha_n + \beta_{1n}\, Mkt_t + \beta_{2n}\, SMB_t + \beta_{3n}\, HML_t + \beta_{4n}\, WML_t + \beta_{5n}\, BMG_t + \epsilon_{nt}, \quad \text{(I.6)}$$

where $r_{nt} - rf_t$ is the return of an asset n minus the risk-free rate, Mkt_t is the mar-

[11] Depending on a company's country of issuance, we use either US or European risk factors.

ket premium, SMB_t is the size premium, HML_t is the value premium, WML_t is the momentum premium, and BMG_t is the carbon premium in month t.

The regression coefficient of interest is β_5, which we call the carbon beta.[12] Carbon beta measures how the stock moves, on average, when the carbon premium portfolio (BMG) increases or decreases in value. A positive carbon beta implies that the stock price moves in accordance with the BMG portfolio, thus similar to that of brown stocks. A negative carbon beta implies that it moves in the opposite direction to that of the BMG portfolio and more in accordance with green firms, representing a hedge against carbon risks. A carbon beta close to 0 means no significant exposure to the BMG portfolio, which would imply no direct carbon risk. We investigate the relationship of the BMG returns to other factor returns in Table A4 in the online appendix and find that BMG is distinct from other common risk factors.

With our model in Equation (I.6), we can compute a quantitative carbon risk measure for every stock using only publicly available market returns data—that is, even for stocks that do not publicly disclose any emissions data. This measure gauges the relation of an equity to the carbon premium portfolio and thus its sensitivity to carbon transition risks. It is a single quantitative measure that is easily interpreted and directly comparable across firms. We compute carbon beta coefficients for all stocks in our sample and report statistics for all sectors (excluding Financials) covered in the Refinitiv Business Classification as well as all the countries that we have data for. We also run the same analyses using the total sample of stocks, which also includes all valid public companies that do not report their emissions data. The results between these samples are not notably different. This finding suggests that our restricted sample of stocks is fairly representative of the whole market.

Figure I.5 shows box plots for the carbon beta distributions of different industries. The sector at the bottom, with the highest carbon beta average, is the Energy sector,

[12] Görgen et al. (2020) also define the coefficient of their BMG factor as the carbon beta. It is critical to underscore that their factor construction is contingent upon their Brown-Green-Score, which amalgamates three distinct company indicators: value chain, public perception, and adaptability. In contrast, our BMG factor is exclusively predicated on quantifiable carbon emission intensities reported by companies.

with a median of 1.04. The Energy sector mainly consists of oil and gas companies, whose main products are very carbon intensive and will have to be phased out during the carbon transition. It is followed by the Utilities sector, with a median of 0.40, and the Basic Materials sector, with a median of 0.04. These are the three sectors that bear the largest carbon risk exposure, and the model predicts that the carbon transition will have a substantial effect on their business models. At the opposite end of the spectrum, the Consumer Cyclicals sector has the largest negative carbon betas, with a median of -0.45. Consumer Cyclicals consists of businesses that depend heavily on prevailing economic conditions and includes furniture and luxury goods retailers. Bansal et al. (2018) find that socially responsible stocks (also called "good" stocks) tend to outperform during good economic times similar to luxury goods. Thus, stocks of the Consumer Cyclicals industry can perform similarly to our green stocks because of similarities in investors' preferences. The Technology sector also has a significant negative carbon beta median, of -0.36. Many technology firms are known to be innovative, forward-thinking, and sustainable. On average these firms present a hedge against carbon risks and can benefit from the transition to a low-carbon or even a carbon-neutral economy. The Consumer Non-cyclicals sector is distributed closely around 0, with a median of -0.04. This industry is composed of firms that produce essential goods, such as food and household products, which are always required, and demand for them will most likely be unaffected by climate policies.

We observe substantial differences in average carbon beta measures between the sectors. The effects of climate policies, positive or negative, vary considerably from sector to sector. It is important to note that there is also a wide distribution of carbon betas within each sector. This might be important for investors that want to diversify their portfolio concentration across various sectors while still divesting their carbon risk exposure. Investors can screen all sectors for firms with low carbon betas. Thus, sector diversity remains possible without the need to increase carbon risk exposure.

Table I.7 provides average carbon intensity, carbon beta, and scope 3 carbon emissions intensity statistics for the sectors and countries. Again we observe stark differences in

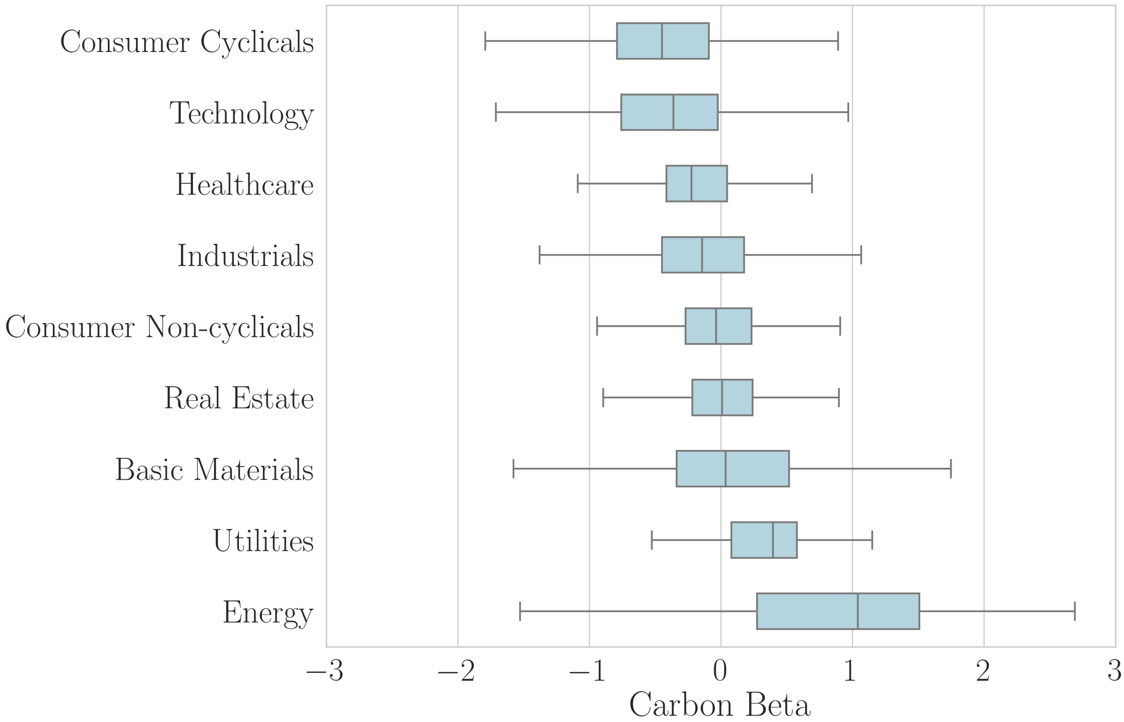


Figure I.5
Carbon beta distributions for industries. This figure shows the carbon beta distributions within sectors as classified by the Refinitiv Business Classification. Carbon betas are computed by regressing monthly excess returns on the carbon premium factor and other risk factors; see Equation (I.6). Carbon betas are computed for all stocks valid in December 2019 using monthly returns from 2009 to 2019. The boxes show the quartiles while the whiskers extend the distribution past 1.5 times the inter-quartile ranges. The bars inside of the boxes mark the medians.

average carbon betas between the countries in our sample. Russia is the country with the highest weighted carbon beta, with a weighted mean of 0.69, most likely because of its very prominent energy sector. Norway, another major oil and gas exporter, has the second highest weighted carbon beta mean, of 0.59. The country with the lowest carbon beta is Greece, with a weighted mean of −0.76, although this might not be representative as the sample is very small, with only 11 equities. Greece is followed by Germany, with a carbon beta of −0.43, and then by France, Denmark, and Finland, with weighted means of −0.38, −0.37, and −0.31, respectively. The United States also has a negative value-weighted carbon beta, of −0.17, which reverses if we consider the slightly positive unweighted mean of 0.11. This difference probably occurs because of large US technology stocks with mostly negative carbon betas and very high market capitalizations.

We generally observe a strong relation between the average carbon intensity and the

Table I.7

Sector and Country Carbon Statistics

This table reports carbon statistics for different countries and sectors for all stocks in our sample valid in December 2019. Carbon betas are computed by regressing monthly excess returns on the carbon premium factor and other risk factors. The scope 3 intensity is the yearly CO_2 equivalent (CO_2e) scope 3 emissions output (in tonnes of CO_2e) divided by the yearly sales (in USD M). Weighting is done by market capitalization. Sectors are classified as per the Refinitiv Business Classification. The country of a stock is determined by the primary country of issuance.

	Unique Firms	Avg. Carbon Intensity	Weighted Avg. Carbon Intensity	Avg. Carbon Beta	Weighted Avg. Carbon Beta	Avg. Scope 3 Intensity	Weighted Avg. Scope 3 Intensity	Firms in Scope 3 Sample
Sectors								
Industrials	396	235	144	-0.15	-0.13	584	1,149	201
Consumer Cyclicals	340	63	46	-0.45	-0.43	473	419	157
Technology	244	34	25	-0.37	-0.43	191	91	155
Basic Materials	204	931	812	0.19	0.31	1,031	2,052	80
Consumer Non-cyclicals	175	104	62	-0.02	0.04	311	447	95
Real Estate	155	81	94	-0.10	0.05	176	320	76
Healthcare	135	32	20	-0.21	-0.12	73	131	63
Energy	123	661	444	0.95	0.96	2,554	2,826	51
Utilities	109	2,480	2,055	0.30	0.37	1,478	1,945	58
Countries								
USA	668	401	203	0.11	-0.09	740	349	285
UK	317	158	210	-0.19	0.09	240	1,394	154
France	114	187	114	-0.36	-0.38	643	629	80
Germany	111	232	218	-0.33	-0.43	589	647	58
Sweden	105	138	49	-0.19	-0.30	282	574	66
Switzerland	74	660	152	-0.16	-0.26	790	213	41
Italy	66	331	403	-0.27	-0.05	489	1,094	30
Spain	53	241	194	-0.17	-0.13	506	869	34
Finland	45	194	443	-0.19	-0.31	575	1,093	33
Netherlands	44	165	114	-0.27	-0.19	715	2,502	27
Norway	37	207	237	0.34	0.59	479	1,999	21
Türkiye	33	1,537	555	-0.06	-0.07	1,187	566	15
Denmark	32	173	135	-0.22	-0.37	331	637	16
Belgium	30	426	180	-0.33	-0.16	298	511	16
Russia	28	3,457	1,038	0.51	0.69	2,793	4,308	7
Austria	28	295	349	-0.04	0.15	1,168	2,129	14
Ireland	27	158	139	-0.27	-0.28	2,105	2,063	12
Poland	21	1,224	1,369	-0.18	-0.09	523	494	4
Luxembourg	18	453	623	0.03	0.25	83	134	9
Portugal	12	347	415	-0.37	0.06	629	1,329	9
Greece	11	773	477	-0.98	-0.76	78	162	4

carbon beta. The magnitude of carbon intensity, however, does not align monotonically with the associated carbon risk, as indicated by the carbon beta. This suggests that while the relationship is strong, the levels of carbon intensity and the corresponding carbon risk can vary significantly. One reason for this could be that we exclude scope 3 emissions for the measurement of the carbon intensity, but that investors are aware of them and we hence see them reflected in the carbon beta. For example, Energy is the sector with the highest average carbon beta but only has the third-highest average carbon intensity. The Utilities sector has an average carbon intensity almost four times that of the Energy sector but its average carbon beta is less than a third of that of the Energy sector. Scope 3 emissions account for a very high proportion of the total emissions of the Energy Sector—their average share is often estimated to range from 85% to 90%—but they are not included in our carbon intensity measure. For the Utilities sector, this share is much lower, and is estimated to range from 40% to 75% (CDP, 2022; Naqvi, 2020). The products of the Energy sector, such as oil and gas, are used as inputs in the Utilities sector. Scope 3 emissions from the Energy sector are therefore reflected in scope 1 emissions from the Utilities sector, which are included in our carbon intensity measure for that sector. We can conclude this from the average scope 3 intensities reported in Table I.7. The Energy sector has a much higher average and weighted average scope 3 intensity than the Utilities sector.

The market, meanwhile, realizes this interrelation and thinks that the underlying carbon risk is much higher for those companies at the beginning of the production chain, in the Energy sector. This market sentiment is reflected in the higher average carbon beta, even though we do not use any scope 3 emissions data in the model. The carbon beta measure reflects more information than merely the emissions data. Our model should help capture this additional market information reflected in stock returns in order to efficiently measure carbon risk, even for companies that do not report their carbon emissions.

Our asset-pricing approach to measuring carbon risk relies on the ability of the BMG portfolio to efficiently represent the carbon premium returns. To construct the BMG portfolio, we use the carbon intensity. While we show its explanatory power in the cross section of returns, another variable might be more appropriate for separating brown from green stocks. This measure of carbon intensity only includes scope 1 and 2 emissions, but scope 3 emissions could be of much greater importance for some companies. As such data are still very limited, for now we have to rely on scope 1 and 2 data alone. The emissions are scaled by total revenues in US dollars. For companies from Europe or the US, exchange rate effects could have an impact on the emission intensity data and influence the analysis. The method for weighting the portfolios also influences the results. We thus tried other methods, including an additional distinction between big and small firms based on the median market value. These other approaches did not alter the qualitative results (which are available from the authors upon request).

I.4 Conclusion

In this paper, we study the effect of carbon risk on equity prices from the US and Europe, using disclosed carbon intensity data from 2009 to 2019. We find that carbon intensity has a significantly negative effect on the cross section of returns. In our time frame and sample, we document a negative carbon premium. In the investment activity of institutional investors, we observe a general aversion to carbon-intensive stocks. This behavior is a potential explanation for the negative carbon premium from 2009 until 2019. In the future, we expect to see this effect reverse and thus a significant positive carbon premium. We find supporting evidence for this theory in the time frame after the Paris Agreement, where brown stocks start to outperform green stocks. Carbon risk should be priced in the long term, and investors with high exposure should be compensated with higher returns.

Having secured evidence of the existence of carbon risk, we use a multi-factor model to measure an asset's exposure as a carbon beta coefficient. We report carbon beta statistics for all industries and countries in our sample. The sectors with the highest exposure are the Energy and the Utilities sectors; those with the lowest carbon betas include the

Consumer Cyclicals and the Technology sectors. The countries with the highest carbon risks are Russia and Norway.

Our model provides a new perspective on the quantification of carbon risk and the assessment of carbon risk implications for individual assets. Further, the model picks up additional carbon risk information from financial market data regarding undisclosed indirect emissions. The resulting evaluation provides the information necessary to allocate investments and to direct climate policies and facilitate a smooth carbon transition.

Bibliography

Alves, R., Krueger, P., & van Dijk, M. A. (2023). Drawing Up the Bill: Is ESG Related to Stock Returns Around the World? *SSRN Electronic Journal*.

Aswani, J., Raghunandan, A., & Rajgopal, S. (2024). Are carbon emissions associated with stock returns? *Review of Finance*, *28*(1), 75–106.

Bansal, R., Wu, D. A., & Yaron, A. (2018). Is socially responsible investing a luxury good? *SSRN Electronic Journal*.

Bauer, M. D., Huber, D., Rudebusch, G. D., & Wilms, O. (2022). Where is the carbon premium? Global performance of green and brown stocks. *Journal of Climate Finance*, *1*, 100006.

Berg, F., Koelbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, *26*(6), 1315–1344.

BlackRock. (2021). The tectonic shift to sustainable investing [Accessed 05-September-2022]. www.blackrock.com/institutions/en-us/insights/investment-actions/sustainable-investing-shift

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Bolton, P., & Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, *78*(6), 3677–3754.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82.

CDP. (2022). CDP Technical Note: Relevance of Scope 3 Categories by Sector [Accessed 01-February-2023]. https://cdn.cdp.net/cdp-production/cms/guidance_docs/

pdfs/000/003/504/original/CDP-technical-note-scope-3-relevance-by-sector.pdf?1649687608

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636.

French, K. R. (2021). Data Library [Accessed 02-November-2021]. mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Garvey, G. T., Iyer, M., & Nash, J. (2018). Carbon footprint and productivity: Does the "E" in ESG capture efficiency as well as environment. *Journal of Investment Management*, *16*(1), 59–69.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., & Wilkens, M. (2020). Carbon risk. *SSRN Electronic Journal*.

Griffin, J. M. (2002). Are the Fama and French factors global or country specific? *The Review of Financial Studies*, *15*(3), 783–803.

Heredia, L., Bartletta, S., Carrubba, J., Frankle, D., McIntyre, C., Palmisani, E., Panagiotou, A., Pardasani, N., Rees, K., Schulte, T., et al. (2021). Global asset management 2021: The $100 trillion machine. *Boston Consulting Group*.

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265–281.

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2023). The pollution premium. *The Journal of Finance*, *78*(3), 1343–1392.

Huij, J., Laurs, D., Stork, P. A., & Zwinkels, R. C. (2021). Carbon beta: A market-based measure of climate risk. *SSRN Electrical Journal*.

In, S. Y., Park, K. Y., & Monk, A. (2017). Is 'being green' rewarded in the market? An empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics (Singapore Issue)*, 46–48.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

Mo, J.-L., Zhu, L., & Fan, Y. (2012). The impact of the EU ETS on the corporate value of European electricity corporations. *Energy*, *45*(1), 3–11.

MSCI. (2022). *MSCI Low Carbon Indexes* (Technical report). MSCI. https://www.msci.com/low-carbon-indexes

Naqvi, M. (2020). It's All Within Scope, With S&P Global Scope 3 Data [Accessed 01-February-2023]. https://www.spglobal.com/esg/insights/it-s-all-within-scope-with-sp-global-scope-3-data

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance*, *54*(6), 2263–2295.

Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking & Finance*, *58*, 294–308.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, *146*(2), 403–424.

Rohleder, M., Wilkens, M., & Zink, J. (2022). The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking & Finance*, *134*, 106352.

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*, *78*(3), 1449–1498.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2023). Pricing climate change exposure. *Management Science*.

S&P Global. (2020). *Index Carbon Metrics Explained* (Technical report). https://www.spglobal.com/spdji/en/documents/additional-material/spdji-esg-carbon-metrics.pdf

van der Beck, P. (2021). Flow-driven ESG returns. *SSRN Electronic Journal*.

Online Appendix

This online appendix contains additional results and robustness checks.

Table A1 supplements the results presented in Table 1 of the paper, reporting quartiles for some key variables and also presents separate results for US and European firms.

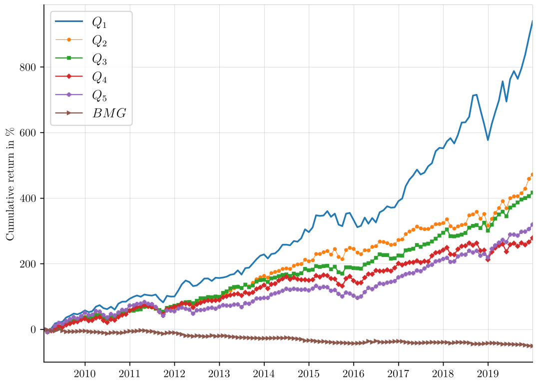
Table A1

Supplementary Data Statistics

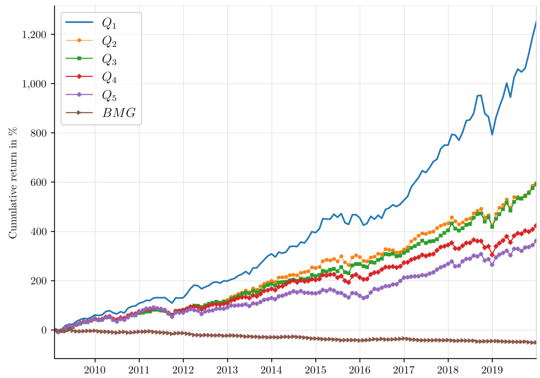
This table reports quartiles (Q1, median, Q3) for some key variables, with separate splits for the US and European companies in our sample. The sample period is 2009–2019. The variables are defined as in Table 1 of the paper.

	Full Sample			Europe			US		
Variable	Q1	Median	Q3	Q1	Median	Q3	Q1	Median	Q3
Monthly Stock Returns (%)	-3.50	1.04	5.67	-3.61	0.94	5.71	-3.25	1.27	5.59
Log CO_2 Intensity (tonnes CO_2e/USD M)	2.79	3.82	5.40	2.60	3.67	5.22	3.15	4.11	5.72
Log Market Capitalization (USD M)	7.62	8.76	9.80	7.21	8.33	9.39	8.64	9.48	10.39
Institutional Ownership (%)	26.14	57.53	84.19	18.05	34.23	58.75	75.13	87.61	96.21

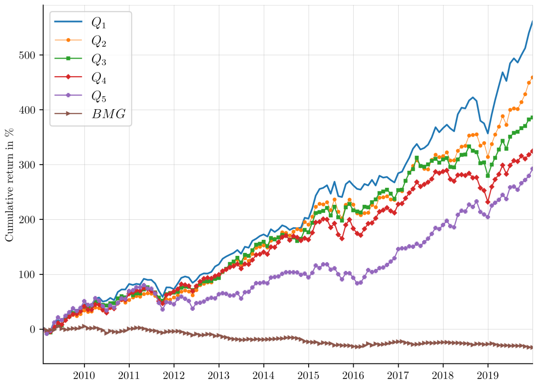
To address potential sample selection biases or other biases stemming from the yearly re-sorting method of the quintile portfolios, Figure A1 shows the performance of the quintile portfolios with varying sorting methods and samples. Notably, in the European sample in Figure A1(c) the performance gap between the Q_1 and Q_5 portfolios is less pronounced. A significant portion of the superior performance of the greenest portfolio (Q_1) is likely attributable to the strong performance of US technology firms during this period. Meanwhile, companies from the Energy sector, which were subject to muchregulation, did not perform well during our observed time frame. For these reasons, we also conduct the analysis excluding any stocks from the Technology and Energy sectors. Despite these variations, the greenest portfolio consistently outperforms the rest by a considerable margin, while browner portfolios continue to yield significantly lower returns. Consequently, the carbon premium portfolio, denoted as BMG, persistently exhibits negative values.



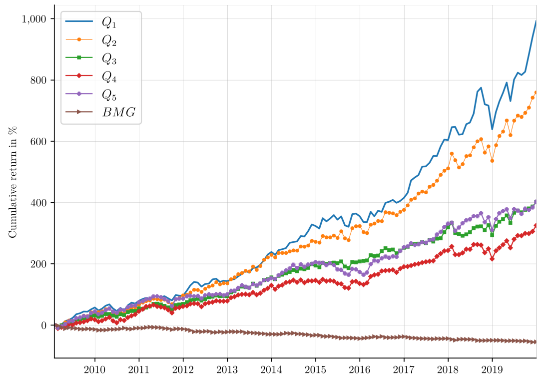
(a) All stocks are sorted into quintiles once at the beginning of the time frame in 2009 and stay fixed. ($n = 494$)



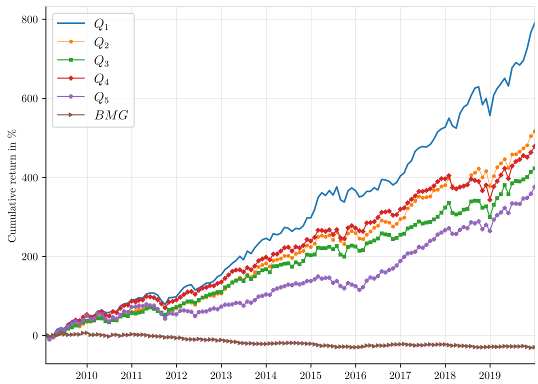
(b) All stocks are sorted into quintiles once at the end of the time frame in 2019 and stay fixed. ($n = 1595$)



(c) Only European stocks with yearly re-sorting and rebalancing.



(d) Only US stocks with yearly re-sorting and rebalancing.



(e) Exclusion of Technology and Energy stocks with yearly re-sorting and rebalancing.

Figure A1
Performance of univariate portfolios sorted by carbon intensity with varying sorting methods and samples. This figure shows the cumulative performance of the quintile portfolios sorted by carbon intensity as well as the BMG portfolio with different sorting methods and samples.

Table 4 in the paper reports the average coefficients of cross-sectional Fama–MacBeth regressions with the next month's return as the dependent variable. We performed robustness checks by using different dependent variables. Table A2 reports the coefficient of the variable $log(CO_2)$ in Fama–MacBeth regressions with different dependent return variables. We observe that the coefficient remains negative and statistically significant at (at least) the 5% level. Additionally, we see that the magnitude of the effect using yearly returns is almost exactly 12 times greater than that of the effect using monthly returns.

Table A2

Fama–MacBeth Regressions with Varying Dependent Variables

This table reports the average coefficient of the carbon intensity in cross-sectional Fama–MacBeth regressions with different dependent variables. The regression model is specified as in Model (3) in Table 4 with different dependent variables. The sample period is 2009–2019. The t-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. All independent variables are winsorized monthly at the 2.5% and 97.5% levels. ***1% significance, **5% significance, *10% significance.

	Monthly Returns	3-Month Average Returns	6-Month Average Returns	12-Month Average Returns	Yearly Returns
$log(CO_2)$	-0.07**	-0.06**	-0.05**	-0.05***	-0.85**
	(-2.42)	(-2.36)	(-2.38)	(-2.89)	(-2.02)

Next, Table A3 supplements Table 5 of the paper and shows cross splits of the European and US samples before and after the Paris Agreement. We find that there is no notable difference in the effects whether we use the full sample or split it between the US and Europe.

Table A3

Average Cross-Sectional Effects with Varying Samples

This table reports the average coefficients of cross-sectional Fama–MacBeth regressions with different samples. The dependent variables are monthly returns. The full regression model is specified as in Model (3) in Table 4. The t-statistics, based on Newey–West adjusted standard errors with three lags, are given below in parentheses. *US* includes only stocks with the country of issuance as the United States. *Europe* restricts the sample to European stocks. *Pre-Paris* concerns the time frame between January 2009 and November 2015. *Post-Paris* concerns the time frame after the Paris Agreement, from December 2015 to December 2019. CO_2 is the carbon intensity. ***1% significance, **5% significance, *10% significance.

	Europe Pre-Paris	Europe Post-Paris	US Pre-Paris	US Post-Paris
$log(CO_2)$	-0.12***	-0.03	-0.12**	0.03
	(-3.02)	(-0.58)	(-1.88)	(0.69)

Table A4 reports the results of time-series regressions of the BMG returns on other common risk factor returns. Model (2) shows that the HML factor has significant explanatory power, with a coefficient of 0.29 that is significant at the 1% level. In Model (3) the coefficient decreases to 0.12 and is no longer significant. The CMA factor also has a positive coefficient, of 0.45, which is significant at the 1% level. No other factor is significant. In sum, the BMG factor cannot be explained well by the other factors as the intercept is still large and highly significant and the model fit, given by the adjusted R^2 ratio, is very low, with a value of only 0.18. This confirms that carbon risk is an additional explanatory factor that can extend the model beyond the common risk factors.

Table A4

Determinants of the Carbon Premium

The sample period is 2009–2019. The dependent variable is the monthly returns of the BMG portfolio. This table reports the results of the time-series regression. The independent variables are the six common risk factors retrieved from the website of Kenneth French. They are further explained in Table 1. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)
Variable	BMG	BMG	BMG
$Intercept$	-0.51***	-0.37**	-0.44***
Mkt		-0.06	-0.03
SMB		0.02	-0.02
HML		0.29***	0.12
WML		0.00	-0.02
RMW			-0.09
CMA			0.45***
Adj. R^2	0.00	0.12	0.18

Table A5 provides an overview of key climate regulations and initiatives in the US and Europe from 2009 to 2019. This time frame is a critical period for policy efforts aimed at enhancing energy efficiency, fostering the transition to clean energy, and mitigating greenhouse gas emissions. Importantly, the table underscores that the Energy sector was the central focus of these initiatives. Our analyses validate the significant exposure of the Energy sector to carbon transition risks.

Table A5

Key Climate Regulations and Initiatives, 2009–2019

Summary of major climate regulations and initiatives in the US and Europe from 2009 to 2019.

Date	Name	Affected Jurisdictions	Description	Source
2009	EU Climate and Energy Package	EU	Aimed for three 2020 targets: 20% cut in greenhouse gas (GHG) emissions from 1990 levels, 20% energy from renewables, and 20% increase in energy efficiency.	[1]
2009	American Recovery and Reinvestment Act	USA	Economic stimulus with key investments in energy efficiency, renewable energy, and green jobs.	[2]
2009	Regional Greenhouse Gas Initiative (RGGI)	USA	Cooperative effort among eastern states to cap and reduce CO_2 emissions from the power sector, initiated in 2009.	[3]
2012	Clean Air Act Mercury and Air Toxics Standards (MATS)	USA	EPA-enforced standards to cut mercury and toxic pollutant emissions from power plants.	[4]
2013	Greenhouse Gas Emissions Reduction Targets	EU	Set a target for the EU to cut GHG emissions to 20% below 1990 levels by 2020.	[5]
2013	Obama Administration's Climate Action Plan	USA	Aimed at cutting carbon pollution, preparing the US for climate change impacts, and leading international efforts to combat global climate change.	[6]
2013	California's Cap-and-Trade Program	USA	Statewide cap on GHG emissions, allowing trading of emission permits.	[7]
2014	2030 Climate and Energy Framework	EU	Targets for 2030: 40% reduction in GHG emissions, 27% renewable energy use, and 27% improvement in energy efficiency.	[8]
2015	Paris Agreement	International	Global treaty committing participants to keeping warming well below 2°C above preindustrial levels and to pursuing efforts for a target of 1.5°C.	[9]
2015	Circular Economy Package	EU	Promotes sustainable growth by increasing recycling, reducing landfilling, and using resources more efficiently.	[10]
2018	Clean Energy for All Europeans Package	EU	Legislative package to transition to clean energy and fulfill the EU's Paris Agreement commitments.	[11]
2018	LULUCF Regulation	EU	Integrates GHG emissions and removals from land use, land change, and forestry into the EU's climate framework.	[12]
2019	Repeal and Replacement of the Clean Power Plan	USA	Replaced the Clean Power Plan with the Affordable Clean Energy rule for more state-level flexibility in emissions standards.	[13]
2019	European Green Deal	EU	Policy initiatives aiming to make Europe climate neutral by 2050, announced in 2019 with ongoing roll-out.	[14]

Sources for Regulations from Table A5

[1] EU Climate and Energy Package:
eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex%3A32009L0028https://climate-laws.org/document/2020-climate-and-energy-package-contains-directive-2009-29-ec-directive-2009-28-ec-directive-2009-31-ec-and-decision-no-406-2009-ec-of-the-parliament-and-the-council-see-below_c91b

[2] American Recovery and Reinvestment Act:
www.govinfo.gov/content/pkg/BILLS-111hr1enr/pdf/BILLS-111hr1enr.pdf

[3] Regional Greenhouse Gas Initiative (RGGI):
www.rggi.org

[4] Clean Air Act Mercury and Air Toxics Standards (MATS):
www.epa.gov/stationary-sources-air-pollution/mercury-and-air-toxics-standards

[5] Greenhouse Gas Emissions Reduction Targets:
https://climate.ec.europa.eu/eu-action/effort-sharing-member-states-emission-targets/effort-sharing-2013-2020-targets-flexibilities-and-results_en

[6] Obama Administration's Climate Action Plan:
obamawhitehouse.archives.gov/sites/default/files/image/president27sclimateactionplan.pdf

[7] California's Cap-and-Trade Program:
ww2.arb.ca.gov/our-work/programs/cap-and-trade-program

[8] 2030 Climate and Energy Framework:
www.consilium.europa.eu/en/policies/climate-change/2030-climate-and-energy-framework/

[9] Paris Agreement:
unfccc.int/sites/default/files/resource/parisagreement_publication.pdf

[10] Circular Economy Package:
environment.ec.europa.eu/strategy/circular-economy-action-plan_en

[11] Clean Energy for All Europeans Package:
energy.ec.europa.eu/topics/energy-strategy/clean-energy-all-europeans-package_en

[12] LULUCF Regulation:
eur-lex.europa.eu/eli/reg/2023/839/oj

[13] Repeal and Replacement of the Clean Power Plan:
www.epa.gov/stationary-sources-air-pollution/electric-utility-generating-units-repealing-clean-power-plan

[14] European Green Deal:
commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en

II. How to Attract ESG Funds

by Arthur Enders[a]

forthcoming in *The Journal of Impact and ESG Investing*

Abstract: This study investigates the influence of Environmental, Social, and Governance (ESG) practices on institutional fund holdings. Considering the growing importance of ESG-focused funds, I differentiate between ESG funds and general institutional funds. As a result, I identify key attractors for both general and ESG funds. Avoiding conventional ESG ratings, I concentrate on foundational ESG determinants like carbon emissions and board diversity, using data from S&P 500 companies from 2010 to 2021. My findings provide actionable guidance for companies aiming to attract ESG funds and improve their market value.

Keywords: Institutional investors, environmental, social, governance, ESG, corporate social responsibility, CSR.

JEL Classification: M14, M41, G23, G34.

Acknowledgements: I thank my supervisor Thomas Lontzek as well as my colleague Marco Thalhammer for their valuable guidance, insightful feedback, and continuous support throughout the development of this work.

Citation: Enders, A., (2025). How to Attract ESG Funds. Forthcoming in *The Journal of Impact and ESG Investing*. Portfolio Management Research.

[a]RWTH Aachen University

II.1 Introduction

As businesses aim for sustainable growth and higher market value, attracting and retaining investors becomes a crucial objective. Institutional investors, in particular, have a strong influence in financial markets. Their investment choices can greatly impact a company's lending opportunities and market value. In recent years, the surging interest in sustainable investments has led to an increasing number of funds that integrate Environmental, Social, and Governance (ESG) criteria into their investment decisions. This tremendous growth of ESG funds and ESG investments shifts institutional funds' portfolio holdings and, as a result, impacts stock prices and, in turn, firm values. Consequently, comprehending the factors that attract institutional funds and particularly ESG funds is critical. In this context, I study the impact of a company's ESG practices on both its general institutional and ESG fund holdings, utilizing data from S&P 500 companies between 2010 and 2021. I identify a range of ESG measures and practices that every company can enhance or adopt to attract more ESG-conscious funds.

The significance of investors' interest in ESG is evident from the substantial influx of capital into ESG funds in the last couple of years. In the first quarter of 2023 alone, global ESG funds attracted USD 29 billion in net flows, growing global ESG fund assets to USD 2.74 trillion from USD 2.55 trillion three months earlier. This 7.5% expansion exceeds the overall global fund market growth of 4%. As a result, the market share of ESG funds continues to grow. In Europe, it rose to 22% from 18% (Morningstar, 2023). In his empirical analysis, van der Beck (2021) shows that the flows toward ESG funds exert a significant price pressure on stocks, driving up the realized returns of "green" or sustainable stocks. ESG investors in particular are shown to be more price inelastic with regard to their portfolio rebalancing, i.e. they tend to hold stocks even after their prices have inflated significantly. This means ESG funds generally exert higher pressure on stock prices than general institutional funds. This raises the question of how companies can most effectively align with the preferences of ESG funds to potentially enhance their access to funding opportunities.

For this analysis, I deliberately avoid using ESG scores or ratings, as they are often inconsistent and heavily dependent on the specific rating agency (Berg et al., 2022). In their survey of institutional investors, Amel-Zadeh and Serafeim (2018) find that 82% of their respondents integrate ESG information in their investment decisions, mostly for performance, financial and ethical reasons. An extensive amount of ESG funds use investment strategies such as exclusionary or best-in-class screening that are solely based on ESG ratings. However, different asset managers rely on distinct ESG scores from various providers. As a result, measuring the direct relationship between certain ESG scores and respective fund holdings can be challenging and potentially perplexing.

I consequently focus on the underlying ESG-related measures and practices adopted by companies. These encompass a spectrum of data points and initiatives, such as disclosing carbon emissions, engaging in political or lobbying activities, diversifying board compositions, and more. While certain measures may not directly influence portfolio managers' perception of a company's sustainability, they substantially impact a multitude of ESG ratings forming the basis of sustainable fund investment decisions. Through my empirical analysis of the direct link between foundational ESG measures and fund holdings, I avoid dealing with the many existing ESG ratings. Ultimately, a company's primary concern is not a singular ESG rating from one specific provider. Instead, it lies in the collective market's assessment of its sustainability. Investors use various ESG ratings to shape their judgement and inform their investment choices. Therefore, I focus directly on the holdings of ESG investment funds to understand the market's view on a company's sustainability. By identifying and analyzing the key ESG practices that influence institutional investment, this study offers valuable insights for companies looking to maximize their appeal to ESG funds.

Numerous research studies focus on the relationships between ESG or corporate social responsibility (CSR)[1] aspects on corporate finance.[2] I focus on the literature that studies fund ownership characteristics and firms' ESG attributes. This strand of research faces the challenge of dual causality, where investors can intervene with firms to modify their

[1]The terms ESG and CSR are often used interchangeably in literature. In this paper, I stick to the notion of ESG.

[2]For an extensive review of the related literature, see S. L. Gillan et al. (2021).

ESG policies, or specific ESG profiles can attract particular types of investors. Additionally, researchers encounter complexities regarding variables that may be correlated with either ownership or ESG scores, such as performance and value. These factors further complicate the analysis and pose challenges for researchers in disentangling the intricate relationships within this field.

In their field surveys, Bauer et al. (2021) find that investors demonstrate a preference for both forms of sustainable investing: investors' engagement with companies on ESG matters and the integration of ESG considerations in the investment process. Several other surveys also explore investor behaviour regarding ESG aspects in their investment decisions. Riedl and Smeets (2017) conduct surveys and experiments and find that socially responsible investment decisions can be attributed to both social preferences and social signaling. Hartzmark and Sussman (2019) examine the impact of the launch of Morningstar's Sustainability Ratings and show that investors value sustainability. Low sustainability rated funds experienced significant outflows whereas high sustainability resulted in substantial inflows. In a recent survey of Vanguard retail investors, Giglio et al. (2023) find that motivations for investing in ESG stocks vary, with 45% having no specific reason, 25% being primarily driven by ethical considerations, and 7% believing in the outperformance of ESG investments. Additionally, 25% of investors perceive ESG investments as a hedge against climate risk.

A multitude of studies relate institutional investor ownership to ESG activity. However, there is no unanimous consensus among these studies regarding the specific nature or direction of the relationship (S. L. Gillan et al., 2021). Furthermore, researchers employ varying metrics to assess firms' ESG profiles. Borghesi et al. (2014) find that companies with higher levels of institutional ownership exhibit a lower propensity to invest in CSR initiatives. Similarly, S. Gillan et al. (2010) find that institutional ownership declines when firms' ESG scores increase. Other research reveals a nuanced relationship in this regard. Nofsinger et al. (2019) determine that while institutional ownership does not exhibit a positive correlation with high environmental and social scores, it has a negative correlation with low environmental and social scores. Supporting this finding, Chava (2014) observes that institutional ownership tends to be lower for firms with poorer environmental profiles.

Other studies further categorize between the types of institutional investors. Hong and Kacperczyk (2009) find that socially constrained institutions, such as pensions, exhibit aversion towards socially irresponsible stocks. Consequently, these stocks tend to be disproportionately held by less constrained institutions, including mutual funds and hedge funds. Another categorization considers mutual fund ownership based on the portfolio manager's political affiliation. Hong and Kostovetsky (2012) discover that mutual fund managers who contribute to Democratic politicians tend to underinvest in socially irresponsible stocks compared to their counterparts.

Fernando et al. (2017) reveal that institutional ownership and environmental performance are related, but the relationship varies across different environmental score ranges. Firms with very high or very low scores have lower institutional ownership compared to those in the moderate range. According to Chung and Zhang (2011), the portion of a company's shares owned by institutional investors increases as its governance structure quality improves. Likewise, their research indicates that the ratio of institutions holding a firm's shares rises alongside the enhancement of its governance quality. Kim et al. (2018) confirm that companies with superior CSR ratings draw in a greater number of institutional investors, particularly those with long-term, lower stakes, and environmentally conscious inclinations, as well as more individual investors.

My study adds to the existing research by focusing on various ESG measures and their impact on fund ownership. Instead of relying on overarching ESG ratings, I examine underlying ESG data points that influence the broad spectrum of ESG ratings. Aided by literature, I look at carbon emissions, emission reduction targets, gender diversity, political and lobbying contributions, human rights compliance, CEO duality, board governance structures, and CSR auditors. These indicators were chosen based on available data, their cross-industry relevance, and the significance of their results in portraying key ESG aspects. I analyse the effects of these measures on the depth (institutional fund ownership) as well as the breadth (number of individual institutional funds) of institutional holdings. A novel aspect of my study is the differentiation between ESG funds and general institutional funds, achieved using keywords tied to E, S or G. This study is the first to specifically examine ESG fund holdings in this detailed manner.

I identify a range of ESG metrics that exert significant influence over both general and ESG fund holdings. I find that environmental measures, such as the reporting of carbon emissions, low carbon intensity in production processes, and the presence of emission reduction targets hold particular importance for ESG funds. On the social front, my findings indicate that ESG funds tend to disfavor companies contributing to political or lobbying efforts. Moreover, the indication of compliance with human rights standards proves to be a strong attractor for ESG funds, likely due to its positive impact on various ESG criteria. Furthermore, my research highlights the preferences of general institutional funds, showing a distinct emphasis on the governance structure of a company's board of directors. Notably, there is a discernible aversion to CEO duality, while the independence of board members is viewed very favorably.

My empirical findings provide valuable insights into the nuanced interplay between firms' ESG endeavors and their portfolio allocations across institutional funds. These findings contribute to the comprehension of the decision-making processes of ESG funds, offering potential guidance for corporate managers in augmenting their appeal to institutional investors, with a specific focus on ESG funds and their fund investors. It is important to highlight that the findings presented herein pertain specifically to the US market, and therefore might not translate to other markets.

The rest of this paper is structured as follows. Section II.2 describes the empirical data. In Section II.3, I introduce the baseline regression models and then show my findings for the environmental, social and governance measures. Finally, I conclude in Section II.4.

II.2 Data

All data is collected from Refinitiv (formerly Thomson Reuters) Datastream. I restrict the sample to US stocks from the S&P 500 index. ESG data is not yet standardized and the data availability and quality substantially differs between firms and even more so between countries. With this restricted sample, we ensure some comparability between the firms. The time period ranges from 2010 to the end of 2021 for a total of 12 years of data. Sustainable finance has only recently gained traction and there is no sufficient amount of ESG funds prior to that time frame to make meaningful analyses.

For specific analyses, I further limit my sample to stocks with available requisite data points. For this reason, the number of observations between the regressions varies noticeably. Table II.1 provides descriptions and summary statistics for all variables.

II.2.1 Financial Data

I collect monthly stock return data and yearly financial data for all stocks in the sample from Refinitiv. I use popular financial values from related literature that are shown to be related to institutional ownership and control for these in my analyses.

The Tobin's Q is the ratio of market capitalization to total assets. Return on Assets (ROA) is calculated by the net income divided by the total assets. Leverage Ratio is the ratio of total debt to total assets. The Book-to-Market Ratio is a company's shareholder's equity divided by the market capitalization. CAPM Beta measures a company's stock price sensitivity to movements in the overall market, calculated over a 5-year period using monthly returns. Annual Stock Return is last year's cumulative stock return. Volatility is the standard deviation of last year's monthly returns.

All observations are required to have all financial data available as they are used as controls in all regressions. I end up with 5,490 valid observations. An average company in my sample has a stock price of 97.58 with a market capitalization of USD 46.988 billion. It has a Tobin's Q of 1.96, a ROA of 6%, a Leverage Ratio of 0.29, and a Book-to-Market Ratio of 0.4. The average CAPM Beta is close to the Market Beta with 1.04. The average

Table II.1

Data Statistics

This table reports general statistics (mean, median, standard deviation, and number of observations) for all variables used in the following analyses. The sample period is 2010–21. All firm-level variables are retrieved from Refinitiv. Tobin's Q is the ratio of market capitalization to total assets. Leverage Ratio is the ratio of total debt to total assets. CAPM Beta is computed over a 5-year rolling horizon using monthly returns. Volatility is the standard deviation of last year's monthly returns. Details on the ESG data are provided in Section II.2.2. Ownership variables state the fractions of the shares held by the specified institutional investors. The Institutional Holdings data is explained in Section II.2.3.

Variable	Mean	Median	Std. Dev.	Observations
Financial Data				
Stock Price	97.58	61.42	177.64	5,490
Market Capitalization (USD M)	46,988	18,996	114,698	5,490
Tobin's Q	1.96	1.27	2.48	5,490
ROA	0.06	0.05	0.07	5,490
Leverage Ratio	0.29	0.27	0.23	5,490
Book-to-Market Ratio	0.4	0.33	0.32	5,490
CAPM Beta	1.04	1.01	0.52	5,490
Annual Stock Return	0.2	0.17	0.34	5,490
Monthly Volatility	0.07	0.06	0.04	5,490
ESG Data				
Reports Emissions (binary)	0.66	1.0	0.47	5,490
CO2 Emission Total (M tonnes CO2e)	6,105	619	16,202	3,647
CO2Intensity (tonnes CO_2e/USD M)	433	40	1,171	3,647
Has Emission Target (binary)	0.54	1.0	0.5	5,249
Emission Reduction Target Year	2,026	2,025	6	1,261
Emission Reduction Target Pctage (%)	38.09	30.0	26.68	1,240
Women Employees (%)	37.28	35.6	15.44	2,640
Women Managers (%)	32.01	30.0	12.76	1,924
Political Contributions (USD M)	1.25	0.28	2.95	1,616
Lobbying Contributions (USD M)	2.33	0.98	3.63	2,724
Fundamental Human Rights (binary)	0.25	0.0	0.43	5,277
Independent Board Members (%)	83.25	85.71	9.59	5,315
CEO Duality (binary)	0.55	1.0	0.5	5,315
Board Gender Diversity (%)	21.04	20.0	10.09	5,315
External Audit CSR Report (binary)	0.64	1.0	0.48	2,197
Institutional Holdings				
Fund Ownership (%)	41.37	41.36	10.37	5,481
ESG Fund Ownership (%)	0.88	0.61	1.11	5,481
Number of Funds	1,813	1,643	1,006	5,481
Number of ESG funds	157	118	132	5,481

annual stock return during this time frame is 20% with a monthly volatility of 7%.

II.2.2 ESG Data

I collect all ESG data points available on Refinitiv for a total of 962 yearly firm-level ESG measures. Refinitiv gathers information from publicly accessible sources, including company websites, annual reports, and corporate social responsibility reports. Additionally, information provided by firms is also collected, audited, and standardized. From this vast amount of data, I identify relevant data points that potentially have an impact on institutional investor ownership based on theories drawn from available literature in this field. Insufficient data availability hindered my ability to draw meaningful conclusions for several measures that I hypothesized as significant for investors, such as water usage and pay gaps. To advance this research, there is a critical need for improved ESG data availability, transparency, and standardized reporting.[3]

While I do collect the Refinitiv ESG score, which are popular among investors, I refrain from using them in my analyses. A majority of investment decisions of active and especially passive funds are made solely based on ESG scores. However, investors use a variety of ESG scores from a variety of providers that are very different in their methodologies. Using certain ESG scores from chosen providers to study investor preferences does not provide a comprehensive and unbiased assessment. Instead, I conduct my analyses based on raw underlying ESG measures and policies of companies. Even if investors do not directly integrate these specific ESG measures into their investment decision making, the ESG measures affect the ESG scores which in turn affect their investment decisions.

I use a variety of measures and policies from all of the ESG pillars. From the environmental pillar, I use the disclosure of carbon emissions, total carbon emissions, carbon intensity, and emission targets. Robinson et al. (2023) suggests that the provision of environmental disclosure is positively correlated with increased ESG fund ownership in subsequent periods, even when accounting for firms' ESG ratings. Bolton and Kacperczyk (2021) find that total carbon emissions and changes in emissions are associated with

[3]ESG data quality will likely improve in the future. The Global Reporting Initiative (GRI) is a leading sustainability reporting standard-setting body that focuses on stakeholders' needs. The International Financial Reporting Standards (IFRS) Foundation is an investor-oriented standard-setter, forming the International Sustainability Standards Board (ISSB). While initially separate, the GRI and ISSB have recently signed a collaboration agreement to coordinate their work and standards. These developments in sustainability standard-setting will offer new research opportunities in the future.

higher stock returns. I use the same definition as Refinitiv for carbon intensity and calculate it as the ratio of total carbon equivalent emissions in a year (in tonnes of CO_2e) to the total revenue in that year (in millions of USD). Total carbon emissions is the aggregated total CO_2 equivalent output in scope 1 and scope 2 as defined by the Greenhouse Gas Protocol (GHGP, 2015)[4]. Enders et al. (2024) show that carbon intensity is significantly related to stock prices and institutional ownership. I restrict carbon emission data to reported emissions and refrain from using any estimated emission data. Lastly, I use companies' emission reduction targets. I use a binary variable that denotes if a company has set itself a target or not. I additionally use the emission target year and the emission target reduction percentage to analyse the effect of the proximity and magnitude of the targets.

For the social pillar, I use the share of women managers and women employees to analyse the effect of general gender diversity inside a company. I also use a company's monetary contributions for political and lobbying purposes. Hill et al. (2013) suggest that managers frequently employ both lobbying and campaign contribution channels to influence the political landscape that impacts their firm. They also show that shareholders appreciate the lobbying efforts made by management on their behalf. Finally, I use a company's commitment to fundamental human rights. To do this, I look if a company claims to comply with the fundamental human rights convention of the International Labour Organization (ILO)[5].

From the governance pillar, I use the percentage of independent board members, CEO duality (an individual holds both CEO and Chairman positions), external CSR auditing and board gender diversity. Nasdaq Rule 5605 outlines listing qualifications for boards of directors and committees. It mandates a majority of independent directors on the board and complete independence for audit, nominating, and compensation committees. The implementation of this rule has made board independence a significant research topic.

[4]Scope 1 includes all direct greenhouse gas emissions from sources that are owned or controlled by the company and used for production, including boilers, furnaces, vehicles, etc. Scope 2 mainly includes the emissions generated by purchased electricity.

[5]This includes the International Labour Organization's (ILO) Declaration on Fundamental Principles and Rights at Work and the United Nations Universal Declaration of Human Rights.

CEO duality, as Krause et al. (2014) note, has been a topic of interest for a long time with many aspects still not fully understood. With the examination of external CSR auditing, I investigate, among other things, the effects of higher ESG data quality assurance, which is still under-researched (Cohen & Simnett, 2015). Finally, I use board gender diversity, which is also a complex topic of discussion with a double-edged nature (Triana et al., 2014). Notably, Liu (2018) find that firms with higher female board representation receive fewer environmental lawsuits.

Emissions are disclosed in approximately 66% of the observations. If a company discloses its emissions, the average total CO_2 emissions are $6,105$ million tonnes of CO_2 with a CO_2 intensity of 433 tonnes CO_2e/USD M. 54% of the observations have an emissions reduction target with the average reduction target year being 2026 and an emission reduction target of 38.09%. In an average company, 37.28% of the managers and 32.01% of the total employees are women. The average yearly company donation to political parties is USD 1.25 million, whereas an average USD 2.33 million is contributed to lobbying purposes. Around 25% of the companies claim to comply with fundamental human rights conventions. The average share of independent board members lies at 83.25% with a 21.04% female representation on the board of directors. In 55% of the observations, the CEO also serves as the chairman of the board. Finally, in around 64% of the valid data points, companies employ an external auditor to audit their CSR report.

II.2.3 Institutional Ownership Data

Institutional holdings data is from the Refinitiv ownership database collected from 13F filings. I collect yearly firm-level fund data for the stocks in the sample. The institutional ownership of a stock is the share of the stock held by major institutions. Major institutions are defined as firms or individuals that exercise investment discretion over the assets of others, in excess of USD 100 million. Major institutions include financial holdings companies, banks, insurance companies, mutual fund managers, portfolio managers, and self-managed pension and endowment funds. Using fund names, fund types and orientations, I can further differentiate between different types of investors/funds.

The fund names allow me to categorize the fund holdings into two groups: general institutional funds and ESG funds.[6] Here, "general institutional funds" refer to all institutional funds, which include the ESG funds I identify. Similar to van der Beck (2021), I use a set of ESG keywords to identify ESG funds. I use his list of keywords and extend it by more terms that often occur in the fund names and can be associated with either E, S, or G. Table II.2 shows the full set of ESG keywords that I use, along with associated fund statistics. Each fund in the sample is uniquely matched to a single ESG keyword from the list.

Figure II.1 shows the ESG ownership and the amount of ESG funds over the time frame. It shows that the number of ESG funds increased substantially. In 2010, the mean ESG ownership in the sample was 0.64%, with a total of 467 unique ESG funds. At the end of 2021, the ESG ownership increased to 1.89% with 2,210 unique ESG funds. This corresponds to an average annual growth rate of 10.35% in mean ESG fund ownership and 14.74% in the unique count of ESG funds. For comparison, the average annual growth rate of general institutional fund ownership was 2.95%, while the number of institutional funds grew annually by 7.51% over the same period.

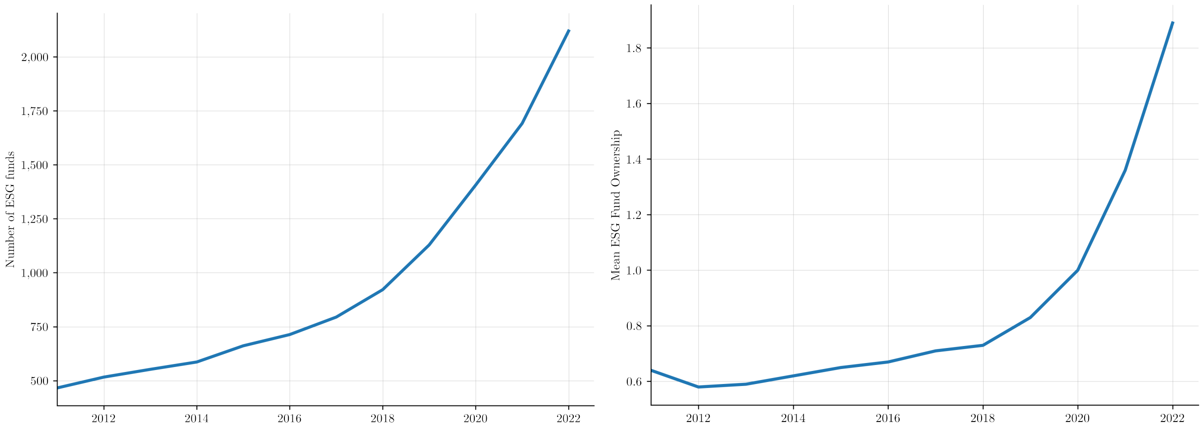


Figure II.1
ESG funds over time. The graph on the left shows the number of unique ESG funds in the data sample over the time frame of the end of 2010 to the end of 2021. The graph on the right shows the average ESG fund ownership in the sample in the same time frame.

Table II.3 shows yearly statistics of the ESG funds over time. From the total market

[6]For brevity, particularly in tables and figures, I often refer to general institutional funds simply as funds.

Table II.2

ESG Fund Keywords and Associated Fund Statistics

This table shows the keywords used to identify ESG funds and reports fund statistics for each keyword. Sum Value Held is the sum of the market value held (in USD M) of stocks in the sample. The sample period is 2010–21. Each fund is uniquely matched to a single ESG keyword. Keywords with only one associated fund are omitted from the list.

ESG Keyword	Number of Unique Funds	Sum Value Held (in USD M)
better world	9	545
biodiversity	2	20
carbon	37	5,233
change	88	7,048
clean	46	4,901
climate	60	10,868
conscious	5	1,030
csr	2	4
earth	6	287
eco	234	47,639
environment	10	3,775
environmental	15	7,470
esg	475	34,520
ethical	32	1,899
ethik	22	938
fair	22	9,416
gender	6	1,082
green	51	1,488
impact	99	6,860
klima	9	837
nachhaltig	84	5,927
paris	25	2,760
planet	24	2,286
positive future	2	5
renewable	8	133
responsible	104	8,636
revolution	20	1,895
screen	43	5,554
sdg	19	3,076
social	23	20,070
socially	16	5,363
solar	7	713
solidario	2	128
sostenible	11	1,156
sri	74	13,332
sustainability	46	6,800
sustainable	488	30,441
thematic	56	9,532
transition	36	7,651
umwelt	6	751
warming	3	1,028
water	41	9,216

capitalization in the sample in 2010, USD 54 billion was held by ESG funds. This value increased to USD 639 billion in 2021.

Table II.3

ESG Funds Statistics

This table reports the annual statistics of ESG funds, including the total number of unique funds, the mean ESG ownership (in %), and the sum of the market value held in USD million. The sample period is from 2010 to 2021.

Year	No. of Unique Funds	Mean ESG Ownership	Sum Value Held
2010	467	0.64	53,625
2011	517	0.58	50,551
2012	553	0.59	60,587
2013	587	0.62	80,202
2014	662	0.65	92,200
2015	714	0.67	92,404
2016	795	0.71	104,104
2017	922	0.73	131,912
2018	1,129	0.83	144,886
2019	1,406	1.00	218,150
2020	1,692	1.36	357,313
2021	2,120	1.89	639,205

II.3 Results

To examine the relationship between institutional fund holdings and ESG metrics, I estimate the following pooled regression:

$$\text{FUND\_METRIC}_{i,t} = \beta_0 + \beta_1\,\text{ESG\_VAR}_{i,t} + \beta_2\,\text{CONTROLS}_{i,t} + \epsilon_{i,t}\,, \tag{II.1}$$

where $\text{FUND\_METRIC}_{i,t}$ represents either the fund ownership, the ESG fund ownership, the natural log of the number of funds, or the natural log of the number of ESG funds of a stock i in year t. $\text{ESG\_VAR}_{i,t}$ comprises individual environmental, social, and governance measures, while $\text{CONTROLS}_{i,t}$ include all the control variables listed in Table II.4. I additionally include year and industry fixed effects. The standard errors are clustered at the firm level.

I first report my baseline models. These baseline models use all control variables, as well as year and industry fixed effects, excluding any ESG variable. Table II.4 presents the coefficients of the pooled regressions for the baseline models. In the following subsections, I introduce the E, S, and G variables to these baseline model specifications individually. As the controls remain the same and due to the numerous regressions conducted, I omit listing each individual control variable in subsequent regression tables.

Table II.4

Baseline model

This table shows my baseline regression models with all control variables without any ESG variable. Data is presented on an annual basis for the sample period from 2010 to 2021. The dependent variables are the total institutional fund ownership (in %), the ESG fund ownership (in %), the number of funds invested (as log), and the number of ESG funds invested (as log). Variable statistics are given in Table II.1 and the variables are further explained in Section II.2. The coefficients are from pooled regressions with standard errors clustered at the firm level. All regressions include separate year and industry fixed effects. ***1% significance, **5% significance, *10% significance.

Variables	(1) Fund Ownership	(2) ESG Ownership	(3) ln(No. Funds)	(4) ln(No. ESG Funds)
Intercept	71.24***	2.04***	3.39***	0.06
ln(Market Cap)	-3.58***	-0.14***	0.37***	0.42***
Tobin's Q	0.48***	0.01	-0.01***	-0.02***
1/Stock Price	-51.81***	-0.49	-0.03	0.38
ROA	-4.99	0.71**	0.41***	0.99***
Leverage Ratio	-2.37**	-0.28***	-0.04	-0.1**
BM Ratio	-0.51	-0.15	0.11***	0.09*
Beta	0.31	0.11	0.02	-0.01
Annual Return	-0.76	0.25***	-0.2***	-0.21***
Volatility	-16.6*	-1.51*	0.81***	0.6*
Year F.E.	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.39	0.16	0.81	0.79
Observations	5481	5425	5481	5426

II.3.1 Environmental Measures

I first investigate the effects of companies' environmental measures. I try a variety of different measures from the large ESG data set that I collected. Given the available data for different measures, the relevance of their results, and their applicability across industries, I limit my reporting and interpretation to six measures. Table II.5 shows the regression coefficients and regression statistics for the different environmental measures. All regressions include all controls from the baseline model of Table II.4 as well as year and industry fixed effects. Standard errors are clustered at the firm level.

Panel A shows the effect of a company disclosing or not disclosing carbon emissions. I show that disclosing carbon emissions increases the ESG fund ownership by 0.15 percentage points and the amount of ESG funds invested by 0.26%, both coefficients are significant at the 1% level. It further significantly increases the general amount of institutional funds invested by 0.13%. It seems that ESG funds value the transparency and reward it with higher and more investments.

In Panel B, I show the effect of total CO_2 equivalent emissions. Higher total emissions, on average, lead to lower general fund ownership as well as ESG fund ownership. Both coefficients are significant at the 1% level. Large carbon emitters contribute strongly to global carbon emissions and, in turn, to increasing global temperature. These major emitters are generally perceived negatively by ESG funds, and it appears this sentiment extends to the broader institutional investor base as well. However, it is worth noting that the total amount of carbon emissions is highly correlated with the size of the company. In Table II.4, I show that the Market Capitalization of a company already has a negative effect on the fund ownership measures. The negative effect of total carbon emissions could also be contributed to the size effect of this measure.

In the next Panel C, I account for this size effect by normalizing the total carbon emissions by the company's revenue. This yields the so called CO_2 intensity which states how carbon intense the production processes of a company are. The CO_2 intensity has significant negative effects on the ESG ownership of -0.09, on the number of funds of -0.01 and the number of ESG funds of -0.03. ESG fund managers have a distaste for carbon

Table II.5

Environmental Impacts

This table shows the effects of various environmental policies and measures of companies on their fund ownership structure. The sample period is 2010–2021 and the variables are yearly. The dependent variables are the total institutional fund ownership (in %), the ESG fund ownership (in %), the number of funds invested (as log), and the number of ESG funds invested (as log). All variables are explained in Table II.1. The controls are all independent variables from the baseline model of Table II.4. The coefficients are from pooled regressions with standard errors clustered at the firm level. All regressions include year and industry fixed effects. ***1% significance, **5% significance, *10% significance.

Variables	(1) Fund Ownership	(2) ESG Ownership	(3) ln(No. Funds)	(4) ln(No. ESG Funds)
Panel A: Disclosing Carbon Emissions				
Reports Emissions (binary)	0.0	0.15**	0.13***	0.26***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.39	0.16	0.82	0.81
Observations	5481	5425	5481	5426
Panel B: Total Carbon Emissions				
ln(CO2 Emission Total) (tonnes CO_2e)	-0.63***	-0.11***	-0.0	-0.02
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.46	0.23	0.86	0.8
Observations	3639	3607	3639	3607
Panel C: Carbon Intensity				
ln(CO2 Intensity) (tonnes CO_2e/USD M)	-0.28	-0.09**	-0.01**	-0.03***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.45	0.23	0.86	0.8
Observations	3639	3607	3639	3607
Panel D: Set Emission Target				
Has Emission Target (binary)	0.41	0.11*	0.07***	0.16***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.16	0.82	0.8
Observations	5241	5196	5241	5196
Panel E: Magnitude and Proximity of Emissions Reduction Target				
Emission Reduction Target Year	-0.0012	-0.0202**	-0.0013	-0.0032
Emission Reduction Target Pctage (%)	0.0014	-0.0004	-0.0002	-0.0001
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.37	0.18	0.83	0.61
Observations	1233	1222	1233	1222

intensive companies and try to divest from them.

In Panel D, I assess whether a company has established a specific target for emissions reduction. The variable *HasEmissionTarget* is a binary variable that is equal to 1 if the company has set an internal target to reduce emissions in the future, and 0 otherwise. The specific reduction magnitude and target proximity are not taken into account in this analysis. I find that simply setting an emission target significantly increases the ESG ownership as well as the total number of institutional and ESG funds invested. This suggests that the adoption of an emission target could be interpreted as a signal that the company cares about sustainability and is actively adapting its business practices to align with the evolving economic landscape.

In Panel E, I continue by investigating the magnitude and proximity of the emission target. For the magnitude, I look at the targeted emission reduction in percentage. For the proximity, I look at the target year. I find that the target year has a significantly negative effect on the ESG ownership of -0.02 that is significant at the 5% level. This implies that extending the target timeframe by a year corresponds to a decrease of -0.02 percentage points in ESG ownership. This observation indicates that investors prioritize actions with immediate impact over those planned for the distant future, highlighting the pressing need for urgent climate action. The magnitude of the target, measured by the percentage of emission reduction, surprisingly demonstrates no notable impact. It appears that the presence of targets holds a stronger influence than the actual stringency of these targets.

In summary, my analysis reveals that disclosing carbon emissions increases ESG fund ownership and investments. Higher total carbon emissions are associated with reduced fund ownership, but this could partly be influenced by firm size. Normalizing emissions by revenue emphasizes the negative impact of carbon intensity. Higher carbon intensity decreases all fund metrics, fund ownership and ESG fund ownership as well as the volume of funds and ESG funds. Emission reduction targets positively impact ESG ownership and fund engagement, with target proximity carrying more weight than target magnitude.

II.3.2 Social Measures

In the next step I investigate the effects of companies' social measures on companies' fund holdings. I restrict the reporting and interpretation to five social measures which I deem most relevant. Table II.6 shows the regression coefficients and regression statistics for the different environmental measures. All regressions include all controls from the baseline model of Table II.4 as well as year and industry fixed effects. Standard errors are clustered at the firm level.

Panel A illustrates the impact of female managers and employees. Nevertheless, I do not observe any statistically significant effects for either measure on institutional fund holdings. This suggests that gender diversity among a company's workforce is not perceived as a significant sustainability factor by fund investors.

Moving to Panel B, I investigate the effects of companies' political donations. Notably, I uncover significant adverse impacts of political contributions on ESG fund ownership and the volume of ESG funds. Heightened monetary donations for political parties is regarded unfavorably by sustainable investors and is likely to negatively impact various ESG ratings.

In Panel C, I observe a similar effect related to companies' lobbying contributions. Increased monetary contributions by companies for lobbying purposes result in reduced ESG fund ownership and a lower amount of ESG funds. The magnitudes of these effects, namely -0.02 and -0.014 respectively, closely resemble the magnitude of the regression coefficients associated with political contributions. These two measures might be viewed in a similar fashion by sustainable investors and could be assigned similar weightings by ESG rating providers.

Finally, Panel D examines the impact of a company's adherence to human rights statutes. The variable *Fundamental Human Rights* is a binary variable that denotes if a company claims to comply with the fundamental human rights convention of the International Labour Organization (ILO) or not. I find that companies demonstrating stronger compliance with human rights regulations tend to exhibit higher ESG fund ownership and a greater volume of general funds and ESG funds. The coefficients measuring the

Table II.6

Social Impacts

This table shows the effects of various social policies and measures of companies on their fund ownership structure. The sample period is 2010–2021 and the variables are yearly. The dependent variables are the total institutional fund ownership (in %), the ESG fund ownership (in %), the number of funds invested (as log), and the number of ESG funds invested (as log). All variables are explained in Table II.1. The controls are all independent variables from the baseline model of Table II.4. The coefficients are from pooled regressions with standard errors clustered at the firm level. All regressions include year and industry fixed effects. ***1% significance, **5% significance, *10% significance.

Variables	(1) Fund Ownership	(2) ESG Ownership	(3) ln(No. Funds)	(4) ln(No. ESG Funds)
Panel A: Women Managers and Employees				
Women Managers (%)	-0.0026	-0.0063	-0.0012	-0.0014
Women Employees (%)	0.0214	0.0006	0.0009	0.0008
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.47	0.22	0.88	0.79
Observations	1792	1771	1792	1771
Panel B: Political Donations				
Political Contributions (USD M)	-0.0715	-0.021**	-0.0025	-0.014**
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.46	0.25	0.86	0.82
Observations	1609	1592	1609	1592
Panel C: Lobbying Contribution				
Lobbying Contributions (USD M)	-0.013	-0.0211***	-0.0031	-0.0187***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.06	0.83	0.75
Observations	2717	2705	2717	2705
Panel D: Human Rights Compliance				
Fundamental Human Rights (binary)	-0.0	0.21**	0.04***	0.11***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.17	0.82	0.79
Observations	5269	5224	5269	5224

impact on ESG fund ownership, log of the number of funds, and log of the number of ESG funds are 0.21, 0.04, and 0.11, respectively. All of these coefficients are highly statistically significant, indicating that companies demonstrating strong compliance with human rights regulations tend to attract more investment from ESG and general funds. This alignment suggests that sustainable investors may consider human rights compliance as equally vital and that ESG rating providers may assign a comparable significance to this aspect.

Summarizing the findings, gender diversity among managers and employees appears to have no significant impact on institutional fund holdings, while political donations demonstrate unfavorable effects on ESG fund ownership and ESG fund numbers, paralleled by lobbying contributions. Companies must weigh whether the benefits of political and lobbying contributions outweigh the associated decline in their perceived social sustainability. Strikingly, companies aligned with human rights statutes exhibit higher ESG fund ownership and volume, accentuating the substantial role of human rights compliance in driving sustainable investments.

II.3.3 Governance Measures

In this section, I delve into the impacts of companies' governance measures on their fund holdings. Among the three ESG pillars, the association between governance measures and shareholder preferences and holdings stands as the most extensively studied. Particularly for institutional shareholders, corporate governance carries significant weight as an investment criterion, as it frequently correlates with their voting power and their influence on the company's decisions. I restrict the reporting and interpretation to five governance measures which I deem most relevant. Table II.7 shows the regression coefficients and regression statistics for the different governance measures. All regressions include all controls from the baseline model of Table II.4 as well as year and industry fixed effects. Standard errors are clustered at the firm level.

The first Panel A in the regression table investigates the effect of CEO duality. CEO duality, where an individual holds both CEO and Chairman positions, can raise concerns due to the potential lack of checks and balances, reduced accountability, and conflicts of interest. I find that, on average, CEO duality significantly decreases institutional fund ownership by 0.81 percentage points and also significantly decreases ESG fund ownership by 0.12 percentage points, both being significant at the 10% level. It suggests that all institutional fund investors prefer a separation of the CEO and Chairman role.

In Panel B, I study the effect of board independence. Board independence means

Table II.7

Governance Impacts

This table shows the effects of various governance policies and measures of companies on their fund ownership structure. The sample period is 2010–2021 and the variables are yearly. The dependent variables are the total institutional fund ownership (in %), the ESG fund ownership (in %), the number of funds invested (as log), and the number of ESG funds invested (as log). All variables are explained in Table II.1. The controls are all independent variables from the baseline model of Table II.4. The coefficients are from pooled regressions with standard errors clustered at the firm level. All regressions include year and industry fixed effects. ***1% significance, **5% significance, *10% significance.

Variables	(1) Fund Ownership	(2) ESG Ownership	(3) ln(No. Funds)	(4) ln(No. ESG Funds)
Panel A: CEO Duality				
CEO Duality (binary)	-0.8062*	-0.1227*	-0.0119	-0.0257
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.16	0.81	0.79
Observations	5315	5270	5315	5270
Panel B: Board Independence				
Independent Board Members (%)	0.1416***	0.0069**	0.0045***	0.0073***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.42	0.16	0.82	0.8
Observations	5315	5270	5315	5270
Panel C: Board Gender Diversity				
Board Gender Diversity (%)	0.0008	0.0063	0.0026***	0.006***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.16	0.82	0.79
Observations	5315	5270	5315	5270
Panel D: External Audit for Sustainability Reporting				
External Audit CSR Report (binary)	0.8608	-0.0026	0.0283	0.0733***
Controls, Year & Industry F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.51	0.23	0.86	0.83
Observations	2189	2167	2189	2167

having directors who are impartial and not linked to the company's management or business interests. These independent directors provide unbiased oversight, ensuring fair decision-making and representing shareholders' and stakeholders' interests effectively. I find that a higher share of independent board members increases all four of the fund metrics, namely the institutional fund and ESG fund ownership as well as the number of institutional funds and ESG funds investing in the company.

The magnitude of the effect on institutional fund ownership is particularly high. An increase in the share of independent board members by 1 percentage point increases the institutional fund ownership by 0.14 percentage points on average, which is also significant at the 1% level. This observation underscores the considerable attention institutional funds bestow upon the governance structure of the board of directors.

Moving on to Panel C, I further examine the effect of the board structure by looking at the board's gender diversity. Here, I only find significant effects on the amount of institutional funds and ESG funds. The regression coefficients are 0.0026 and 0.006 respectively, which are both significant at the 1% level. It is worth noting that the impact on ESG funds is notably stronger compared to general institutional funds. ESG-conscious investors place significantly greater emphasis on the gender aspect.

In Panel D, the variable of External Audit CSR Report is a binary indicator that denotes if a company employs an external auditor to review their CSR data and reports. I examine its effect to gauge the impact of ESG data transparency and quality. This specific data point entails a smaller sample, comprising around 2,200 observations. I identify a solitary statistically significant regression coefficient for its effect on the number of ESG funds.

On average, the employment of an external auditor for CSR reports increases the number of ESG funds by 0.07%, which is significant at the 1% level. This outcome suggests that improved ESG data quality can attract a broader range of ESG investors. However, it does not significantly increase the investment volume from either ESG or general institutional funds.

In summary, I investigate various corporate governance factors' impact on institutional and ESG fund ownership and the number of funds and ESG funds. CEO duality lowers both types of fund ownership, emphasizing the preference for separate CEO and Chairman roles. Board independence positively affects all fund metrics, particularly institutional fund ownership. Gender diversity on the board significantly impacts the number of institutional funds and ESG funds, with ESG funds showing stronger responsiveness. External audit of CSR reports solely increases the ESG fund number. In contrast to the environmental and social metrics, the governance measures exhibit the strongest and most significant impacts on general institutional fund holdings.

II.4 Conclusion

I explore the effects of companies' ESG measures and policies on both the depth (share of institutional fund ownership) and breadth (number of institutional funds) of institutional investors. Using a set of unique ESG related keywords, I identify ESG funds, which allows me to differentiate between general institutional funds and ESG funds. I employ a range of foundational E, S, and G measures to directly assess the link between a company's ESG practices and its appeal to investors, avoiding reliance on ESG ratings. My comprehensive analysis sheds light on the complex dynamics between corporate ESG practices and institutional fund ownership.

For environmental measures, carbon emissions disclosure is a crucial factor influencing ESG fund ownership and the number of invested funds. This is emphasized by the inverse relationship between total carbon emissions and fund ownership. Normalizing carbon emissions by revenue highlights the negative effect of carbon intensity on ESG holdings. Additionally, having emission reduction targets positively influence ESG ownership and fund engagement, with target proximity being more significant than target magnitude.

Regarding social measures, my study highlights nuanced effects of gender diversity and political engagement. Gender diversity among managers and employees does not markedly affect institutional fund holdings. However, the adverse effects of political donations on ESG fund ownership and volume, along with the implications of lobbying contributions, indicate heightened scrutiny of companies' ethical stances. Notably, adherence to human rights standards significantly boosts sustainable fund investments.

In corporate governance, I find that CEO duality reduces both general institutional and ESG fund ownership. Board independence positively influences all fund metrics, with a noticeable impact on institutional fund ownership. Gender diversity on the board of directors is a significant driver of fund volumes, especially for ESG funds. An external audit of CSR reports, signaling higher ESG data quality, predominantly enhances ESG fund numbers. This mirrors the emphasis on accountability and transparency in ESG investment decisions. Interestingly, while environmental and social metrics impact ESG funds, governance measures most strongly affect general institutional fund holdings.

In conclusion, my research deciphers the complex relationship between corporate ESG behaviors and institutional fund dynamics. I discover pivotal factors that impact ESG fund appeal and shed light on how companies can enhance their sustainable market perception. As sustainable investing evolves, my findings offer crucial insights for companies and investors to align with responsible investment imperatives.

Bibliography

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal*, *74*(3), 87–103.

Bauer, R., Ruof, T., & Smeets, P. (2021). Get real! Individuals prefer more sustainable investments. *The Review of Financial Studies*, *34*(8), 3976–4043.

Berg, F., Koelbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, *26*(6), 1315–1344.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Borghesi, R., Houston, J. F., & Naranjo, A. (2014). Corporate socially responsible investments: CEO altruism, reputation, and shareholder interests. *Journal of Corporate Finance*, *26*, 164–181.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, *60*(9), 2223–2247.

Chung, K. H., & Zhang, H. (2011). Corporate governance and institutional ownership. *Journal of Financial and Quantitative Analysis*, *46*(1), 247–273.

Cohen, J. R., & Simnett, R. (2015). CSR and assurance services: A research agenda. *Auditing: A Journal of Practice & Theory*, *34*(1), 59–74.

Enders, A., Lontzek, T., Schmedders, K., & Thalhammer, M. (2024). Carbon risk and equity prices. *Forthcoming in The Financial Review.*

Fernando, C. S., Sharfman, M. P., & Uysal, V. B. (2017). Corporate environmental policy and shareholder value: Following the smart money. *Journal of Financial and Quantitative Analysis*, *52*(5), 2023–2051.

GHGP. (2015). The Greenhouse Gas Protocol - A Corporate Accounting and Reporting Standard [Accessed 2-December-2021]. ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf

Giglio, S., Maggiori, M., Stroebel, J., Tan, Z., Utkus, S., & Xu, X. (2023). *Four Facts About ESG Beliefs and Investor Portfolios* (tech. rep.). National Bureau of Economic Research.

Gillan, S., Hartzell, J. C., Koch, A., & Starks, L. T. (2010). Firms' environmental, social and governance (ESG) choices, performance and managerial motivation. *Unpublished working paper*, *10*.

Gillan, S. L., Koch, A., & Starks, L. T. (2021). Firms and social responsibility: A review of ESG and CSR research in corporate finance. *Journal of Corporate Finance*, *66*, 101889.

Hartzmark, S. M., & Sussman, A. B. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance*, *74*(6), 2789–2837.

Hill, M. D., Kelly, G. W., Lockhart, G. B., & Van Ness, R. A. (2013). Determinants and effects of corporate lobbying. *Financial Management*, *42*(4), 931–957.

Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, *93*(1), 15–36.

Hong, H., & Kostovetsky, L. (2012). Red and blue investing: Values and finance. *Journal of Financial Economics*, *103*(1), 1–19.

Kim, J.-B., Li, B., & Liu, Z. (2018). Does social performance influence breadth of ownership? *Journal of Business Finance & Accounting*, *45*(9-10), 1164–1194.

Krause, R., Semadeni, M., & Cannella Jr, A. A. (2014). CEO duality: A review and research agenda. *Journal of Management*, *40*(1), 256–286.

Liu, C. (2018). Are women greener? Corporate gender diversity and environmental violations. *Journal of Corporate Finance*, *52*, 118–142.

Morningstar. (2023). Global Sustainable Fund Flows: Q1 2023 in Review. *Morningstar Manager Research*.

Nofsinger, J. R., Sulaeman, J., & Varma, A. (2019). Institutional investors and corporate social responsibility. *Journal of Corporate Finance*, *58*, 700–725.

Riedl, A., & Smeets, P. (2017). Why do investors hold socially responsible mutual funds? *The Journal of Finance*, *72*(6), 2505–2550.

Robinson, S., Rogers, J. L., Skinner, A. N., & Wellman, L. (2023). Environmental Disclosures and ESG Fund Ownership. *Available at SSRN 4344219*.

Triana, M. d. C., Miller, T. L., & Trzebiatowski, T. M. (2014). The double-edged nature of board gender diversity: Diversity, firm performance, and the power of women directors as predictors of strategic change. *Organization Science*, *25*(2), 609–632.

van der Beck, P. (2021). Flow-driven ESG returns. *SSRN Electronic Journal*.

III. Predicting Returns of Listed Private Equity

by Michèl Degosciu[a], Arthur Enders[b], Karl Schmedders[c], Maximilian Werner[c]

available at *SSRN:* ssrn.com/abstract=4955587

Abstract: We examine the predictive power of the net asset value (NAV)/price ratio for the LPX50 index, a key benchmark in the field of listed private equity, using monthly data from 2002 to 2024. A risk factor model reveals the index's significant exposure to small-cap and value stocks. Autocorrelation tests indicate market inefficiencies and suggest potential predictability of future returns. Both in-sample and out-of-sample analyses confirm the NAV/price ratio as a significant predictor of future returns, particularly over longer investment horizons and when excluding periods of financial instability. When the index's NAV is relatively high compared to its market price, investors can increase their exposure to value risk and potentially achieve excess returns. Our study offers practical insights for fund managers and institutional investors seeking to navigate this emerging asset class and underscores the relevance of fundamental valuation metrics in predicting returns.

Keywords: Listed private equity, return prediction, factor investing.

JEL Classification: G11, G12, G17.

Citation: Degosciu, M., Enders, A., Schmedders, K., Werner, M. (2024). Predicting Returns of Listed Private Equity. Available at *SSRN*: ssrn.com/abstract=4955587.

[a]LPX AG
[b]RWTH Aachen University
[c]International Institute for Management Development Lausanne

III.1 Introduction

Listed private equity (LPE) has emerged as a viable and more accessible alternative to traditional private equity (Huss & Zimmermann, 2012), offering liquidity and transparency by being traded on public exchanges, which mitigates the typical illiquidity of private equity (Cumming et al., 2011). These features, along with a potential for high returns, make LPE appealing to a broad range of fund managers and other investors, including those previously excluded from making such investments due to illiquidity and high investment thresholds. Despite LPE's attractiveness, there is only limited understanding of the factors driving returns. This paper addresses this gap by examining the predictive power of financial ratios in the LPE market. To our knowledge, it is the first to explore return predictability using proprietary data from the LPX index provider, revealing the role of the net asset value (NAV)/price ratio in forecasting returns. This study advances academic knowledge and offers practical insights for institutional investors targeting undervalued opportunities in a typically illiquid market.

The increasing popularity of LPE naturally leads to greater interest in understanding the efficiency and predictability of LPE assets. The Efficient Market Hypothesis (EMH), introduced by Fama (1970), is a foundational concept in finance that suggests that asset prices fully reflect all available information, making it impossible to consistently achieve returns that exceed the market average on a risk-adjusted basis. However, empirical studies increasingly question this hypothesis, uncovering various anomalies and patterns that suggest certain metrics may hold predictive power over future returns. The academic literature on return predictability explores various financial ratios—including the dividend–price ratio, the earnings–price ratio, and the book-to-market ratio—and their role in the prediction of future stock returns (Campbell & Shiller, 1988; Fama & French, 1988). Early evidence supporting the predictive power of value-based metrics comes from Rosenberg et al. (1985), who document that stocks with higher book-to-market ratios earn higher subsequent returns. This finding is further developed by Fama and French (1992), who show that the cross section of expected stock returns in the US can be largely explained by size and book-to-market factors. Extending this evidence to international markets, Fama and French (1998) demonstrate that value strategies outperform growth strategies in a wide range of countries. These studies firmly establish the book-to-market ratio as a robust predictor of future returns, providing a strong motivation for examining whether a similar value-based measure, such as the NAV/price ratio, can predict returns in the LPE market.

In the context of private equity, the NAV/price ratio shares conceptual similarities with the book-to-market ratio, which compares the book value of equity to its market value. The NAV represents the intrinsic value of a private equity company's assets, while the market price reflects the collective market perception of the company's worth. The ratio of these two values can provide insights into whether an asset in the LPE class is overvalued or undervalued relative to its underlying assets. A high NAV/price ratio suggests that the intrinsic asset value is high compared to the market price, indicating that the asset may be undervalued by the market. Conversely, a low NAV/price ratio suggests that the market price far exceeds the intrinsic asset value, indicating potential overvaluation. The LPX50 index, which tracks the performance of the 50 largest and most liquid LPE companies globally, serves as a key benchmark for the asset class.[1] With a total market capitalization of approximately EUR 223 billion,[2] it presents a significant investment opportunity, reflecting the scale and depth of the LPE market. Understanding the predictive power of the NAV/price ratio within this index could provide institutional investors with a tool with which to better time their investments and potentially enhance returns.

Cochrane (2008) suggests that return predictability can be more pronounced over longer horizons, where the effects of temporary market inefficiencies are more likely to dissipate, allowing fundamental value to play a greater role in determining prices. This is particularly relevant for the NAV/price ratio in LPE, as private equity investments typically involve long-term horizons and strategic interventions aimed at improving the value of the underlying companies. Additionally, the inherent illiquidity and lack of

[1]The LPX50 index is used as a benchmark by several asset managers, including Allianz Global Investors and Swiss Life, as well as by financial regulators such as Germany's BaFin.

[2]According to the index's factsheet as of November 29, 2024: www.lpx-group.com/lpx_indexing/index-information/index-factsheets.

transparency of private equity assets even when listed may contribute to mispricing that the NAV/price ratio could help identify.

In one of the first empirical studies on LPE stocks, Bilo et al. (2005) investigate the risk and return characteristics of different LPE portfolios. They find that this asset class offers high risk-adjusted performance, even after accounting for potential trading biases. Kraeussl and Brown (2012) identify differences in risk and returns between LPEs and traditional limited partnership funds (LPFs). Lahr and Kaserer (2010) study the behavior of NAV discounts and premia in LPE funds, finding that premia could predict future stock returns, which they attribute to a mean reversion effect. Döpke and Tegtmeier (2018) examine the influence of macroeconomic risk factors on the expected returns of LPE indices and find that LPEs have a different risk–return profile relative to country equity indices. Bachmann et al. (2019) test the "Sell in May" effect in LPE markets, while Steinborn (2023) investigates the "day-of-the-week" effect. However, each study finds only limited statistically significant evidence for the respective effect. Tegtmeier (2021) tests the efficiency of LPE indices and demonstrates that the returns do not follow a random walk. Kurtović et al. (2023) study LPEs as a proxy for the risk and performance of unlisted private equities. Kurtović and Markarian (2024) further examine the tail risks of private equity by analyzing LPE performance during the COVID-19 crisis.

In this paper, we investigate the predictive power of the NAV/price ratio for the LPX50 index, using monthly data from December 2002 to February 2024. Our analysis suggests that in the LPE market segment, where asset values may not be fully reflected in market prices, the NAV/price ratio could be a key indicator of future returns. Our analysis reveals important implications for investors seeking to enhance their returns by identifying undervalued opportunities within the LPE sector. We employ a structured approach, including risk factor analysis, market efficiency testing, and predictive regressions, both in sample and out of sample.

Firstly, we apply the Fama–French six-factor model to understand the underlying risk exposures of the LPX50. This analysis allows us to understand the extent to which the index is influenced by common risk factors such as market, size, value, momentum, profitability, and investment, which are commonly known to drive asset returns. We find that the index exhibits significant exposure to the size and value factors, consistent with private equity's strategy of acquiring smaller and undervalued private companies.

Secondly, we assess the market efficiency of the LPX50 by examining autocorrelations in its return series. We find statistically significant autocorrelations at the 1% level with lagged returns. This suggests that the index returns are not fully efficient and do not follow a random walk, potentially indicating return predictability based on past price information.

Lastly, we assess the predictive power of the lagged NAV/price ratio by performing both in-sample and out-of-sample regressions on future returns across various time horizons. In the in-sample analysis, we find positive and statistically significant coefficients for 6-, 12-, and 24-month-ahead returns. The regression fit, as measured by the adjusted R^2, also improves substantially with longer horizons, indicating that return predictability strengthens over extended periods. Therefore, the NAV/price ratio has historically been a significant predictor of returns within our sample period. Additionally, this predictive power becomes even more pronounced during periods of financial stability, particularly when we exclude the COVID-19 crisis from the sample period.

The out-of-sample regressions also demonstrate that the NAV/price ratio has statistically significant predictive power for forecasting future returns beyond the initial training period. The out-of-sample R^2 shows that the predictive regression model significantly outperforms the historical mean, particularly for longer-term horizon returns. This performance is also influenced by the choice of sample split for training and testing. To ensure robustness, we conduct multiple tests using various sample splits and excluding outlier events such as the COVID-19 pandemic. These tests further support the evidence that the NAV/price ratio is a significant predictor of returns.

Our findings have important implications for LPE investors and contribute to the literature on return predictability. We show that the NAV/price ratio has significant predictive power for the LPX50, particularly over longer investment horizons. Investors who monitor this ratio can identify undervalued periods with a high NAV/price ratio, increase their exposure to value risk, and potentially achieve excess returns. Our results also highlight the sensitivity of predictive models to financial instability such as that caused by the COVID-19 pandemic, emphasizing the need to consider broader economic conditions. LPE is especially attractive to institutional investors due to its potential for excess returns and outperformance of benchmarks, offering ambitious portfolio managers a distinct opportunity for superior performance. Additionally, its predictability is more reliable over longer horizons, making it more suitable for long-term investments than for short-term trades. Successful use of these predictions also requires strategic timing and sufficient cash reserves to capitalize on undervalued periods.

The remainder of this paper is structured as follows: The next section presents the data and methodology. Subsequently, the main section of the paper outlines the results of our empirical analysis, including the risk factor model, market efficiency tests, and both in-sample and out-of-sample return predictability. The last section concludes.

III.2 Data

We focus on one of the most popular LPE indices, the LPX50, provided by LPX. According to LPX, the LPX50 is designed to represent the global performance of the 50 most highly capitalized and liquid LPE companies.[3] All index data were provided by the LPX Group. We use monthly returns calculated as real total returns based on USD index prices and our observation period ranges from December 2002 to February 2024.

The LPX50 index includes only publicly traded private equity firms. The constituents are the 50 largest and most liquid LPE companies worldwide, providing a representative benchmark for the performance of the global LPE market. Examples of constituents include well-known firms such as Onex, 3i Group, and Apollo Global Management.

When we refer to the NAV, we are referring to the aggregation of the publicly available net asset values of the constituents of the LPX50. The NAV represents the fair value of the underlying investments held by these LPE firms. LPX collects and continuously

[3]For more details on the index, we refer the reader to the website of the LPX Group: www.lpx-group.com.

updates these NAV data based on constituent disclosures, including earnings reports, ad hoc deal announcements, and other re-evaluation events.

To ensure consistency and comparability across the constituents, LPX employs a standardized NAV model. This model adjusts for differences in reporting standards and valuation methodologies among the firms, providing a uniform basis for analysis. LPX also provides an LPX50 NAV index based on the NAV values we use in this paper.[4]

Table III.1 provides summary statistics for the LPX50 over the observed time frame. The index has an average monthly return of 1.07% with a volatility of 7.10%.

Table III.1
Data Statistics

Variable	**Mean**	**Median**	**SD**	**Observations**
LPX50 index price	2 154.13	1 926.77	1 167.70	255
Monthly return (in %)	1.07	1.79	7.10	255
Net asset value (NAV)	261.24	251.29	101.56	255
NAV/price ratio	0.13	0.12	0.04	255
1-month-ahead return (in %)	1.08	1.79	7.11	254
3-months-ahead return (in %)	3.52	4.05	13.92	252
6-months-ahead return (in %)	7.33	8.44	21.33	249
12-months-ahead return (in %)	14.06	17.99	31.06	243
24-months-ahead return (in %)	25.88	21.39	43.45	231

Note: This exhibit reports general statistics (mean, median, and standard deviation) for all variables of the LPX50 index used in the following analyses. The sample period is 2002–2024. Net asset value (NAV) is the book value of the LPE's investments.

The NAV of the index is the weighted book value of all its constituents. This value is given as an index starting from 100. For our analyses, we use the ratio of the NAV divided by the index price. Figure III.1 presents the NAV/price ratio over our time frame. During periods of crisis the ratio significantly increases. Investing in the index during these times means that investors receive more book value for their investment. Since we are dealing with index values, the actual value of this variable is not directly interpretable.

In our analyses, we use various time horizons to predict future returns, differentiating

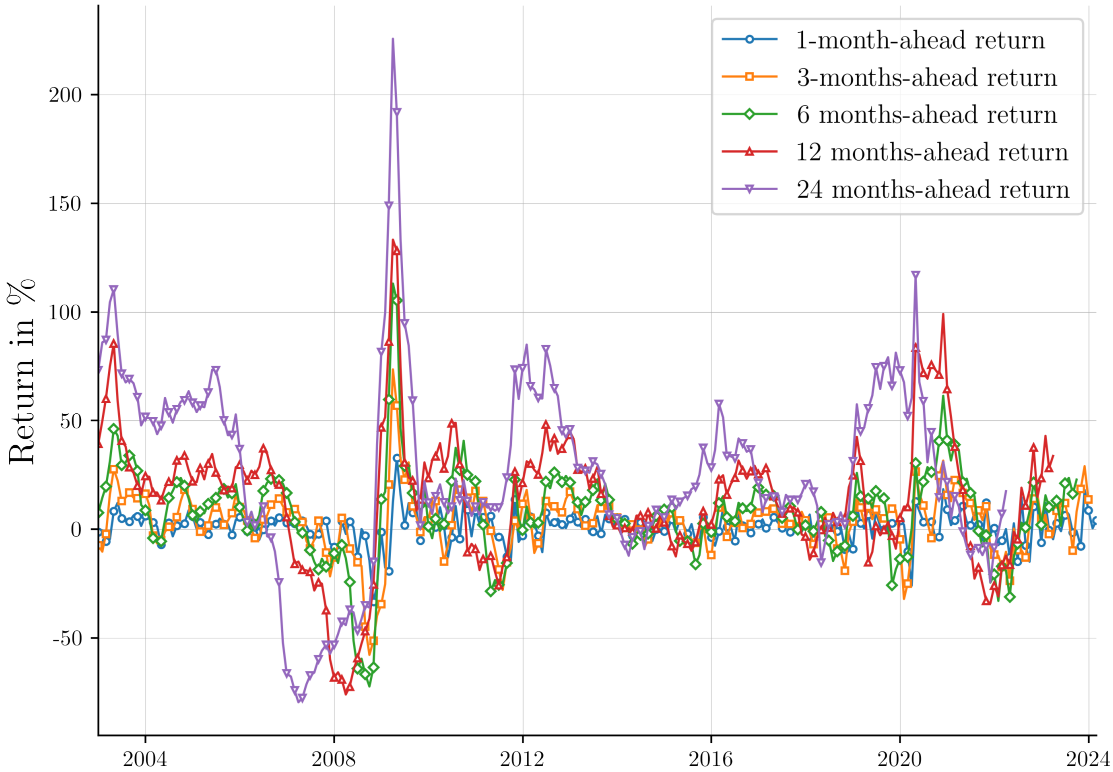
[4]Detailed guidelines for the LPX NAV indices methodology are available from LPX Group upon request.

Figure III.1
NAV/Price Ratio

Note: This exhibit shows the NAV/price ratio over our time frame. The data are monthly, ranging from December 2002 to February 2024.

between 1, 3, 6, 12, and 24 months ahead. This approach allows us to investigate both short-term and long-term predictability. Figure III.2 illustrates the forward returns for these different horizons within our time frame.

Figure III.2
Forward Returns of the LPX50



Note: This exhibit shows forward returns of the LPX50 for different horizons. The data are monthly, ranging from December 2002 to February 2024.

III.3 Results

We begin by conducting a risk factor analysis, using the Fama–French six-factor model to explain the historical returns of the index. Next we assess the market efficiency of the index by examining the autocorrelation within the returns. Lastly, we use our proprietary data on the underlying book value to predict forward returns across different horizons.

III.3.1 Risk Factor Analysis

There are a variety of risk factors and risk factor models in the finance literature. The Fama–French model remains the most popular, and Fabozzi et al. (2024) show that it has explanatory power similar to that of newer factor models, particularly in realistic investment settings. We thus use the Fama–French model and obtain the risk factors and risk-free rates from the website of Kenneth R. French. According to Griffin (2002), risk factors are country specific. Although the majority of the index constituents are US-based, they invest in international companies, and their valuations impact the index's performance. Therefore, we use the Developed Market Factors for the market factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (WML), profitability factor (RMW), and investment factor (CMA). Table III.2 presents the coefficients of the time-series regression of the LPX50 excess returns on these risk factors.

Table III.2
Fama–French Risk Factor Analysis

	(1)	**(2)**	**(3)**
Dependent Variable	LPX50 Excess Returns	LPX50 Excess Returns	LPX50 Excess Returns
Alpha	-0.13	-0.13	0.0
Mkt-RF	1.46***	1.44***	1.34***
SMB		0.32***	0.27**
HML		0.20**	0.44***
WML			-0.15
RMW			0.1
CMA			-0.59***
Adj. R^2	0.85	0.86	0.87
Observations	255	255	255

Note: Monthly returns in % from 2002–2024. Standard errors are Newey–West adjusted with four lags ($T^{\frac{1}{4}}$ based on Greene, 2003). Mkt-RF is the monthly excess returns of a value-weighted stock portfolio over the risk-free rate. SMB reflects returns from being long in small-cap stocks and short in large-cap stocks. HML captures returns from being long in value stocks and short in growth stocks. WML indicates returns from being long in winning stocks and short in losing stocks. RMW denotes returns from being long in high-profitability stocks and short in low-profitability stocks. CMA denotes returns from being long in conservative investment stocks and short in aggressive ones. ***1% significance, **5% significance, *10% significance.

For the most comprehensive model, in column (3), which includes all risk factors, we find a market beta of 1.34, significantly higher than that of the general market. The size factor has a positive coefficient of 0.27, significant at the 5% level, indicating the index's exposure to smaller-sized companies. This suggests that a portion of its return is derived from the risks associated with smaller firms, aligning with private equity's typical investment in small-to-medium-sized private companies. Additionally, we observe a highly significant and positive value factor exposure, with a coefficient of 0.44, indicating that the index disproportionately includes value companies with high book-to-market ratios. These findings are consistent across the different model specifications. Private equity firms often employ a value investing strategy, seeking out undervalued companies with potential for turnaround or improvement. By buying these companies at a lower price relative to their intrinsic value, private equity firms can realize significant returns if the companies perform better under their management.

We also observe a significantly negative coefficient for the CMA risk factor. The CMA factor represents the premium earned by conservative firms (low asset growth) compared to those with aggressive investment policies (high asset growth). A negative coefficient indicates that the index aligns with stocks exhibiting aggressive investment policies, suggesting a heavier weighting toward firms with aggressive strategies. This is consistent with private equity firms' focus on high-growth opportunities, where they can add substantial value through strategic changes and operational improvements.

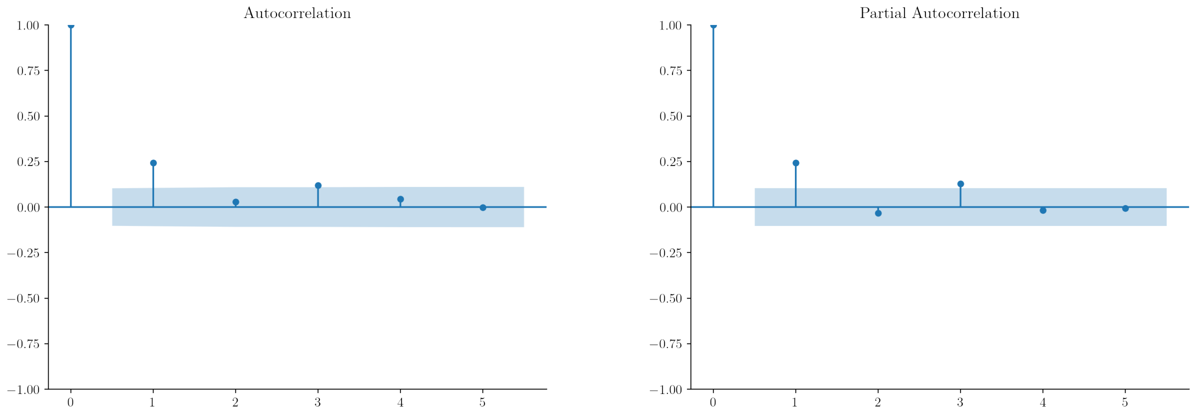
Notably, the intercept (Alpha coefficient) is 0.0 and, as expected, not significant. This suggests that the model, with these risk factors, explains the historical returns very well, as indicated by the high adjusted R^2 of 0.87. Aghassi et al. (2023) argue that factors continue to be effective even in the new economy and across various markets and conditions. Our findings also show that these established factors remain robust, despite the unique nature of the index and its having experienced multiple financial crises during the sample period.

III.3.2 Market Efficiency

Tegtmeier (2021) analyzes the weekly return data of nine LPE indices and finds that all of them reject the random walk hypothesis, exhibiting significant autocorrelation. Using our updated dataset of monthly returns, we also investigate this hypothesis. Figure III.3 displays the autocorrelation and partial autocorrelation functions for the returns of the LPX50 up to 5 lags. We observe significant autocorrelation and partial autocorrelation at lags 1 and 3, with the autocorrelation at lag 1 being significant at the 1% level. Additionally, the Ljung–Box test (Ljung & Box, 1978) up to 10 lags rejects the null hypothesis at the 1% significance level, suggesting significant autocorrelation in the return series. Significant autocorrelation in asset returns suggests that past returns contain predictive information about future returns, indicating potential deviations from market efficiency due to delayed price adjustments or information processing inefficiencies.

Figure III.3
Autocorrelation and Partial Autocorrelation Functions

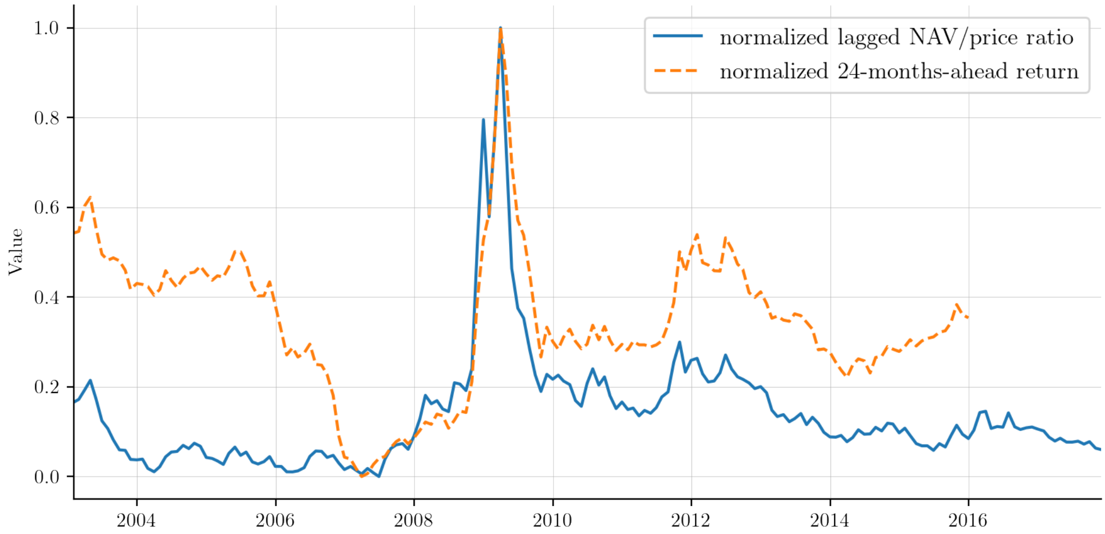
(a) **(b)**



Note: Panel (a) shows the autocorrelation function and Panel (b) shows the partial autocorrelation function for the LPX50 for up to 5 lags using monthly real returns. The shaded areas represent the 5% confidence intervals. The data range from December 2002 to February 2024.

The results indicate that the index returns are not fully efficient and do not follow a random walk. This suggests that past returns could be used to predict future prices. Additionally, a portion of the index's return can be attributed to its sensitivity to value stocks. We consequently use the ratio of the index's NAV to its price to forecast future returns across different horizons. Figure III.4 shows the normalized 1-month-lagged NAV/price ratio and the normalized 24-month-ahead return (both scaled between 0 and 1) to visualize their correlation. The plot reveals that high NAV/price ratios are associated with high long-horizon forward returns. Therefore, an investor who buys the index when the NAV/price ratio is high may benefit from exceptional future performance and potentially generate attractive excess returns. In the next step, we use this relation to predict the index's returns.

Figure III.4
Lagged NAV/Price Ratio and 24-Months-Ahead Returns



Note: Values are normalized between 0 and 1. The data are monthly, ranging from January 2003 to February 2024.

III.3.3 Return Predictability

Following the existing literature (see, e.g., Golez & Koudijs, 2018; Rapach et al., 2005), we analyze stock return predictability using a predictive regression framework. The predictive regression model is formulated as follows:

$$r_t^k = \alpha + \beta\, z_{t-1} + \epsilon_t^k\,, \tag{III.1}$$

where r_t^k is the real return from holding the index from period $t-1$ to $t+k$, z_{t-1} is the variable believed to potentially predict future returns, and ϵ_t^k is a disturbance term. In our analyses, z_{t-1} is the NAV/price ratio. To account for potential heteroscedasticity and autocorrelation in the residuals, we employ Newey and West (1987) standard errors with $[1.5 \cdot k]$ lags, where $[\cdot]$ denotes the nearest integer function.

We conduct both in-sample and out-of-sample return predictability tests using the framework of Equation III.1. The in-sample analysis uses the entire sample period from December 2002 to February 2024, testing the lagged NAV/price ratio, z_{t-1}, for its significant predictive power for future returns across various horizons. Table III.3 reports the coefficients from the time-series regression. We find consistently positive coefficients for the examined variable across all return horizons, with significant coefficients for the 6-, 12-, and 24-months-ahead returns. The effect's magnitude increases with the horizon length. Additionally, the adjusted R^2 shows a substantial increase, from 0.00 for next-month returns to 0.27 for the longest horizon, of 24 months, indicating that long-horizon predictability is more achievable.

Table III.3
Return Predictability

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	1-Month Return	3-Month Return	6-Month Return	12-Month Return	24-Month Return
const	0.37	-5.12	-19.26*	-31.31***	-58.74***
lag_NAV_P_ratio	5.33	64.95	199.56**	339.06***	627.31***
Adj. R^2_{IS}	0.00	0.02	0.10	0.15	0.27
R^2_{OOS}	-0.00	0.01	0.04**	0.10***	0.11***
R^2_{OOS} CW t-statistic	-0.01	1.13	1.93	3.12	3.93
Observations	254	252	249	243	231

Note: The table presents in-sample and out-of-sample predictability test results. The regression model is described in Equation III.1. 2003:12–2013:24 out-of-sample period. R^2_{OOS} compares the model's predictive power to the historical mean, as defined in Equation III.2. Significance levels based on Newey–West standard errors. ***1% significance, **5% significance, *10% significance.

The out-of-sample tests divide the total sample T into a training set (the first R observations) and a testing set (the last P observations), using a rolling forecast scheme. The predictive model is trained via OLS on all observations of the training set, employing a constant and the NAV/price ratio as specified in Equation III.1. The initial out-of-sample return forecast, $\hat{r}^k_\tau$, for period τ is calculated for the first value of the testing set based on the coefficients $\hat{\alpha}$ and $\hat{\beta}$ obtained from the regression model. The forecast error is then determined as $\hat{\epsilon}^k_t = r^k_t - \hat{r}^k_t$. For the subsequent forecast—in period $\tau + 1$—we extend the training set to include data from period τ, retrain the regression model with the updated training data, and use the new coefficients to forecast the next return, $\hat{r}^k_{\tau+1}$. Forecast errors are computed for each period across all return horizons, and this process is repeated for all values in the testing set.

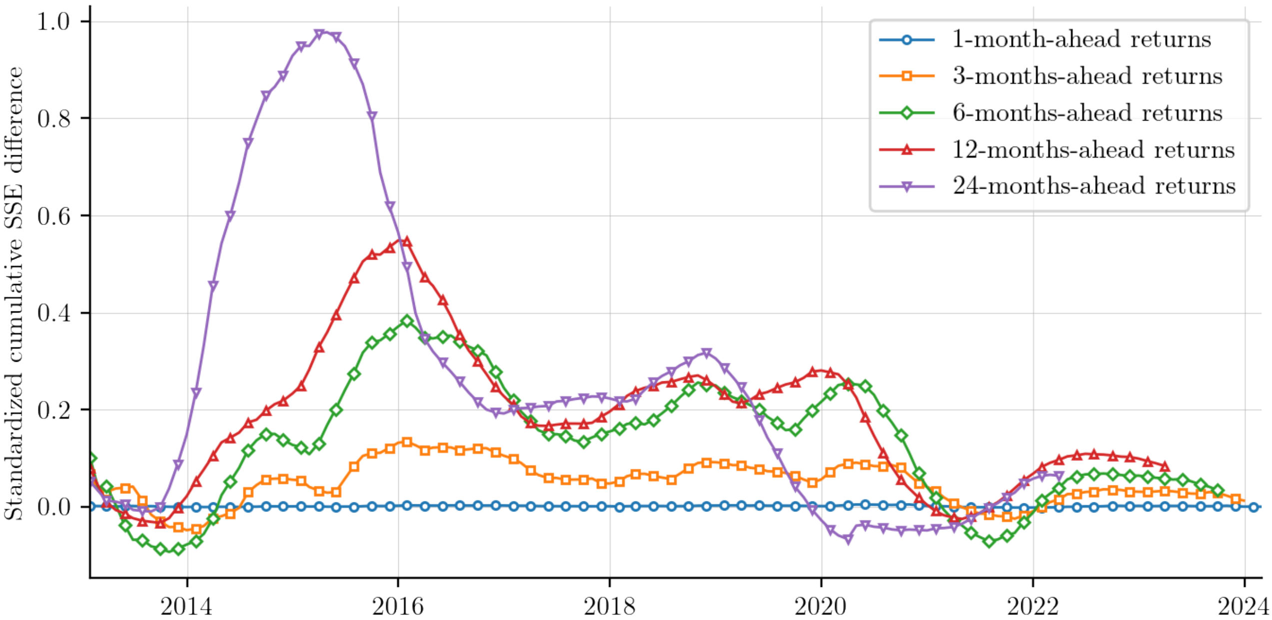
We compare the forecast errors of our unrestricted model to those of a simple historical mean model. To assess our model's performance, we follow Welch and Goyal (2008) and compute an out-of-sample R^2 for the testing set as

$$R^2_{\mathrm{OOS}} = 1 - \frac{\sum_{\tau=P}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=P}^{T}(r_\tau - \bar{r}_\tau)^2}\,, \tag{III.2}$$

where r_τ is the actual return, $\hat{r}_\tau$ is the predicted return from our model, and $\bar{r}_\tau$ is the mean return up to $\tau - 1$. To test the significance of the out-of-sample R^2, we use the Clark and West (2007) test. If the t-statistic is sufficiently large, the null hypothesis is rejected, indicating that the complex model has significantly better predictive accuracy.

Table III.3 presents the out-of-sample statistics for our primary analysis, with the initial training set spanning from 2002 to 2011 and out-of-sample forecasts covering the months from January 2012 to February 2024. For all horizons except next-month returns, the R^2_{OOS} is positive and increases with the length of the horizon, ranging from 1% to 11%. However, these values are highly sensitive to the specific sample split chosen. Additionally, our time frame includes extraordinary events, including the COVID-19 pandemic in 2020, which significantly affected index returns and the accuracy of our model. Figure III.5 shows variations in the out-of-sample R-squared values of the model, allowing us to explore specific points in time that enhance or diminish return predictions. Notably, the analysis provides strong evidence that the COVID-19 pandemic in the year 2020 significantly reduced the accuracy of our model. Such a drastic, nonlinear shock to the financial system severely impairs the effectiveness and applicability of the linear regression model, thereby disturbing the results.

Figure III.5
Out-of-Sample Return Predictive Regressions



Note: Out-of-sample predictions are based on an expanding window. The initial training period is 2003–2012 and the first out-of-sample prediction is in 2013. Each line plots $(SST_1^t - SSE_1^t)/SST_1^T$, where $SST_1^t = \sum_{\tau=1}^{t}(r_\tau - \bar{r}_\tau)^2$, $SSE_1^t = \sum_{\tau=1}^{t}(r_\tau - \hat{r}_\tau)^2$, and $SST_1^T = \sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)^2$, with r_τ the respective observed return, $\hat{r}_\tau$ the return predicted by the model on the sample up to $\tau - 1$, and $\bar{r}_\tau$ the mean return up to $\tau - 1$. The last observation (T) corresponds to the out-of-sample R-squared.

To ensure the robustness of our results, we conduct the same analyses excluding all observations impacted by the COVID-19 pandemic. Table III.4 replicates Table III.3, but with a shorter time frame that omits the onset of the pandemic for each forward return. The in-sample statistics show that the coefficients do not differ significantly. However, the out-of-sample statistics increase substantially, with positive R-squared values across all returns, reaching as high as 0.55. This indicates that while our model, which uses the lagged NAV/price ratio, demonstrates high predictive power for future returns, it does so particularly during periods of financial stability. It also again highlights that the out-of-sample statistics are highly sensitive to the specific sample split used.

Rossi and Inoue (2012) and Kolev and Karapandza (2017) demonstrate that out-of-sample return forecast results are highly dependent on the sample split. Following their methodology, we conduct analyses using all possible splits, ranging from 20% to 80% of

Table III.4
Return Predictability Excluding COVID-19

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	1-Month Return	3-Month Return	6-Month Return	12-Month Return	24-Month Return
const	0.46	-6.85	-24.24**	-35.1**	-72.48**
lag_NAV_P_ratio	3.53	72.23	221.91**	346.46***	684.19***
Adj. R^2_{IS}	0.00	0.03	0.13	0.17	0.31
R^2_{OOS}	0.00	0.08***	0.26***	0.29***	0.55***
R^2_{OOS} CW t-statistic	0.99	2.66	4.71	4.96	7.61

Note: This table presents in-sample and out-of-sample predictability test results. The regression model is described in Equation III.1. 2003:12–2013:20 out-of-sample period. R^2_{OOS} compares the model's predictive power to the historical mean, as defined in Equation III.2. Significance levels based on Newey–West standard errors. ***1% significance, **5% significance, *10% significance.

the data for the initial training set. Table III.5 reports the mean out-of-sample R-squared values across these sample splits. Panel A uses the full sample period, from 2003 to 2024. For longer horizons starting from 6-months-ahead returns, we observe positive mean out-of-sample R-squared values of up to 0.13, with a mean Clark and West (2007) t-statistic of 3.52. Panel B excludes observations affected by COVID-19 for each forward return. In this restricted sample, the R-squared values substantially increase, reaching 0.47 for the longest horizon, of 24 months. This finding confirms that our regression model exhibits significant out-of-sample predictive power for longer return horizons, independent of the specific sample split.

In summary, we find that the NAV/price ratio holds significant predictive power for the LPX50, particularly over longer investment horizons and in the absence of nonlinear financial shocks. The analysis shows that part of the returns is linked to the index's exposure to value risk. Investors can use information about underlying book values to increase their exposure to this risk. By doing so, they have the potential to increase their returns, especially during periods when the book value is relatively high compared to the price, making this an attractive strategy when the market perceives the index as undervalued.

Table III.5
Out-of-Sample Return Predictability with Multiple Sample Splits

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	1-Month Return	3-Month Return	6-Month Return	12-Month Return	24-Month Return
Panel A: Full sample					
Mean R^2_{OOS}	-0.02	-0.02	0.02	0.09	0.13
Mean R^2_{OOS} CW t-statistic	-0.04	0.91	1.73	2.84	3.52
Panel B: COVID excluded					
Mean R^2_{OOS}	-0.06	-0.01	0.15	0.21	0.47
Mean R^2_{OOS} CW t-statistic	0.42	1.96	3.68	4.10	5.51

Note: Out-of-sample predictability test results with monthly sample splits from 20% to 80% training data. The regression model is described in Equation III.1. R^2_{OOS} compares the model's predictive power to the historical mean, as defined in Equation III.2.

III.4 Conclusion

This paper fills a critical gap in our understanding of the predictive power of financial ratios in the LPE market, specifically by investigating the NAV/price ratio for the LPX50 index, a prominent benchmark for LPE. To the best of our knowledge, it is the first study to examine return predictability using proprietary data from the LPX index provider, and offers new insights into the NAV/price ratio's role in forecasting returns. We use monthly data from the LPX Group—covering the period from December 2002 to February 2024—to explain empirical returns with a risk factor model, test the market efficiency of the index based on autocorrelations, and explore both in-sample and out-of-sample price predictability using the lagged NAV/price ratio. This study not only advances academic knowledge, it also provides practical benefits for fund managers and other investors targeting undervalued opportunities in an otherwise illiquid and opaque market.

The risk factor analysis reveals that the LPX50 has significant exposure to smaller and value stocks, which aligns with typical private equity investment strategies. The autocorrelation tests indicate significant autocorrelation with past returns, suggesting that the index is not fully efficient and may exhibit some degree of predictability for future returns. We leverage this insight and use the net asset value-to-price ratio of the index to forecast future index returns.

Both the in-sample and the out-of-sample predictive regressions demonstrate significant predictive power for the NAV/price ratio. Investors can leverage this information to increase their exposure to value risk and potentially achieve excess returns, particularly when the index's NAV is relatively high compared to its market price. Moreover, the analyses indicate that the index's return predictability improves with a longer investment horizon, and that the model's predictive power is more pronounced when periods of financial instability, such as the COVID-19 crisis, are excluded.

While our findings underscore the predictive power of the NAV/price ratio for the LPX50, some limitations should be noted. The model's accuracy is sensitive to periods of financial instability, which may reduce its effectiveness in volatile markets. Additionally, the analysis is based on a specific period and a single index, which may limit the generalizability of the results. Future research could explore the use of the NAV/price ratio across different indices or in combination with other metrics to enhance predictive accuracy.

Bibliography

Aghassi, M., Asness, C., Fattouche, C., & Moskowitz, T. (2023). Fact, fiction, and factor investing. *The Journal of Portfolio Management*, *49*(2), 57–94.

Bachmann, C., Tegtmeier, L., Gebhardt, J., & Steinborn, M. (2019). The “Sell in May” effect: An empirical investigation of globally listed private equity markets. *Managerial Finance*, *45*(6), 793–808.

Bilo, S., Christophers, H., Degosciu, M., & Zimmermann, H. (2005). *Risk, returns, and biases of listed private equity portfolios* (tech. rep.). WWZ working paper.

Campbell, J. Y., & Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *The Journal of Finance*, *43*(3), 661–676.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, *138*(1), 291–311.

Cochrane, J. H. (2008). The dog that did not bark: A defense of return predictability. *The Review of Financial Studies*, *21*(4), 1533–1575.

Cumming, D., Fleming, G., & Johan, S. A. (2011). Institutional investment in listed private equity. *European Financial Management*, *17*(3), 594–618.

Döpke, J., & Tegtmeier, L. (2018). Global risk factors in the returns of listed private equity. *Studies in Economics and Finance*, *35*(2), 340–360.

Fabozzi, F. J., Huang, D., Jiang, F., & Wang, J. (2024). What difference do new factor models make in portfolio allocation? *Journal of International Money and Finance*, *140*, 102997.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), 3–25.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427–465.

Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The Journal of Finance*, *53*(6), 1975–1999.

Golez, B., & Koudijs, P. (2018). Four centuries of return predictability. *Journal of Financial Economics*, *127*(2), 248–263.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Griffin, J. M. (2002). Are the Fama and French factors global or country specific? *The Review of Financial Studies*, *15*(3), 783–803.

Huss, M., & Zimmermann, H. (2012). Listed private equity: A genuine alternative for an alternative asset class. *The Oxford Handbook of Private Equity*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195391589.013.0022

Kolev, G. I., & Karapandza, R. (2017). Out-of-sample equity premium predictability and sample split–invariant inference. *Journal of Banking & Finance*, *84*, 188–201.

Kraeussl, R., & Brown, C. (2012). Risk and return characteristics of listed private equity. *The oxford handbook of private equity* (Ch–21). Oxford University press.

Kurtović, H., & Markarian, G. (2024). Tail risks and private equity performance. *Journal of Empirical Finance*, *75*, 101457.

Kurtović, H., Markarian, G., Breuer, P., Faye, B., Le Fur, E., Joenväärä, J., Kauppila, M., Tolonen, P., Mason, P., Utke, S., et al. (2023). The risk and performance of listed private equity. *The Journal of Alternative Investments*, *26*(1), 77–94.

Lahr, H., & Kaserer, C. (2010). *Net asset value discounts in listed private equity funds* (tech. rep.). Center for Entrepreneurial and Financial Studies (CEFS), Technische Universität München.

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703–708.

Rapach, D. E., Wohar, M. E., & Rangvid, J. (2005). Macro variables and international stock return predictability. *International Journal of Forecasting*, *21*(1), 137–166.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, *11*(3), 9–16.

Rossi, B., & Inoue, A. (2012). Out-of-sample forecast tests robust to the choice of window size. *Journal of Business & Economic Statistics*, *30*(3), 432–453.

Steinborn, M. (2023). Does the day-of-the-week effect exist in other asset classes? Investigation of the globally listed private equity markets. *Studies in Economics and Finance*, *41*(1), 102–124.

Tegtmeier, L. (2021). Testing the efficiency of globally listed private equity markets. *Journal of Risk and Financial Management*, *14*(7), 313.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), 1455–1508.