SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

ESSAYS ON PENSION RISKS

PhD dissertation

Mathias Danielsen Plovst

Aarhus University, BSS
Department of Economics and Business Economics

2024

To my loving wife, Mia

PREFACE

This dissertation was written between September 2021 and October 2024, marking the culmination of my three-year enrollment as a PhD student at the Department of Economics and Business Economics at Aarhus University. I am deeply grateful to the department for providing an excellent and inspiring research environment and for their financial support, allowing me to attend courses, conferences, and research visits abroad. As this chapter of my life comes to an end, I reflect on the fond memories that fill me with joy and gratitude.

First and foremost, I would like to express my deepest gratitude to my supervisors, Peter Løchte Jørgensen and Malene Kallestrup-Lamb, for believing in me and encouraging me to apply for the PhD program. Your invaluable expertise and guidance within the academic world have allowed me to pursue one of my greatest goals in life. I have cherished every moment working with you on the first two chapters and appreciate the time spent discussing various topics, including which Formula One team performed best during race weekends. The combination of Peter's expertise and network with Malene's tireless encouragement has set me up for success, and I could not have asked for a better match of supervisors. I am particularly grateful for Peter's connection with Bjarne Graven Larsen at Qblue Balanced, which has been immensely helpful to me. I thank the incredible team at Qblue Balanced, especially Martin Richter. Your expertise in Sustainable Finance is genuinely inspiring. I am deeply thankful for your support and understanding during the good and challenging times of my PhD studies.

I would also like to thank my co-author, Anne G. Balter, for collaborating on the second chapter. Your attention to detail was impressive, and I learned so much from working with you – thank you for your patience and for never giving up on my seemingly endless questions.

During my PhD, I had the privilege of visiting Heriot-Watt University in Edinburgh under the guidance of Andrew Cairns. I am grateful for the opportunity to present and discuss my second chapter at The Department of Actuarial Mathematics and Statistics. Attending and presenting at the first in-person IME congress since 2019, held at the university, was the perfect conclusion to my stay.

I also want to thank my colleagues at the department for making my time as a PhD student memorable. It would not have been the same without being surrounded

by so many brilliant minds and for our many coffee breaks. To my office and co-office mates at the ”depression hall" – Tobias, Magnus, Sam, Fynn, and Marcel – your great company and helpful discussions have been invaluable during my PhD. I would also like to extend my gratitude to fellow PhD students, Dorethe, Christine, Mathias, Thomas, Melanie, Sebastian, Peter, Lau, Kenneth, Camille, Hans, and Malthe, who have all made my time here much more enjoyable.

Finally, I am beyond grateful for the unwavering support and comforting conversations from my parents, Helle and Keld, my brother and sister, Kasper and Freja, and my parents-in-law, Michala and Claus. Most importantly, I could not have accomplished this without my wife, Mia, and her unconditional love, support, patience, and encouragement throughout the PhD. You have listened to countless discussions, and I am forever indebted to you. Thank you for always challenging my sense of what’s achievable and for encouraging me to get our wonderful dog, Millie – your combined love has helped me clear my thoughts during our many walks. Thank you for everything.

Mathias Danielsen Plovst
Aarhus, October 2024

Updated preface

The pre-defence was held on November 12, 2024, in Aarhus, Denmark. I am deeply grateful to the members of the PhD comittee – Professor Svein-Arne Persson (Norwegian School of Economics), Associate Professor Linda Sandris Larsen (Copenhagen Business School), and Associate Professor Niels Strange Grønborg (Aarhus University) – for their meticulous attention to detail, insightful comments, and constructive suggestions, all of which have significantly improved this thesis. Following the pre-defence, many of their suggestions have been incorporated into the current version of the dissertation, while others remain for future research.

Mathias Danielsen Plovst
Aarhus, December 2024

Contents

BRIEF SUMMARY

This dissertation comprises three self-contained chapters, each addressing critical aspects of risks associated with pension products. The first chapter explores the growing interest in responsible investment products and the integration of sustainability issues in pension products. It documents that this integration carries significant risks, with a non-negligible insurance premium required to cover these risks. The second chapter studies longevity risk in pension products, introducing a novel multiple-horizon approach for simulating future longevity scenarios. The findings reveal that the willingness to pay to avoid this risk – i.e., the risk premium required to bear it – is substantial. The third chapter examines the role of green innovation as a complementary metric to enhance sustainability assessments. This chapter first analyzes the interaction of existing sustainability metrics with green innovation at the firm-level. It then examines how patenting activities can predict changes in environmental and sustainable development goal ratings, uncovering a significant relationship, albeit in opposite directions. For investors, integrating green innovation into the assessment framework can help identify firms well-positioned for the transition to a low-carbon economy, adding a "real-world impact"dimension alongside traditional risk and return metrics. It is crucial to understand how green innovation can complement ESG integration, enabling pension products to more effectively achieve sustainability goals while aligning with investor preferences.

KORT RESUMÉ

Denne afhandling består af tre selvstændige kapitler, som hver især omhandler væsentlige aspekter af risici forbundet med pensionsprodukter. Det første kapitel undersøger den voksende interesse for ansvarlige investeringsprodukter og integrationen af bæredygtighedsproblematikker i pensionsprodukter. Resultaterne viser, at denne integration indebærer betydelige risici, som kræver en ikke ubetydelig forsikringspræmie for at afdække disse usikkerheder. Det andet kapitel undersøger levetidsrisici i pensionsprodukter og introducerer en ny dynamisk tilgang til at simulere fremtidige levetidsscenarier. Resultaterne viser, at villigheden til at betale for at undgå denne risiko – dvs. den risikopræmie, der kræves for at bære denne risiko – er betydelig. Det tredje kapitel undersøger rollen af grøn innovation som en komplementær metrik til at forbedre bæredygtighedsvurderinger. Dette kapitel analyserer først, hvordan eksisterende bæredygtighedsmetrikker interagerer med grøn innovation på virksomhedsniveau. Dernæst undersøges, hvordan patentaktiviteter kan forudsige ændringer i bæredygtighedsmetrikker og verdensmålene for bæredygtig udvikling og dokumenterer en signifikant sammenhæng, omend i modsatrettede retninger. For investorer kan integrationen af grøn innovation i vuderingsprocessen bidrage til at identificere virksomheder, der er godt positioneret til en lavemissionsøkonomi og dermed tilføje en ekstra bæredygtighedsdimension ved siden af den traditionelle afvejning mellem risiko og afkast. Det er afgørende at forstå, hvordan grøn innovation kan komplementere eksisterende bæredygtighedsmetrikker, så pensionsprodukter mere effektivt kan opnå bæredygtighedsmål og samtidig tilpasses investorers præferencer.

SUMMARY

Across the world, pension systems encounter diverse risks that impact both individual retirement planning and the efforts of governments and the pension industry to develop sustainable retirement solutions. In response to these challenges, there has been a shift towards annuity products that mitigate various risks impacting pension fund liabilities, with pension holders often bearing all risks themselves (Brown, 2016; Balter et al., 2021). In parallel, the growing emphasis on sustainable investing[1] – such as integration of Environmental, Social, and Governance (ESG) factors into investment portfolios and aligning strategies with the UN's Sustainable Development Goals (SDGs) (Yang et al., 2024) – has introduced several risks. For instance, one potential risk is the exclusion of firms with low ESG ratings from portfolios to enhance the sustainability profile, which could lead to reduced diversification or missed opportunities. Another risk arises from a reliance on ESG ratings to assess the sustainable impact of portfolios, given the variability in rating methodologies. Considering the significant growth in sustainable investments globally, addressing these risks is crucial (GSIA, 2022).

The three self-contained chapters of this dissertation each focus on different aspects of the risks associated with pension products. Chapter 1 addresses the risk of excluding firms from portfolios, a practice adopted by several institutional investors, by quantifying the fair price of insurance against the underperformance of a sustainable index relative to a broader, unrestricted market index. Chapter 2 examines a different risk inherent in pension products linked to life expectancy, namely longevity risk. This study proposes a new multi-horizon framework to quantify this risk by dynamically evaluating welfare in retirement and assessing agents' willingness to pay for insurance against longevity risk. The findings of both studies document that the insurance premium is large and significant. Chapter 3 revisits the topic of sustainability in investment portfolios through a comprehensive empirical study on the relationship between green innovation and sustainability metrics. The results indicate that green innovation complements existing sustainability metrics and can serve as a valuable tool for identifying firms with potential for future improvements in

[1] The number of signatories at the United Nations Principles for Responsible Investment, has grown from 73 at its launch in 2006, to 5306 in 2024, with total assets under management of $128 trillion. (See, https://www.unpri.org/)

sustainability. This insight enables investors to better align their portfolios with sustainable preferences and goals, such as the SDGs, which are increasingly prioritized by pension holders (Bauer et al., 2021).

Chapter 1 – *The Cost Of Insuring Against Underperformance Of ESG Screened Index Funds* (joint work with Peter Løchte Jørgensen)[2] – examines the underperformance risk in sustainable and ESG screened investment products relative to the unrestricted market portfolio. While the ESG acronym has been around for almost 20 years,[3] it is only recently that ESG considerations have gained widespread attention in the investment community. Particularly in Europe, sustainable investments accounted for 80% of the USD 150.3bn global ESG fund inflows during the fourth quarter of 2021 (Morningstar, 2022). A large body of literature has already explored various aspects of ESG investing. Coqueret (2021) provides a comprehensive survey with over 550 references, noting that a significant part of the literature is devoted to empirically investigating whether ESG risk factors are priced and how they link to financial performance at the firm level. In a meta-study of over 2,000 empirical studies, Friede et al. (2015) find, that the business case for ESG investing is well-founded. However, other studies challenge these findings, resulting in mixed conclusions throughout the literature. For instance, Flammer (2015) shows that higher levels of corporate social responsibility positively affect financial performance, whereas Hong and Kacperczyk (2009) find that *sin stocks* have higher expected returns than comparables. While being widely cited papers, their conclusions point in different directions. Khajenouri and Schmidt (2021) find ESG screened index funds to have provided better risk-adjusted returns during the period 2013-2020, while Renneboog et al. (2008) find SRI funds to underperform. Capelle-Blancard and Monjon (2014); Geczy et al. (2019); Hoepner and Schopohl (2018); Hornuf and Yÿ́ksel (2022); Humphrey and Lee (2011); Humphrey and Tan (2014); Lee et al. (2010); Milonas et al. (2022) and Sharma et al. (2021) all present variants of the conclusion that exclusions have little or no impact on fund performance. With the increased attention towards sustainability, we study the situation where a socially responsible investor seeks broad market exposure but omits firms with poor ESG profiles. This raises some natural questions: What is the risk that a given ESG screened index fund will underperform its corresponding classical unscreened index fund, and how can we measure this risk? Also, what would be the cost of insuring against this risk? Based on incorporating an *option to exchange one asset for another* (Margrabe, 1978), we develop a simple way to quantify the underperformance risk, expressing the fair price of insuring against the underperformance of a given sustainable index relative to a broad and unrestricted market index. We determine the insurance premium, using data from BlackRock's iShares universe of exchange-traded funds, as the price of the option, requiring only the estimation of a single parameter - a *relative index volatility*. We document that the cost of insurance

[2] Published in *Journal of Sustainable Finance & Investment, 13(4), 1534-1553*

[3] The The UN Global Compact (2004) is often credited with coining the term 'ESG'.

against underperformance ranges from approximately 50 to 300 basis points annually, depending on the geographical region and the index's sustainability level.

Chapter 2 – *Systematic Longevity Risk: The Willingness To Pay* (joint work with Anne G. Balter and Malene Kallestrup-Lamb) – documents the willingness of agents to pay for insurance against systematic longevity risk in annuity products. We define *systematic longevity risk* as the uncertainty surrounding an entire pool of individuals living longer than expected. The literature lacks consensus on quantifying this risk in life annuity products. Richards et al. (2014) propose a Value-at-Risk framework to manage unfavorable developments in longevity over a one-year horizon. De Waegenaere et al. (2017) incorporate parameter risk by re-estimating best estimates based on one-year forecasts from the Lee and Carter (1992) (LC) model, finding that the impact on pension annuity values differs between young and old cohorts. Dees et al. (2021) argue that longevity risk from stochastic variation is negligible compared to financial risk, while Maurer et al. (2013) and Boon et al. (2020) consider stochastic variation the main source of systematic longevity risk, focusing on deviations from the expected biometric returns. However, most of the literature emphasizes stochastic variation within a mortality model on a one-year horizon, which we refer to as *trend risk*. This approach, however, overlooks the long-term nature of longevity risk. We propose to capture systematic longevity risk by calculating deviations in best-estimate survival probability forecasts, updated based on new observations incorporated into the mortality model. To quantify this risk over multiple horizons, we shock the current best estimates with plausible deviations independent of the current mortality model. This approach allows for unanticipated deviations not predicted by the model. Our study focuses solely on systematic longevity risk, assuming the idiosyncratic risk is fully diversified and disregards financial risk. We consider a scenario where an average agent at retirement is offered two products – a *defined benefit (DB)*-type annuity with fixed payments and no longevity risk and a *defined contribution (DC)*-type annuity with variable payments due to longevity risk, similar to group self-annuitization products (see, e.g., Piggott et al. (2005); Qiao and Sherris (2013)). We introduce a utility framework to measure the welfare implications of longevity risk from the perspective of agents maximizing their retirement welfare, given their risk preferences and retirement horizon. Our findings indicate that agents require compensation when choosing between two products at retirement, with the value of longevity risk depending on both horizon and risk-aversion. Compensation requirements increase in both dimensions, suggesting that an agent's welfare in retirement could be significantly impacted by longevity risk exposure if not adequately compensated. We show that agents demand a risk premium ranging from 5% to 10% on a horizon of 15 years into retirement relative to their pension income without longevity risk. In the time dimension, the risk premium rises from 0% to 10% for a relative risk aversion level of $\gamma = 5$, relative to income based on life tables available at retirement. Additionally, our approach yields negligible values for agents' willingness to pay for insurance against systematic longevity risk on a one-year horizon. We conduct several robustness checks to validate our findings, including varying the country or cohort and relate our results to trend, model, and financial risks.

Chapter 3 – *Green Innovation as a Complementary Sustainability Metric* – shows that firms innovating in green technologies (GTs), as measured by their patent activity, serves as a complementary metric to enhance sustainability assessments. This approach enables investors to manage firms' environmental risks (as indicated by E ratings) while assessing their sustainable impact (as indicated by their patenting intensity). Green innovation (GI) is believed to bring fundamental changes by addressing environmental issues through technological advancements (Kraus et al., 2020). Prior studies explores GI's role in enhancing firms' competitive advantages (Chen, 2008; Qiu et al., 2020) and its impact on environmental performance and emissions (Cohen et al., 2020; Bolton et al., 2023). In 2022, 25% of total assets under management globally were sustainably invested (GSIA, 2022), with most investors integrating sustainability into their portfolios through ESG integration (Fiaschi et al., 2020; Linnenluecke, 2022; Scheitza et al., 2022). However, this approach has faced criticism, reflected in significant outflows of ESG-screened funds.[4] This likely stems from the way ESG ratings are constructed, with a primary focus on financial materiality, especially how climate risks affect financial performance (Popescu et al., 2021).[5] This study examines how patents in GTs can be a complementary metric to existing sustainability metrics, analyzing their interaction with these and making a novel contribution to the literature through the use of SDGs. The incorporation of GI into existing metrics lack clarity and is not transparently detailed by data vendors. This is particularly true for SDG ratings, which, despite being relatively new, are gaining increasing attention in sustainable finance (see, Van Tulder and van Mil, 2022). The paper constructs an unbalanced panel dataset, drawing from multiple sources: patents from Google's Patent Database, financial data from Worldscope, and sustainability metrics from MSCI, Refinitiv, and Robeco. The dataset includes 17,411 unique firms spanning the period from 1995 to 2023. First, the paper examines how firms' sustainability metrics interacts with their GI by using the ratio of granted patents in GTs relative to total granted patents, which is a strong proxy for GI (Desheng et al., 2021). The results show that a one-standard-deviation increase in MSCI environmental ratings increases GI, equal to 145% of its standard deviation, in the following year. These findings support the path-dependency hypothesis (Popp, 2002; Aghion et al., 2016). Further analysis reveals that this effect persists when conditioning on firms with granted patents. Moreover, the effect intensifies for firms with

[4] See, https://www.ft.com/content/cf9001ab-e326-4264-af5e-12b3fbb0ee7b

[5] Bloomberg refers to an "*ESG mirage*," highlighting that several controversial firms with adverse impacts still receive high ESG ratings. Their findings reveal that only 1 out of 155 ESG rating upgrades by MSCI in 2020-2021 cited actual reductions in emissions. Notably, firms with controversial climate change records managed to receive an upgrades by performing well in the Social and Governance pillars. (https://www.bloomberg.com/graphics/2021-what-is-esg-investing-msci-ratings-focus-on-corporate-bottom-line/)

higher E ratings following the Paris Agreement in 2015. The study also finds that the results for SDG ratings are similar to those for E ratings, though dependent on the data provider. Ultimately, the impact of GI on future improvements in sustainability metrics suggests that investors can incorporate GI to identify firms with higher future sustainable impact, measured by SDG ratings. Specifically, GI does not predict MSCI E ratings in the short term, but a significant decrease in the medium-term, equal to 2-2.6% of MSCI E ratings standard deviation. The effect is qualitatively similar for Refinitiv E ratings, while ESG ratings are affected across all horizons (2.2%-4.4%). This is primarily driven by large firms, which often experience a size bias in ESG ratings compared to smaller firms (Akgun et al., 2021; Dobrick et al., 2023). In contrast, SDG ratings increase by 2.9%-3.4% across most horizons, and He et al. (2024) do not observe the same size bias for SDG ratings. As institutional investors increasingly integrate ESG factors, incorporating complementary metrics, such as GI for sustainable impact into investment strategies, offers a way to fulfill their market and societal roles while remaining accountable to beneficiaries. By leveraging GI, investors can identify firms with greater potential for future sustainable impact, positioning them better for the transition to a low-carbon economy. This not only strengthens their competitive advantage but also adds a "real-world impact" dimension to the traditional risk and return framework, aligning investment strategies with broader sustainability objectives.

References

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., Van Reenen, J., 2016. Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy* 124 (1), 1–51.

Akgun, O. T., Mudge, T. J., Townsend, B., 2021. How company size bias in ESG scores impacts the small cap investor. *The journal of impact and ESG investing* 1 (4), 31–44.

Balter, A. G., Kallestrup-Lamb, M., Rangvid, J., 2021. Macro longevity risk and the choice between annuity products: Evidence from Denmark. Insurance: Mathematics and Economics 99, 355–362.

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

Bolton, P., Kacperczyk, M. T., Wiedemann, M., 2023. *The co2 question: Technical progress and the climate crisis.* Available at SSRN: https://ssrn.com/abstract=4212567 or http://dx.doi.org/10.2139/ssrn.4212567.

Boon, L.-N., Brière, M., Werker, B. J. M., 2020. Systematic longevity risk: To bear or to insure? *Journal of Pension Economics & Finance* 19 (3), 409–441.

Brown, E. F., 2016. Lessons from efforts to manage the shift of pensions to defined contribution plans in the United States, Australia, and the United Kingdom. *American Business Law Journal* 53, 315.

Capelle-Blancard, G., Monjon, S., 2014. The performance of socially responsible funds: Does the screening process matter? *European Financial Management* 20 (3), 494–520.

Chen, Y.-S., 2008. The positive effect of green intellectual capital on competitive advantages of firms. *Journal of business ethics* 77, 271–286.

Cohen, L., Gurun, U. G., Nguyen, Q. H., 2020. The ESG-innovation disconnect: Evidence from green patenting. Tech. rep.

Coqueret, G., 2021. Perspectives in ESG equity investing. working paper.

De Waegenaere, A., Melenberg, B., Markwat, T., 2017. Risk sharing rules for longevity risk: Impact and wealth transfers. Netspar Industry Paper 66.

Dees, B., de Jong, F., Nijman, T. E., 2021. Variable annuities with financial risk and longevity risk in the decumulation phase of Dutch DC products. Netspar Design Paper 168.

Desheng, L., Jiakui, C., Ning, Z., 2021. Political connections and green technology innovations under an environmental regulation. *Journal of Cleaner Production* 298, 126778.

Dobrick, J., Klein, C., Zwergel, B., 2023. Size bias in refinitiv ESG data. *Finance Research Letters* 55, 104014.

Fiaschi, D., Giuliani, E., Nieri, F., Salvati, N., 2020. How bad is your company? Measuring corporate wrongdoing beyond the magic of ESG metrics. *Business Horizons* 63 (3), 287–299.

Flammer, C., 2015. Does Corporate Social Responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science* 61 (11), 2549–2568.

Friede, G., Busch, T., Bassen, A., 2015. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance and Investment* 5 (4), 210–233.

Geczy, C., Guerard, J., Samonov, M., 2019. Efficient SRI/ESG portfolios. working paper.

GSIA, 2022. Global Sustainable Investment Review. Accessed 21 June 2024 from: https://www.gsi-alliance.org/wp-content/uploads/2023/12/GSIA-Report-2022.pdf.

He, L., Lohre, H., van Zanten, J. A., 2024. Sustainability Matters: Company SDG Scores Need Not Have Size, Location, and ESG Disclosure Biases. *Available at SSRN: https://ssrn.com/abstract=4886097.*

Hoepner, A., Schopohl, L., 2018. On the price of morals in markets: An empirical study of the Swedish AP-funds and the Norwegian Government Pension Fund. *Journal of Business Ethics* 151 (3), 665–692.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. *Journal of Financial Economics* 93 (9), 15–36.

Hornuf, L., Yỳksel, G., 2022. The performance of socially responsible investments: A meta-analysis. working paper.

Humphrey, J. E., Lee, D. D., 2011. Australian socially responsible funds: Performance, risk and screening intensity. *Journal of Business Ethics* 102 (4), 519–535.

Humphrey, J. E., Tan, D. T., 2014. Does it really hurt to be responsible? *Journal of Business Ethics* 122 (3), 375–386.

Khajenouri, D., Schmidt, J., 2021. Standard or Sustainable - Which offers better performance for the passive investor? *Journal of Applied Finance and Banking* 11 (1), 61–71.

Kraus, S., Rehman, S. U., García, F. J. S., 2020. Corporate social responsibility and environmental performance: The mediating role of environmental strategy and green innovation. *Technological forecasting and social change* 160, 120262.

Lee, D. D., Humphrey, J. E., Benson, K. L., Ahn, J. Y., 2010. Socially responsible investment fund performance: The impact of screening intensity. *Accounting and Finance* 10 (2), 351–370.

Lee, R. D., Carter, L. R., 1992. Modeling and forecasting US mortality. *Journal of the American Statistical Association* 87 (419), 659–671.

Linnenluecke, M. K., 2022. Environmental, social and governance (ESG) performance in the context of multinational business research. *Multinational Business Review* 30 (1), 1–16.

Margrabe, W., Mar. 1978. The Value of an Option to Exchange One Asset for Another. *Journal of Finance* XXXIII (1), 177–186.

Maurer, R., Mitchell, O. S., Rogalla, R., Kartashov, V., 2013. Lifecycle portfolio choice with systematic longevity risk and variable investment—linked deferred annuities. Journal of Risk and Insurance 80 (3), 649–676.

Milonas, N., Rompotis, G., Moutzouris, C., 2022. The performance of ESG funds vis-a-vis Non-ESG funds. *Journal of Impact and ESG Investing* 2 (4), 96–115.

Morningstar, 2022. Global Sustainable Fund Flows: Q1 2022 in Review, Morningstar Manager Research.

Piggott, J., Valdez, E. A., Detzel, B., 2005. The simple analytics of a pooled annuity fund. Journal of Risk and Insurance 72 (3), 497–520.

Popescu, I.-S., Hitaj, C., Benetto, E., 2021. Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance. *Journal of Cleaner Production* 314, 128016.

Popp, D., 2002. Induced innovation and energy prices. *American economic review* 92 (1), 160–180.

Qiao, C., Sherris, M., 2013. Managing Systematic Mortality Risk With Group Self-Pooling and Annuitization Schemes. Journal of Risk and Insurance 80 (4), 949–974.

Qiu, L., Jie, X., Wang, Y., Zhao, M., 2020. Green product innovation, green dynamic capability, and competitive advantage: Evidence from Chinese manufacturing enterprises. *Corporate Social Responsibility and Environmental Management* 27 (1), 146–165.

Renneboog, L., Horst, J. T., Zhang, C., 2008. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance* 14 (3), 302–322.

Richards, S. J., Currie, I. D., Ritchie, G. P., 2014. A Value-at-Risk framework for longevity trend risk. textitBritish Actuarial Journal 19 (1), 116–139.

Scheitza, L., Busch, T., Metzler, J., 2022. The impact of impact funds–A global analysis of funds with impact-claim. *Journal of Financial Transformation*.

Sharma, G. D., Talan, G., Bansal, S., Jain, M., 2021. Is there a cost for sustainable investments: Evidence from dynamic conditional correlation. *Journal of Sustainable Finance and Investment*.

The UN Global Compact, 2004. Who cares wins: Connecting financial markets to a changing world. Report.

Van Tulder, R., van Mil, E., 2022. Principles of sustainable business: Frameworks for corporate action on the SDGs. *Routledge*.

Yang, X., Chen, Z.-H., Feng, Y., Gao, X., Koedijk, K. G., 2024. Corporate SDG performance and investor trading behavior. *Finance Research Letters*, 105659.

CHAPTER 1

THE COST OF INSURING AGAINST UNDERPERFORMANCE OF ESG SCREENED INDEX FUNDS

PUBLISHED IN JOURNAL OF SUSTAINABLE FINANCE & INVESTMENT 13(4), 1534-1553

Peter Løchte Jørgensen
Aarhus University

Mathias Danielsen Plovst
Aarhus University

Abstract

In recent years, investors have shown significant interest in responsible investment products, including sustainable and ESG screened index funds. A natural concern for prospective investors in such funds is that a sustainable fund might underperform its classical, unscreened counterpart. This paper argues that this underperformance risk can be analyzed by way of an *option to exchange one asset for another*, and we derive a simple formula that quantifies the fair annual insurance premium for covering this risk. Only a single parameter is needed to apply the formula. This parameter – a relative index volatility – is readily estimated from market data. Our empirical work utilizes data from BlackRock's ETF (iShares) universe to estimate the cost of insuring against underperformance risk of some common ESG screened funds. We find that the fair cost of underperformance insurance typically corresponds to sacrificing in advance between 0.5% and 3.0% of the annual return.

1.1 Introduction

This paper relates to two megatrends that are currently sweeping through the investment world. The first is the rise in passive index fund investing. According to Morningstar (2019), assets under management (AUM) by index tracking US equity funds (USD 4.271 trillion) surpassed the AUM in corresponding actively managed funds (USD 4.246 trillion) for the first time in September 2019. By December 2021, US equity index funds had further increased their market share by managing a total asset value of USD 7.454 trillion against active funds' AUM of USD 6.078 trillion (Morningstar, 2021). The new leading position of index funds is of course notable, but the passive share has been steadily increasing since the mid-1990s (see, e.g., Anadu et al., 2020); therefore, the development was anticipated, and similar developments have been seen in Europe and Asia (see, e.g., Bhattacharya and Galpin, 2011; Sushko and Turner, 2018). It is likely that several factors have contributed to this active-to-passive shift but investors' increasing awareness of the importance of a low-cost focus and the solid scientific evidence of underperformance of active managers (see, e.g., French, 2008) have undoubtedly been key drivers in this development.

The second financial market megatrend concerns the massively increased investor focus on responsible investing and on issues and risks in relation to Environmental, Social, and Governance (ESG) factors. When the ESG acronym was first introduced almost 20 years ago, few investors knew what it meant.[1] Today, ESG issues are on agendas everywhere in the investment community, and large sums of money have been flowing into sustainable, responsible, and ESG focused funds. The trend is particularly strong in Europe, where sustainable investments accounted for 80% of the USD 150.3bn global ESG fund inflows in the fourth quarter of 2021 (Morningstar, 2022a). In the United States, it took just nine months of 2021 to match the 2020 flow of money into sustainable funds. Notably, 2020 alone set a remarkable record by more than doubling the inflow of 2019 (Morningstar, 2022b).

Asset managers and investment fund providers have responded to these trends. Classical index funds are available for countless asset classes, submarkets, and geographical regions, and recent years have seen the introduction of a wide range of index funds with various types of *ESG overlay*. This means that investors who want broad, passive exposure to a certain market can get this exposure via funds that track a given reference index closely, but where companies with poor ESG profiles have been omitted to some extent.

Despite the popularity of ESG funds, regulators, researchers, and financial media experts have expressed concern that some asset managers exaggerate or misrepresent the sustainability characteristics of their ESG funds to attract business – a practice that has been referred to as portfolio greenwashing (see, e.g., Amenc et al., 2021; Fletcher and Oliver, 2022). Others have pointed to the risk that a green bubble could

[1] The UN Global Compact (2004) is often credited with coining the term "ESG".

develop as a result of the high demand for sustainable investment opportunities (see, e.g., BIS, 2021). Nevertheless, these new investment opportunities continue to appeal to many investors (see the remarks on sustainable fund inflows given above).

The recently introduced sustainable or ESG screened index funds track their traditional unscreened reference funds (and their benchmark indexes) closely. However, because they are not identical, their performance may differ. Some natural questions may thus arise for investors who are considering transferring their investments to ESG screened funds. For example, what is the risk that a given ESG screened index fund will underperform its corresponding classical unscreened index fund, and how can this risk be measured? Also, what would be the cost of insuring against this risk? These are questions that we attempt to answer in this paper. It should be emphasized that we are not biased against sustainable and ESG focused investment strategies. If proper performance measures are applied, there is no reason to expect sustainable funds to underperform, just as there is no reason to expect them to outperform. There is, however, always a *risk* that a sustainable fund will underperform relative to a more classical benchmark. Although we might just as well have focused on the reverse risk (that a classical index fund underperforms relative to a sustainable fund), we argue that the perspective taken in this paper is more representative of the typical prospective ESG investor. This view is partly justified by the current substantial flow of money into sustainable funds, as documented above. To a certain extent, investors are abandoning traditional unrestricted index investment strategies and joining the responsible investment trend by investing in ESG screened index funds. As always, when a new strategy is implemented, there is a natural concern regarding whether the new strategy will work. This is why we focus on the risk that “modern" sustainable index investment strategies underperform their “classical" unrestricted counterparts.

The remainder of the paper is structured as follows. First, Section 1.2 summarizes related literature. In Section 1.3, we present our analytical framework and derive a formula that expresses the theoretical cost of insuring against the underperformance of ESG screened index funds. In Section 1.4, we present empirical results based on data from BlackRock’s iShares universe of exchange-traded funds (ETFs). Last, Section 1.5 concludes the paper.

1.2 Related Literature

There is already a large body of literature examining various aspects of ESG investing. Coqueret (2021) is a comprehensive survey that synthesizes models and results from the academic literature on socially responsible investing (SRI) in equity markets. The survey article contains more than 550 references. A significant part of the literature is occupied with empirical investigations of whether ESG risk factors are priced and whether there is a link between ESG criteria and financial performance at the corporate level. Friede et al. (2015) conduct a meta-study of more than 2000 individual empirical studies and conclude that the business case for ESG investing is empirically very well-founded. This is disputed in other studies, and results are indeed mixed. Flammer (2015) and Hong and Kacperczyk (2009) are widely cited papers with conclusions that point in different directions. Flammer (2015) finds that a higher level of corporate social responsibility affects financial performance positively, whereas Hong and Kacperczyk (2009) find that stocks that are neglected by norm-constrained investors, also known as *sin stocks*, have higher expected returns than otherwise comparable stocks. Hűbel and Scholz (2020) also conclude that taking ESG risk factors into account significantly enhances the explanatory power of standard asset pricing models. A number of studies focus particularly on the consequences of portfolio screenings and ESG motivated exclusions. Khajenouri and Schmidt (2021) report that, from 2013–2020, ESG screened index funds have consistently provided better risk-adjusted returns than their conventional equivalents. Conversely, Renneboog et al. (2008) find that SRI funds generally underperform conventional funds. Luo and Balvers (2017) reconcile the above-mentioned sin stock abnormal return with a systematic “boycott risk premium," and Berle et al. (2022) find that portfolios formed from the exclusion list of the Norwegian Oil Fund significantly outperform their benchmarks. Capelle-Blancard and Monjon (2014), Geczy et al. (2019), Hoepner and Schopohl (2018), Hornuf and Yÿksel (2022), Humphrey and Lee (2011), Humphrey and Tan (2014), Lee et al. (2010), Milonas et al. (2022), and Sharma et al. (2021) all present variants of the conclusion that exclusions have little or no impact on fund performance. Geczy et al. (2005) is an early study that relates to ours but uses an entirely different empirical approach to estimate the financial costs associated with investing in ESG- or SRI-constrained mutual funds. Matallin-Saez et al. (2021) and Renneboog et al. (2011) are interesting empirical studies on how money flows into and out of conventional and SRI funds depending on past returns and ethical profiles. Significant theoretical contributions to ESG investing are found in Berk and van Binsbergen (2021) and Pastor et al. (2021), which study the quantitative impact of ESG motivated investing and divestitures, as well as Pedersen et al. (2021) which derives an ESG adjusted capital asset pricing model and studies the costs and benefits of responsible investing.

1.3 Analytical Framework and Model

We wish to analyze the following situation: An investor plans to make an index fund investment in a particular market (e.g., a specific geographical region) at time 0, and he is considering two ways in which the decision can be implemented. One is the “old-fashioned" approach, where he buys a classical (or “Core") index fund, and the other is a more “modern" and sustainable approach, where he buys a corresponding ESG screened index fund. By design, these investments are highly but not perfectly correlated, and a natural concern of the investor is whether the sustainable fund will underperform the classical fund. The investor might, therefore, be interested in measuring this underperformance risk and possibly also in information on the cost of insuring against it.

To analyze this situation more formally, let $I_C(t)$ and $I_S(t)$ denote the values of the Core and the Screened index funds, respectively, at time t, $t \geq 0$. With the investment decision to be made at time 0, it will be natural to set $I_C(0) = I_S(0)$, but we postpone this assumption until we need it.

Assuming now that the investor's time horizon is $T > 0$ and that the funds do not pay dividends before time T, the screened index fund will have underperformed the Core fund when $I_C(T) - I_S(T) > 0$. Perfect insurance against this non-zero probability event can, therefore, be obtained by supplementing the screened index fund investment with a European-style derivative with time T payoff

$$c(T) = \max\Big(I_C(T) - I_S(T); 0\Big) = \Big[I_C(T) - I_S(T)\Big]^+. \tag{1.1}$$

In this way, the investor's time T payoff will be

$$\begin{aligned} I_S(T) + c(T) &= \begin{cases} I_S(T) + I_C(T) - I_S(T) = I_C(T) & \text{when } I_C(T) \geq I_S(T) \\ I_S(T) & \text{when } I_C(T) < I_S(T) \end{cases} \\ &= \max\Big(I_C(T); I_S(T)\Big). \end{aligned} \tag{1.2}$$

The last expression in (1.2) explains why the derivative defined in (1.1) has been labeled the *option to exchange one asset for another* (Margrabe, 1978). In the present context, the instrument clearly provides an option to exchange the screened index fund for the Core fund at maturity. As (1.2) makes clear, the option will be exercised when $I_S(T) < I_C(T)$.

One may note that a certain duality also applies since we have

$$I_S(T) + \max\left\{I_C(T) - I_S(T); 0\right\} = I_C(T) + \max\left\{I_S(T) - I_C(T); 0\right\}. \tag{1.3}$$

This means that a portfolio consisting of the screened fund plus an option to exchange the screened fund for the Core fund is equivalent to a portfolio consisting of the Core fund plus the option to exchange this fund for the screened fund. The option valuation implication of this duality is that if $I_S(0) = I_C(0)$, then the two exchange options have identical time zero values. This again means that our analysis also covers the situation where the concern is to insure a core fund against underperforming a sustainable fund.

The screened index investor can measure the risk of underperformance, for example, by the probability of the event $\left\{I_C(T) - I_S(T) > 0\right\}$ or by the fair price of insuring against it. This price must equal the time zero value of the exchange option. For a more precise determination of any of these measures, additional assumptions will be needed.

Margrabe (1978) established the solution to the problem of valuing the option to exchange one asset for another in a Black-Scholes framework (Black and Scholes,

1973) extended to two correlated risky assets. It is well-known that the assumptions underlying this model do not represent a perfect description of real-world financial markets where investors must deal with, e.g., jump risk, stochastic volatility, and log-returns that are often less than perfectly normally distributed. We nevertheless adopt the Black-Scholes assumptions here because they lead to a convenient closed-form solution and because we are more concerned with developing a reasonably accurate and easy-to-use measure of underperformance risk than with pricing imaginary options to penny accuracy. It can also be noted that we will apply the model exclusively to index markets where jump risk is of lesser importance than when options on individual stocks are considered. In the following, we briefly summarize the Margrabe (1978) model and its solution.

1.3.1 The Margrabe Model Solution

We consider a simple and perfect continuous time financial market in which the values of the two risky and non-dividend-paying index funds evolve through time according to a system of geometric Brownian motions, i.e.

$$dI_C(t) = \mu_C I_C(t)\,dt + \sigma_C I_C\,dW_C(t) \tag{1.4}$$

$$dI_S(t) = \mu_S I_S(t)\,dt + \sigma_S I_S\,dW_S(t), \tag{1.5}$$

where $W_C(t)$ and $W_S(t)$ are standard correlated Brownian motions with

$$dW_C(t) \cdot dW_S(t) = \rho\,dt. \tag{1.6}$$

The constant coefficients μ_C, μ_S, σ_C, and σ_S are the expected returns and volatility coefficients of the Core and the screened index fund, respectively, and ρ is the constant coefficient of correlation. We could assume the existence of a riskless asset – a money market account with a riskless rate of return r, as in the original Black-Scholes economy – but it does not serve any purpose here.

Under these assumptions, the unique arbitrage-free time 0 price of the option to exchange one index for the other with payoff as defined in (1.1) is given by

$$c(0) = I_C(0)N\big(d_+\big) - I_S(0)N\big(d_-\big), \tag{1.7}$$

with

$$d_\pm = \frac{\ln \frac{I_C(0)}{I_S(0)} \pm \frac{1}{2}\bar{\sigma}^2 T}{\bar{\sigma}\sqrt{T}}, \tag{1.8}$$

and

$$\bar{\sigma}^2 = \sigma_C^2 + \sigma_S^2 - 2\sigma_C\sigma_S\rho, \tag{1.9}$$

where $N(\cdot)$ is the standard normal distribution function. A summary of the proof of (1.7) is provided in Appendix A.1. The formula is known as Margrabe's formula (Margrabe, 1978).

1.3.2 Practical Application Of The Margrabe Formula

In this section, we make a couple of observations in relation to the application of the Margrabe formula in the present context.

First, because it is natural to assume $I_C(0) = I_S(0) \equiv I(0)$, we note that in this special case, the price of the exchange option relative to the initial index investment value, i.e. $\pi(0) = \frac{c(0)}{I(0)}$, can be expressed as follows

$$\pi(0) \equiv \frac{c(0)}{I(0)} = N(d_+) - N(d_-) = 2N\left(\frac{1}{2}\bar{\sigma}\sqrt{T}\right) - 1, \tag{1.10}$$

where the last equality in (1.10) follows from the definitions of $d_\pm$ in (1.8) and from the symmetry properties of the normal distribution. Note from (1.10) that a strictly positive $\bar{\sigma}$ implies a strictly positive option premium.

When an investment horizon of one year is considered, equation (1.10) can be simplified further. Setting $T = 1$ in (1.10) the annual fair premium, $\bar{\pi}$, for insurance against underperformance of one index relative to the other becomes simply

$$\bar{\pi} = 2N\left(\frac{1}{2}\bar{\sigma}\right) - 1, \tag{1.11}$$

where $\bar{\sigma}$ is defined as in (1.9) and where $\bar{\pi}$ is the insurance premium expressed as a fraction of the initial investment as in (1.10). Formulas (1.10) and (1.11) can be seen as corollaries of Margrabe's formula.

The fair insurance premium determined in equation (1.11) can alternatively be interpreted as an approximate foregone annual return, i.e., as the part of the annual return that must be relinquished in advance in return for insurance against underperformance. To illustrate this point, suppose, for example, that the 1-year option premium is 0.0050 (50 bps) and that at the end of the year, one index has returned 6% while the other has returned 7%. The realized (discrete) return will be $1.07/1.005 - 1 = 6.47\%$ or 53 bps ($\approx$ 50 bps) lower than the maximum of the two returns.

A second observation concerns parameter estimation. Looking at formula (1.11), we see that three parameters, σ_C, σ_S, and ρ, need to be estimated in order to determine the $\bar{\sigma}$-estimate and evaluate formula (1.11). The estimation of these three parameters from time series data on the $I_C(t)$ and $I_S(t)$ processes is a straightforward exercise and may be of independent interest. However, regarding the estimation of $\bar{\sigma}$, we may use a more direct approach that also facilitates the assessment of the accuracy of the parameter estimate. As Appendix A.1 shows, $\bar{\sigma}$ is the return volatility of the $\frac{I_C(t)}{I_S(t)}$-process, which, under the present assumptions, is also a geometric Brownian motion. This means that we can estimate the volatility parameter directly and obtain the associated confidence bounds using time series data on the I_C/I_S-process. In the next section, we introduce our data and apply this procedure to determine $\bar{\sigma}$-estimates, and we henceforth refer to $\bar{\sigma}$ as the *relative index volatility*.

1.4 Data and Results

1.4.1 iShares Equity Based Index Funds

The empirical analysis in this section utilizes data from BlackRock's iShares universe of exchange-traded funds. ETFs are similar to mutual funds in that they are pooled investment vehicles that track an index or a basket of underlying securities. In addition to often being passively managed, ETFs are priced continuously by the market, whereas mutual funds typically trade based on net asset values (NAVs) that are updated less frequently. This makes ETF price data a good choice for our empirical study.

We choose to utilize ETF data from BlackRock's iShares for two primary reasons. The first is that iShares is the World's largest provider of passive exchange-traded index funds, so their wide range of individual ETFs tend to be the most liquid funds available. As of mid-February 2021, iShares manages about USD 2.1 trillion in 374 ETF funds. Vanguard comes second, with an AUM of USD 1.6 trillion in 81 ETF funds, and State Street is the third-largest manager with an AUM of USD 886 billion in 141 ETF funds.[2]

The second reason for concentrating on data from the iShares universe is that iShares has introduced a well-described "Sustainable Range" of equity-index-based ETFs for a number of geographical regions for which traditional, unscreened index funds are also available (iShares, 2020). The latter funds are often labeled as "Core" funds. The idea behind Core funds is to provide broad, diversified exposure to the entire market in the given region, and it is natural to let these Core funds serve as the point of reference for evaluating the underperformance risk of sustainable funds. The structure of iShares' Sustainable Range of index ETFs is illustrated in Table 1.1. Each framed cell in the table represents a tradable iShares index fund.[3] The cells contain three numbers: the MSCI ESG Quality Score ("ESG Score"), the MSCI Carbon Intensity Score, and the number of constituents (i.e., the number of shares held) for the fund as of October 2020 (see p. 10 in iShares, 2020). The ESG Scores and the Carbon Intensity Scores are both provided by MSCI and are calculated as weighted averages of the individual holdings' scores. The ESG Quality Score is a metric on a 0–10 scale (with 0 as the lowest and 10 as the highest possible fund score) for the ability of the underlying holdings to manage risks and opportunities from ESG factors. The Carbon Intensity is the portfolio's weighted average (Scopes 1+2) carbon emissions in metric tons per million dollar of sales.[4] In Appendix A.2, we provide more detailed information on the funds in Table 1.1 (e.g., net asset value, base currency, benchmark index, Bloomberg Ticker code, ISIN code, fund launch date, and total expense ratio).

[2] Source: The ETF Database, https://etfdb.com/etfs/.

[3] In fact, iShares typically offer both an accumulating and a dividend distributing version of the funds represented in Table 1.1.

[4] For more, see www.ishares.com and www.msci.com.

Table 1.1: MSCI Weighted Average ESG Scores, Carbon Intensity Scores, and Number Of Constituents Of iShares Index Funds (iShares, 2020)

EMU refers to the European Monetary Union. The union comprises the 19 developed countries that cooperate on the coordination of economic and fiscal policies, a common monetary policy, and a common currency, the euro.† EM refers to the following group of 27 Emerging Market countries: AE, AR, BR, CL, CN, CO, CZ, EG, GR, HU, ID, IN, KR, KW, MY, MX, PE, PH, PK, PL, QA, RU, SA, TH, TR, TW, and ZA. The EM IMI (Investable Markets Index) covers app. 99% of the market cap. whereas the EM index leaves out the small cap segment and covers app. 85% of the market cap. in these countries.††

			iShares' Sustainable Range of funds		
Region	Characteristic	Core fund	ESG Screened	ESG Enhanced	SRI fund
World	ESG Score	6.29	6.31	7.09	8.05
	Carbon Intensity	145	93	99	58
	# of constituents	1607	1509	1505	373
USA	ESG Score	5.99	5.99	6.50	7.64
	Carbon Intensity	143	83	93	55
	# of constituents	619	580	576	133
Europe	ESG Score	7.47	7.62	7.82	9.13
	Carbon Intensity	140	123	105	60
	# of constituents	436	412	412	110
EMU†	ESG Score	7.48	7.64	7.94	8.87
	Carbon Intensity	175	140	123	108
	# of constituents	247	234	234	49
Japan	ESG Score	5.93	5.98	6.41	7.84
	Carbon Intensity	79	62	64	51
	# of constituents	320	308	308	64
EM††		EM IMI/EM	EM IMI	EM	EM
	ESG Score	4.80/4.89	4.87	5.79	6.84
	Carbon Intensity	267/253	201	155	136
	# of constituents	2,942/1,387	2,825	1,305	177

Table 1.1 shows that the first step in the direction of sustainability in the iShares Sustainable Range (i.e., as we move from left to right in the table) is an "ESG Screened" fund corresponding to the reference Core fund. The approach taken in constructing these funds is purely exclusionary in the sense that the ESG Screened fund portfolios are obtained by simply dropping a number of names (i.e., companies) with problematic ESG profiles from the corresponding Core fund. In iShares' own words, the purpose of the screening is to "eliminate exposures to companies or activities that pose certain risks or which violate investor values" (iShares, 2020). The ESG screening in this first step of the range is fairly light, maintaining well above 90% of the names from the traditional reference fund. The step from Core to ESG Screened fund increases the ESG Score (and lowers the Carbon Intensity Score) but for some regions only marginally so.

The second step in the iShares Sustainable Range universe consists of the "ESG Enhanced" funds, where screening criteria are slightly tougher, and where the funds' portfolios are rearranged to maximize the ESG scores for a given target tracking error relative to the traditional parent index. The ESG Enhanced range of funds generally manages to maintain more than 90% of traditional benchmark names in the final portfolios. The step from ESG Screened to ESG Enhanced fund increases the MSCI ESG Quality Score further. However, as Table 1.1 also shows, the effect on the Carbon Intensity Score of the second step is ambiguous. In the World, USA, and Japan regions, the Carbon Intensity Score increases slightly in the step from ESG Screened to ESG Enhanced fund. This illustrates that ESG score optimization involves a multitude of criteria from all three ESG dimensions, and a result of that process can be that a single criterion, like the Carbon Intensity Score from the E-dimension, comes out a bit worse.

The companies excluded from iShares' ESG Screened and ESG Enhanced index funds are companies with business models related to civilian firearms, controversial weapons, nuclear weapons, oil sands, thermal coal, and tobacco, as well as companies in violation of the UN's Global Compact principles (iShares, 2020).

The third and final step in the iShares Sustainable Range is the "Socially Responsible Investment range." The SRI range of funds is "designed for investors with the highest commitment to or conviction toward the top ESG performers" (iShares, 2020) and is constructed from portfolios with exposures only to top ESG scoring companies. The screening in the SRI range of funds is severe, with the final portfolios typically maintaining only 20–25% of the names from the traditional benchmark. In addition to the exclusions made in the ESG Screened and the ESG Enhanced funds, the SRI range also excludes companies with business models related to, e.g., alcohol, adult entertainment, gambling, genetically modified organisms, nuclear power, unconventional oil and gas, oil and gas power generation, thermal coal, and oil sand reserves. The ESG Scores are naturally highest (and Carbon Intensities the lowest) for the SRI funds.

1.4.2 Parameter Estimates and Option Values

In order to estimate model parameters, we have collected a dataset of daily NAVs from which daily log-returns can be calculated for each of the 24 iShares ETF funds in Table 1.1.[5] The iShares Sustainable Range of funds is marketed primarily in Europe and traded on European exchanges, so the NAVs of the funds are given in euros (EUR). Although data for some of the funds are available from as early as September 2009, most of the ESG funds were introduced in 2018–2019. Moreover, because it is neither necessary nor appropriate to use too many observations in constructing historical return volatility estimates, we collect time series only for a more recent period beginning in mid-April 2019 and ending on December 1, 2020.[6] Daily data for this period are available for all funds included in Table 1.1. These time series are also sufficiently long to allow us to experiment with the length of the estimation

[5] In the EM region, we chose the EM IMI index fund as the reference Core fund.

[6] Hull (2018), p. 325 recommends using the most recent 90 to 180 daily observations for a good historical return volatility estimate.

window and with data periods before, during, and after the COVID-19 pandemic's significant disturbance of markets in the first part of 2020. The World's main stock indices dropped by more than 30% in the short period from around mid-February to late March 2020, and historical volatility estimates spiked as a consequence. For example, for the iShares World index funds, we estimated pre-pandemic annual volatilities (based on 90 observations of daily returns) in the 10–15% interval. The volatilities spiked to 40% halfway into 2020 but then started to decrease as markets also recovered. By late 2020, the volatilities of the iShares World index funds were all but normalized. The point estimates of all fund volatilities by December 1, 2020 are provided later in the paper. We found volatility and correlation estimates to be quite stable with respect to the length of the estimation window. The volatility estimates that we report below are based on the 90 daily returns observed prior to December 1, 2020.

To illustrate the typically strong correlation between the four types of funds represented in the horizontal dimension of Table 1.1, the daily NAV developments (indexed to 100 as of April 18, 2019) of the four World index funds in our dataset have been plotted in Figure 1. It is seen that the four fund values shadow each other closely and that in this particular period, the SRI fund outperforms the three other funds. The ESG Screened and the ESG Enhanced fund value time series are nearly identical, and both funds perform marginally better than the Core fund during this period. The early 2020 COVID-19 induced drop of more than 30% in all four ETF NAVs is also clearly visible in the plot. As explained above, our volatility estimation window starts in late July 2020, which is more than four months after the occurrence of this sudden and significant drop in market values.

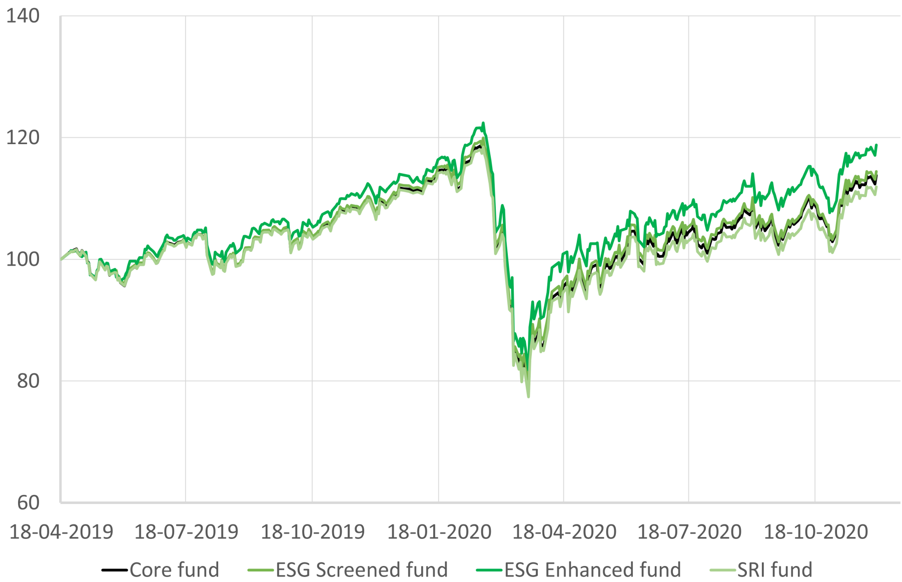
As explained earlier, we only need to estimate the relative index volatility, $\bar{\sigma}$, in order to apply the formula that calculates the cost of insuring against underperformance of a sustainable index fund relative to a traditional, unscreened index fund. Because the $\bar{\sigma}$s depend on the individual index return volatilities and their correlations, and because these parameter values may be of some interest in themselves, we first present estimates of these parameters in Table 1.2.[7]

As Table 1.2 shows, the individual index fund return volatilities are estimated in the range of 15–20% (all standard errors lie within the range of 1.1–1.5%). Within regions, the estimated volatilities exhibit only limited variation across fund types, indicating that sustainable funds can be chosen without significantly increasing absolute risk per se. In fact, we estimate volatilities that are lower for the most sustainable SRI funds than for the Core funds in the USA and EMU regions. The differences are not large but may be related to the lower exposure of SRI funds to the energy and information technology sectors. These sectors are normally associated with above-average volatilities, particularly in the regions mentioned. Table 1.2 also shows that for any given region, the return correlations are generally very high (all but one are

[7] The full correlation matrices are available from the authors on request.

Figure 1.1: Daily Net Asset Value for iShares MSCI World Index ETFs

Daily Net Asset Value for iShares MSCI World Index ETFs – Core, Screened, Enhanced, and SRI Funds (18 April 2019–1 December 2020).



above 95%) between the Core fund and any of the three types of sustainable index funds. However, as also visualized in Figure 1.2, the correlation tends to decrease with the level of sustainability (i.e., in the steps from the ESG Screened fund to the SRI fund). This is as expected, as we have seen earlier that the fund portfolios also become narrower as the screening becomes harder and the ESG Score rises.

Table 1.2: Point Estimates Of Individual iShares Index Fund Return Volatilities and Correlations With A Corresponding Core Fund

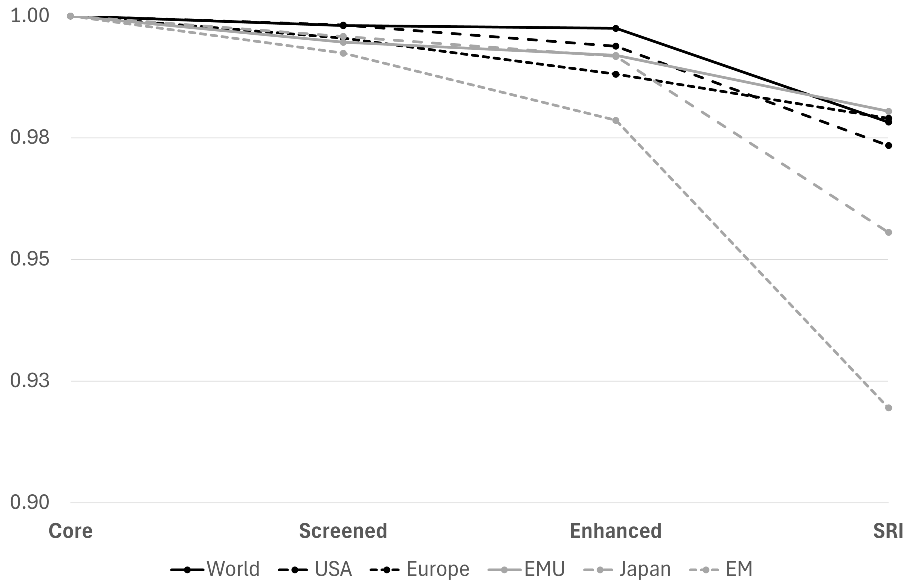
The iShares fund that tracks the MSCI USA Index does actually not carry the "Core" label. Apparently, iShares has reserved this label for their S&P 500 index fund, but it is the broader MSCI USA Index tracking fund that we have used here and which is also the reference fund for iShares' sustainable ETFs in the US region.† See note to Table 1.1 for remarks on the difference between EM IMI and EM.††

Region Fund type	Annualized return volatility	Correlation with Core fund
World		
Core	16.78%	1.0000
ESG Screened	16.71%	0.9980
ESG Enhanced	16.94%	0.9975
SRI	17.02%	0.9782
USA		
Core†	18.28%	1.0000
ESG Screened	18.51%	0.9982
ESG Enhanced	18.44%	0.9938
SRI	17.71%	0.9734
Europe		
Core	18.42%	1.0000
ESG Screened	18.33%	0.9954
ESG Enhanced	18.11%	0.9881
SRI	18.41%	0.9790
EMU		
Core	20.46%	1.0000
ESG Screened	20.25%	0.9946
ESG Enhanced	20.48%	0.9919
SRI	18.91%	0.9804
Japan		
Core	15.18%	1.0000
ESG Screened	14.94%	0.9958
ESG Enhanced	15.32%	0.9917
SRI	15.51%	0.9556
Emerging Markets††		
Core (EM IMI)	15.81%	1.0000
ESG Screened (EM IMI)	15.75%	0.9924
ESG Enhanced (EM)	16.37%	0.9786
SRI (EM)	17.34%	0.9195

We now turn our attention to the estimates of the relative index volatilities, $\bar{\sigma}$. Recall that the relative index volatility is the volatility coefficient of the $I_C(t)/I_S(t)$-process where the Core fund value is deflated by the value of one of the three corresponding sustainable fund values. Recall also that this is the only parameter we need to evaluate formula (1.10), which determines the fair price of insurance against underperformance of a sustainable index fund relative to a Core index fund over

Figure 1.2: iShares Sustainable Range Fund Correlation

iShares Sustainable Range fund correlation with the corresponding Core fund by region. Estimates based on 90 daily returns prior to 1 December 2020.



some fixed horizon. An interpretation of the relative index volatility is that it measures the variation in the deviation between the log-returns of two indexes. The natural implication is that a high relative index volatility implies a high risk of underperformance of one index fund relative to the other. Moreover, a high relative index volatility translates directly to a high exchange option price, as $\bar{\sigma}$ is the sole argument of the expression for the price of insurance against underperformance given in formulas (1.10) and (1.11).

Under the assumptions introduced in Section 1.3, the $I_C(t)/I_S(t)$-process is a geometric Brownian motion for which it is straightforward to estimate the (relative index) volatility from its log-returns. Our estimates of the $\bar{\sigma}$s are presented in Table 1.3, along with standard errors. The volatilities are estimated on the basis of daily log-returns of the iShares NAV data for the 90-day period immediately prior to December 1, 2020. As expected, a 90-day estimation period is sufficient to obtain very small standard errors of the volatility estimates. This means that we can calculate option values with very little error. The 1-year option prices implied by our estimates of the relative index volatilities are provided in the rightmost column of Table 1.3, along with 95% confidence bands implied by the standard errors of the relative index volatility estimates.

Table 1.3 shows that all relative index volatilities are quite low, varying in the

1–7% range, with most volatilities lying at the low end of this interval. This is another indication that the sustainable funds generally track the Core fund closely. If the returns of two indexes were always identical, their relative index volatility would be zero. The lowest relative index volatilities are observed when using the lightly ESG Screened index fund values as the deflators, whereas the highest are observed when using the SRI indexes as deflators. This aligns with the correlation estimates in Table 1.2. Not surprisingly, these results imply that the estimated price of insurance against the event that a sustainable index underperforms a core index increases with the level of sustainability. Recall that the insurance premium is established as the value of a 1-year option to exchange the core index for the sustainable index. Some variation in the insurance premia/option values across geographical regions is also observed. Note, for example, that the lowest insurance premium of 42 bps of the invested capital relates to insuring the World ESG Screened index fund against underperforming the World Core index fund. This reflects the fact that these two indexes move very closely together (see Figure 1). Despite being relatively low, 42 bps must still be considered a significant premium for ensuring that the lightly ESG screened World index fund investment does not underperform the Core fund on a 1-year horizon.

At the other end of the sustainability spectrum, we see that it is generally more expensive to insure the SRI index funds against underperformance relative to the corresponding core funds. The lowest of these annual premia, 137 bps, is estimated for the World region. For the Emerging Markets region at the bottom of the table, the insurance premium peaks at 272 bps.

Table 1.3: Relative Index Volatilities and 1-year Exchange Option Values

Estimates based on 90 daily returns prior to December 1, 2020.

Region Fund type	$\bar{\sigma}$-estimate (std. error)	Option value, π (95% conf. int.)
World		
ESG Screened	1.05% (0.08%)	42 bps [36 bps;48 bps]
ESG Enhanced	1.21% (0.09%)	48 bps [41 bps;55 bps]
SRI	3.44% (0.26%)	137 bps [117 bps;158 bps]
USA		
ESG Screened	1.14% (0.08%)	45 bps [39 bps;52 bps]
ESG Enhanced	2.05% (0.15%)	82 bps [70 bps;94 bps]
SRI	4.19% (0.31%)	167 bps [143 bps;192 bps]
Europe		
ESG Screened	1.76% (0.13%)	70 bps [60 bps;80 bps]
ESG Enhanced	2.84% (0.21%)	113 bps [97 bps;130 bps]
SRI	3.77% (0.28%)	151 bps [129 bps;173 bps]
EMU		
ESG Screened	2.12% (0.16%)	85 bps [72 bps;97 bps]
ESG Enhanced	2.60% (0.19%)	104 bps [89 bps;119 bps]
SRI	4.16% (0.31%)	166 bps [142 bps;190 bps]
Japan		
ESG Screened	1.40% (0.10%)	56 bps [48 bps;64 bps]
ESG Enhanced	1.97% (0.15%)	79 bps [67 bps;90 bps]
SRI	4.59% (0.34%)	183 bps [156 bps;210 bps]
Emerging Markets		
ESG Screened (EM IMI)	1.95% (0.15%)	78 bps [66 bps;89 bps]
ESG Enhanced (EM)	3.38% (0.25%)	135 bps [115 bps;154 bps]
SRI (EM)	6.82% (0.51%)	272 bps [232 bps;312 bps]

1.5 Conclusion

When investors deviate from holding the market portfolio in any given market, they become active investors (Sharpe, 1991). *Ex post* the decision to become an active investor may, of course, be good or bad, but *ex-ante*, it introduces underperformance risk relative to the market index – a risk that increases as investors distance themselves from the broad market portfolio. Even though this insight is not new, prospective investors in ESG screened index funds should keep it in mind. This is important because sustainable and ESG screened index investment products are narrowing down the investment universe by excluding shares in companies with problematic business models in some more precisely defined sense. Investors in passive ESG screened index funds are thus in effect active investors.

In this paper, we have developed a simple way to quantify the underperformance risk of sustainable and ESG screened investment products relative to the unrestricted market portfolio investments. The risk measure that we propose basically expresses the fair price of insuring against the underperformance of a given sustainable index relative to a broad and unrestricted market index. We show that this insurance premium can be determined as the price of an *option to exchange one asset for another*, and we provide a simple formula that expresses the annual premium as a fraction of initial invested capital. Evaluating the formula requires only that a single parameter – a *relative index volatility* – is estimated. Finally, using ETF data from BlackRock's iShares universe, we estimate that for a range of highly popular and liquid sustainable index funds, the cost of insurance against underperformance ranges from approximately 50 to 300 basis points on an annual basis, depending on the geographical region and level of sustainability of the index.

Acknowledgements

For helpful comments and suggestions, we thank three anonymous referees, conference participants at the 2022 Netspar International Pension Workshop, and the seminar participants at the Finance internal seminar held by the Department of Economics and Business Economics, Aarhus University.

1.6 References

Amenc, N., Goltz, F., Liu, V., 2021. Doing good or feeling good? Detecting greenwashing in climate investing. August 2021, EDHEC Business School.

Anadu, K., Kruttli, M., McCabe, P., Osambela, E., 2020. The shift from active to passive investing: Potential risks to financial stability. *Financial Analysts Journal* 76 (4), 23–29.

Berk, J. B., van Binsbergen, J. H., 2021. The impact of impact investing. George Mason University Law and Economics Research Paper Series, 21-26, (available at http://ssrn.com/abstract=3909166).

Berle, E. C., He, W., Ødegaard, B. A., 2022. The expected returns of ESG excluded stocks. The case of exclusions from Norway's oil fund. working paper, (available at https://ssrn.com/abstract=4095395).

Bhattacharya, U., Galpin, N., 2011. The Global Rise of the Value-weighted Portfolio. *Journal of Financial and Quantitative Analysis* 46 (3), 737–756.

BIS, 2021. International Banking and Financial Market Developments. *BIS Quarterly Review September 2021*, Bank for International Settlements.

Bjőrk, T., 2009. Arbitrage Theory in Continuous Time, 3rd Edition. Oxford University Press.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of political economy* 81 (3), 637–654.

Capelle-Blancard, G., Monjon, S., 2014. The performance of socially responsible funds: Does the screening process matter? *European Financial Management* 20 (3), 494–520.

Coqueret, G., 2021. Perspectives in ESG equity investing. working paper, EMLYON Business School, (available at https://ssrn.com/abstract=3715753).

Flammer, C., 2015. Does Corporate Social Responsibility lead to superior financial performance? A regression discontinuity approach. *Management Science* 61 (11), 2549–2568.

Fletcher, L., Oliver, J., 2022. Green investing: The risk of a new mis-selling scandal, Financial Times, February 20, 2022.

French, K. R., 2008. Presidential Address: The Cost of Active Investing. *Journal of Finance* LXIII (4), 1537–1573.

Friede, G., Busch, T., Bassen, A., 2015. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance and Investment* 5 (4), 210–233.

Geczy, C., Guerard, J., Samonov, M., 2019. Efficient SRI/ESG portfolios. working paper, (available at https://ssrn.com/abstract=3011644).

Geczy, C., Stambaugh, R. F., Levin, D., 2005. Investing in Socially Responsible Mutual Funds. Wharton School, working paper, (available at http://ssrn.com/abstract=416380).

Geman, H., El-Karoui, N., Rochet, J.-C., 1995. Changes of Numeraire, Changes of Probability Measure and Option Pricing. *Journal of Applied Probability* 32, 443–458.

Hűbel, B., Scholz, H., 2020. Integrating sustainability risks in asset management. Journal of Asset Management 21 (1), 52–69.

Hoepner, A., Schopohl, L., 2018. On the price of morals in markets: An empirical study of the Swedish AP-funds and the Norwegian Government Pension Fund. *Journal of Business Ethics* 151 (3), 665–692.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. *Journal of Financial Economics* 93 (9), 15–36.

Hornuf, L., Yÿksel, G., 2022. The performance of socially responsible investments: A meta-analysis. working paper, CESifo WP No. 9724, (available at https://ssrn.com/abstract=4097850).

Hull, J. C., 2018. Options, Futures, and other Derivatives, 9th Edition. Pearson.

Humphrey, J. E., Lee, D. D., 2011. Australian socially responsible funds: Performance, risk and screening intensity. *Journal of Business Ethics* 102 (4), 519–535.

Humphrey, J. E., Tan, D. T., 2014. Does it really hurt to be responsible? *Journal of Business Ethics* 122 (3), 375–386.

iShares, 2020. iShares Sustainable Range. Slideset dated October 2020, iShares by BlackRock.

Khajenouri, D., Schmidt, J., 2021. Standard or Sustainable - Which offers better performance for the passive investor? *Journal of Applied Finance and Banking* 11 (1), 61–71.

Lee, D. D., Humphrey, J. E., Benson, K. L., Ahn, J. Y., 2010. Socially responsible investment fund performance: The impact of screening intensity. *Accounting and Finance* 10 (2), 351–370.

Luo, A., Balvers, R., 2017. Social screens and systemic investor boycott risk. *Journal of Financial and Quantitative Analysis* 52 (1), 365–399.

Margrabe, W., Mar. 1978. The Value of an Option to Exchange One Asset for Another. *Journal of Finance* XXXIII (1), 177–186.

Matallin-Saez, J. C., Soler-Dominguez, A., Navarro-Montoliu, S., de Mingo-Lopez, D. V., 2021. Investor behavior and the demand for conventional and socially responsible mutual funds. *Corporate Social Responsibility and Environmental Management* 29 (1), 46–59.

Milonas, N., Rompotis, G., Moutzouris, C., 2022. The performance of ESG funds vis-a-vis Non-ESG funds. *Journal of Impact and ESG Investing* 2 (4), 96–115.

Morningstar, 2019. Morningstar U.S. Fund Flows: Fed Rate Cut Doesn't Spur Inflows, Morningstar Research, August 2019.

Morningstar, 2021. U.S. Fund Flows smashed records in 2021, Morningstar web article (available at https://www.morningstar.com/articles/1075161/us-fund-flows-smashed-records-in-2021).

Morningstar, 2022a. Global Sustainable Fund Flows: Q1 2022 in Review, Morningstar Manager Research.

Morningstar, 2022b. Sustainable funds landscape – Highlights and observations, Morningstar web article (available at https://www.morningstar.com/articles/1080300/sustainable-funds-landscape-highlights-and-observations).

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

Pedersen, L. H., Fitzgibbons, S., Pomorski, L., 2021. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics* 142 (2), 572–597.

Renneboog, L., Horst, J. T., Zhang, C., 2008. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. *Journal of Corporate Finance* 14 (3), 302–322.

Renneboog, L., Horst, J. T., Zhang, C., 2011. Is ethical money financially smart? Non-financial attributes and money flows of socially responsible investment funds. Journal of Financial Intermediation 20 (4), 562–588.

Sharma, G. D., Talan, G., Bansal, S., Jain, M., 2021. Is there a cost for sustainable investments: Evidence from dynamic conditional correlation. *Journal of Sustainable Finance and Investment*.

Sharpe, W. F., 1991. The arithmetic of active management. *Financial Analysts Journal* 47 (1), 7–9.

Sushko, V., Turner, G., 2018. The implications of passive investing for securities markets. *BIS Quarterly Review* , March, 113–131.

The UN Global Compact, 2004. Who cares wins: Connecting financial markets to a changing world. Report, United Nations.

Appendix

A.1 Proof Of The Margrabe (1978) Formula

An easy proof of the Margrabe (1978) formula is obtained via the Equivalent Martingale Measure (EMM) theorem (see, e.g., Geman et al., 1995; Bjőrk, 2009) and by using one of the traded and non-dividend paying indexes, say I_S, as the *numeraire* (or deflator) asset.

Consider the process $f(\cdot) = \frac{I_C}{I_S}$ and the stochastic differential equation that describes its dynamics which follows from Ito's lemma (using familiar short-hand notation):

$$\begin{aligned} df &= \frac{\partial f}{\partial I_C} dI_C + \frac{1}{2}\frac{\partial^2 f}{\partial I_C^2}(dI_C)^2 + \frac{\partial f}{\partial I_S} dI_S + \frac{1}{2}\frac{\partial^2 f}{\partial I_S^2}(dI_S)^2 + \frac{\partial^2 f}{\partial I_C \partial I_S} \\ &= \frac{1}{I_S} dI_C + 0 - \frac{I_C}{I_S^2} dI_S + \frac{1}{2}\big(2\frac{I_C}{I_S^3}\big)(dI_S)^2 - \frac{1}{I_S^2} dI_C dI_S \\ &= \frac{I_C}{I_S}\left(\frac{dI_C}{I_C} - \frac{dI_S}{I_S} + (\frac{dI_S}{I_S})^2 - \frac{dI_C}{I_C}\frac{dI_S}{I_S}\right) \\ &= f\Big(\mu_C\, dt + \sigma_C\, dW_C - \mu_S\, dt - \sigma_S\, dW_S + \sigma_S^2\, dt - \sigma_C\sigma_S\rho\, dt\Big) \\ &= f\Big(\big(\mu_C - \mu_S + \sigma_S^2 - \sigma_C\sigma_S\rho\big)\, dt + \sigma_C\, dW_C - \sigma_S\, dW_S\Big) \\ &= f\Big(\big(\mu_C - \mu_S + \sigma_S^2 - \sigma_C\sigma_S\rho\big)\, dt + \bar{\sigma}\, d\bar{W}\Big), \end{aligned} \tag{A.1}$$

where in the last line we make use of the fact that $\sigma_C\, dW_C - \sigma_S\, dW_S$ can be represented as $\bar{\sigma}\, d\bar{W}$, where $\bar{W}(t)$ is a standard Wiener process and where $\bar{\sigma}^2 = \sigma_C^2 + \sigma_S^2 - 2\sigma_C\sigma_S\rho$.

According to the EMM theorem, there exists an equivalent probability measure, say Q', such that all asset prices deflated by I_S are Q'-martingales. In particular, this means that

$$\frac{df}{f} = \sigma_C\, dW_C^{Q'} - \sigma_S\, dW_S^{Q'} \equiv \bar{\sigma}\, d\bar{W}^{Q'}, \tag{A.2}$$

and that

$$\frac{c(0)}{I_S(0)} = E_0^{Q'}\left\{\frac{\big[I_C(T) - I_S(T)\big]^+}{I_S(T)}\right\} = E_0^{Q'}\left\{\big[f(T) - 1\big]^+\right\}, \tag{A.3}$$

where $E_0^{Q'}\{\cdot\}$ denotes expectation formed under the Q'-measure conditional on time 0 information. It follows from (A.2) that $f(T)$ is lognormally distributed, and the expectation on the right-hand side of (A.3) is thus easily established:

$$
\begin{aligned}
E_0^{Q'}\left\{\left[f(T)-1\right]^+\right\} &= E_0^{Q'}\left\{\left[f_0\cdot e^{-\frac{1}{2}\bar{\sigma}^2T+\bar{\sigma}\bar{W}^{Q'}(T)}-1\right]^+\right\} \\
&= \int_d^{\infty}\left(f_0\cdot e^{-\frac{1}{2}\bar{\sigma}^2T+\bar{\sigma}\sqrt{T}\cdot u}-1\right)n(u)\,du \\
&= \dots \\
&= f_0\left(N\big(-d+\bar{\sigma}\sqrt{T}\big)\right)-N\big(-d\big)
\end{aligned}
\tag{A.4}
$$

where

$$d=\frac{-\ln f_0+\frac{1}{2}\bar{\sigma}^2T}{\bar{\sigma}\sqrt{T}}.$$

Therefore

$$c(0)=I_C(0)N\big(d_+\big)-I_S(0)N\big(d_-\big) \tag{A.5}$$

where

$$d_{\pm}=\frac{\ln\frac{I_C(0)}{I_S(0)}\pm\frac{1}{2}\bar{\sigma}^2T}{\bar{\sigma}\sqrt{T}}. \tag{A.6}$$

A.2 Fund Details - Data as of Dec. 1, 2020

Table A.1: Descriptics on iShares World MSCI funds

Name of Fund	iShares Core MSCI World UCITS ETF	iShares MSCI World ESG Screened UCITS ETF	iShares MSCI World ESG Enhanced UCITS ETF	iShares MSCI World SRI UCITS ETF
BlackRock Ticker	SWDA	SAWD	EDMW	SUSW
Bloomberg Ticker	EUNL GY	SNAW GY	EDMW GY	SUSW LN
ISIN	IE00B4L5Y983	IE00BFNM3J75	IE00BHZPJ569	IE00BYX2JD69
Currency	EUR	EUR	EUR	EUR
Constituents	1,596	1,494	1,372	366
Benchmark	MSCI World Index	MSCI World ESG Screened Index	MSCI World ESG Enhanced Focus Index (NET)	MSCI World SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	1,583	1,493	1,480	358
Parent Index		MSCI World Index (SM)	MSCI World Index (SM)	MSCI World Index (SM)
Parent Constituents		1,583	1,583	1,583
Stock Exchange	Xetra	Xetra	Xetra	London
Net Assets	$ 27,351,255,723	$ 677,667,400	$ 226,292,191	$ 1,788,692,186
Inception Date	25th September 2009	19th October 2018	16th April 2019	12th October 2017
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.20%	0.20%	0.20%	0.20%

Table A.2: Descriptics on iShares USA MSCI funds

Name of Fund	iShares MSCI USA UCITS ETF	iShares MSCI USA ESG Screened UCITS ETF	iShares MSCI USA ESG Enhanced UCITS ETF	iShares MSCI USA SRI UCITS ETF
BlackRock Ticker	CSUS	SASU	EDMU	SUAS
Bloomberg Ticker	SXR4 GY	SGAS GY	EDMU GY	QDVR GY
ISIN	IE00B52SFT06	IE00BFNM3G45	IE00BHZPJ908	IE00BYVJRR92
Currency	EUR	EUR	EUR	EUR
Constituents	621	582	580	127
Benchmark	MSCI USA Index	MSCI USA ESG Screened Index	MSCI USA ESG Enhanced Focus Index (NET)	MSCI USA SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	620	581	573	126
Parent Index		MSCI USA Index	MSCI USA Index	MSCI USA Index
Parent Constituents		620	620	620
Stock Exchange	Xetra	Xetra	Xetra	Xetra
Net Assets	$ 749,863,958	$ 1,505,943,820	$ 823,174,784	$ 4,511,220,208
Inception Date	12th January 2010	19th October 2018	16th April 2019	11th July 2016
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.33%	0.07%	0.07%	0.20%

Table A.3: Descriptics on iShares Europe MSCI funds

Name of Fund	iShares Core MSCI Europe UCITS ETF EUR (Acc)	iShares MSCI Europe ESG Screened UCITS ETF	iShares MSCI Europe ESG Enhanced UCITS ETF	iShares MSCI Europe SRI UCITS ETF
BlackRock Ticker	SMEA	SAEU	EDM6	IESE
Bloomberg Ticker	EUNK GY	SLMC GY	EDM6 GY	IUSK GY
ISIN	IE00B4K48X80	IE00BFNM3D14	IE00BHZPJ783	IE00B52VJ196
Currency	EUR	EUR	EUR	EUR
Constituents	439	417	416	110
Benchmark	MSCI Europe Index	MSCI Europe ESG Screened Index	MSCI Europe ESG Enhanced Focus Index (NET)	MSCI Europe SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	432	411	409	106
Parent Index		MSCI Europe Index	MSCI Europe Index	MSCI Europe Index
Parent Constituents		432	432	432
Stock Exchange	Xetra	Xetra	Xetra	Xetra
Net Assets	€3,197,871,094	€519,486,706	€117,678,460	€2,336,347,752
Inception Date	6th July 2007	19th October 2018	16th April 2019	25th February 2011
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.12%	0.12%	0.12%	0.20%

Table A.4: Descriptics on iShares EMU MSCI funds

Name of Fund	iShares Core MSCI EMU UCITS ETF	iShares MSCI EMU ESG Screened UCITS ETF	iShares MSCI EMU ESG Enhanced UCITS ETF	iShares MSCI EMU SRI UCITS ETF
BlackRock Ticker	CSEMU	SAUM	EDM4	SMUA
Bloomberg Ticker	SXR7 GY	SLMA GY	EDM4 GY	SMUA NA
ISIN	IE00B53QG562	IE00BFNM3B99	IE00BHZPJ015	IE00BJLKK341
Currency	EUR	EUR	EUR	EUR
Constituents	243	231	230	49
Benchmark	MSCI EMU Index	MSCI EMU ESG Screened Index	MSCI EMU ESG Enhanced Focus Index (NET)	MSCI EMU SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	237	226	224	48
Parent Index		MSCI EMU Index	MSCI EMU Index	MSCI EMU Index
Parent Constituents		237	237	237
Stock Exchange	Xetra	Xetra	Xetra	Euronext Amsterdam
Net Assets	€1,861,565,107	€1,026,815,206	€112,630,819	€5,057,872
Inception Date	12th January 2010	19th October 2018	16th April 2019	3th March 2020
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.12%	0.12%	0.12%	0.20%

Table A.5: Descriptics on iShares Japan MSCI funds

Name of Fund	iShares Core MSCI Japan IMI UCITS ETF	iShares MSCI Japan ESG Screened UCITS ETF	iShares MSCI Japan ESG Enhanced UCITS ETF	iShares MSCI Japan SRI UCITS ETF
BlackRock Ticker	SJPA	SAJP	EDMJ	SUJP
Bloomberg Ticker	EUNN GY	SGAJ GY	EDMJ GY	SXR6 GY
ISIN	IE00B4L5YX21	IE00BFNM3L97	IE00BHZPJ452	IE00BYX8XC17
Currency	EUR	EUR	EUR	EUR
Constituents	1,266	292	292	63
Benchmark	MSCI Japan Investable Market Index (IMI)	MSCI Japan ESG Screened Index	MSCI Japan ESG Enhanced Focus Index (NET)	MSCI Japan SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	1,280	292	292	63
Parent Index		MSCI Japan Index	MSCI Japan Index	MSCI Japan Index
Parent Constituents		301	301	301
Stock Exchange	Xetra	Xetra	Xetra	Xetra
Net Assets	$ 3,687,173,526	$ 198,714,490	$ 120,177,584	$ 399,735,988
Inception Date	25th September 2009	19th October 2018	16th April 2019	6th March 2017
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.15%	0.15%	0.15%	0.20%

Table A.6: Descriptics on iShares EM MSCI funds

Name of Fund	iShares Core MSCI EM IMI UCITS ETF	iShares MSCI EM IMI ESG Screened UCITS ETF	iShares MSCI EM ESG Enhanced UCITS ETF	iShares MSCI EM SRI UCITS ETF
BlackRock Ticker	EIMI	SAEM	EDM2	SUSM
Bloomberg Ticker	IS3N GY	AYEM GY	EDM2 GY	QDVS GY
ISIN	IE00BKM4GZ66	IE00BFNM3P36	IE00BHZPJ239	IE00BYVJRP78
Currency	EUR	EUR	EUR	EUR
Constituents	2,818	1,767	968	186
Benchmark	MSCI EM Investable Market Index (IMI)	MSCI EM IMI ESG Screened Index	MSCI EM ESG Enhanced Focus Index (NET)	MSCI EM SRI Select Reduced Fossil Fuel Index
Benchmark Constituents	3,073	2,957	1,251	178
Parent Index		MSCI EM Index (IMI)	MSCI EM Index	MSCI EM Index
Parent Constituents		3,073	1,381	1,381
Stock Exchange	Xetra	Xetra	Xetra	Xetra
Net Assets	$ 16,264,271,006	$ 921,490,865	$ 337,259,431	$ 1,345,911,723
Inception Date	30th May 2014	19th October 2018	22th October 2019	11th July 2016
Domicile	Ireland	Ireland	Ireland	Ireland
Total Expense Ratio	0.18%	0.18%	0.18%	0.25%

A.3 Full Correlation Matrices

Table A.7: Correlation Matrices For All Regions and Funds Over Estimation Period (90-days Prior To December 1, 2020.)

iShares MSCI World funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.998	1		
Enhanced	0.997	0.996	1	
SRI	0.978	0.979	0.980	1
iShares MSCI USA funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.998	1		
Enhanced	0.993	0.992	1	
SRI	0.973	0.973	0.970	1
iShares MSCI Europe funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.995	1		
Enhanced	0.988	0.986	1	
SRI	0.978	0.981	0.969	1
iShares MSCI EMU funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.994	1		
Enhanced	0.991	0.990	1	
SRI	0.980	0.978	0.977	1
iShares MSCI Japan funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.995	1		
Enhanced	0.991	0.995	1	
SRI	0.955	0.963	0.963	1
iShares MSCI EM funds				
	Core	Screened	Enhanced	SRI
Core	1			
Screened	0.992	1		
Enhanced	0.978	0.980	1	
SRI	0.919	0.922	0.914	1

CHAPTER 2

SYSTEMATIC LONGEVITY RISK: THE WILLINGNESS TO PAY

Anne G. Balter
Tilburg University and Netspar
Malene Kallestrup-Lamb
Aarhus University and PeRCent
Mathias Danielsen Plovst
Aarhus University

Abstract

Increasing life expectancy has led to a global transition in pension systems towards more variable products in which risk is explicitly borne by the participants, necessitating a thorough understanding of longevity risk. This risk is explicitly transferred to policyholders contrasting with earlier implied hedges. Our goal is to quantify longevity risk through its impact on welfare, i.e., the willingness to pay. Longevity risk can be categorized into idiosyncratic and systematic, with the latter representing changes in life tables being the focus of our study. The risk is determined as life expectancy changes over time beyond the already incorporated projected increase. Addressing the gap in quantifying systematic longevity risk, we introduce a multiple-horizon approach to calculate the realized "unexpected" deviations in best estimated survival rates due to the arrival of new observations in the mortality model. Our findings unveil that the willingness to pay to avoid the systematic longevity risk, i.e., the risk premium required to bear this risk, is substantial. We conduct extensive sensitivity analyses, exploring cross-country variations, different stochastic longevity models, and gender differentials, amongst others, contributing novel insights to the literature on the size of systematic longevity risk.

2.1 Introduction

Pension systems worldwide are struggling with unexpected improvements in life expectancy, persistently low interest rates, and stricter capital requirements. These factors significantly impact pension fund liabilities and have prompted a worldwide transition towards annuity products in which pension holders explicitly bear both longevity and financial risks (Brown, 2016; Balter et al., 2021). This transition from Defined Benefit (DB)-type of pension schemes to Defined Contribution (DC)-type of pension schemes marks a significant shift in retirement planning and risk management. While many pension holders are aware of the financial risk, they remain largely unaware of the shift in longevity risk and its implications. This lack of awareness is further exacerbated by the consistent underestimation of improvements in life expectancies by both academics and industry experts (Oeppen and Vaupel, 2002; Pascariu et al., 2018). When realized longevity rates deviate from expected levels or when expectations change over time, longevity carries the risk that pension funds offering traditional annuity products will be unable to meet their financial obligations, as these funds guarantee individuals a lifelong income stream independently of how long they live. This systematic longevity risk that captures the uncertainty of the entire pool of individuals living longer than expected cannot be mitigated by pooling enough individuals (Hari et al., 2008).[1]

While there is a well-established framework for measuring financial risk, there is no consensus in the literature on how to quantify systematic longevity risk in life annuity products. Richards et al. (2014) propose a Value-at-Risk framework to ensure that unfavorable developments in longevity over a one-year horizon are manageable. De Waegenaere et al. (2017) incorporate parameter risk by re-estimating best estimates based on one-year forecasts of the Lee and Carter (1992) (LC) model and find that the impact on the value of pension annuities to be different between young and old cohorts. Broeders et al. (2021) disentangle systematic longevity risk into two components: stochastic variation, which refers to the randomness embedded in the stochastic mortality model, and parameter risk, which involves the risk of re-estimation after observing stochastic variation. They focus on a 10-year horizon and demonstrate the advantages of risk sharing among different age groups due to differences in how cohorts are affected. Dees et al. (2021) look at quantiles within the LC-model and argue that the longevity risk due to stochastic variation is negligible compared to financial risk. Maurer et al. (2013) and Boon et al. (2020) also consider stochastic variation as the main source of systematic longevity risk, which they refer to as deviations from the expected biometric return and which they simulate from the fitted stochastic mortality model. Piggott et al. (2005) and Qiao and Sherris (2013)

[1] Idiosyncratic longevity risk, which captures the uncertainty of an individual's lifespan, can be diversified by pooling a large number of individuals. The rationale is that while some individuals will live longer and others shorter than expected, these variations will, on average, offset each other, enabling the pension fund to manage and diversify this risk effectively.

consider both random deviations from the expected mortality forecasts and permanent shocks to the underlying mortality. For illustrative purposes of the permanent shock, Piggott et al. (2005) hypothetically assume the lifetable for Australian men in 2000 to be updated by those for females, whereas Qiao and Sherris (2013) simulate from the mortality model estimated at the current time in order to investigate risk sharing across cohorts. Hence, the majority of the literature tends to focus on stochastic variation within a mortality model on a one-year horizon, which we refer to as trend risk. However, doing so neglects the fact that longevity risk lies in the long-term trend.

This paper proposes to capture systematic longevity risk by calculating deviations in best-estimate survival probability forecasts that arise from updating these forecasts based on new observations incorporated into the mortality model. We quantify systematic longevity risk in a multiple horizon setting based on shocking the current best estimates with a set of plausible deviations without relying on the current mortality model. Hence, we do not sample from the stochastic model fitted to the current time but rather allow for unanticipated deviations not predicted by the model. Since we interpret systematic longevity risk as the change in life tables causing best-estimate survival probabilities to deviate from previous expectations, we propose considering historic deviations between consecutive forecasts as plausible deviations for future scenarios. We focus solely on systematic longevity risk while disregarding financial risk and assuming the idiosyncratic longevity risk to be fully diversified.[2] To evaluate the size of the deviation risk between the survival probability forecasts, we draw data from the Human Mortality Database (Human Mortality Database, 2024), to which we apply the Lee and Carter (1992) model. We analyze data from the United Kingdom as a representative country that has undergone a transition from traditional DB to DC pension schemes (ONS, 2019). Next, we derive the perceived value depending on agents' risk aversion by evaluating welfare in retirement. For this, we introduce a utility framework that allows us to quantify the willingness to pay, i.e., the certainty equivalent, risk premium, and relative risk premium for horizons longer than, e.g., one year. This is especially important as we show that the value of systematic longevity risk increases with the horizon.

We examine two distinct pension products that differ in terms of systematic longevity risk. The first product is a *defined benefit (DB)*-type annuity that offers a fixed payment on a regular basis until the death of the individual. Within the fund, idiosyncratic longevity risk is diversified away, allowing for a biometric return, while the pension provider bears the systematic longevity risk. If the population is expected to live longer than anticipated, the payments will thus not be decreased and vice versa. As a result, the DB-type annuity has a built-in longevity hedge for the agent's exposure to longevity risk. The second product is a *defined contribution (DC)*-type

[2] We use interchangeably longevity risk as a synonym for systematic longevity risk, also known as macro longevity risk.

annuity that offers variable payments on an annual basis until the death of the agent. The yearly return is not known at retirement, as it consists of the financial and the biometric returns, with the latter being sensitive to systematic longevity risk. Thus, if the life expectancies change over time, the potential decrease (or increase) in pension payments is to be incurred by the agent. The DC type of product in which the annuitants bear the systematic risk, but the pool shares idiosyncratic risk, is similar to what is known as group self-annuitization (GSA) (see, e.g., Piggott et al., 2005; Qiao and Sherris, 2013; Boon et al., 2020). Optimal demand for different types of products that hedge systematic longevity risk is investigated by Cocco and Gomes (2012) in the context of longevity bonds and by Stevens (2009) in the context of deferred annuities.

We find that agents require compensation when they have to choose between two products at retirement: a DB-type product without longevity risk and a DC-type product with longevity risk. We show that the value of longevity risk is dependent on both the horizon and risk aversion considered by the agent. Interestingly, the required compensation for agents taking on systematic longevity risk increases in both dimensions, reflecting that the welfare of agents in retirement could be significantly affected by their exposure to longevity risk if they are not compensated accordingly. Thus, future pension income is uncertain not only due to financial risk but also because of the significant uncertainty generated by longevity risk. We show that agents require a risk premium ranging from 5% to 10% on a horizon of 15 years into retirement relative to their pension income without longevity risk. In the time dimension, we see that risk premia increase from 0% to 10% for a relative risk aversion level of $\gamma = 5$ relative to the income conditional of the life tables available at retirement. Furthermore, we show that our approach leads to negligible values for agents' willingness to pay for insurance against systematic longevity risk in annuity products on a one-year horizon. However, we find that risk premiums are substantial when updates to the best estimates occur more frequently over multiple time horizons.

To ensure the validity of our findings, we consider several robustness checks. First, we consider the robustness of our results by changing the country from the United Kingdom to one of the following: Denmark, USA, and Australia. Most interestingly, we find that different populations have experienced relatively similar unexpected longevity shocks. However, the accumulated effect of these deviations results in vastly dissimilar risk premia. In particular, we find that risk premia in the USA are of opposite sign as in the UK, reflecting that the expected trend has been overestimated. Second, we investigate the sensitivity of the risk premia for different cohorts, retirement ages, maximum ages, genders, fitting periods, and frequency of the updates. We demonstrate that when the underlying population is limited to males, the compensation for systematic longevity risk becomes larger compared to that for females. Third, we show how our findings relate to trend risk investigated in the longevity literature and further discuss the comparison of financial risk and model risk with longevity risk. We find that the willingness to pay for financial risk typically has the opposite sign than for longevity risk. From the portfolio choice literature, we know it is welfare enhancing to invest in risky assets to benefit from the risk-return trade-off, which is absent in the context of longevity risk for most countries. This implies a willingness to pay to face this risk (negative risk premium), as agents derive higher welfare from bearing financial risk due to the positive return premium associated with risky assets.

The remainder of the paper is organized as follows. In Section 2.2, we describe the model framework. Section 2.3 introduces data and estimated parameters. Section 2.4 provides the main results, and Section 2.5 provides the sensitivity analysis. Section 2.6 concludes.

2.2 Model

2.2.1 Annuity and Risk Premium

We differentiate between two types of pension products that differ in terms of systematic longevity risk. As such, these two products coincide with the decumulation phase of DB- and DC-type pension schemes, respectively. In specific, the variability of the latter is assumed to be solely driven by longevity risk in this context. To value welfare implications due to the presence of longevity risk in pension products, we decide to refrain from modeling financial risk. In the sensitivity analysis, we model financial risk and assess the size relative to longevity risk.

To measure the welfare implications driven by longevity risk, we first calculate the expected utility from the two products separately. Secondly, we calculate the certainty equivalents and define the risk premium as the value required for the agent to be indifferent. The agent evaluates the offered products by calculating the expected utility of benefits based on the remaining life expectancy as

$$\mathbb{E}_t\left[u\big(W_{t+h}(t+h)\big)\right], \tag{2.1}$$

where $W_{t+h}(t+h) > 0$ is the pension payment valued and received at time $t+h$. We denote the pension payments from the DB- and DC-type products by $W^{DB}_{t+h}(t+h)$ and $W^{DC}_{t+h}(t+h)$, respectively. The agents' certainty equivalent (CE) is defined by

$$CE_{t+h} = u^{-1}\left(\mathbb{E}_t\left[u\big(W_{t+h}(t+h)\big)\right]\right), \tag{2.2}$$

which is the certain value that makes the agent indifferent to receiving the pension payment $W_{t+h}(t+h)$. Hence, for the DB-type product, this simply reduces to the fixed payment itself since $u^{-1}\left(u\left(W^{DB}_{t+h}(t+h)\right)\right) = W^{DB}_{t+h}(t+h)$. For the DC-type product, it is the monetary value that makes the agent indifferent between receiving $CE_{t+h} = u^{-1}\left(\mathbb{E}_t\left[u\left(W^{DC}_{t+h}(t+h)\right)\right]\right)$ and variable payment, $W^{DC}_{t+h}(t+h)$, sensitive to longevity risk.

For the risk premium, we need to calculate the agents' willingness to pay to avoid, or to bear the systematic longevity risk. Equivalently, the risk premium Π_{t+h} is defined as the value by which the fixed DB payment can be lowered such that the agent is indifferent with the variable DC payment given by

$$\mathbb{E}_t\left[u\left(W_{t+h}^{DC}(t+h)\right)\right] = u\left(W_{t+h}^{DB}(t+h) - \Pi_{t+h}\right), \tag{2.3}$$

which implies

$$\Pi_{t+h} = W_{t+h}^{DB}(t+h) - u^{-1}\left(\mathbb{E}_t\left[u\left(W_{t+h}^{DC}(t+h)\right)\right]\right) = W_{t+h}^{DB}(t+h) - CE_{t+h}, \tag{2.4}$$

where Π_{t+h} is the risk premium at time $t+h$. Equation (2.4) explicitly states the one-to-one relation between the risk premium and certainty equivalent (Pratt, 1964). As the risk premium is in monetary units, its size relative to the payment without longevity risk is typically more informative. Therefore, we introduce the *relative risk premium* (RRP)

$$\pi_{t+h} = \frac{\Pi_{t+h}}{W_{t+h}^{DB}(t+h)}, \tag{2.5}$$

which can be interpreted as a measure of welfare loss.

We assume that agents' preferences over wealth in retirement are described by power (CRRA) utility, given by

$$u(x) = \begin{cases} \frac{x^{1-\gamma}}{1-\gamma} & \text{if } \gamma > 0, \gamma \neq 1 \\ \ln(x) & \text{if } \gamma = 1, \end{cases} \tag{2.6}$$

where γ is the relative risk aversion level. The application of power utility in evaluating annuity products is well-established (see, e.g., Boon et al. (2020); Stevens et al. (2010)). Theoretically, its mathematical properties allow for closed form solutions, making it particularly suitable for our analysis on quantifying longevity risk.

For the annuitization, we follow Balter and Werker (2020) by allocating wealth to *buckets* or *pension pots*, where each bucket serves as a reservation for a pension payment at a specific point in time. Formally, assume the agent enters retirement in year t with a total pension wealth of W_t. Let $W_t(t+h)$ be the pension wealth at time t reserved for the payment in year $t+h$. Thus, the budget constraint on the division of total wealth over the retirement horizon is defined as

$$W_t = \sum_{h=0}^{\infty} W_t(t+h). \tag{2.7}$$

We assume that after age x_{max}, the survival probabilities are zero. This implies that the sum effectively consists of the number of years between the retirement age and the maximum attainable age, thus $h = \{0, 1, ..., H\}$ where $H = x_{max} - x_R$ with x_R being the (retirement) age at time t. At time t, the x-aged agent is expected to have a remaining life expectancy of $LE_{x,t}$. On average, without longevity risk, this cohort survives until the expected lifetime. However, the individual may as well survive until, in the limit, the maximum attainable age x_{max}, whereafter he dies.

The assumed interest rate (AIR), $a_t(t+h)$, determines the division of total wealth across buckets and is given by

$$\frac{W_t(t+h)}{W_t} = e^{-ha_t(t+h)}, \tag{2.8}$$

which jointly with the budget constraint (2.7), implies

$$\frac{W_t(t+h)}{W_t} = \frac{W_t(t+h)}{\sum_{k=t}^{\infty} W_t(t+k)}$$

and thus

$$W_t(t+h) = W_t \frac{e^{-ha_t(t+h)}}{\sum_{k=t}^{\infty} e^{-ka_t(t+k)}}. \tag{2.9}$$

Equation (2.9) determines the fraction of total wealth to be allocated to the wealth bucket reserved for time $t+h$ valued at time t. Thus, the choice variable on how to allocate total wealth into buckets, i.e., how much to reserve for each pension payment, is captured by the AIR. We set the AIR such that pension payments are expected to be constant over the remaining lifetime.[3]

As we disregard financial risk, we only consider the risk-free asset which follows a money market account with a deterministic interest rate $r > 0$, given by $dB_t = rB_t dt$. Moreover, the *biometric return*[4], $r^b_{x,t}$, is defined as $r^b_{x,t} = -\frac{1}{h} \cdot \ln\left({}_h p_{x,t}\right)$, where ${}_h p_{x,t}$ is the survival probability of an agent aged x in year t, surviving h years. The biometric return results from sharing idiosyncratic longevity risk when pooling the agents' pension wealth, i.e., the remaining wealth is owned by the collective and distributed as a return to the survivors (Donnelly et al., 2013). Together, this implies the following pension wealth process for each separate bucket

$$W_{t+h}(t+h) = W_t(t+h) \times e^{h(r+r^b_{x,t})} \tag{2.10}$$

$$= W_t(t+h) \times e^{hr} \frac{1}{{}_h p_{x,t}}. \tag{2.11}$$

Utility is received from the actual pension payments, which are equal to $W_t(t)$, $W_{t+1}(t+1), ..., W_{t+H}(t+H)$ conditional on being alive in each period. Initially, at time t, wealth is distributed over $H+1$ buckets with values $W_t(t), W_t(t+1), ..., W_t(t+H)$.

[3]The AIR can be chosen based on various targets, e.g., to maximize expected utility (Balter and Werker, 2020; Munk, 2024).

[4]Also known as mortality credit.

Each consecutive year, one bucket is paid out, and the remaining buckets evolve dynamically over time to, e.g., at time $t+h$, $W_{t+h}(t+h), W_{t+h}(t+h+1), \dots, W_{t+h}(t+H)$.

The AIR that leads to constant pension expectations is given by

$$a_t(t+h) = r - \frac{1}{h}\ln({}_h p_{x,t}), \tag{2.12}$$

which, by including survival probabilities is a straightforward extension of Balter and Werker (2020). Even though the agent divides wealth such that, in expectation, he would receive equal payments throughout retirement, the evolution of each bucket will be random. This occurs due to longevity risk in retirement as agents' survival probabilities may be updated to reflect current conditions. Thus, the longevity risk may cause survival probabilities to deviate from the best-estimate scenario, causing a random biometric return to be experienced. We define a best-estimate scenario as the expected future value based on the central forecast of a stochastic mortality model.

2.2.2 Longevity Model

We use the following relation between survival rates and central death rates

$${}_h p_{x,t} = \prod_{i=0}^{h} \exp\left(-m_{x+i,t+i}\right) = \exp\left(-\sum_{i=0}^{h} m_{x+i,t+i}\right), \tag{2.13}$$

where ${}_h p_{x,t}$ is the h-year survival probability of an individual aged x at time t, and $m_{x,t}$ represents the central death rate. We model the central death rates using the stochastic mortality model by Lee and Carter (1992), which is a widely accepted model for performing long-run forecasts of age-specific mortality rates (Lee and Miller, 2001; Booth et al., 2002). It allows for the incorporation of future mortality improvements and uncertainty. However, its limitations, particularly the lack of explicit cohort effects and its uniform treatment of all ages, make it less suitable for certain applications.[5] Nevertheless, the LC model generates plausible forecasts that remain closely aligned with those produced by other models (Cairns et al., 2011).

The model is given by

$$\ln(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \epsilon_{x,t}, \tag{2.14}$$

where α_x describes the overall log-mortality trend for each specific age x, κ_t captures the overall trend in log-mortality over time t and is often referred to as the *mortality index*, and β_x captures how much of the change in log-mortality is explained at age

[5] Several refinements of the LC model address these shortcomings. For example, the Cairns-Blake-Dowd model (CBD) (Cairns et al., 2006) address the treatment of ages by employing linear predictors of logit mortality. Similarly, The PLAT model combines features of both the Lee-Carter and CBD models (Plat, 2009), while the age-period-cohort model (APC) incorporates cohort effects for groups born in the same period.

x when κ_t changes. The error term $\epsilon_{x,t}$ is standard normally distributed with mean zero and variance $\sigma^2_{\epsilon,x}$.

A unique solution for (2.14) is found by imposing the following constraints on the parameters $\sum_x \beta_x = 1$ and $\sum_t \kappa_t = 0$. The only time-varying component of the model is κ_t, which is modeled as a random walk with drift (RWD) given by

$$\kappa_t = c + \kappa_{t-1} + \delta_t \tag{2.15}$$

where c is the drift term of the process and the error term, δ_t, is normally distributed with mean zero and variance σ^2_δ. We assume that the error terms in (2.14) and (2.15) are uncorrelated for any year t and age x.[6]

We define the *best-estimate*, in year t, of κ_{t+h} as

$$\hat{\kappa}^{BE}_{t+h} \equiv \mathbb{E}_t\left[\hat{\kappa}_{t+h}\right] = h\hat{c} + \kappa_t. \tag{2.16}$$

This enables us to calculate the best estimate of the forecasted log central death rates, based on data until year t as

$$\ln(\hat{m}^{BE}_{x,t+h}) = \hat{\alpha}_x + \hat{\beta}_x \hat{\kappa}^{BE}_{t+h}. \tag{2.17}$$

Plugging this into (2.13) results in the best estimate of the future survival probability

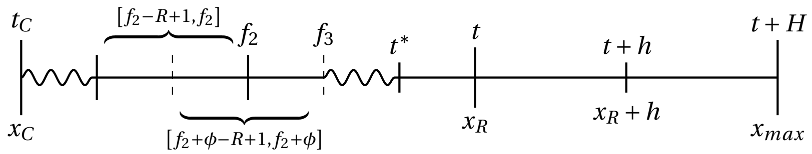
$${}_h p^{BE}_{x,t} = \exp\left(-\sum_{i=0}^{h} \hat{m}^{BE}_{x+i,t+i}\right). \tag{2.18}$$

To address our main research question, we propose, as the first in the literature, to quantify systematic longevity risk by accounting for historical deviations of best estimates of survival probabilities. These deviations effectively capture the re-estimation risk of the parameters in the mortality model and represent a range of plausible future mortality forecasts. The estimates, $\hat{\alpha}_x, \hat{\beta}_x, \hat{c}$, depend on the chosen fitting period, which we denote by $\left[f_i - R + 1, f_i\right]$ where R represents the length of the fitting period and f_i is the last year included in the data set. We now allow the endpoint of the fitting period to change, and in order to keep the number of observations equal, we fix the length of the rolling window R. As new data comes in, we then re-estimate the Lee-Carter model and calculate an updated best estimate of the survival probability for each age x, time t, and horizon h, based on fitting periods $f_0, f_1, f_2, \ldots$ until $f_i = t^*$, where t^* is the year of the most recent observations. Figure 2.1 illustrates the approach.

[6] We adjust the $\hat{\kappa}_t$ by refitting a Poisson regression model to the annual number of deaths at each age x as in Booth et al. (2002). This enables the model to assign more significance to age groups with a higher count of deaths.

Figure 2.1: Timeline of the fitting and retirement periods

The cohort is born in year t_C with x_C being the age at birth. Up until the year of the most recent observations t^*, we estimate the Lee-Carter model using a sequence of fitting periods from $f_0, f_1, f_2, \ldots, f_i$, where f_2 and f_3 in the figure indicate the second and third fitting period in the sequence. For consequtive annual updates with $\phi = 1$, we use that $f_3 = f_2 + \phi$. The agent retires in year t at age x_R. The agent is exposed to longevity risk from retirement until the maximum age x_{max}.



Next, we define a historical *deviation rate* between the two survival probability forecasts as

$$
{}_h d_{x,t}^{f_i,f_j} = \ln\left(\frac{{}_h p_{x,t}^{BE,\left[f_j-R+1,f_j\right]}}{{}_h p_{x,t}^{BE,\left[f_i-R+1,f_i\right]}}\right), \tag{2.19}
$$

where ${}_h d_{x,t}^{f_i,f_j}$ represents the h-year deviation rate of the agent aged x, in year t, based on the change in fitting period from $[f_i - R + 1, f_i]$ to $\left[f_j - R + 1, f_j\right]$. We define the updating frequency, denoted as ϕ, to represent the number of years between two updates. As new data becomes available annually, we adopt the highest possible updating frequency, assuming $f_j = f_i + \phi$, where $\phi = 1$. Note that t_C defines the birth year of the cohort. If the data ranges from t_C to t^* and the length of the fitting period is assumed to be R, then there are $t^* - R - t_C + 2$ survival forecasts, implying $n = t^* - R - t_C + 2 - \phi$ deviation paths. Due to the h-year survival probabilities being multiplicative versions of one-year survival probabilities, we can calculate the h-year deviation rates as the sum of one-year deviation rates.[7] A positive deviation rate indicates an unanticipated increase in the forecasted survival probability for the same agent in the same year, and vice versa for negative values.

The dynamic approach represents a scenario in which agents are exposed to updates in their lifetables whenever new data becomes available. Simulating such a scenario requires a set of plausible deviations, for which we suggest the described method relying on historical changes in lifetables. However, this serves mainly as an illustration to quantify the impact on pension payments, but is not unique. Other methods to construct such sets are equally valid and interesting to explore further.[8] Moreover, deviations would not occur when the mortality model is perfectly specified. Hence, systematic longevity risk could be interpreted as model risk.

[7] ${}_h d_{x,t}^{f_i,f_j} = {}_1 d_{x,t}^{f_i,f_j} + {}_1 d_{x+1,t+1}^{f_i,f_j} + \ldots + {}_1 d_{x+h-1,t+h-1}^{f_i,f_j}$

[8] See, e.g., Cocco and Gomes (2012) who discuss the ad hoc improvement rates that are intended to reflect plausible alternative assumptions by the UK Government Actuary's Department (GAD).

Utilizing the ex post systematic longevity risk present in the deviation rates, we incorporate this as ex-ante possibilities of unexpected changes in survival probabilities. We use the historical deviation rates in survival probability forecasts to shock the best-estimate forecast of survival probabilities based on the most recent observations until time t^*. These generate shocked future longevity scenarios. The survival probability forecast, including the deviation rate risk, is denoted ${}_hp^d_{x,t}$ and is given by

$$
{}_hp^d_{x,t} = {}_hp^{BE,[t^*-R+1,t^*]}_{x,t} \times e^{h d^{f_i,f_j}_{x,t}}, \tag{2.20}
$$

where ${}_hp^{BE,[t^*-R+1,t^*]}_{x,t}$ is the best-estimate survival probability forecast based on the fitting period from $t^* - R + 1$ up to t^*. From (2.20), we can examine several alternative scenarios of how future survival probabilities may behave by analyzing different deviation rates.

2.2.3 Product Design

We examine two distinct pension products that differ in terms of longevity risk. The first product is a *defined benefit (DB)*-type annuity that offers a fixed payment on a regular basis until the death of the individual. Without loss of generality, we assume a yearly frequency of the payments. Within the fund, idiosyncratic longevity risk is diversified away, allowing for a biometric return, while the fund bears the systematic longevity risk. The yearly return is known to the agent at retirement, based on the risk-free rate and the best-estimate of the life expectancy available at retirement. If the population is expected to live longer than anticipated, the payments will thus not be decreased. Hence, the same level of pension will be paid out for longer, and thus, the fund faces higher costs than initially expected. On the other hand, if the population is expected to live shorter, pension payments are paid out to the agent over a shorter period. As a result, the DB-type annuity has a built-in longevity hedge for the agent's exposure to longevity risk.

Moreover, the added financial commitment of the fund due to the potentially unanticipated increase in life expectancies introduces default risk. This fact motivates why there is a global transition ongoing from DB-type products to DC-type products, in which agents explicitly bear risk. Funds facing larger mismatches between their liabilities and asset sides circumvent default by such product transitions. Therefore, it is important to quantify the impact of both financial risk and systematic longevity risk on future pension payments. In our setting, the trigger towards transitioning is not relevant for assessing the impact of systematic longevity risk, which we investigate by comparing the welfare effects of the two products. Thus, we ignore default risk and leave it for further research to assess how it affects the comparison of the products.[9]

[9] From the agents' perspective, introducing default risk into a DB-type annuity transforms it from a 'risk-free' product into a risk-bearing one. The degree of riskiness depends on the nature of the default risk.

To determine how much money needs to be reserved for each pension payment, the AIR in the DB-type product has to be (2.12) where the survival rate equals the best-estimate (2.18). This determines the agent's allocation of wealth to the h-year bucket, valued at time t. Based on the information available at retirement, we do this so that the pension remains constant over time. Similarly, the wealth buckets evolve over time, as expressed in (2.11), where the biometric return is defined by the best-estimate survival probability (2.18) and thus leads to

$$W_{t+h}^{DB}(t+h) = W_t^{DB}(t+h) \times e^{rh} \frac{1}{{}_hp_{x,t}^{BE}}, \tag{2.21}$$

where $W_t^{DB}(t+h)$ represents the amount of wealth allocated in the DB product to the h-year bucket when valued at time t, e^{rh} denotes the h-year return on the agent's buckets, and $\frac{1}{{}_hp_{x,t}^{BE}}$ represents the biometric return under the best-estimate probability forecast.

The dependence of the best-estimate based on the fitting period $\left[t^* - R + 1, t^*\right]$ highlights explicitly why changes in mortality do not impact the agent's pension payments under this product. However, this does not exclude the agent from living longer, as longevity shocks affect the remaining life expectancy. If the agent outlives the best-estimate life expectancy, the payments continue until death at an unchanged fixed level.

The second product is a *defined contribution (DC)*-type annuity that offers variable payments on an annual basis until the death of the agent. The yearly return is not known at retirement, as it consists of the risk-free rate and the biometric return, with the latter being sensitive to systematic longevity risk. Thus, the pension payments may differ from those under the best-estimate survival probability. Furthermore, if the life expectancies change over time, the potential decrease (or increase) in pension payments is to be incurred by the agent.

To ensure that pension payments are expected to be constant during the agent's remaining lifetime after each update of the forecasted survival probabilities, the AIR (2.12) is a function of (2.20). Hence, the allocation depends on the survival rate, including longevity risk, measured by the deviations. This may lead to a lower (higher) amount of wealth being placed in each bucket, compared to the DB case, due to survival probabilities on average being higher (lower). Similarly, the wealth buckets evolve over time, as expressed in (2.11), where the biometric return is now defined by updated survival probability subject to deviation risk (2.20) and thus leads to

$$W_{t+h}^{DC}(t+h) = W_t^{DC}(t+h) \times e^{rh} \frac{1}{{}_hp_{x,t}^{d}}. \tag{2.22}$$

For instance, a complete bankruptcy of the annuity provider entails significantly greater risk compared to a scenario where a government intervenes to assume part of the obligations. In either scenario, our results are likely lowered.

We differentiate between a *static*, i.e., a one-time update, and a *dynamic*, i.e., a sequence of updates over time. Rather than the best-estimates based on data up to t^*, systematic longevity risk implies that an update of the survival forecasts deviates from the best-estimate. Historic one-year deviations are used as plausible scenarios for the shock in best-estimates. Under the set of alternative survival rates, we calculate the constant pension payment for each scenario. The set of deviations consists of n paths. Hence, we obtain n potential payment levels reflecting longevity risk. We refer to this as the static or one-year update.

However, our interest lies in exploring a version that spans multiple periods. In the static one-year update, the pension payments remain constant throughout the remaining lifetime. However, after one more year, one could again follow the same reasoning that the survival rates in that specific scenario could deviate due to the arrival of another year of data. Thus, to quantify longevity risk, we propose a generalization of the single horizon to a multiple horizon framework. We refer to this as the dynamic or multiple horizon update.

Consider an agent who enters retirement in year t, with an initial wealth of W_t and allocates his wealth according to (2.12) using the best-estimate survival probability forecast, (2.18), based on the most recent fitting period $\left[f_i - R + 1, f_i\right]$, where $f_i = t^* = t - 1$. By design, this leads to an expected constant payment stream, $W_t(t), E_t[W_{t+1}(t+1)], \ldots, E_t[W_{t+H}(t+H)]$, until death. During the first year in retirement, he will receive $W_t(t)$. Next year $(t+1)$, he has a remaining wealth of W_{t+1} from which the first payment is subtracted and to which the risk-free rate and the biometric return are added.[10] The agent faces the risk that new observations between t^* and t^*+1 change the forecasted survival probabilities. Therefore, he considers the hypothetical updates of the best-estimate, (2.20), as potential scenarios. From the set consisting of n potential paths (2.19), we draw one and recalculate the remaining pension buckets $W_{t+1}(t+1), W_{t+1}(t+2), ..., W_{t+1}(t+H)$ from which the agent receives $W_{t+1}(t+1)$. Note that the number of potential pension payments in year $t+1$ equals the number of times (N) we simulate from the set of deviations. Based on these values, one can now calculate the expected utility or its certainty equivalent. Recall that the new buckets are determined in such a way that the payments remain constant throughout the agent's lifetime under the assumption that the updated survival rates do not change.

If the average deviation rate is positive (negative), this will cause the new constant payment until death to become lower (higher) than the previous. However, these updated survival rates can again deviate in each subsequent year due to the arrival of new data, hence requiring iterating the described procedure multiple times. After subtracting $W_{t+1}(t+1)$ based on the shocked best-estimates and adding the risk-free rate and shocked biometric return, the remaining wealth at time

[10] In the absence of systematic longevity risk, the agent could now calculate how his remaining wealth should be allocated using the same best-estimate survival probabilities as before. This would yield a constant payment stream equal to that calculated in the previous year.

$t+2$ equals W_{t+2}. The updated survival probabilities are now subject to another potential shock of deviations. These determine the new division of pension buckets $W_{t+2}(t+2), W_{t+2}(t+3), \ldots, W_{t+2}(t+H)$ from which the agent receives $W_{t+2}(t+2)$. This procedure is repeated until death, implying that a single payment stream consists of $x_{max} - x_R + 1$ payments.

2.3 Data

To evaluate the size of the deviation risk between the survival probability forecasts, we draw data from the Human Mortality Database (Human Mortality Database, 2024). We analyze data from the United Kingdom[11] as a representative country that has undergone a transition from traditional DB to DC pension schemes (ONS, 2019). We assume that individuals enter retirement at the age of 66. To estimate the Lee and Carter (1992) model and forecast future mortality rates, we draw information from the database on the number of deaths and exposures. This enables us to calculate the central death rates as

$$m_{x,t} = \frac{D_{x,t}}{E_{x,t}}, \tag{2.23}$$

where the number of deaths is denoted by $D_{x,t}$ and $E_{x,t}$ denotes the exposure. We use data from 1954 until 2019 for all ages up to the maximum attainable age assumed to be 100. The main analysis disregards any data points related to the COVID-19 pandemic. Furthermore, since pension payments are gender neutral, our analysis uses data from both sexes combined.

We estimate the model using a rolling window of $R = 30$ years to balance the trade-off between producing stable forecasts and incorporating more recent mortality trends. For the most recent fitting period, 1990 – 2019, the estimated drift term is $\hat{c} = -1.83$, which implies a downward trend in mortality rates. This captures the anticipated increase in future life expectancies. However, these life expectancies can change due to the arrival of new data. It is exactly this unexpected risk that we want to measure by the deviation rates. This coincides with changes in model parameters when re-estimated. The volatility is $\hat{\sigma}_\delta = 1.91$, implying that the random walk with drift does not fit the observed data perfectly, introducing a risk surrounding the time trend. For each fitting period, the Lee-Carter model produces the forecasted mortality rates for all ages until the maximum attainable age of 100. Since we consider data from the cohort $t_C = 1954$ until $t^* = 2019$ and a rolling window of $R = 30$ years, we obtain $n+1 = 37$ forecasts.[12]

[11] Data for the United Kingdom are supplied by the Office for National Statistics (ONS), the Northern Ireland Statistics and Research Agency (NISRA), and National Records of Scotland (NRS).

[12] As the annual deviations are defined as yearly differences in forecasted survival rates, $\phi = 1$, there are $n = 36$ deviation paths.

Table 2.1: Remaining Life Expectancy In UK For Selected Fitting Periods

The remaining life expectancy of the cohort $t_C = 1954$, which retires in year $t = 2020$ at the age of $x_R = 66$, is shown for four different fitting periods. We use the Lee and Carter (1992) mortality model to produce best-estimate survival probability forecasts based on the fitting period. We calculate the remaining life expectancy using (2.24). Each column shows the effect on the remaining life expectancy when we use a more recent fitting period. For example, based on the first fitting period, we expect the cohort to survive for 17 years and 5 months conditional on survival to the retirement age of 66 in year 2020. Using a more recent fitting period, the estimates are adjusted upwards, reflecting the systematic longevity risk for this particular age.

Age of agent	30	42	54	66
Fitting Period / Conditional	1984	1996	2008	2020
1954 - 1983	48y9m	37y3m	26y6m	17y5m
1966 - 1995		39y1m	28y1m	18y3m
1978 - 2007			30y4m	20y2m
1990 - 2019				20y4m

To investigate the differences among the various forecasts, we calculate the remaining life expectancy for an x-year old in year t by

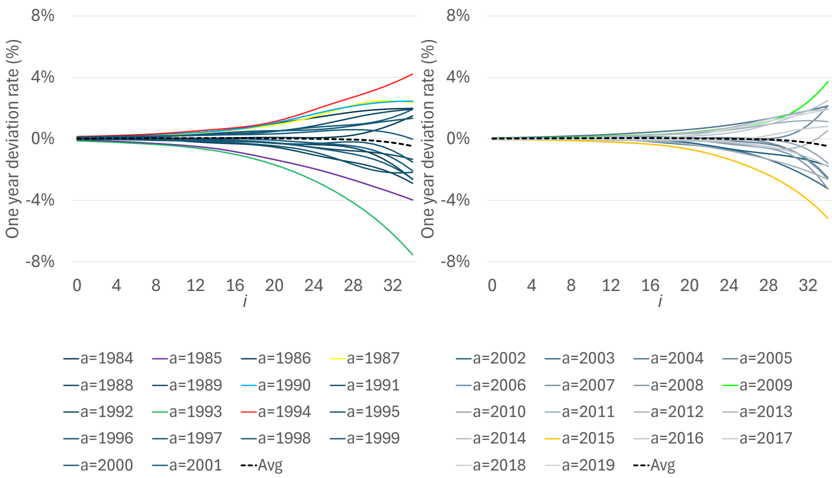
$$LE_{x,t} = \sum_{h=1}^{\infty} {}_h p_{x,t}^{BE,[f_i-R+1,f_i]} \tag{2.24}$$

where ${}_h p_{x,t}^{BE,[f_i-R+1,f_i]}$ denotes best-estimate survival probability forecasts based on the fitting period $f_i - R + 1$ to f_i. Table 2.1 shows the remaining life expectancies of the cohort born in 1954 for four different fitting periods. This cohort reaches the retirement age of 66 in 2020. We see that the remaining life expectancy increases when a more recent fitting period is considered. This reflects an unanticipated change in the remaining life expectancy. Based on the data from 1954 to 1983, the forecasts would yield a remaining life expectancy of 17 years and 5 months. However, if we use data from 1966 to 1995 instead, we expect the same individual to live longer than what we anticipated before, i.e., a remaining life expectancy of 18 years and 3 months conditional on being alive in 2020. The most recent best estimate would yield a remaining life expectancy of 20 years and 4 months. We thus find a total difference of 2 years and 11 months in our expectations of the remaining life expectancy of the 66-year-old individual in 2020. As such, the risk of unforeseen changes in mortality forecasts, represented by each column, captures the systematic longevity risk for that particular age and thus can cause the DC-type product payments to change due to these unforeseen deviations. We investigate the impact of systematic longevity risk on the payment levels in the DC-type product when allowing for mortality table updates.

Figure 2.2 shows all $n = 36$ one-year deviation rates for the 1954 cohort, as given by ${}_1 d_{x+i,t+i}^{a-1,a}$ in (2.19). We use i to control the age of the cohort, starting at $x_R = 66$. The deviation rates are calculated on the basis of two fitting periods with a denoting the end year of a fitting period. A positive deviation rate implies that the updated, more recent forecast is higher than previously forecasted, i.e., ${}_h d_{x,t}^{a,a+1} > {}_h d_{x,t}^{a-1,a}$, and vice versa for negative deviations. We observe that comparing best-estimate survival probability forecasts based on fitting periods from the eighties and nineties resulted in more extreme updates than those from more recent updates. The selection criterion for a non-blue color is that the sum of squared deviation from the average deviation is at least 0.5% to signal a more extreme deviation.[13] At the extremes, we observe one path to yield a positive (negative) one-year deviation rate of 4.2% (−7.5%), illuminating that the LC model forecast from the previous period was too low (high). The average deviation shown in Figure 2.2 is slightly positive up to $x_R + i = 66 + 24 = 90$ while negative at very old ages. Note that the deviation is defined in relative terms, hence at the very old ages, the absolute difference is much smaller due to the typical decline in survival probabilities across age.

Figure 2.2: One-Year Deviation Rates For UK

One-year deviation rates ${}_1d^{a-1,a}_{x+i,t+i}$ are shown as a function of i comparing forecasts based on data up to $a-1$ versus a, for $x = 66$ and $t = 2020$. E.g., the red line for $a = 1994$ shows the deviation rate between the forecasts based on the fitting period $[1964, 1993]$ versus $[1965, 1994]$. Therefore, the horizontal axis shows these deviations in the one-year survival probability of a 66-year old in 2020 until the 100-year old in 2054. The dashed line shows the average calculated by ${}_1\bar{d}_{x+i,t+i} = \frac{1}{36}\sum_{a=1984}^{2019} {}_1d^{a-1,a}_{x+i,t+i}$ for $x = 66$ and $t = 2020$.



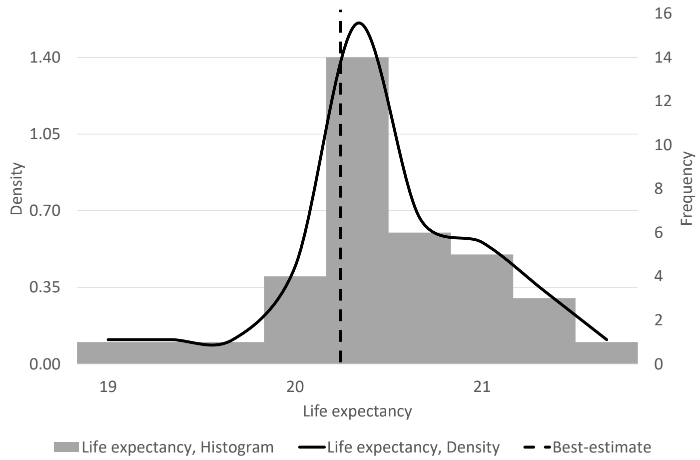
Next, we show the accumulated effect of the hypothetical deviations on the remaining life expectancy of a 66-year-old in 2020 in Figure 2.3. The black dashed line shows the best estimate based on the most recent fitting period, as already provided in Table 2.1. The histogram shows the life expectancy for each of the $n = 36$ possible deviations applied to the most recent best estimate based on the fitting period, 1990, to the year prior to retirement, 2019. Thus, we consider the set of deviation rates as depicted in Figure 2.2 as unforeseen changes applied to the most recent best estimate and calculate new life expectancies based on these shocked survival probabilities. We plug in the survival probabilities from (2.20) into (2.24). We find the life expectancies

[13] $\sum_i (d^{a-1,a}_{x+i,t+i} - \bar{d}_{x+i,t+i})^2 > 0.5\%$ where $\bar{d}_{x+i,t+i}$ is the average deviation across the fitting periods, a.

under longevity risk skewed to the left, implying that, on average, we observe an underestimation of the life expectancies. We approximated the risk of possible updates of future best estimates by using historical deviation as a plausible uncertainty set implying a range of life expectancies as shown in Figure 2.3. This range reflects the variability of considering a static update, which we generalize to a dynamic setting for which we derive the welfare effects below.

Figure 2.3: Density Of Life Expectancies Under Longevity Risk

The black dashed line shows the remaining life expectancy of a 66-year-old in 2020 based on the best estimate survival probability forecast using the most recent fitting period. We use the deviation rates depicted in Figure 2.2 to create the histogram and insert them in (2.20). The solid black line shows the hypothetical kernel density of the remaining life expectancy.



2.4 Results

We assume that the agent has a normalized wealth at retirement of $W_t = €100,000$. As explained in Section 2.3, the retirement age is set to $x_R = 66$, and the maximum attainable age is assumed to be $x_{max} = 100$. We use mortality data from the UK to produce survival forecasts for the cohort that reaches the retirement age in $t^* = 2020$. We use the best-estimate forecasts from 2020 to 2054, whereafter this cohort reaches the maximum attainable age. Therefore, there are 35 buckets to which the pension wealth is distributed since the first payment occurs at the retirement age 66 and the last payment at the age of 100, conditional on survival. The financial market only consists of a money market account, for which we use a constant risk-free rate of $r = 2.7\%$.[14]

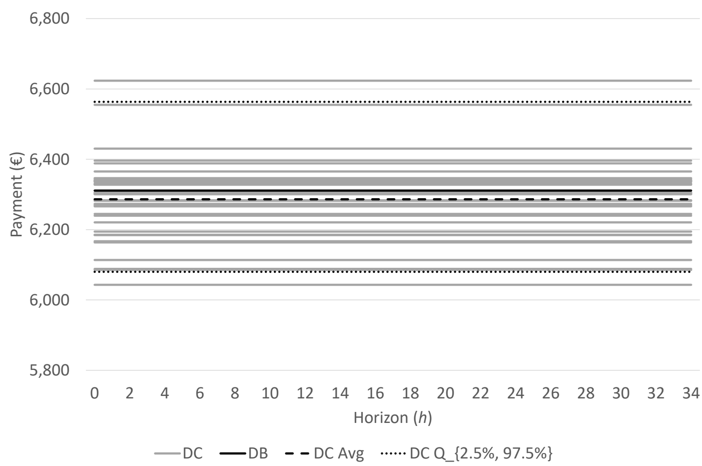
[14]The average 3-month treasury bill from January 1990 until December 2019 constitutes our risk-free rate – https://fred.stlouisfed.org/series/TB3MS.

First, we show in Figure 2.4 the yearly pension payments for the DB-type and DC-type products under the static version of systematic longevity risk, calculated by (2.21) and (2.22). The DB payments in Figure 2.4a (the solid black line) are not exposed to any risk and are based on the best-estimate of the survival forecasts with the most recent fitting period. The DC payments are sensitive to potential changes in the survival forecasts, which is captured by the static one-time update via shocking the best-estimate with one of the $n = 36$ deviation paths. For each potential deviation, the associated pension level (the solid gray lines) is shown, which yields, on average (the black dashed line), lower payments than the DB payments. In Figure 2.4b, the levels of the constant pension payments are depicted against the remaining life expectancy, where the latter coincides with the life expectancies under systematic longevity risk, as depicted in Figure 2.3. Here, we see that DC payments (triangles) are lowered in cases where life expectancies are higher than the best-estimate. Unlike financial risk, where we typically see a risk-return trade-off, those facing longevity risk experience a risk-loss effect due to life expectancies being, on average, underestimated.

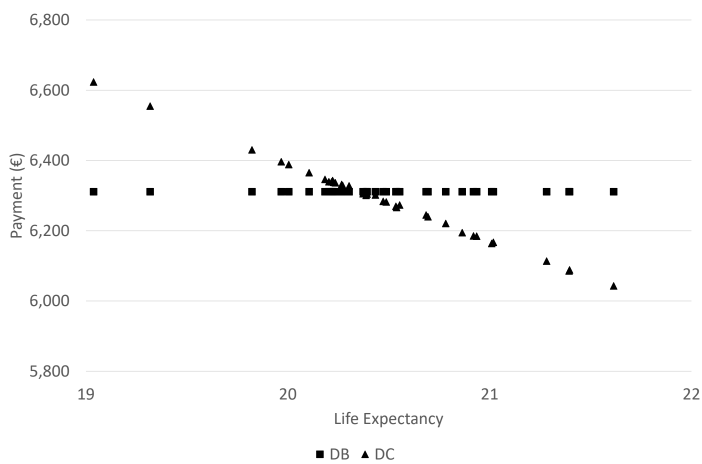
Figure 2.4: Payments With Longevity Risk - Static Update

Panel (a) shows the yearly pension payments for the DB-type, calculated by (2.21), as a solid black line. The DC-type payments, calculated by (2.22), are shown as solid grey lines, of which each represents one of the $n = 36$ possible deviation paths under the static version of systematic longevity risk. The dashed line represents the average DC payment of the solid grey lines. The dotted lines represent the confidence interval of the DC-type payments. We assume initial wealth to be $W_t =$ €100,000 at the retirement age of $x_R = 66$ in year $t^* = 2020$. Panel (b) shows the levels of the constant pension payments under the DB-type (square) and DC-type (triangle) against the remaining life expectancy under systematic longevity risk. The $n = 36$ deviation paths produce an equal number of points representing the different levels of constant pension payments under each product.

(a) Payments Over The Horizon



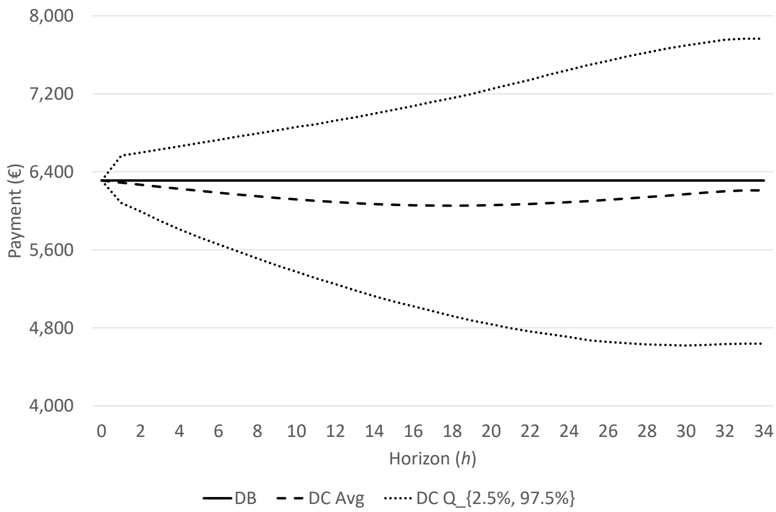
(b) Payments Against Life Expectancy



Based on the multiple horizon approach, we essentially mimic the situation of agents being exposed to longevity risk at each horizon, affecting their future survival probabilities, and thus, their payments. In Figure 2.5, we present the variability

Figure 2.5: Payments With Longevity Risk - Dynamic Update

The pension payments $W_{t+h}(t+h)$ as a function of h are shown for the DB product by the solid line, for the DC product by the dashed line for the average, and the dotted lines show the 95% confidence interval. At each horizon, we simulate $N = 100,000$ scenarios from the set of $n = 36$ deviations.



in payments when updating the best estimate survival forecasts using the dynamic approach rather than the static one. We simulate $N = 100,000$ scenarios of deviations.

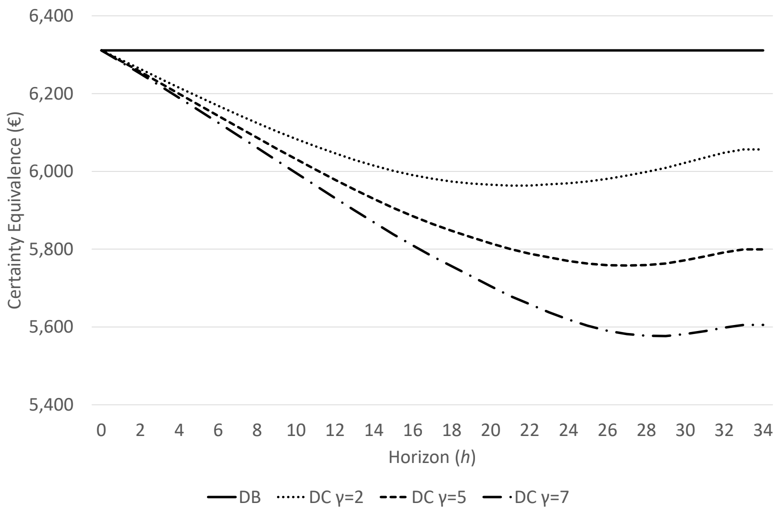
Per definition, the DC-product pays out the same level as the DB-payment at the retirement age, i.e., €6.311 when $h = 0$. However, the retirees face the risk that next year's payment is subject to an unforeseen change in the survival forecasts. This we model by drawing from the set of deviation paths generating a range of potential payments at $h = 1$ conditional on surviving to age 67. The confidence interval widens over the horizon as the updated survival rates are re-updated every year.

We also see that the average DC payments are declining as one ages, until the age of 84 at $h = 18$. For the late horizons, we observe that the average payments are in fact increasing – however, the average DC payments stay below those of the DB product. The average payments exhibit a non-monotone shape caused by average negative deviations at very old ages, starting to dominate earlier positive deviations as the individual ages. This is due to the relatively small impact of (updated) survival rates at higher ages compared to lower ages, i.e., see (2.20). Despite the average deviations being negative when $h \geq 24$, the average DC payments remain below the DB level. This can be explained by the difference in remaining pension wealth. In particular, the lower average biometric returns experienced within the DC product imply a lower pension wealth even though the remaining life expectancy at these high ages has, on average, been overestimated.

We consider the utility framework introduced in Section 2.2.1 to investigate the

Figure 2.6: Certainty Equivalents As A Function Of h

The welfare implications are illustrated in terms of the certainty equivalent CE_{t+h} as a function of h. The solid black line shows the certainty equivalent for the DB-type product, while the other lines show the certainty equivalents for the DC-type product for different levels of risk aversion $\gamma = \{2, 5, 7\}$.

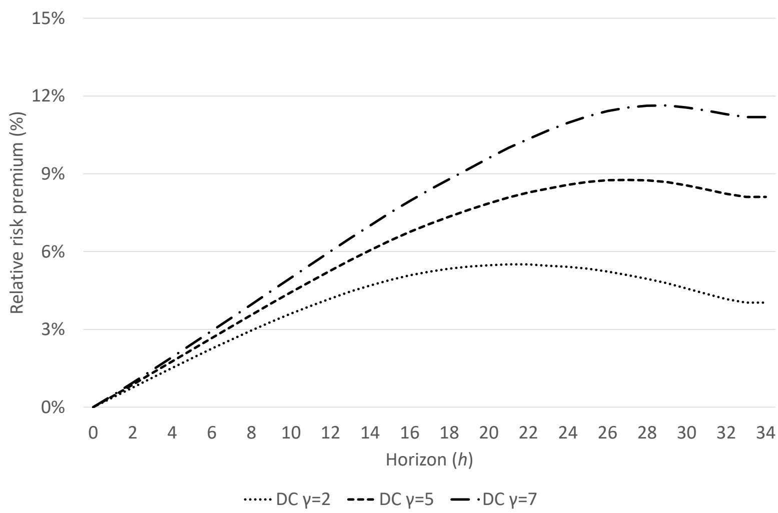


welfare implications. Figure 2.6 shows the certainty equivalents as a function of either the risk aversion or the horizon. The solid black line reflects the certainty equivalent related to the DB-type product, which equals $CE^{DB} = W_t^{DB}(t)$, while the other lines are related to the DC-type product. As the riskiness increases with the horizon and the average DC payments decrease, agents require lower certainty equivalents. The individual's risk aversion balances the trade-off between the mean and volatility. For example, consider a horizon of $h = 5$ years into retirement for the 71-year-old individual with a risk aversion level of $\gamma = 5$. For this horizon, the individual is indifferent between receiving €6,171 and receiving the risky payment that is, on average, €6,205, with a 95% confidence interval between €5,730 and €6,696, as can be seen in Figure 2.5. In Figure 2.7, we display the associated risk premia as defined by (2.5). This reflects the willingness to pay, relative to the DB-type payment, in order to avoid the systematic longevity risk. These risk premia allow for direct comparisons as they are defined in relative terms. As introduced above, the risk premium of the 71-year-old individual with a risk aversion of $\gamma = 5$ equals (€6,311 - €6,171)/€6,311=2.2%. Figure 2.7b shows how the risk premia depends on the level of risk aversion, where those with higher levels are willing to pay more to avoid the riskiness caused by systematic longevity risk. Furthermore, we find for $h = 1$ that agents require risk premia of about 0.5% only. Thus, the one-year shock of longevity updates clearly underestimates the multi-horizon effect of longevity risk.

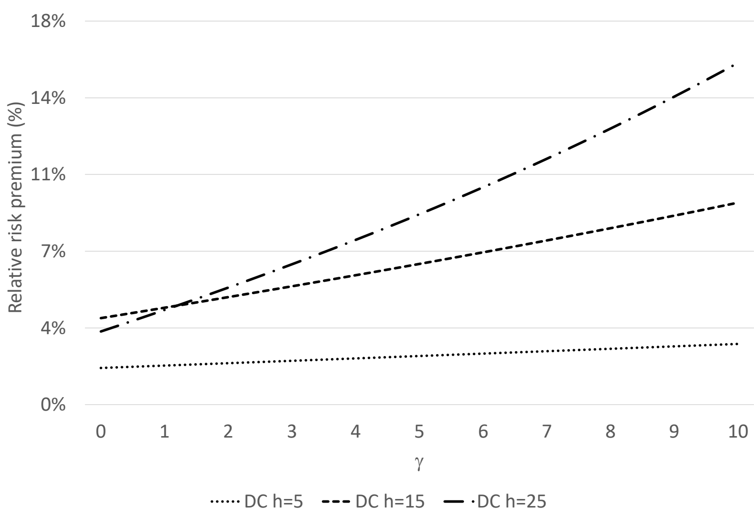
Figure 2.7: Relative Risk Premia

Panel (a) shows the relative risk premia π_{t+h} as a function of h for different levels of risk aversion γ, and in panel (b) as a function of γ for different horizons. We use (2.5) to calculate the relative risk premia, which represent the willingness to pay in order to avoid the systematic longevity risk relative to the DB-type payment.

(a) π As A Function Of h



(b) π As A Function Of γ



2.5 Robustness

First, we consider the robustness of our results by changing the country from the United Kingdom to one of the following: Denmark, USA, or Australia. Second, we investigate the sensitivity of the risk premia for cohorts, retirement ages, maximum ages, genders, fitting periods, and frequency of the updates. Third, we compare our results to the risk premia based on considering only the stochasticity within the Lee-Carter model as potential deviations as a proxy for longevity risk, to the variability caused by exposure to financial risk, and to the choice of the mortality model.

2.5.1 Countries

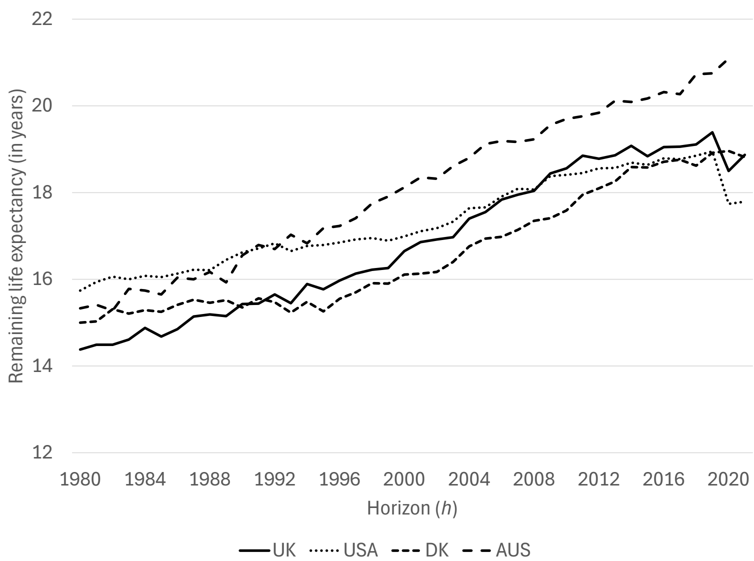
Designs of pension systems are changing globally, which is caused by several factors. In particular, the positive trend in life expectancies motivated transitions to DC-like products, in which the payments are often linked to the development in life expectancies (Brown, 2016; Balter et al., 2020; OECD, 2021). In order to check the robustness of our country choice, the United Kingdom, we investigate whether results are robust for countries that have undergone similar transitions. Even though the period life expectancies show a similar upward trend – Figure 2.8 shows the period life expectancies for a 66-year-old in the United Kingdom, USA, Australia, and Denmark – the risk in potential deviations in forecasted cohort life expectancies differs among them, Figure 2.9a shows the deviations for these countries.

The average life expectancy in Australia is higher than in the UK, as indicated by Figure 2.8. This explains the lower DB payment in Figure 2.9d versus Figure 2.9c (which is identical to Figure 2.5). The difference between the DB and DC payments in Australia is slightly smaller than in the UK due to the lower deviations, explaining the lower relative risk premia as shown in Figure 2.9b. In Denmark, Figure 2.9e shows that the average DC payment at extremely old ages is higher than the DB payment due to the on average lower deviations compared to the UK. However, despite this rise in payments, the risk premium still remains positive. This can be explained by the fact that for this level of risk aversion ($\gamma = 5$), the slightly higher average is not enough to compensate for the increase in riskiness.

In the UK, we observe positive deviations during the first two decades, see Figure 2.9a, while negative deviations at very old ages. Since the mortality rates at younger ages get more weight, i.e., it is less likely to attain extremely high ages, the negative deviations have less impact on the remaining life expectancy. Therefore, on average, a 66-year-old faces the risk of living longer than expected. However, in the USA, the dominating effect of the early deviations does not offset the negative deviations at older ages because both the early deviations are lower, i.e., around zero, while the later deviations are more extreme, i.e., more negative. Hence, a 66-year-old in the USA who takes into account longevity risk lives, on average, shorter. Therefore, pension products that are sensitive to changes in mortality forecasts will, on average,

Figure 2.8: Period Life Expectancies

Period life expectancies for a 66-year-old in the UK, USA, Denmark, and Australia are shown. We use life table data from the period 1980 to 2021.

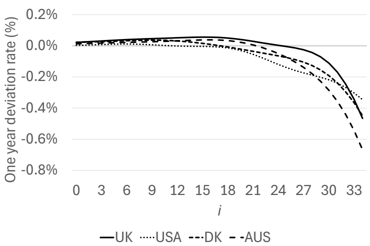


be adjusted upwards, as we see in Figure 2.9f. Thus, those facing longevity risk receive larger pensions than those with the DB-type product. Therefore, they receive more utility from the DC than the DB product, i.e., they are willing to pay to face longevity risk, and thus, the risk premia are negative, as can be seen in Figure 2.9b.

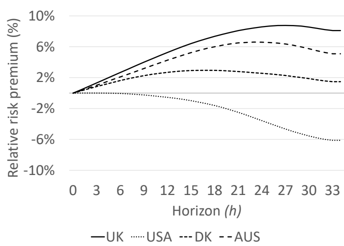
We can conclude that the model set-up can capture the different developments in systematic longevity risk reflected by the various scenarios seen in each country. In the UK, it appears that the forecasted trend in life expectancies is systematically underestimated, requiring a positive risk premium. In contrast, in the USA, the forecasted trend is overestimated, causing the annuity payments of the DB product to be set too conservative.

Figure 2.9: Countries

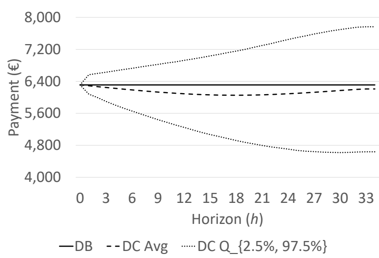
Panel (a) shows the average deviations ${}_1\bar{d}_{x+i,t+i} = \frac{1}{36}\sum_{a=1984}^{2019} {}_1d_{x+i,t+i}^{a-1,a}$ for $x = 66$ and $t = 2020$ for the UK, USA, Denmark, and Australia, panel (b) shows the relative risk premia π_{t+h} for $\gamma = 5$, and panel (c) to (f) show the payments excluding and including systematic longevity risk, the DB and DC product, respectively, as well as the 95% confidence interval of the DC product.



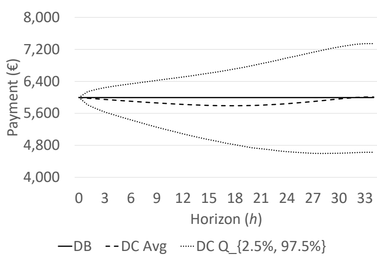
(a) Deviations



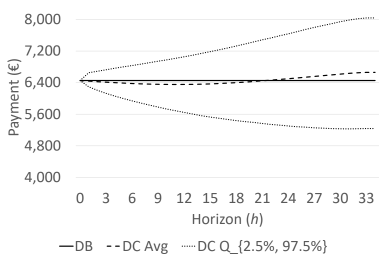
(b) Relative Risk Premia



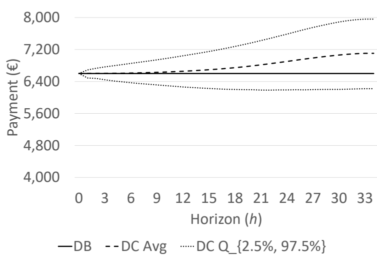
(c) United Kingdom



(d) Australia



(e) Denmark



(f) United States

2.5.2 Sensitivity

We now investigate the sensitivity of the risk premia for different cohorts, retirement ages, maximum ages, genders, fitting periods, and frequency of the updates in Figure 2.10. The main results shown are based on the 1954 cohort, a retirement age of 66 and a maximum attainable age of 100, the total population in the UK, a fitting period of 30 years, and the frequency of yearly updates. In Appendix A.1, we show the associated average deviations and payments figures for the sensitivity analysis in Figure A.1 and Figure A.2, respectively.

To investigate the cohort effect, we consider the previous and following two cohorts relative to those born in 1954, see Figure 2.10a. In specific, the cohorts born in $t_C = 1952$ to $t_C = 1956$ who reach the retirement age of $x_R = 66$ in the year $t^* = 2018$ to $t^* = 2022$, respectively. Thus, the data used for the 1955 and 1956 cohorts includes COVID-19 years. The differences in the risk premia reflect the fact that cohorts are affected differently by longevity risk, e.g., the lower risk premia for the 1955 and 1956 cohorts match the excess mortality observed in those years, thus affecting both the set of deviations and the most recent best estimate, see Figure A.1a.

Second, we analyze the effect of increasing the retirement age in Figure 2.10b. Thus, we allow the 1954 cohort to retire one, two, three, and four years later, conditional on survival until the respective retirement age. A higher retirement age implies fewer years in retirement and, therefore, a higher annual payment when the retirement wealth is assumed to be fixed, in this case set to €100,000. This causes the payments in Figure A.2b to increase with retirement age. Moreover, the deviations at higher ages get more weight, explaining the smaller gap between the DB and DC payments. Therefore, the numerator and denominator, defining the risk premia in (2.5), decrease and increase, respectively, causing the risk premia to be lower, as seen in Figure 2.10b.

Third, changing the maximum age from 100 to either 95 or 105 does not affect the main results by much, as seen in Figure 2.10c. The average deviations are overall slightly higher – since the negative deviations at high ages are not attainable – while the remaining life expectancy is lower due to cutting off early, for a lower maximum age, mainly offset each other when valued in terms of risk premia. As Ji and Zhou (2017) argue, mortality statistics for high ages are often found to be unreliable. Therefore, we choose 100 as the maximum attainable age.

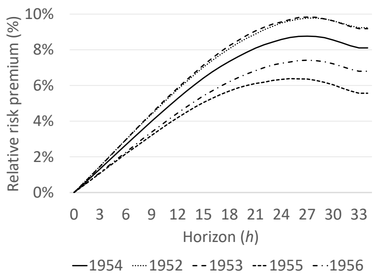
Fourth, as pointed out in the literature (Oeppen and Vaupel, 2002), there exists heterogeneity in life expectancy between genders as men live, on average, shorter lives. However, recently, we have seen a higher improvement rate for men, implying that their life expectancies are converging towards those of women (Mateos et al., 2022; Jarner et al., 2008). This means that the historic deviations are higher for men, and thus, men require higher risk premia, as shown in Figure 2.10d.

Fifth, Figure 2.10e shows the sensitivity of the risk premia when changing the length of the rolling window to which the Lee-Carter model is fitted. Shorter fitting periods lead to more volatile deviations, as seen in Figure A.3, and thus higher risk premia. In the other scenario, we consider an expanding window in which the fitting period starts with 30 years of data as input to the Lee-Carter model, and each year, one more year of observations is added. This implies that the parameter estimates are more stable and amount to risk premia that align with the results in the main section. This highlights the importance of the selection of the fitting period due to sensitivity to structural breaks in shorter fitting periods.

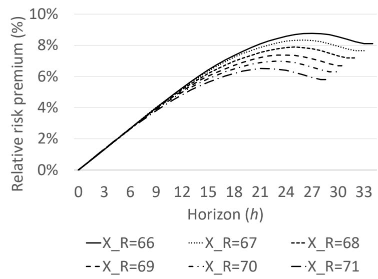
Sixth, we consider less frequent updates of the best-estimate in Figure 2.10f. Now, the deviations between survival forecasts are based on data from the interval $[f_i - R+1, f_i]$ compared to forecasts based on data from the interval $[f_i + \phi - R + 1, f_i + \phi]$. On average, pension payments that are based on misestimated survival rates are paid out for longer, causing future payments to compensate for it. This implies larger but less frequent shocks. The result is that welfare losses are higher the less frequently the best-estimates are updated.

Figure 2.10: Risk Premia

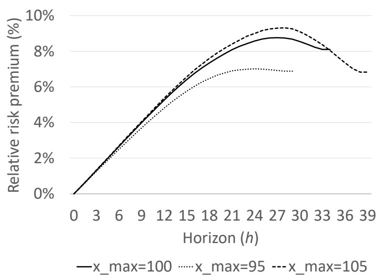
Panel (a) displays the risk premia for different cohorts that reach the retirement age $x_R = 66$ between the years $t^* = 2018$ to $t^* = 2022$. Panel (b) shows the effect of increasing the retirement age from $x_R = 66$ to $x_R = 71$ for the cohort born in $t_C = 1954$. Panel (c) illustrates the effect of changing the maximum age $x_{max} = 100$ to either 95 or 105. In panel (d), gender specific risk premia are shown. Panel (e) shows the effect of changing the length of the rolling window from $R = 30$ to $R = 20$ or an expanding window. Finally, panel (f) demonstrates how the risk premia changes when the update is bi-annual ($\phi = 2$) or quadrennial ($\phi = 4$).



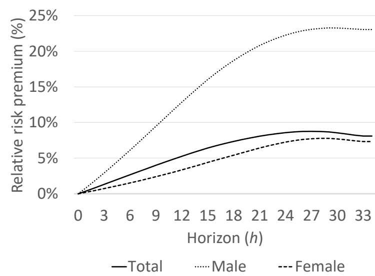
(a) Cohorts



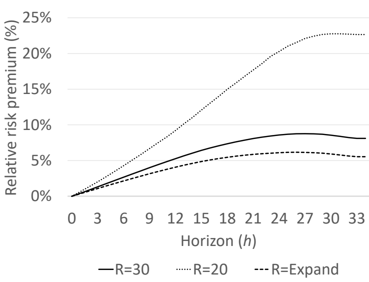
(b) Retirement Age



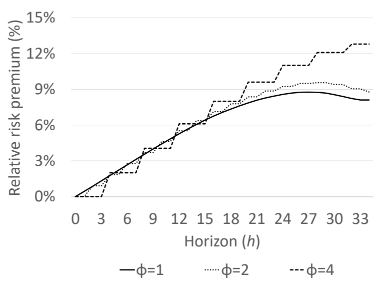
(c) Maximum Age



(d) Gender



(e) Fitting Period



(f) Frequency

2.5.3 Risk

Next, we consider trend risk, model risk, and financial risk, respectively. A large strand of the literature considers stochastic variation as the main source of systematic longevity risk, e.g., see Dees et al. (2021), Maurer et al. (2013), and Boon et al. (2020), which we refer to as trend risk.[15] First, as there exists uncertainty surrounding the time trend of the best-estimate, we address this stochastic variation behavior by following the literature, and drawing the error term, δ, in (2.15).[16] Plugging this into (2.17), we calculate simulated log central death rates to address trend risk within the LC model. We allocate wealth according to the best-estimate survival probability forecast and let the biometric return be given by the random draws. Figure 2.11a shows the fluctuations in payments where systematic longevity risk is measured by trend risk labeled DC, while DB refers to the payments without longevity risk. Since, by definition, the average error term is zero, the average forecasted probabilities equal the best-estimates. Hence, trend risk generates risk but no premium. However, the arrival of new data and re-estimation risk of the survival forecasts are ignored, and thus, the fluctuations shown capture only scenarios that are anticipated ex-ante. In fact, the shown variability driven by trend risk does not influence the payments as pension providers use merely the best-estimate. Therefore, trend risk captures fundamentally different deviations than unexpected deviations, which we aim to measure in this paper to assess the impact of systematic longevity risk on pension payments. As shown in Figure 2.11b, we find indeed clear evidence that longevity risk is negligible when measured as trend risk. While this occurs due to the drawn error terms cancelling out on average, it is not the case when capturing systematic longevity risk using unexpected deviations from historical deviation rates. Allowing for multiple shocks throughout retirement mimics a more realistic scenario with continued longevity risk exposure.

To investigate how our measure of systematic longevity risk depends on the model choice, we examine the robustness of our results when using other stochastic mortality models than Lee-Carter. We look at the age-period-cohort model (APC), which is a substructure of the Renshaw and Haberman (2006) model, the Cairns-Blake-Dowd model (CBD) from Cairns et al. (2006), and the PLAT model who combines features of the Lee-Carter and CBD model (Plat, 2009). Fitting the CBD and PLAT models to 30 years of data produces fluctuating deviation rates, hence these models are rather sensitive. This generates a high volatility in both the deviation rates and the risk premia. The latter is depicted in Figures 2.11c and 2.11d. Expanding the fitting period, ranging from 30 years of data up to 66 years produces more stable results. In the

[15] Stochastic variation refers to the uncertainty and randomness in observed and forecasted mortality rates. For the former, it represents the residual difference when fitting the Lee-Carter model in Eq. (2.14). For the latter, which the literature uses as the source of systematic longevity risk, it captures how simulations of κ_{t+h} may deviate from the best estimate (Broeders et al., 2021).

[16] Following the literature (Boon et al., 2020), we draw δ_s for the horizons $s = \{1, \ldots, h\}$ to obtain future stochastic paths of the time trend, which gives $\hat{\kappa}^{\text{trend}}_{t+h} = h\hat{c} + \kappa_t + \sum_{s=t}^{h} \delta_s$.

end, systematic longevity risk can be interpreted as model risk, i.e., a perfect model choice that captures the true data-generating process will not cause any deviations. However, (structural) changes in the data or changes in model selection do have an impact on pension payments as the right model does not exist.

Variability in a DC product can also be driven by other risk factors, such as financial risk, including equity risk and interest rate risk. We address this by examining the risk premia when only considering financial risk and neglecting the longevity risk. To model financial risk, we consider two assets – a risk-free and a risky – described by Merton (1971) and Black and Scholes (1973). The first asset follows the money market account with a deterministic interest rate r, $dB_t = rB_t dt$. The second asset is assumed to evolve according to a geometric Brownian motion (GBM), with a diffusion process for the price S_t at time t

$$dS_t = \mu S_t dt + \sigma S_t dZ_t, \tag{2.25}$$

where S_t is the stock price process, μ is the expected return, σ is the stock return volatility, and Z is a standard Brownian motion.

We consider each wealth bucket $W_t(t+h)$ to be invested in a continuously rebalanced investment strategy with a fraction of ω in the risky asset S_t and the remainder in the risk-free asset B_t. Standard calculations allow us to define the wealth bucket process for the pension payment at time $t+h$

$$dW_t(t+h) = (r + \omega(\mu - r))W_t(t+h)dt + \omega\sigma W_t(t+h)dZ_t, \text{ for } t \leq h. \tag{2.26}$$

We add survival probabilities to the model considered in Balter and Werker (2020). If the AIR is set to

$$a_t(t+h) = -\frac{1}{h}\ln({}_hp_{x,t}^{BE}), \tag{2.27}$$

then, each bucket contains the same starting value corrected for the survival probabilities, i.e., when returns are zero, the DB payments would be constant. For this AIR, the expected pension payments are increasing in h – see Figure 2.11e – as the variable payments, including financial risk, evolve as follows

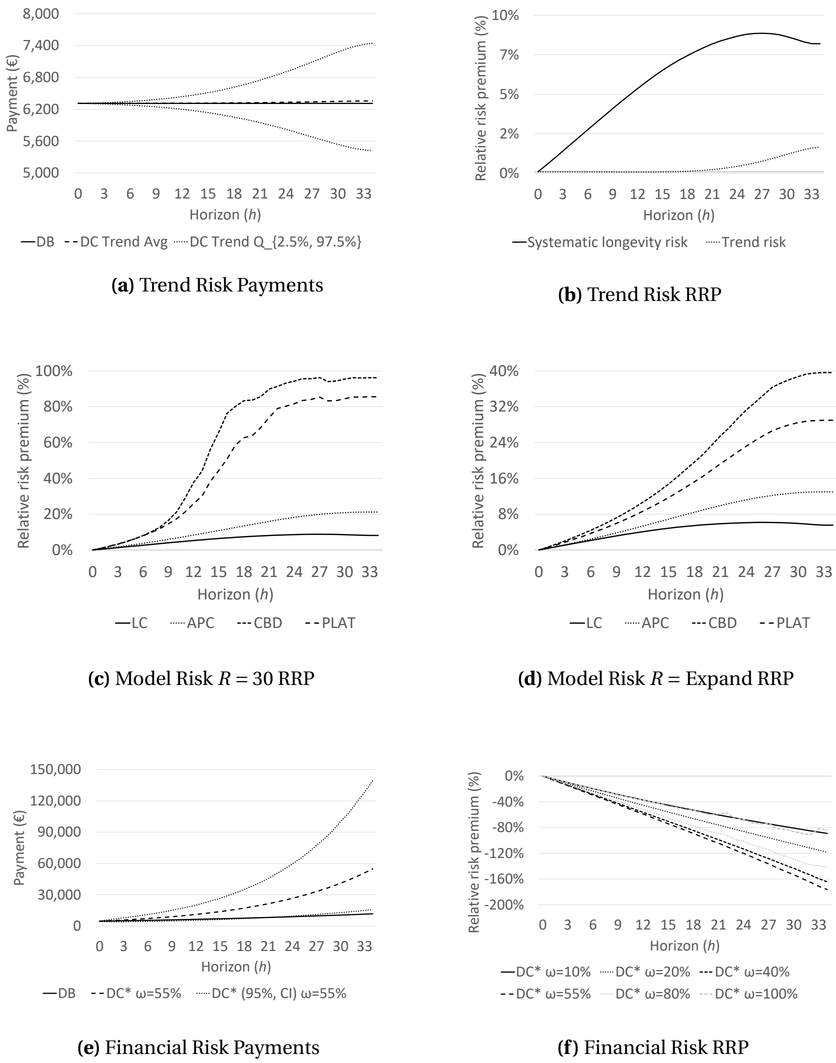
$$W_{t+h}^{DC^*}(t+h) = W_t(t+h) \times e^{(r+\omega(\mu-r)-\frac{1}{2}\omega^2\sigma^2)h+\omega\sigma\varepsilon_S\sqrt{h}} \frac{1}{{}_hp_{x,t}^{BE}}, \tag{2.28}$$

where ε_S is standard normally distributed with mean zero and variance one.

For Figures 2.11e and 2.11f, we assume a constant risk-free rate of $r = 2.7\%$, the expected rate of return for the risky asset is set to $\mu = 10.95\%$, with an annualized standard deviation of the risky asset being $\sigma = 17.30\%$, for which we used the S&P 500 from January 1990 to December 2019. Figure 2.11f shows the associated risk premia, which are negative and decreasing with the horizon when $\omega = \{10\%, 20\%, 40\%, 55\%, 80\%, 100\%\}$. First, negative risk premia reflect that the expected

Figure 2.11: Risk

Panel (a) shows variable payments where systematic longevity risk is measured by trend risk labeled DC, while DB refers to the payments without longevity risk. The comparison of the risk premia between systematic longevity risk, as found in Figure 2.7, and trend risk is displayed in panel (b). Panel (c) illustrates the effect of choosing either the age-period-cohort model, the Cairns-Blake-Dowd model, and the PLAT model, instead of the Lee and Carter model for a rolling window length of $R = 30$, and in panel (d) for an expanding window. Panel (e) shows payments where we disregard systematic longevity risk and allow for financial risk with a risky asset exposure of $\omega = 55\%$. Lastly, panel (f) shows the associated risk premia for a risky asset exposure from $\omega = 10\%$ to $\omega = 100\%$.



(a) Trend Risk Payments

(b) Trend Risk RRP

(c) Model Risk $R = 30$ RRP

(d) Model Risk R = Expand RRP

(e) Financial Risk Payments

(f) Financial Risk RRP

utility from the product, including financial risk, is higher than the utility from the fixed annuity. This implies a willingness to pay to face this risk rather than to avoid this risk. In other words, the more negative the risk premium is, the higher the welfare from bearing the risk. This phenomenon is well known as the risk-return trade-off, i.e., higher exposure to the financial market increases the expected excess return while at the same time also increasing the risk. The optimal level of risk versus return can be determined for each level of risk aversion. The welfare is maximized when the risk exposure ω equals the optimal investment strategy of Merton (1969): $\omega^* = \frac{\mu - r}{\sigma^2 \gamma} = 55\%$. Both higher and lower ω are suboptimal and also mismatches between the risk exposure and the preference for risk aversion can cause welfare losses. In fact, for an investor with $\gamma = 5$, the risk premia due to longevity risk coincide with the losses resulting from an investment strategy of $\omega \approx 145\%$. In general, we find longevity risk to increase risk and simultaneously lower the expected return as long as unforeseen shocks in forecasted survival rates lead to unanticipated rises in life expectancies. While the investment policy can be tailored to balance the level of risk versus return up to the level at which risk preferences can be elicited accurately.

2.6 Conclusion

We model how unforeseen longevity shocks affect pension income over multiple periods and derive a method that quantifies the willingness to pay to avoid systematic longevity risk over multiple horizons. Our measure for systematic longevity risk accounts for historical deviations in the best-estimate survival probability forecasts. In practice, this reflects the uncertainty of life tables being updated by national actuarial agencies. We show that our approach leads to low values for agents' willingness to pay for insurance against systematic longevity risk in annuity products on a one-year horizon. However, our main contribution is that extending the horizon leads to economically important results, as agents require an increasing compensation for taking on the systematic longevity risk, and thereby allowing, e.g., pension funds to off-load their exposure onto agents. We show that agents require up to 10% of the pension payment without longevity risk on a horizon of 15 years as compensation for risk aversion levels up to 10.

Unexpected updates of the forecasted survival probabilities can have several causes, ranging from updating the data period used for calibration of the mortality model or ad-hoc changes in the model selection governed by national agencies. The deviations used to measure systematic longevity risk rely on a status quo of the model selection and are merely based on an update of the data used for calibration. Therefore, the relative risk premia serve as a lower bound as the risk is probably underestimated. In fact, quantifying the impact of systematic longevity risk in terms of risk premia can serve various purposes, ranging from determining individual preferences between products, compensation required to move individuals from one product type to the other, or for awareness and communication of the risks pension holders face. An important question confronting pension funds is how to effectively convert accumulated capital into a sustainable income stream, such that retirees can utilize their savings despite the uncertainty of their lifespan. This paper only offers insight into the latter part of the challenge the pension funds face, namely quantifying systematic longevity risk.

2.7 References

Balter, A. G., Kallestrup-Lamb, M., Rangvid, J., 2020. Variability in pension products: A comparison study between The Netherlands and Denmark. *Annals of Actuarial Science* 14 (2), 338–357.

Balter, A. G., Kallestrup-Lamb, M., Rangvid, J., 2021. Macro longevity risk and the choice between annuity products: Evidence from Denmark. Insurance: Mathematics and Economics 99, 355–362.

Balter, A. G., Werker, B. J. M., 2020. The effect of the assumed interest rate and smoothing on variable annuities. *ASTIN Bulletin: The Journal of the International Actuarial Association* 50 (1), 131–154.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy* 81 (3), 637–654.

Boon, L.-N., Brière, M., Werker, B. J. M., 2020. Systematic longevity risk: To bear or to insure? *Journal of Pension Economics & Finance* 19 (3), 409–441.

Booth, H., Maindonald, J., Smith, L., 2002. Applying Lee-Carter under conditions of variable mortality decline. *Population Studies* 56 (3), 325–336.

Broeders, D., Mehlkopf, R., van Ool, A., 2021. The economics of sharing macro-longevity risk. *Insurance: Mathematics and Economics* 99, 440–458.

Brown, E. F., 2016. Lessons from efforts to manage the shift of pensions to defined contribution plans in the United States, Australia, and the United Kingdom. *American Business Law Journal* 53, 315.

Cairns, A. J. G., Blake, D., Dowd, K., 2006. A two-factor model for stochastic mortality with parameter uncertainty: Theory and calibration. *Journal of Risk and Insurance* 73 (4), 687–718.

Cairns, A. J. G., Blake, D., Dowd, K., Coughlan, G. D., Epstein, D., Khalaf-Allah, M., 2011. Mortality density forecasts: An analysis of six stochastic mortality models. *Insurance: Mathematics and Economics* 48 (3), 355–367.

Cocco, J. F., Gomes, F. J., 2012. Longevity risk, retirement savings, and financial innovation. Journal of Financial Economics 103 (3), 507–529.

De Waegenaere, A., Melenberg, B., Markwat, T., 2017. Risk sharing rules for longevity risk: Impact and wealth transfers. Netspar Industry Paper 66.

Dees, B., de Jong, F., Nijman, T. E., 2021. Variable annuities with financial risk and longevity risk in the decumulation phase of Dutch DC products. Netspar Design Paper 168.

Donnelly, C., Guillén, M., Nielsen, J. P., 2013. Exchanging uncertain mortality for a cost. *Insurance: Mathematics and Economics* 52 (1), 65–76.

Hari, N., De Waegenaere, A., Melenberg, B., Nijman, T. E., 2008. Longevity risk in portfolios of pension annuities. *Insurance: Mathematics and Economics* 42 (2), 505–519.

Human Mortality Database, 2024. Human Mortality Database. University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany), (available at www.mortality.org – data downloaded on 25.01.2024).

Jarner, S. F., Kryger, E. M., Dengsøe, C., 2008. The evolution of death rates and life expectancy in Denmark. *Scandinavian Actuarial Journal* (2-3), 147–173.

Ji, M., Zhou, R., 2017. Demographic risk in deep-deferred annuity valuation. *Annals of Actuarial Science* 11 (2), 286–314.

Lee, R. D., Carter, L. R., 1992. Modeling and forecasting US mortality. *Journal of the American Statistical Association* 87 (419), 659–671.

Lee, R. D., Miller, T., 2001. Evaluating the performance of the Lee-Carter method for forecasting mortality. *Demography* 38 (4), 537–549.

Mateos, J. T., Fernández-Sáez, J., Marcos-Marcos, J., Álvarez-Dardet, C., Bambra, C., Popay, J., Baral, K., Musolino, C., Baum, F., 2022. Gender equality and the global gender gap in life expectancy: An exploratory analysis of 152 countries. *International Journal of Health Policy and Management* 11 (6), 740.

Maurer, R., Mitchell, O. S., Rogalla, R., Kartashov, V., 2013. Lifecycle portfolio choice with systematic longevity risk and variable investment—linked deferred annuities. Journal of Risk and Insurance 80 (3), 649–676.

Merton, R. C., 1969. Lifetime portfolio selection under uncertainty: The continuous-time case. *Review of Economics and Statistics*, 247–257.

Merton, R. C., 1971. Optimum consumption and portfolio rules in a continuous-time model. *Journal of Economic Theory* 3 (4), 373–413.

Munk, C., 2024. Optimal retirement saving and dissaving. Available at SSRN 4850121.

OECD, 2021. OECD Pensions at a Glance 2021. OECD, (available at https://doi.org/10.1787/ca401ebd-en).

Oeppen, J., Vaupel, J. W., 2002. Broken limits to life expectancy. textitScience 296 (5570), 1029–1031.

ONS, 2019. Occupational Pension Schemes Survey, UK: 2018. Office for National Statistics.

Pascariu, M. D., Canudas-Romo, V., Vaupel, J. W., 2018. The double-gap life expectancy forecasting model. textitInsurance: Mathematics and Economics 78, 339–350.

Piggott, J., Valdez, E. A., Detzel, B., 2005. The simple analytics of a pooled annuity fund. Journal of Risk and Insurance 72 (3), 497–520.

Plat, R., 2009. On stochastic mortality modeling. textitInsurance: Mathematics and Economics 45 (3), 393–404.

Pratt, J. W., 1964. Risk aversion in the small and in the large. textitEconometrica 32 (1–2), 122–136.

Qiao, C., Sherris, M., 2013. Managing Systematic Mortality Risk With Group Self-Pooling and Annuitization Schemes. Journal of Risk and Insurance 80 (4), 949–974.

Renshaw, A. E., Haberman, S., 2006. A cohort-based extension to the Lee–Carter model for mortality reduction factors. textitInsurance: Mathematics and economics 38 (3), 556–570.

Richards, S. J., Currie, I. D., Ritchie, G. P., 2014. A Value-at-Risk framework for longevity trend risk. textitBritish Actuarial Journal 19 (1), 116–139.

Stevens, R., 2009. Annuity decisions with systematic longevity risk. Working Paper.

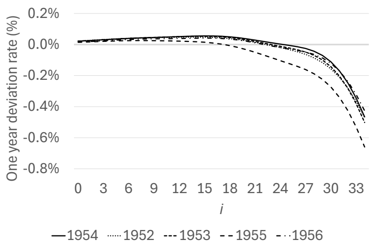
Stevens, R., De Waegenaere, A., Melenberg, B., 2010. Longevity risk in pension annuities with exchange options: The effect of product design. *Insurance: Mathematics and Economics* 46 (1), 222–234.

Appendix

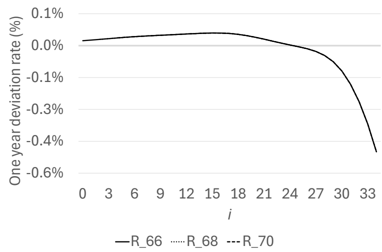
A.1 Payments and Deviations for Sensitivity Analysis

Figure A.1: Sensitivity: Deviations

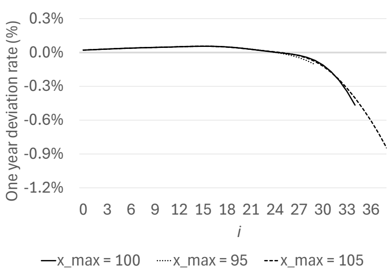
All panels display the one-year deviation rate in percentage for the scenarios considered in Figure 2.10.



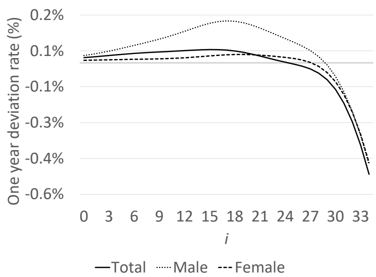
(a) Cohorts



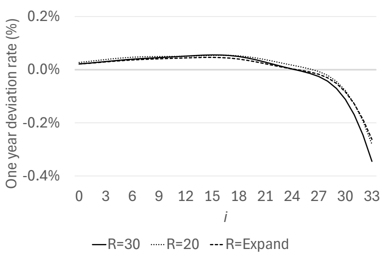
(b) Retirement Age



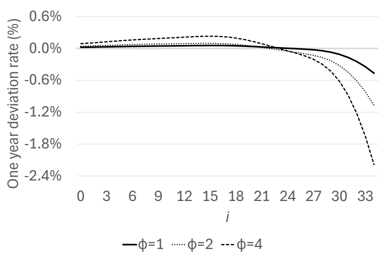
(c) Maximum Age



(d) Gender



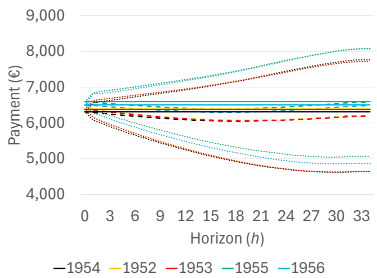
(e) Fitting Period



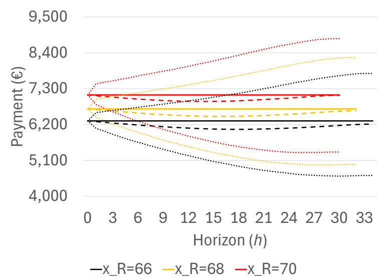
(f) Frequency

Figure A.2: Sensitivity: Payments

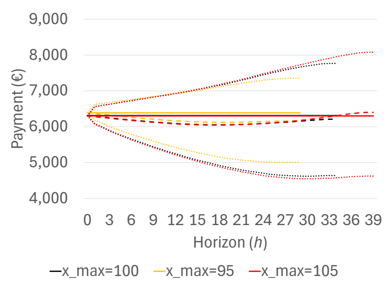
All panels display the payments for the scenarios considered in Figure 2.10.



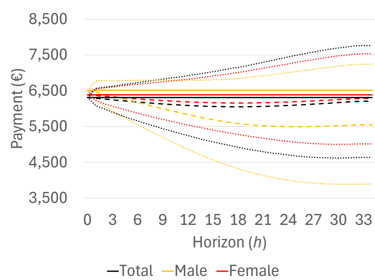
(a) Cohorts



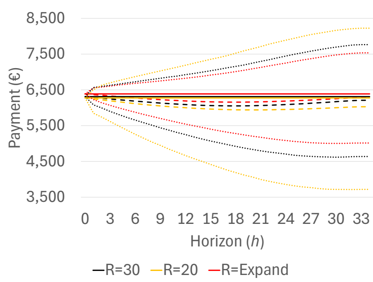
(b) Retirement Age



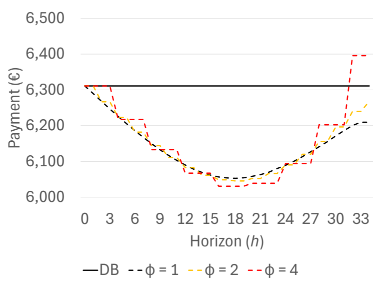
(c) Maximum Age



(d) Gender



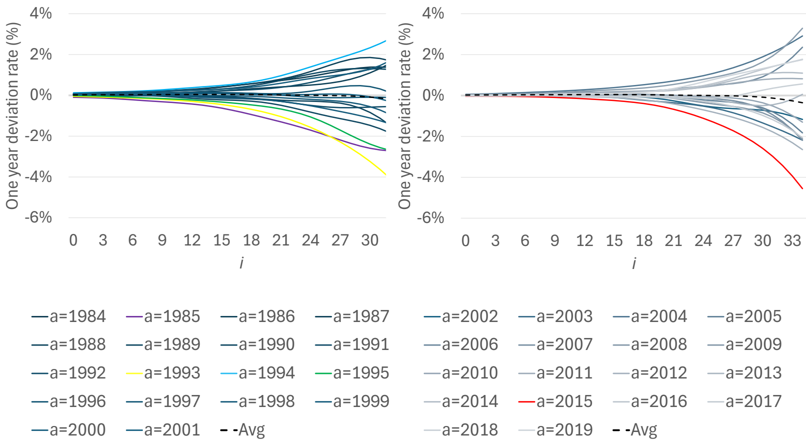
(e) Fitting Period



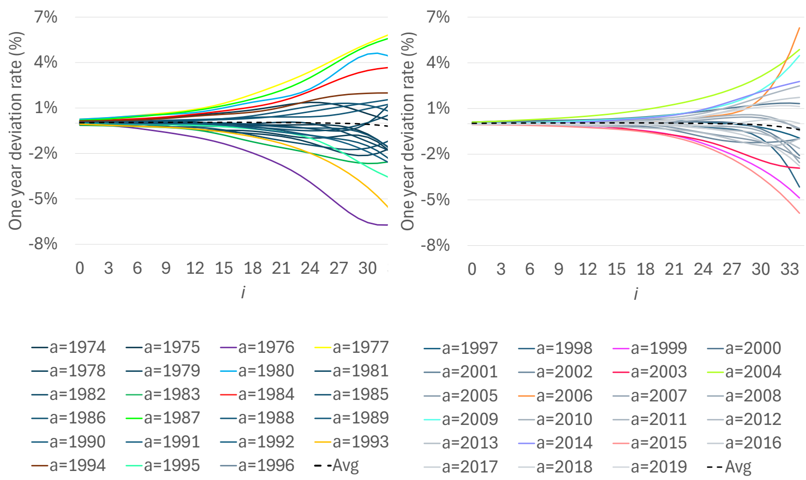
(f) Frequency

Figure A.3: One-Year Deviation Rates

Both panels show the one-year deviation rates similar to those in Figure 2.2 for the case where the length of the rolling window is changed from $R = 30$ to $R = 20$ or an expanding window.



(a) Fitting Period: Expanding window



(b) Fitting Period: Rolling Window $R = 20$

CHAPTER 3

Green Innovation as a Complementary Sustainability Metric

Mathias Danielsen Plovst
Aarhus University

Abstract

How does innovation in green technologies interact with sustainability metrics? This paper address this question in two ways. First, I examine how firms with green innovation activity are described by MSCI Environmental ratings. I find a positive and significant relationship, indicating that firms with high E ratings tend to increase their green innovation activity. I also find that this relationship becomes even more pronounced following a shift in awareness among socially responsible investors after 2015. While ESG ratings face significant criticism, I make a novel contribution by incorporating the Sustainable Development Goals as a sustainability metric, and find similar patterns as those observed with E ratings. Second, I examine whether firms' green innovation predicts future sustainability performance, proposing that it should be considered a complementary metric. Despite a sustained focus on green innovation over the sample period, I find that patenting activities are "punished" by lower environmental ratings in the medium term (three years after a patent is granted) while SDG ratings improve. These findings suggest that green innovation can enhance the total assessment of a firm's sustainable impact, offering a "real-world impact" dimension to investment portfolios that seek to balance financial materiality with sustainability objectives.

3.1 Introduction

Advancements in technology are often seen as key to solving global challenges (IEA, 2023). Green innovation (GI) is particularly important for addressing environmental issues like global warming and energy conservation (Kraus et al., 2020). Prior studies explore GI's role in enhancing firms' competitive advantages (Chen, 2008; Qiu et al., 2020) and its impact on environmental performance and emissions (Cohen et al., 2020; Bolton et al., 2023). Throughout this paper, I define *sustainability metrics* as those measuring firms' sustainable impact and behavior. As sustainable investing grows – accounting for 25% of global assets under management in 2022 (GSIA, 2022) – investments must support firms developing green solutions.[1] Most investors assess firms' sustainability through Environmental, Social, and Governance (ESG) metrics, known as *ESG integration* (Fiaschi et al., 2020; Linnenluecke, 2022; Scheitza et al., 2022). However, this approach has faced criticism, reflected in significant outflows of ESG-screened funds.[2] This likely stems from how ESG ratings are constructed, primarily focusing on financial materiality, especially how climate risks affect financial performance (Popescu et al., 2021). Bloomberg's reference to an "*ESG mirage*" underscores the flaws in the ESG framework, where firms with negative environmental impacts can still receive high ESG ratings. This highlights the need for complementary metrics in investment strategies. For investors, ensuring that investments align with sustainable goals is crucial to making a meaningful impact.

This paper examines how patents in green technologies (GTs) can complement existing sustainability metrics by analyzing their interaction with these. I focus on the relationship between E ratings and GI while introducing the use of Sustainable Development Goal (SDG) ratings as a novel contribution to the literature. The incorporation of GI into existing metrics lacks clarity, and data vendors do not transparently detail it. This is particularly true for SDG ratings, which, despite being relatively new, are gaining increasing attention in sustainable finance (see Van Tulder and van Mil, 2022). My primary analysis uses the number of granted GT patents as a proxy for GI (Desheng et al., 2021; Ghisetti and Quatraro, 2017; Acs et al., 2002; Hall et al., 1984; Kemp and Pearson, 2007), although there exist other measures to quantify firms' GI (see Hirshleifer et al., 2013). Regressions using GT patent ratios - proportions of GT patents relative to total patents - show how firms' sustainability metrics interact with their innovation activity, depending on whether they are classified as "*green*" (high E rating) or "*brown*" (low E rating). Several reasons drive firms to engage in GI activities. From an economic perspective, the dominant hypothesis is the opportunity cost of not doing so, as engagement could be more profitable than non-engagement.

[1] Excluding US data, 38% of total assets under management (AUM) is invested sustainably in 2022. Sustainable investing in the US has experienced a significant drop of 51% due to lower reported AUM by sustainable funds and a change in verifying fund statements incorporating ESG.

[2] Global investors have withdrawn a net $40bn from ESG-screened funds in 2024, driven by increasing concerns over *greenwashing* and regulatory risks. These issues have also led to the removal of several ESG labels from fund names – See `https://www.ft.com/content/cf9001ab-e326-4264-af5e-12b3fbb0ee7b`

Achieving the SDGs is also expected to be a key driver of future global economic growth.[3] Additionally, I assess the impact of firms' GI on future sustainability metrics by running predictive regressions from the short term (one year after a patent is granted) to the medium-term (three years after a patent is granted). Balancing return and risk is crucial for investors, but it is equally important to understand how GI can complement sustainability frameworks – beyond ESG integration – to achieve sustainability objectives.

I construct an unbalanced panel data set incorporating patents, financial data, and sustainability metrics at the firm-level. First, patent grants from 1995 to 2023 are downloaded from Google's patent database, identifying over 14 million patents linked to 17,411 publicly traded firms through a harmonization process (Peeters et al., 2010).[4] This study considers three patent offices (POs): The United States Patent and Trademark Office (USPTO), The European Patent Office (EPO), and a self-constructed global patent office (GPO). Patents are classified in two ways: as "*green*" using the IPC Green Inventory (WIPO) and according to Frietsch et al. (2016), who classify patents into six classes, each addressing key global challenges – termed *Societal Grand Challenges* (SGC).[5] This study primarily uses *energy* (climate change mitigation technologies) and *climate* (technologies related to climate action or resource efficiency) classifications from SGCs. To the best of my knowledge, this classification has not yet been applied in the economics literature on innovation, highlighting a significant gap.[6] These classes represent patenting in GTs. I use Worldscope for financial data, with ESG and carbon emission metrics from MSCI and Refinitiv and SDG ratings from Robeco and MSCI. These ratings evaluate sustainability alignment, particularly with the 17 SDGs, while enabling an analysis of divergences among data providers due to the inherent subjectivity in these ratings.

Using a Pseudo Poisson Maximum Likelihood model with firm characteristics and fixed effects, I find that a one-standard-deviation increase in MSCI environmental ratings significantly increases energy patenting, equal to 145% of its standard deviation, in the following year. A similar but smaller effect of 53% is observed for green patenting, while the impact on climate patenting is insignificant. These results align with the path-dependency hypothesis (Popp, 2002; Aghion et al., 2016), which suggests that greener firms (higher E rating) are more likely to engage in GI and vice versa. A robustness check using direct carbon emissions provides no clear support,

[3] `https://www.unpri.org/sustainable-development-goals/the-sdgs-will-drive-global-economic-\growth/307.article` – Accessed June 2024

[4] Each patent is classified using the international patent classification (IPC) or cooperative patent classification (CPC) codes and is assigned to the relevant granting patent office.

[5] The term *Societal Grand Challenges* and the six classes are defined in the *Horizon2020* EU program. The classes are: *Health*, *Bioeconomy*, *Energy*, *Transport*, *Climate*, and *Security*. I include the remaining SGC classes in the Appendix for completeness (`https://www.h2020.md/en/content/societal-challenges`).

[6] The dominant classification scheme in innovation studies relies on the WIPO green inventory. However, several other patent classifications exist seeking to capture green patents, such as OECD environmental technology (ENV-TECH) and Y02/Y04 Tagging Scheme (see, e.g., Favot et al., 2023).

though SDG ratings partially confirm the hypothesis.

Patent activity varies across firms, with some engaging in minimal patenting and others as large innovators. To avoid bias from distributional differences, I condition the regressions on firms with at least one granted patent in GT classes. The main finding for the energy class holds, though with a reduced economic effect, equal to an increase of 8.5% of its standard deviation. Notably, the significant effect of green patenting disappears. In contrast, a significant negative economic effect of 7.9% is observed for climate patenting, likely due to the firm's lack of materiality in this patent class.

Research in sustainable finance documents a shift in socially responsible investors (SRI) awareness (Chang et al., 2024; Cepni et al., 2023; Avramov et al., 2022; Monasterolo and De Angelis, 2020). The Paris Agreement in 2015 is often cited as a turning point, marking a shift in beliefs and serving as a shock. This year also coincides with the adoption of the SDGs by all UN member countries (UN, 2015b). I find that increases in MSCI E rating post-2015 significantly increase GI by more, likely reflecting heightened SRI awareness, which has widened the gap in patenting activity between low and high E-rated firms. To further support these findings, I incorporate climate exposure metrics from Sautner et al. (2023) and show that firms with climate-related opportunities also tend to increase their GI activity globally.

I focus on the predictability of GI for future sustainability metrics. For SRIs, using GI as a complementary metric for improvements in firms' sustainability ratings is crucial for ensuring the desired impact of their portfolios. I find that GT patenting does not significantly affect MSCI E ratings in the short term, but there is a significant decrease, equal to 2-2.6% of its standard deviation, in the medium term. A similar effect is observed for Refinitiv E ratings, with ESG ratings showing negative effects across all horizons (2.2%-4.4%). This effect is driven primarily by larger firms, which experience a size bias in ESG ratings compared to smaller firms (Akgun et al., 2021; Dobrick et al., 2023). However, SDG ratings, particularly from Robeco, show significant increases of 2.9%-3.4% across all horizons, with similar positive effects for SDGs 7 and 13, which target climate challenges. He et al. (2024) find no size bias for SDG ratings using Robeco data. Using MSCI data, the evidence for a positive effect on SDGs is less robust, likely due to the limited data period. These findings suggest that investors can use GI as a complementary sustainability metric to identify firms whose activities are more aligned with driving the world toward a more sustainable future.

My findings contribute to the growing literature on the role of finance in the transition to a green economy. As financial markets increasingly prioritize sustainability, understanding how GI interacts with and predicts sustainability metrics is essential for research and investment strategies. Bolton and Kacperczyk (2021, 2023) find that equity markets already reflect the transition to a low-carbon economy, while Ilhan et al. (2021) show that carbon risk is priced into options. In a related study, Bolton et al. (2023) examine the link between patenting and carbon emissions, finding no significant effect of GI on future direct carbon emissions, which aligns with my results. However, I find scope 3 emissions are negatively predicted by GI, suggesting that firms with high GI could serve as a hedge against climate-related risks.

GI can complement traditional ESG and SDG ratings in portfolio decisions, providing a more comprehensive view of firms likely to achieve long-term sustainable impact beyond what existing metrics capture. Cohen et al. (2020) find that firms in the energy sector receive lower E ratings despite higher GI activity. While such firms are often excluded from portfolios,[7] incorporating GI activity adds an additional dimension to assessing firms' sustainable impact. This is particularly relevant for investors, who aim to construct sustainable portfolios that align with both financial and sustainability goals.[8] Given the mixed results of fund performance integrating ESG factors (Khajenouri and Schmidt, 2021; Khan et al., 2016; Renneboog et al., 2008), adding GI as a portfolio sorting variable for sustainable impact offers a promising area for further research. Additionally, exploring the relationship between GI and stock returns through a factor model could determine whether GI serves as a proxy for systematic risks or influences firms' expected returns due to factors such as reduced environmental and regulatory exposure. This approach complements Leippold and Yu (2023) findings of a negative High-minus-Low portfolio using GI from USPTO.

This study also adds to the literature on using SDGs in sustainable finance. Van Tulder and van Mil (2022) argue that SDGs represent the most all-encompassing action-oriented agenda for global progress, likely due to the widespread agreement on a universally shared framework to address sustainable development issues (Bauckloh et al., 2023; Pattberg and Widerberg, 2016; Stevens and Kanie, 2016; UN, 2015b,a). SDG ratings are increasingly used to evaluate firms' sustainability performance in investment strategies (Van Zanten et al., 2023), assess investments in firms with varying SDG scores (van Zanten and Rein, 2023), and gauge pension members' sustainability preferences for selected SDGs (Bauer et al., 2021). However, like ESG ratings, SDG ratings are subject to discrepancies across data vendors (Bauckloh et al., 2023; Berg et al., 2022). I contribute to this literature by showing that the six classes by Frietsch et al. (2016) align patents with their expected SDG areas and that GI predicts future improvements in SDG ratings.

The remainder of the paper is organized as follows. Section 3.2 introduces data and descriptive statistics. Section 3.3 describes the model framework and provides the main results and robustness analysis. Section 3.4 concludes.

[7] For instance, see https://gofossilfree.org/divestment/what-is-fossil-fuel-divestment/, or *exclusion lists* by pension funds.

[8] Denmark's largest pension firm, PFA, has recently launched four new thematic funds focused on sustainability, each targeting specific sustainable development goals – See https://www.europeanpensions.net/ep/Denmark-PFA-launches-four-new-sustainability-funds.php. Velliv, the third largest Danish pension firm, construct their sustainable portfolio using four categories, where GI contribute to at least one – See https://www.velliv.dk/dk/privat/aftryk

3.2 Data

3.2.1 Data Collection

I construct the data by focusing on publicly listed global firms granted patents between 1995 and 2023, filtering out private firms and individuals. I identify firms in the following databases: Google Patent Database, Worldscope, MSCI, and Robeco.[9] Google's patent database includes over 120 million patent publications from 100+ patent offices worldwide, from which I download individual patent documents. I narrow the dataset to 29 POs that have granted patents,[10] focusing on three POs throughout the paper, The United States Patent and Trademark Office, the European Patent Office, and a Global Patent Office (including all POs).[11] I exclude patent applicants with non-Latin alphabet names, resulting in a loss of approximately two-thirds of all patent grants. I then apply a harmonization procedure based on Peeters et al. (2010) to clean applicant names and match patents to specific firms. I refer to this as the "*harmonized sample*".[12] Finally, I match this sample with firms in the Worldscope database using a two-step process: 1) forced matching for identical names and 2) *Fuzzy name matching* based on the Levenshtein distance.[13]

By the end of 2023, 69,682,035 granted patents are under coverage from the 29 POs, with 14,357,957 (20%) identified as belonging to a common assignee name.[14] This represents the *full sample* without any restrictions on whether the patent can be identified as belonging to a publicly listed firm. Of these, 1,435,295 (10%) are classified as *green* according to the WIPO green inventory, while 5,996,309 (42%) fall into one or more SGC classes based on Frietsch et al. (2016). To be included in the final *patent sample*, each patent assignee must be identified as a publicly traded firm within the Worldscope database, leading to 6,971,182 (48%) patent observations being lost. This is comparable to the 56% loss reported by Kogan et al. (2017) when they match applicant names to public firms in the Center for Research in Security Prices. Overall, 52% of patents with a common applicant match with publicly traded firms. Table A.5 in the Appendix provides a detailed overview of patent counts by country and classification for the three POs in the full sample. For the remaining

[9] Ulbricht and Weiner (2005) thoroughly discuss why Thomson Reuters Worldscope data as a source of accounting and financial data is comparable to its often-used counterpart, Compustat, in the literature.

[10] Half of these are under Google's coverage of full-text documents, thus providing me with complete documentation of the individual patent scope.

[11] In total, 29 national patent offices are considered. They are distributed among the following three geographical groups – USA (4%): USPTO, Europe (41%): AT, BE, DE, DK, EPO, ES, FI, FR, GB, IT, LU, NL, and the rest of the world (55%): AP, AR, AU, BA, CA, CL, CN, DZ, EG, GC, JO, JP, KR, RU, SU, TW

[12] For a comprehensive overview of the general approach to assigning and matching firms using data from Google's Patent Database, I refer interested readers to the online appendix of Kogan et al. (2017).

[13] The Levenshtein distance (LD) quantifies the similarity between two strings by calculating the number of transformations required to convert one string into the other. A higher LD value indicates greater dissimilarity between two strings.

[14] Status as of February 2024. The total value of granted patents includes all patent applicants. Thus, based on names in the Latin alphabet, the total number is, in fact, 23,227,345 granted patents.

sections, I focus on firms' patent grants at USPTO to align with the literature and due to their significance in the data set. I include EPO and GPO in the Appendix for comparison.

I use Worldscope for financial data, including company balance sheets, income statements, and valuation metrics. I require firm-level observations for accounting variables for firms in the restricted *patent sample* – assets, liabilities, property, plant and equipment (PPE), capital expenditure, cash, debt, and EBIT following Sautner et al. (2023). Enforcing this restriction causes a total of 34,765 firm-year observations to be lost. Additionally, I require financial performance variables – beta, volatility, previous year's December return, and market capitalization – for robustness checks, leading to another 9,137 firm-year observations being lost. I refer to this dataset as the *financial sample*, with all variables defined in Table A.3.

I incorporate firm-level ESG ratings from MSCI into the *financial sample* and include data from Refinitiv to address ESG rating divergences across data vendors. Berg et al. (2022) find these vendors to have low correlations in ratings when ranking data providers. The MSCI ESG metrics are reported bi-annually and are divided into three pillars – E, S, and G – each rated from 0-10. Following the definition from MSCI, the Environmental rating assesses firms' ability to reduce emissions, material use, energy, water consumption, and environmental opportunities. The Social rating evaluates diversity, human rights adherence, and business ethics, while the Governance rating measures commitment to corporate governance, shareholder equality, and integration of economic (financial), social, and environmental practices. These pillars combine into an overall ESG rating reflecting a firm's performance as a single measure.[15] I have MSCI ESG data from 2008 to 2023, while Refinitiv data starts in 2002. Initially, both datasets primarily cover US and EU firms, with data available for 8% (MSCI) and 9% (Refinitiv) of firm-year observations. By the end of the sample, this coverage increases to 54% and 44%, respectively. Although US and EU firms represent 74% of global sustainable investing (GSIA, 2022), they account for only 37% of firm-year observations, which may explain the limited data availability. Restricting the sample to begin in 2002 (2008) leads to 6,622 (24,358) firm-year observations being lost. I also include data on all firm-level carbon emissions from MSCI.[16]

Penultimately, I incorporate SDG ratings from two providers – Robeco and MSCI – to assess firms' positive and negative alignment with each of the 17 SDGs. Robeco's SDG ratings range from -3 (negative impact) to +3 (positive impact). An overall SDG

[15] MSCI's latest methodology report (April 2024) has become less transparent regarding the role of patents in assessing firms' opportunities in clean tech. In contrast, Refinitiv employs a binary variable to indicate firms' exposure to innovation. For more information on MSCI ESG ratings, see `https://www.msci.com/zh/esg-ratings` – For Refinitiv ESG ratings, see `https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores`

[16] I use Scope 1 emissions, which captures direct emissions from sources owned or controlled by the company; Scope 2, which captures indirect emissions from the consumption of, e.g., purchased electricity, heat, or steam; and Scope 3, which captures upstream and downstream emissions in the value chain, such as those related purchased goods and services. I use MSCI to obtain data on CO2 metrics and refer to Bolton et al. (2023), who thoroughly describes all carbon emission metrics.

rating is calculated for all covered firms using a min-max rule: if all SDG ratings are positive (negative), the most positive (negative) rating is used as the overall rating. The most extreme negative rating is selected for firms with both positive and negative ratings. MSCI provides ratings on firms' operational, product, and net (average of operational and product) alignment, totaling 51 ratings. These are scaled from -10 to +10 for each SDG, where ratings above +5 indicate strong alignment, and -10 signifies strong misalignment and are only given if a firm generates over 50% of its revenue from products and services with adverse impact or due to a severe controversy.[17] Like other sustainability metrics, SDG ratings are subjective and vary depending on the chosen methodology, leading to divergence in these ratings. Robeco data begin in 2010, while MSCI data were introduced in 2020, warranting a cautious interpretation of the findings herein. Both are included in the *financial sample*.

Ultimately, I merge the *financial sample* with the *patent sample* to create the final sample, referred to as the – *merged sample* – which includes patents, financial, environmental, and SDG data. The sample has a total of 102,728 firm-year observations, thus I lose 38% of the patent sample firm-year observations.

3.2.2 Data Description

I now describe the firm-year observations in the *merged* sample. Table 3.1 shows the distribution of firm-year observations by country, conditional on financial data availability. Columns 1 to 3 report the number of observations for firms granted a green patent and those granted an SGC patent at USPTO. In total, there are 102,728, with 33,129 classified as green and 70,134 as SGC. Six countries – the United States, Japan, Chinese Taipei (Taiwan), the Republic of Korea, the United Kingdom, and China – account for 69% of firm-year observations. Thus, approximately 1/3 of the sample is represented by the remaining 54 countries, providing me with a broad cross-country representation. The US alone represents a significant share, with 37% more firm-year observations than Japan, the second-largest innovative country. This aligns with the larger share of publicly listed companies in the US.[18] Columns 4 to 6 and 7 to 9 show firm-year observations for patents granted at EPO and GPO, respectively. EPO has 40% fewer firm-year observations, even though firms receiving granted patents at EPO often have more significant and enduring innovations due to their known reputation for a rigorous filing process. An explanation could be that firms in the sample conduct most of their business in the US. Thus, patenting here is more beneficial. The distribution of countries with at least one SGC (green) patent is skewed, with the US and Japan representing nearly 50% of all observations. Table A.6 in the Appendix, provides the same breakdown for the *patent sample*, with similar

[17] Bauckloh et al. (2023) provides a comprehensive overview of the different SDG providers and their methodologies.

[18] The floating adjusted market cap in USD millions for MSCI ACWI is 72,346,901, while for MSCI USA, it is 46,157,862 as of May 2024.

conclusions. From here, I focus on analyzing the six SGC classes separately, as these target different innovations.

Table 3.1: Firm-Year Observations By Country

The sample period is 2002-2023. I report the number of firm-year observations by country for USPTO, EPO, and GPO, conditional on availability of financial data. Within each patent office, I report the number of firm-year observations for the total, green, and SGC samples. A single firm may be granted a patent at any patent office in a given year, therefore columns (1) to (3) represent firm-year observations conditional on a patent grant at USPTO. Consequently, columns (1) and (4) do not sum up to the total in column (7), as they represent different samples. Furthermore, patents may be included in both classification schemes, resulting in discrepancies between the total column and the sum of green and SGC classifications. Comparisons of firm-year observations are only valid within patent office.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		at USPTO			at EPO			at GPO	
Country	Total	Green	SGC	Total	Green	SGC	Total	Green	SGC
AT	350	97	275	347	117	283	490	212	413
AU	2,434	546	1,527	1,212	213	813	3,709	1,007	2,622
BE	583	225	454	487	201	386	717	343	602
BR	422	95	255	258	47	171	576	151	376
CA	2,325	583	1,501	964	217	657	3,059	936	2,177
CH	1,513	533	1,151	1,388	481	1,065	1,803	773	1,500
CN	4,543	874	2,206	1,819	297	1,101	5,977	1,257	3,285
DE	2,875	1,092	2,180	2,659	1,019	2,086	3,760	1,740	3,080
DK	591	226	464	504	188	420	738	358	621
ES	522	145	375	467	90	342	818	306	657
FI	715	226	509	603	199	464	1,005	406	797
FR	2,702	1,065	2,075	2,315	875	1,890	3,542	1,606	2,916
GB	4,883	1,443	3,391	3,137	834	2,292	6,045	2,298	4,687
GR	360	61	218	186	27	123	528	100	354
HK	3,508	759	1,958	1,393	323	920	4,574	1,223	2,865
IL	675	172	389	341	87	227	877	247	565
IN	2,822	673	1,853	1,555	363	1,118	3,973	1,063	2,774
IT	912	286	591	909	288	652	1,298	462	962
JP	19,245	6,869	13,740	13,324	4,343	9,734	24,099	9,207	18,138
KR	6,487	1,592	3,977	3,047	781	2,123	8,550	2,299	5,632
MY	512	110	301	221	43	150	759	200	488
NL	666	282	521	559	242	449	795	419	686
NO	600	155	422	411	104	293	804	282	615
NZ	280	59	180	145	16	110	415	105	296
PH	346	99	235	166	40	120	486	153	352
PL	464	72	260	277	30	172	773	136	492
SE	1,963	583	1,445	1,495	443	1,106	2,469	953	1,982
SG	1,012	200	583	446	77	276	1,482	313	927
TH	827	217	480	330	96	205	1,175	342	744
TW	9,170	2,447	4,858	3,116	579	1,756	11,602	3,611	7,132
US	26,356	10,887	20,492	15,612	5,393	12,184	29,100	13,681	23,835
ZA	581	127	357	326	93	220	907	236	631
Others South America	230	48	121	92	15	57	320	70	193
Others Asia	446	112	270	240	57	166	649	169	428
Others Europe	507	100	329	392	77	292	809	179	588
Others Africa	301	69	191	143	22	92	478	114	327
Total	102,728	33,129	70,134	60,886	18,317	44,515	129,161	46,957	94,739

Figure A.1 shows the yearly distribution of firm-year observations separated by patent class and PO. Panel A presents firms granted a patent at USPTO, where I observe a steady increase in the number of innovating firms across all classes. Thus, firms innovate more over the years. Innovation activity peaked in 2022, with nearly 9,000 firms granted a patent, though this number slightly dropped to just under 8,000 in 2023, possibly due to lower R&D spending in the preceding years. Panel B and C, which present the distribution for EPO and GPO, respectively, show similar patterns. The intensity of patent activity varies in the cross-section of firms, as documented in the literature (Sautner et al., 2023). Figure A.2 illustrates that firms either engage in low patenting activity or are large innovators, with the distribution heavily skewed towards firms with fewer than 10 patents, representing nearly 50% of total firm-year observations.

Patent counts often measure innovation activity, but comparing innovation solely based on the number of patents can bias results toward larger firms. To address this, I follow the literature and calculate patent ratios for all classes, conditional on the PO, by taking the number of patents within a class relative to the total patent count (Bolton et al., 2023; Cohen et al., 2020; Leippold and Yu, 2023). The ratios are HealthRatio, BioeconomyRatio, EnergyRatio, TransportRatio, ClimateRatio, SecurityRatio, and GreenRatio, with identifiers (US, EPO, GPO) indicating the PO. Table A.2 provides definitions for all patent variables used. In Table A.7, I show the firm-year patent ratio by country. On average, the SGC classes health, bioeconomy, and transport have the highest ratios (0.131, 0.137, 0.146, respectively), while energy, climate, and security have the lowest ratios (0.055, 0.033, 0.079, respectively). The lower energy ratio is partly due to the absence of observations before 2010. The average green ratio is 0.105, which is higher than previous studies (Bolton et al., 2023; Cohen et al., 2020), though similar ratios are observed at EPO. While the green ratio remains relatively consistent across POs, SGC ratios vary, with firms patenting at EPO showing larger individual SGC class ratios.[19]

Large differences in patenting activity exist across industries. Table A.8 highlights this using the 74 GICS industry classifications, where each patent class captures different industries that excel in innovation intensity. Disregarding discontinued industries, I find the Independent Power and Renewable Electricity Producers to have the highest green ratio (0.319), followed closely by Electric utilities (0.277), Multi-Utilities (0.228), Oil, Gas & Consumable Fuels (0.213), and Gas Utilities (0.212). These findings are consistent with Cohen et al. (2020) and Bolton et al. (2023) for the US and global data, although some energy-intensive industries show higher ratios in this sample. For health and bioeconomy, Biotechnology stands out with the highest ratios (0.654 and 0.536, respectively). The energy class resembles the green class but with lower ratios. The Automobiles (0.409) and Containers & Packaging (0.323) industries lead in transport, while Water Utilities (0.283) and Multi-Utilities (0.091) top the climate class. Health Care Technology (0.207) and Health Care Equipment & Supplies (0.174) rank highest in security. This breakdown demonstrates that the SGC classes, aside from health and bioeconomy, capture different industries, allowing investors to pursue various sustainability objectives through sector tilts. The similarity between

[19]Among the top 3 countries with the highest green ratios at USPTO are: Denmark (0.162), Thailand (0.159), and New Zealand (0.155). For SGC ratios, Denmark, New Zealand, and Spain (Belgium) lead in health (bioeconomy); Thailand, the Philippines, and Canada for energy; Austria, Finland, and Germany for transport; Malaysia, Norway, and Austria for climate; and Norway, Thailand and South Africa for security. "Other regions" have been excluded from this analysis, though they show the highest ratios for several individual SGC classes.

the energy and green classes suggests they may produce comparable results.[20] The ranking of industries remains consistent across POs (see Panels B and C).

The large differences in patenting activity across industries align with the notion that, for instance, oil companies, which are major contributors to carbon emissions and typically receive lower ESG ratings, are also among the most active innovators in GTs. Continued innovation is essential for these industries to be viewed as more climate-friendly. Otherwise, they risk being left with "*stranded*" assets (Van Tulder and van Mil, 2022).

I conclude this section by presenting descriptive summary statistics for the patent ratios, financial variables, and sustainability metrics in the merged sample, including the mean, median, and standard deviation. Additionally, I report the distribution of firms in the bottom and top deciles based on their green ratio. To further assess innovation quality, I incorporate a measure from the literature – *forward patent citation* ratios – calculated similarly to patent ratios (Cohen et al., 2020; Abrams et al., 2013; Hirshleifer et al., 2013).[21]

Table 3.2 presents summary statistics for patents granted at USPTO (Panel A).[22] Columns 1 to 3 cover the merged sample, while columns 4 to 6 and 7 to 9 split the data by bottom and top deciles based on firms' average GreenRatio. Notably, firms in the bottom decile, representing 64% of total firm-year observations, typically exhibit no green patenting activity. In contrast, firms in the top decile have an average GreenRatio of 0.742, representing 4% of total firm-year observations. Nevertheless, considerable heterogeneity in patenting activity is observed in the sample, as shown in Panel A.1. Firms with no GreenRatio are still active across all SGC classes, suggesting that these entities are large and diversified in their technological focus rather than solely concentrating on GTs. Additionally, the two deciles have a significant difference in patenting activity within SGC classes. Another interesting point is that, on average, firms tend to have higher patent ratios across all classes for patents granted at EPO, supporting the notion that EPO patents are more substantial. This may be linked to the origin of sustainable investing in Europe, where such patents hold greater significance. In Panel A.2, I present the financial and environmental variables, maintaining the same decile sorting as in Panel A.1. Notably, firms at USPTO tend to have lower carbon emissions while also being smaller in size (lower LogSize), with fewer assets (lower LogAssets and LogPPE), less R&D spending, lower overall ESG ratings from both data vendors, and weaker alignment with SDGs, compared to firms at EPO.

[20] The energy class is based on the Y02/Y04 tagging scheme, which, according to Favot et al. (2023), complements the WIPO green inventory classification.

[21] Highly cited patents signify significant technological contributions and are often used to evaluate a firm's capacity to drive advancements within their industry (Cohen et al., 2020).

[22] EPO (Panel A), and GPO (Panel B) is presented in Table A.10 in the Appendix.

Table 3.2: Firm-Year Summary Statistics

The table reports sample averages, medians, and standard deviations of several firm-level characteristics for the sample period 2002-2023. Panel A's columns are based on firms' patenting at USPTO. Table A.10 in the Appendix, are based on firms' patenting at EPO (Panel A), and at GPO (Panel B). Columns (1) to (3) aggregate all firm-years in the sample. Column (4) to (6) aggregate firm-years in the bottom decile based on a firm's average *GreenRatio* across the entire period. The bottom decile includes only firm's with 0 green patents and represents about 64% of total firm-year observations. Column (7) to (9) aggregate firm-years in the top decile based on a firm's average *GreenRatio* across the entire period. The top decile includes only firm's with a high number of green patents (above 50%), representing about 4% of total firm-year observations. All variables are defined in Table A.3.

Panel A: Conditioning on patenting at the United States Patent and Trademark Office

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Merged Sample			Bottom decile green ratio			Top decile green ratio		
	Panel A.1: Patent Ratios								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
GreenRatio US	0.105	0.000	0.237	0.000	0.000	0.000	0.742	0.726	0.245
HealthRatio US	0.131	0.000	0.288	0.130	0.000	0.299	0.155	0.000	0.315
BioeconomyRatio US	0.137	0.000	0.280	0.119	0.000	0.280	0.263	0.000	0.387
EnergyRatio US	0.055	0.000	0.175	0.030	0.000	0.142	0.200	0.000	0.339
TransportRatio US	0.146	0.000	0.274	0.112	0.000	0.264	0.340	0.143	0.391
ClimateRatio US	0.033	0.000	0.141	0.022	0.000	0.126	0.104	0.000	0.261
SecurityRatio US	0.079	0.000	0.208	0.081	0.000	0.228	0.074	0.000	0.209
GreenCit US	0.081	0.000	0.223	0.000	0.000	0.000	0.528	0.554	0.423
HealthCit US	0.107	0.000	0.276	0.099	0.000	0.277	0.124	0.000	0.302
BioeconomyCit US	0.100	0.000	0.257	0.083	0.000	0.249	0.188	0.000	0.359
EnergyCit US	0.043	0.000	0.166	0.021	0.000	0.127	0.147	0.000	0.318
TransportCit US	0.126	0.000	0.275	0.095	0.000	0.259	0.270	0.000	0.394
ClimateCit US	0.025	0.000	0.128	0.017	0.000	0.115	0.067	0.000	0.222
SecurityCit US	0.070	0.000	0.209	0.068	0.000	0.222	0.063	0.000	0.209
	Panel A.2: Financial & Environmental variables								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
LogS1Tot	10.055	9.892	3.074	9.498	9.297	2.992	10.432	10.180	3.542
LogS2Tot	10.612	10.638	2.308	10.114	10.162	2.196	10.381	10.523	2.547
LogS3Tot	12.478	12.668	3.170	11.910	12.176	3.013	12.711	12.948	3.481
LogSize	6.531	6.518	2.286	6.081	6.033	2.130	6.271	6.214	2.215
LogPPE	9.376	8.639	5.1	9.116	8.518	5.068	9.339	8.871	5.308
LogAssets	10.952	10.22	4.858	10.716	10.126	4.834	10.816	10.276	5.03
Cash/Assets	170,982	123,733	161,368	173,779	126,134	163,644	181,008	125,097	180,775
PPE/Assets	0.298	0.257	0.228	0.299	0.258	0.239	0.331	0.288	0.234
EBIT/Assets	0.086	0.069	0.139	0.086	0.069	0.160	0.081	0.064	0.079
Debt/Assets	0.257	0.221	0.454	0.256	0.215	0.509	0.271	0.224	0.432
R&D/Assets	0.059	0.023	1.463	0.062	0.021	1.852	0.067	0.023	0.162
LogCash	22.513	21.735	5.051	22.279	21.681	5.051	22.374	21.656	5.132
LogR&D	7.909	7.489	4.853	7.608	7.531	4.797	7.791	7.419	4.966
LogCapex	7.169	6.471	5.129	6.869	6.295	5.085	7.104	6.590	5.325
$ESG_{Refinitiv}$	46.401	46.250	19.429	43.538	42.510	19.273	45.698	45.670	18.833
$E_{Refinitiv}$	48.095	49.250	26.248	43.099	41.550	25.881	47.819	48.885	25.531
$S_{Refinitiv}$	49.238	48.810	24.023	45.772	44.240	23.467	47.900	47.690	23.116
$G_{Refinitiv}$	52.794	53.840	22.278	50.615	51.040	22.153	51.819	52.480	21.868
ESG_{MSCI}	4.864	4.900	1.049	4.783	4.800	1.073	4.867	4.800	1.095
E_{MSCI}	5.173	5.000	2.178	5.002	4.700	2.257	5.086	5.000	1.992
S_{MSCI}	4.657	4.700	1.649	4.621	4.600	1.635	4.636	4.700	1.722
G_{MSCI}	5.362	5.400	1.803	5.369	5.400	1.835	5.235	5.300	1.779
SDG Net 7	1.063	1.000	1.431	0.903	0.000	1.359	0.863	1.000	1.379
SDG Net 13	1.307	1.000	1.436	1.173	1.000	1.390	1.064	1.000	1.442
SDG Overall^{Robeco}	0.582	1.000	1.432	0.556	1.000	1.406	0.503	1.000	1.597

Interestingly, patent ratios show close to zero correlation with ESG (SDG) ratings from any provider, as seen in Figure A.5. In contrast, patent counts are positively correlated (Figure A.6). Additionally, the correlation between ESG and SDG overall ratings is near zero, indicating that these metrics capture fundamentally different concepts. Figure A.3 further illustrates the distribution of SDG ratings, showing a skew towards positive ratings (61%) at Robeco, particularly for SDGs linked to sustainable innovation (SDG 7, 9, 11, 12, & 13), which predominantly receive positive or neutral ratings. However, a significant portion of SDG ratings (51% on average) are neutral.[23]

3.3 Model and Results

Through technological innovation, firms are (re)shaping our world in what is known as the "*Digital Revolution*" (TWI2050, 2019). Firms allocate capital to R&D and engage in GI for several reasons. One reason is the opportunity cost, as engaging in innovation could be more profitable than not doing so. For instance, the Carbon Disclosure Project (2019) reports that climate-related opportunities could yield $2.1 trillion in market value, while failing to innovate, might leave firms with "*stranded*" assets.[24] Another reason is the potential for firms to enhance their competitiveness within their industry, as green innovations offer a higher likelihood of sustainable impact. While being granted green patents does not necessarily imply that firms have a sustainable impact, it at least signals the potential to do so. As such, these firms can be considered as frontrunners in the transition to a low-carbon economy. Furthermore, innovation is argued to be a key component in addressing the climate crisis, alongside global economic growth, which the SDGs are anticipated to be a major driver of (IEA, 2023). However, while firms' R&D expenditures are transparently reported, it remains challenging to determine how much of this investment is directed specifically toward green innovation. To address this, I utilize classifications of granted patents to identify firms with substantial shares of green technology patents, thereby providing a complementary metric of their focus on sustainability.

However, disagreement persists on how to measure firms' sustainability performance. While ESG integration is one of the most prominent sustainability metrics in finance, it faces significant criticism for failing to adequately reflect firms' adverse impacts on the climate. This has led several news outlets, such as Bloomberg, to refer to it as an "*ESG mirage*", with The Economist arguing that ESG "*won't save the planet*". While ESG is under fire, firms with higher E ratings may still be more likely to engage in green innovation, as future climate risks can, to some extent, be lowered through technology advancements. Thus, firms with higher E ratings may view green innovation as a means of preparing for a low-carbon economy. In a related study,

[23] In Table A.11, I present the top 50 firms sorted by 1) quantity of patents (Panel A) and 2) E ratings (Panel B). Interestingly, Aramco (Saudi Arabian Oil) ranks 29th among firms granted patents at USPTO, with an E rating of 6 (average within its industry) and a Scope 1 value that is 3,397% higher than the second-largest emitter in the table. Robeco assigns the worst SDG rating (-3), while it is not covered in the MSCI SDG data. Panel B also highlights that even best-in-class firms with the highest E ratings do not receive positive SDG ratings uniformly.

[24] Technological advancements are crucial within the energy sector, as the Global Commission on the Economy and Climate (2018) estimates a total of $12 trillion in *stranded* assets in fossil fuel by 2035.

Bolton et al. (2023) find carbon-intensive firms to pursue less green innovation, and more brown efficiency-improving R&D. This behavior is well-documented in the economics literature on innovation and is described as "path-dependency", where firms with a history of dirty innovation are likely to continue their R&D efforts in this area in the future (Acs et al., 2002; Popp, 2002; Aghion et al., 2016). With the heightened focus on sustainability performance, similar patterns should also be expected when using ESG or SDG ratings. Furthermore, Van Zanten and Huij (2024) evaluate ESG and SDG ratings in terms of their alignment with the sustainability preferences of investors, regulators, and climate scientists'. They find SDG ratings to be more closely aligned with the preferences of all three key stakeholders, as they, for example, assign low ratings to firms on exclusion lists, and high ratings to firms in sustainable thematic investment strategies. ESG ratings, on the other hand, lack this alignment. However, as major data vendors have only recently started providing such ratings, it remains challenging to fully use SDGs when creating sustainable portfolios. Several questions arise. First, if ESG ratings do not adequately reveal sustainable investor preferences, what type of metrics could complement the assessment of whether firms should be considered sustainable? Second, how does complementary metrics interact with existing ones? Third, and lastly, could firms' green innovation serve as a complement to existing metrics by predicting their future sustainability performance? I address these questions in the following subsections.

3.3.1 The Interaction Of Environmental Ratings And Innovation

I start the analysis by examining the interaction between existing metrics, such as firms' Environmental ratings from MSCI, and their green innovation intensity, using the ratios of SGC and green patents as the dependent variables. While both the investment community and the literature critize E ratings for being insufficient, understanding this relationship is important. Some SGC classes, such as the energy class, are more directly related to climate change, focusing on patents within climate mitigation or adaptation technologies. In contrast, the health class includes patents aimed at improving individual health. Given its direct relevance to climate change, I use the energy class in the main analysis and include the others in the Appendix. Initially, I consider all firms in the merged sample. Given that many firms do not focus on GI, resulting in a large proportion of zero values in the dependent variables, a standard OLS regression is not suitable for estimating the relationship in the data (Cameron and Trivedi, 2005). Following the literature, I instead estimate a Pseudo Poisson Maximum Likelihood model.[25] I estimate the following model to describe

[25] Cohn, Liu, and Wardlaw (2022) find two advantages of this modeling approach. First, Poisson regressions are well-suited for handling the distributional characteristics of the count-based outcomes, as they provide unbiased estimates for dependent variables that exhibit a large concentration of zero values combined with significant skewness. Second, it allows me to include industry-year fixed effects without introducing bias in the estimation by effectively addressing the issue of separable group fixed effects.

the relationship between next year's patent ratios and this year's E rating for firm i in year t:

$$\text{Patent Ratio}_{i,t+1} = \exp\left(\alpha + \beta \cdot E_{i,t}^{MSCI} + \gamma \cdot \mathbf{C}_{i,t} + \textit{Fixed Effects} + \epsilon_{i,t+1}\right) \tag{3.1}$$

where Patent Ratio$_{i,t+1}$ represents one of the patent class ratios in year $t+1$, and $E_{i,t}^{MSCI}$ is the MSCI E rating in year t. The vector $\mathbf{C}_{i,t}$ includes the following variables: LogAssets, Debt/Assets, PPE/Assets, EBIT/Assets, CAPEX/Assets, and R&D/Assets. These variables follow Sautner et al. (2023) in their economic application with green patents and align with the *quality* factor.[26] I use the control variables from Bolton et al. (2023) as a robustness check.[27] I estimate all models with country and year-fixed effects to account for observed variation at both levels. Standard errors are double-clustered at the firm and year levels to account for cross-sectional and serial dependence in the residuals.[28] The coefficient of interest in Eq. (3.1) is β.

Table 3.3 presents the results of several model specifications using the *EnergyRatio US* as the dependent variable. Table A.12 in the Appendix shows the results at EPO (Panel A) and GPO (Panel B). In columns 1 to 3, I report the results without control variables, while columns 4 to 6 include these controls. Across all columns except 1 and 4, the coefficient of MSCI E ratings is positive and statistically significant at the 1% level. Notably, only the model specifications incorporating industry or industry-year fixed effects (F.E) yield significant coefficient estimates. This suggests that the substantial variation in patenting activity across industries and over time necessitates controlling for unobserved heterogeneity to produce reliable and interpretable coefficient estimates. Moving forward, I focus on model specification (6), which includes controls and all F.E. To assess the economic significance of the results, I calculate the absolute one-standard-deviation change in the independent variable relative to the standard deviation of the dependent variable. Thus, a one-standard-deviation increase in E^{MSCI} in year t is associated with a 145% increase of the standard deviation of the EnergyRatio in the following year ($t+1$). The positive relationship confirms the ex-ante expectations of path-dependency, namely, that high E-rated firms focus on enhancing their sustainable profile and mitigating related financial risks, which increases in energy patents help achieve. I find similar conclusions at EPO and GPO.

[26] Madhavan et al. (2021) find funds with high ESG scores to have high quality and momentum factor loadings.

[27] The control variables used are Logsize, Logppe, Leverage, ROE, M/B, Capex/A, Beta, Volatility, Cumulative Return, Return December, and the MSCI indicator. These variables align with *quality*, *value*, and *momentum* factors.

[28] Clustering at the firm and year levels accounts for the possibility of autocorrelation in firm-level residuals over time while addressing cross-sectional correlation among residuals across all firms.

Table 3.3: Energy Patent Ratio and E Ratings

The observation unit is firm-year, with the dependent variable being *EnergyRatio US*. The sample period spans from 2008 to 2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions include country and year-fixed effects. Columns (2) and (5) include MSCI GICS-industry fixed effects, while columns (3) and (6) include both MSCI GICS-industry fixed effects and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, and the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
E^{MSCI}	0.008	0.063***	0.066***	0.021	0.103***	0.107***
	(0.011)	(0.014)	(0.015)	(0.016)	(0.020)	(0.022)
LogAssets				0.078***	0.017	0.015
				(0.022)	(0.021)	(0.021)
Debt/Assets				-0.353	-0.335*	-0.369*
				(0.229)	(0.185)	(0.192)
Cash/Assets				0.000	0.000**	0.000*
				(0.000)	(0.000)	(0.000)
PPE/Assets				0.877***	0.237	0.175
				(0.266)	(0.256)	(0.265)
EBIT/Assets				-1.908***	-1.322***	-1.220***
				(0.367)	(0.322)	(0.333)
CAPEX/Assets				1.644	2.113**	2.180**
				(1.317)	(0.900)	(0.973)
R&D/Assets				-1.080	-0.204	-0.199
				(0.705)	(0.561)	(0.596)
Constant	-2.615***	-2.734***	-2.689***	-3.640***	-3.119***	-3.060***
	(0.061)	(0.075)	(0.080)	(0.270)	(0.260)	(0.267)
Controls				✓	✓	✓
Country F.E.	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓
Industry-Year F.E.			✓			✓
Observations	24560	24534	24227	24560	24534	24227
Pseudo R^2	0.019	0.070	0.086	0.033	0.090	0.099
Dep. Variable: STD	0.159	0.159	0.159	0.159	0.159	0.159
Ind. Variable: STD	2.148	2.148	2.149	2.148	2.148	2.149
Economic effect	0.103	0.853	0.893	0.284	1.391	1.446

Table 3.4: Patent Ratio And E Ratings For All Patent Classes

The observation unit is firm-year. I consider all patent ratios as the dependent variable for patents granted at USPTO. In Table A.13 in the Appendix, Panel A, I condition on patents granted at EPO. In Panel B, I condition on patents granted at GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	(1) GreenRatio US	(2) HealthRatio US	(3) BioeconomyRatio US	(4) EnergyRatio US	(5) TransportRatio US	(6) ClimateRatio US	(7) SecurityRatio US
E^{MSCI}	0.051***	-0.007	-0.025*	0.107***	0.009	0.002	0.017
	(0.018)	(0.012)	(0.013)	(0.022)	(0.013)	(0.028)	(0.017)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	24618	24473	24621	24227	24738	23265	23778
Pseudo R^2	0.076	0.303	0.160	0.099	0.108	0.142	0.117
Dep. Variable: STD	0.187	0.269	0.235	0.159	0.222	0.100	0.146
Ind. Variable: STD	1.973	1.973	1.972	2.149	1.973	1.946	1.967
Economic effect	0.533	0.048	0.206	1.446	0.080	0.047	0.226

In Table 3.4, I estimate Equation (3.1) across all patent classes at USPTO (see Table A.13 in the Appendix for EPO and GPO). Notably, only the GreenRatio shows a positive and significant coefficient estimate (at the 1% level) across all POs, while the BioeconomyRatio is negative and significant (at the 10% level) at USPTO. The remaining SGC ratios are insignificant. The economic effect on GreenRatio (53%) is less than half of that for EnergyRatio. The positive relationship follows the same arguments for the energy class, and again, confirm the expected relationship.

There are several considerations to take into account in this analysis. First, patents represent innovative output of a lenghty R&D process, causing a long-term time lag structure to exist (Hirshleifer et al., 2013). While this structure may make the effects from E ratings challenging to interpret, examining the short-term effects of E ratings on patenting activity allows me to analyze how an existing sustainability metric interacts with firms' that continously innovate. Second, reverse causality – where GI influences E ratings – is possible. Lagging E ratings by one year mitigates this concern, as E ratings are reflective of a firm's current innovation intensity in year t. Furthermore, using granted patents prevents any potential look-ahead bias, while the lack of transparency in E ratings adds to the argument that GI is unlikely to influence the rating by much. For instance, GI may be included in 1 out of 13 key issues considered in MSCI's E ratings methodology. Third, by controlling for *quality* variables and including FEs, I reduce the risk of omitted variable bias, thereby strengthening the credibility of the causal relationship.[29]

3.3.1.1 Robustness

I conduct several robustness checks, detailed in the Appendix. First, I replace the GICS industries (74 industries) with the GICS industry groups (25 industries), as shown in Table A.14. The results for energy and green classes remain consistent. However, the transport class is positive and significant (10%) at both EPO and GPO. Second, I explore other sustainability metrics and their interaction with patenting activity, varying by PO (Table A.15). For the energy ratio (Panel A), the S and G ratings are insignificant at USPTO but show a significant positive effect at EPO. The combined ESG rating is positively significant (1%) across all POs, suggesting that highly ESG-rated firms tend to increase energy patenting. For green patenting (Panel B), significance is only observed for ESG at EPO. In contrast, climate patenting (Panel C) has a stronger effect with S and G ratings. *Refinitiv* data yields similar, though less pronounced, results. Contrary to Bolton et al. (2023), higher direct emissions (Scope 1) positively influence energy, green, and climate innovation, indicating that the relationship between GI and carbon emissions is more complex than their study suggests. Third, I address industry variation by restricting the sample to individual industries (Table A.16). Of 52 industries, 29 show a positive E-rating coefficient,

[29] A contemporaneous regression of patenting activity on E ratings suggests that an immediate causal relationship does not exist.

with 12 (5) being significantly positive (negative). Notably, Independent Power and Renewable Electricity Producers, Semiconductors, and Tobacco exhibit significant positive coefficients, aligning with top decile rankings for Altria and British American Tobacco.[30] A similar conclusion applies to green and climate patenting. Fourth, using forward citation ratios to measure innovation quality does not alter the conclusions or economic effects (Table A.17). Fifth, I test different control variables from Bolton et al. (2023). I find that while the positive and significant results for energy and green classes persist across all POs, the economic effect is reduced by up to 50% (Table A.18). Sixth and last, replacing patent ratios with total patent counts yields positive and significant effects for all classes except climate (Table A.19), likely reflecting a size bias since the level of GI activity may influence E ratings.[31]

3.3.2 Innovating Firms

Until now, I have considered the merged sample of all firms. However, given the large dispersion in patenting activity across firms, it is reasonable to expect differences between firms with and without patents in GI. To address this, I narrow the focus to firms granted at least one patent within the relevant patent class. The distributional characteristics of this sample allow the use of Ordinary Least Squares (OLS) for model estimation, as the dependent variable becomes continuous. I am still interested in determining the extent to which E-ratings interacts with firms patenting activity. Table 3.5 presents these results.

Table 3.5: Patent Ratios and E Ratings (Innovating Firms)

The observation unit is firm-year, with the dependent variable being one of the patent classes. The sample period spans from 2008 to 2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for estimation. All regressions include country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
E^{MSCI}	0.001	-0.006*	-0.010***	0.008**	-0.006*	-0.007***	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	12444	10247	11877	10217	14368	5729	10420
Adj. R^2	0.303	0.714	0.475	0.301	0.363	0.332	0.309
Dep. Variable: STD	0.211	0.326	0.267	0.178	0.237	0.159	0.178
Ind. Variable: STD	1.899	1.991	1.900	1.854	1.920	1.784	1.998
Economic effect	0.009	0.040	0.070	0.085	0.045	0.079	0.019

The results for the energy class remain qualitatively similar, with an increased adjusted R^2 but a reduction in the economic effect. Notably, the impact of E ratings

[30] https://freebeacon.com/latest-news/how-tobacco-companies-are-crushing-esg-ratings/

[31] In this context, I interpret a size bias as stemming from larger firms having more substantial R&D departments, enabling them to produce more patents than smaller firms. Additionally, larger firms typically have more comprehensive sustainability departments, allowing them to report on broader issues, which may be reflected in higher ESG scores overall (Dobrick et al., 2023).

on green patenting becomes insignificant, while higher E ratings are negatively associated with climate patenting. This suggests that although firms with high E ratings invest more in climate mitigation technologies (energy), they reduce innovation in areas such as waste management (climate). A plausible explanation is that, despite being beneficial for the climate, these technologies do not present significant financial risks and are not a primary focus for firms with high E ratings. Similar results for other POs are provided in Table A.20 in the Appendix.

3.3.3 Climate Exposures and Changes in Sustainable Beliefs

The literature on sustainable finance extensively documents the increasing sustainable awareness among SRIs (Chang et al., 2024; Cepni et al., 2023; Avramov et al., 2022; Monasterolo and De Angelis, 2020). The adoption of the SDGs by all United Nations member countries (UN, 2015b) and the Paris Agreement in 2015 marks a pivotal moment for assessing whether changes in sustainable beliefs have led to an increased interaction between existing sustainability metrics and GI.[32] A related body of literature examines how earnings call participants' focus on climate change topics, particularly in assessing firms' risks and opportunities in this area (Sautner et al., 2023; Bingler et al., 2022; Webersinke et al., 2021; Varini et al., 2020). If firms have responded to this increased sustainable awareness, similar patterns to those observed by Sautner et al. (2023) – where firms with greater climate change exposure innovate more to mitigate future risks – should be expected. This section explores these hypotheses.

To capture period differences, I define an indicator variable, I_{2015}, which equals 1 for the years after 2015 and 0 otherwise. I incorporate this indicator into the Poisson model in Equation (3.1). For climate exposures, I use the time-varying data from Sautner et al. (2023) as the independent variable of interest in Equation (3.1).[33] First, I assess the impact of changes in sustainable beliefs by estimating Equation (3.2).

$$\begin{aligned}\text{Patent Ratio}_{i,t+1} = \exp\Big(&\alpha + \beta \cdot E^{MSCI}_{i,t} + \gamma \cdot \left(E^{MSCI}_{i,t} \cdot I_{2015,t+1}\right) \\ &+ \delta \cdot \mathbf{C}_{i,t} + \textit{Fixed Effects} + \epsilon_{i,t+1}\Big)\end{aligned} \tag{3.2}$$

where the coefficient of interest is γ, which measures the change in effect post-2015 relative to the pre-2015 period. The interaction term captures how the change in effect is related to variations in MSCI E ratings. Table 3.6 presents the results.

I find that γ is positive and significant in the model specifications with green patenting at USPTO, indicating that the increased sustainable belief after the 2015 Paris Agreement has widened the gap in green patenting between high and low E-rated firms. This result aligns with other studies on sales growth and profitability

[32] The Paris Agreement in December 2015 outlines a global commitment to limit the rise in global temperature to no more than 2°C. – https://unfccc.int/process-and-meetings/the-paris-agreement

[33] The publicly available dataset was accessed in June 2024 – https://osf.io/fd6jq/

(Chang et al., 2024) and carbon emissions (Bolton et al., 2023). Similarly, patent grants at EPO classified as energy show positive and significant results (Table A.21), suggesting that patents may impact firms' environmental risks differently depending on the granting PO. As a robustness check, I examine whether the shift in beliefs has affected the importance of sustainable patents. The results remain relatively robust, as shown in Table A.22 in the Appendix, with high E-rated firms experiencing an increase in forward citations for green and climate (energy) classes in the post-2015 period at USPTO (EPO).

Table 3.6: Changes in Sustainable Beliefs on Innovation and E ratings

The observation unit is firm-year, with the dependent variable being *GreenRatio US*, *EnergyRatio US*, or *ClimateRatio US*. The sample period spans from 2008 to 2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.2). All regressions include country and year-fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable and the independent variable. *** 1% significance, ** 5% significance, * 10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		GreenRatio US			EnergyRatio US			ClimateRatio US	
E^{MSCI}	-0.062***	-0.015	-0.012	0.025	0.084***	0.096***	-0.099***	0.011	-0.031
	(0.019)	(0.020)	(0.020)	(0.021)	(0.018)	(0.017)	(0.027)	(0.028)	(0.031)
$E^{MSCI} \times I_{2015}$	0.068***	0.069***	0.073***	-0.004	0.025	0.013	0.021	-0.011	0.039
	(0.017)	(0.019)	(0.021)	(0.021)	(0.021)	(0.023)	(0.029)	(0.027)	(0.035)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	24847	24847	24618	24560	24534	24227	24832	24765	23265
Pseudo R^2	0.017	0.067	0.077	0.034	0.091	0.099	0.071	0.129	0.143
Dep. Variable: STD	0.188	0.188	0.187	0.159	0.159	0.159	0.098	0.098	0.100
Ind. Variable: STD	1.971	1.971	1.973	2.148	2.148	2.149	1.972	1.968	1.946

Second, I analyze the results for firms' climate exposures in Table A.23. Consistent with Sautner et al. (2023), I find that firms with greater overall climate, opportunity, and regulatory exposures engage in more green, energy and climate innovation in the following year. The economic effect is nearly three times larger than their findings, likely due to their focus on US firms.[34] The results are qualitatively similar across POs (untabulated).

Overall, I find that firms with higher E ratings, which already had strong sustainability profiles, responded most to changes in sustainable beliefs by increasing their GI activities. In a global context, GI firms are driven by climate opportunities and regulatory risks, necessitating further innovation. Notably, the transport and climate classes are the only ones affected by higher physical risks, consistent with the automobile industry's risk of being stranded with combustion-engine cars.

[34] Their green patent measures' mean and standard deviation (patent counts and ratios) are much lower than in my sample. For example, my sample shows a mean of 18.39 green patents and a standard deviation of 59.17, compared to their 0.28 and 4.07, respectively.

3.3.4 The Interaction With SDG Ratings

With the emergence of SDG ratings across data vendors, investors are offered a new sustainability metric to assess corporate sustainability, complementing ESG ratings. Van Zanten and Huij (2024) find that SDG metrics align more closely with sustainability preferences, EU taxonomy regulation, and climate change mitigation than ESG ratings. This alignment makes it particularly interesting to also explore whether firms' SDG ratings interacts with their level of GI.[35] This is why including the SGC patent classification is crucial, as it allows patents to be classified according to SDG objectives. Furthermore, the green class may be too broadly defined for investors targeting specific SDGs. For example, given its focus on climate change mitigation technologies, energy patents are expected to be linked to SDG 7 (Clean energy) and SDG 13 (Climate action). Table A.4 in the Appendix outlines the expected links between SDG and SGC patent classes. I estimate the Poisson model in Equation (3.1), replacing the MSCI E rating with SDG ratings from different vendors. Due to limited data availability, I cautiously interpret the effects using MSCI ratings. The results using Robeco SDG ratings are presented in Table 3.7. In contrast, coefficient-only results for other patent classes, at EPO and GPO, are in Table A.24. Results for MSCI product and operational alignment are shown in Table A.25 and A.26.

Several key findings emerge. First, SDG Overall, SDG 7, and SDG 13 show no significant effect on EnergyRatio at USPTO. However, higher SDG 13 ratings significantly increase GreenRatio. This effect is even more pronounced at GPO, where SDG 7 has a positive and significant effect. Additionally, climate (transport) patenting ratios are positively (negatively) affected by SDG 6 (9). Second, SDGs related to sustainable infrastructure (SDG 9), sustainable urbanization (SDG 11), and sustainable consumption and production (SDG 12) exhibit a positive and significant effect, aligning with existing thematic investment strategies.[36] Third, MSCI SDG data confirms that $SDG^{Product}$ 7 and 13 significantly (1% level) positively influence energy patenting ratios, validating the ex-ante link.

A similar effect is observed for the green class in Table A.25 for MSCI product alignment. The climate class shows the expected sign for relevant SDGs, though not for SDG 13. Other notable links include higher ratings in quality education (SDG 4), gender equality (SDG 5), and decent work & economic growth (SDG 8), which leads to lower energy patenting ratios at USPTO. This suggests that if institutional investors prioritize firms that perform well within these SDGs, such firms may not necessarily be the frontrunners in the transition to a green economy. This highlights the challenges faced by SRI's in assessing sustainable firms. This complexity is further explored in the literature on SDG interlinkages, known as the *nexus challenge*

[35] The Resource-Based View theory suggests that firms with strong sustainability commitments can develop unique resources that drive innovation. This supports my hypothesis that high SDG ratings positively affect GI the following year (Hart, 1995; Russo and Fouts, 1997).

[36] https://www.unpri.org/sustainable-development-goals/the-sdgs-will-drive-global-economic-\growth/307.article

(Van Tulder and van Mil, 2022; Van Zanten and van Tulder, 2021). The results remain qualitatively similar across POs.

When using MSCI SDG Operational ratings, which reflect firms' operational alignment with SDGs, most of my results become insignificant or change sign. This may be due to the "stickiness" in operational ratings, as implementing new policies, initiatives, or targets to align firms' operations is challenging. Given the prevalence of neutral (zero) ratings, I examine whether differences exist for firms that receive non-zero ratings. Despite a reduced sample size (below 2,000 observations), I find that SDG 7 (and 13) positively and significantly affect energy patenting at USPTO (GPO) for Robeco SDGs, with similar robustness for MSCI (untabulated). This suggests that firms with non-neutral SDG ratings interacts positively with patenting activity in relevant SDG areas. To my knowledge, I am the first to document this relationship.

Table 3.7: Energy Patent Ratio and SDG Ratings

The observation unit is firm-year, with the dependent variable being *EnergyRatio US*. The sample period spans from 2010 to 2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions include country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. Due to only zero ratings for SDG 5 and 10, these have been discarded. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
SDG Overall	0.026															
	(0.035)															
SDG 1		-0.299*														
		(0.164)														
SDG 2			-0.017													
			(0.090)													
SDG 3				0.075												
				(0.083)												
SDG 4					-0.392											
					(0.303)											
SDG 6						0.448***										
						(0.136)										
SDG 7							0.069									
							(0.058)									
SDG 8								0.015								
								(0.103)								
SDG 9									-0.003							
									(0.099)							
SDG 11										0.115						
										(0.073)						
SDG 12											0.014					
											(0.049)					
SDG 13												0.088				
												(0.066)				
SDG 14													0.031			
													(0.103)			
SDG 15														0.011		
														(0.111)		
SDG 16															-0.030	
															(0.048)	
SDG 17																0.058
																(0.088)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016	14016
Pseudo R2	0.099	0.099	0.099	0.099	0.099	0.100	0.100	0.099	0.099	0.100	0.099	0.100	0.099	0.099	0.099	0.099
Dep. Variable: STD	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
Ind. Variable: STD	1.452	0.060	0.232	0.907	0.062	0.235	0.675	0.581	0.786	0.542	0.444	0.543	0.231	0.225	0.437	0.029
Economic effect	0.242	0.116	0.026	0.442	0.157	0.682	0.299	0.058	0.014	0.405	0.040	0.308	0.046	0.016	0.084	0.011

3.3.5 Innovation As A Predictor Of Future Sustainability Performance

I document that existing sustainability metrics interacts with the green innovation activity of firms. However, it is unclear whether these innovations predict future improvements in sustainability metrics. Especially, given the differences in sustainability metrics assessment of sustainable firms. For instance, the company examples provided in Van Zanten and Huij (2024) showcase several diverging results when comparing ESG and SDG ratings of specific firms. While the firm "*Daqo New Energy*" receives a *B* (below 2.8) MSCI ESG rating due to human capital development, the Robeco SDG rating is +3, as 100% of the firm's revenues align with EU taxonomy, reflecting its contribution to Climate Action. Another example is the firm "*British American Tobacco*", who receives an average ESG rating of *BBB* (4.2-5.7), and simultaneously the lowest SDG rating of -3, due to its tobacco and cigarette products. This discrepancy highlights the need to complement the sustainability framework beyond ESG integration with metrics that focus only on assessing firms' sustainability performance.

I examine whether patenting activity can predict future improvements in sustainability metrics, focusing on E and SDG ratings while including other metrics for broader alignment with the literature. Ex-ante, I expect several relationships to emerge. First, higher patent ratio intensity should predict future improvements in related SDGs, as they are universally shared and more focused on specific sustainable development objectives. Second, I expect the predictability of E-ratings to be ambigious, as firms patenting activity may not reduce the financial risk imposed on the firm to significantly affect its rating. Third, if green innovations are to be thought of as a complementary sustainability metric, firms' carbon emissions should be negatively predicted, as this would align with the Paris Agreement in 2015. For SRIs, ensuring that ESG investment strategies effectively meet sustainable objectives is crucial, thus if GI serves as a predictor of sustainability performance, it is likely to enhance such strategies, and allocate capital to sustainable firms (Dimson et al., 2020).

I use the following regression model to link future sustainability metrics, such as MSCI E ratings, to contemporaneous patent ratios, incorporating lagged controls.[37] To start, I include all firms when estimating the following OLS model:

$$\mathbf{Y}_{i,t+h} = \alpha + \beta \cdot \text{Patent Ratio}_{i,t} + \gamma \cdot \mathbf{C}_{i,t-1} + \text{Fixed Effects} + \epsilon_{i,t} \qquad (3.3)$$

where $\mathbf{Y}_{i,t+h}$ represents the dependent variables: i) MSCI ESG ratings, ii) Refinitiv ESG ratings, iii) Robeco SDG ratings, iv) MSCI SDG ratings, v) log total emission from Scope 1-3, and vi) climate change exposures, all measured in year $t+h$. I consider $h = \{1,3\}$ years forward from time t to account for the possibility of a "time to build" lag in corporate adjustments and the average two-year application-grant lag at patent offices (Hirshleifer et al., 2013). I use the same definition of Patent Ratio as in previous sections, with the same control variables. All regressions include country, year, and firm fixed effects.[38] Likewise, I double-cluster standard errors at the firm and year

[37] By using lagged control variables, I can control for decisions made in the year prior to the observed patent ratio, thereby establishing a more apparent causal relationship.

[38] Following Bolton et al. (2023), firm fixed effects are included. A firm-level MSCI E rating regression

levels. The coefficient of interest is β, which captures how patent ratios predict future corporate sustainability metrics. Table 3.8 presents the results for energy patenting ratios at USPTO, EPO, and GPO.

Patenting activity predicts several sustainability metrics. First, my main finding is that MSCI E ratings are not predicted by increases in energy patenting ratios in the short term (one-year post-grant), but they are negatively predicted in the medium-term (three years post-grant), with a 2-2.6% decrease of the standard deviation of MSCI E ratings, for a one-standard-deviation increase in energy patenting ratios. This pattern is qualitatively similar for Refinitiv E and ESG ratings, with the latter showing a 2.2%-4.4% decrease at both horizons. Second, another key finding is that energy patenting ratios positively and significantly predict Robeco's overall SDG ratings (2.9%) and SDG 13 (4.5%) in the short term and SDG 7 (3.9%) in the medium-term at USPTO. For MSCI, only $SDG^{operational}$ shows a positive prediction (3.4%) in the medium-term. These findings suggest that while energy patenting is not rewarded by higher E (or ESG) ratings, it is by SDG ratings, highlighting the complementary role of GI in sustainable investment strategies. Third, increased patenting activity is associated with a 0.7% decrease in indirect emissions, reinforcing that firms with higher GI, e.g., energy patenting, could hedge against climate risks. Fourth, energy innovating firms predict increases in overall climate change exposure and climate opportunities in the short term, which may explain why E ratings do not show a positive prediction, as the increased focus on climate exposure in earnings calls may be challenging to quantify or may be interpreted differently by stakeholders.

Replacing the patent ratio with the green class (see Table A.27), I only find the overall ESG metric (4.0%) and Scope 3 emissions (1.7%) to be negative and significant in the medium-term. Additionally, SDG^{Robeco} 7 (2.7%) is predictable in the short term, while SDG^{Robeco} 13 is significant at both horizons (4.5%). The $SDG^{Operational}$ 7 is also positively and significantly predicted at EPO in the short term (5.4%). For the climate class (see Table A.28), MSCI E ratings show similar results (0.9%), with a positive and significant (10% level) prediction for Refinitiv E-ratings in the short term (1.5%). However, the results for SDG ratings are insignificant.

on firm fixed effects yields an adjusted R-squared of 0.746, compared to 0.346 with industry fixed effects, indicating that most variation in E ratings occurs within firms rather than across industries (Engle et al., 2020). For Refinitiv E ratings, the adjusted R-squared is 0.622 (0.068) for firm (industry) FE.

Table 3.8: Sustainability Metrics and Energy Patent Ratios

The observation unit is firm-year. The dependent variables are MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I focus on 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2002-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions include country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A.1: $h = 1$ year lagged Energy Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio US, $h = 1$	-0.133	0.002	-0.034	0.003	0.007	-1.498	-0.250	-1.644	0.273**	0.140	0.156*
	(0.100)	(0.092)	(0.086)	(0.037)	(1.404)	(1.430)	(1.506)	(1.131)	(0.111)	(0.085)	(0.084)
Observations	14909	14909	14908	13987	16350	17773	17773	13503	13807	13807	13807
Adj. R^2	0.773	0.684	0.552	0.772	0.790	0.790	0.603	0.767	0.633	0.625	0.483
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	0.003	1.449	0.668	0.542
Ind. Variable: STD	0.149	0.149	0.149	0.152	0.141	0.140	0.140	0.135	0.156	0.156	0.156
Economic Effect	0.010	0.000	0.003	0.000	0.000	0.009	0.002	0.037	0.029	0.033	0.045
Panel A.2: $h = 1$ year lagged Energy Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio EPO, $h = 1$	-0.186	0.171	0.025	0.018	-0.758	-1.151	-0.875	-2.125*	0.151	0.072	0.072
	(0.115)	(0.115)	(0.102)	(0.053)	(1.378)	(1.360)	(1.256)	(1.164)	(0.102)	(0.095)	(0.091)
Observations	11248	11248	11248	10506	13025	13849	13849	10355	10362	10362	10362
Adj. R^2	0.771	0.690	0.535	0.763	0.783	0.789	0.602	0.759	0.629	0.627	0.490
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	0.003	1.461	0.660	0.534
Ind. Variable: STD	0.166	0.166	0.166	0.170	0.157	0.155	0.155	0.150	0.176	0.176	0.176
Economic Effect	0.016	0.017	0.002	0.003	0.005	0.007	0.006	0.022	0.018	0.019	0.024
Panel A.3: $h = 1$ year lagged Energy Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio GPO, $h = 1$	-0.124	0.106	-0.147	0.008	-1.258	-4.060**	-1.180	-3.002**	0.223*	0.132	0.120
	(0.110)	(0.091)	(0.107)	(0.035)	(1.515)	(1.496)	(1.427)	(1.246)	(0.122)	(0.075)	(0.070)
Observations	16631	16631	16630	15668	18178	19861	19861	14806	15314	15314	15314
Adj. R^2	0.781	0.689	0.572	0.781	0.789	0.790	0.610	0.768	0.624	0.594	0.455
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	0.003	1.463	0.678	0.559
Ind. Variable: STD	0.145	0.145	0.145	0.147	0.137	0.136	0.136	0.129	0.154	0.154	0.154
Economic Effect	0.009	0.009	0.012	0.001	0.007	0.023	0.007	0.030	0.023	0.03	0.033
Panel A.4: $h = 3$ year lagged Energy Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio US, $h = 3$	-0.270***	0.158	-0.029	-0.006	-2.842	-2.796*	1.018	-2.344	0.306**	0.166*	0.181**
	(0.086)	(0.111)	(0.114)	(0.050)	(1.643)	(1.401)	(1.602)	(1.495)	(0.119)	(0.082)	(0.077)
Observations	13403	13403	13402	12559	14471	15415	15415	11512	11391	11391	11391
Adj. R^2	0.769	0.680	0.543	0.769	0.806	0.801	0.610	0.767	0.625	0.620	0.482
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.94	24.117	21.706	0.003	1.451	0.669	0.545
Ind. Variable: STD	0.148	0.148	0.148	0.151	0.134	0.134	0.134	0.128	0.159	0.159	0.159
Economic Effect	0.020	0.014	0.002	0.001	0.015	0.016	0.006	0.027	0.034	0.039	0.053
Panel A.5: $h = 3$ year lagged Energy Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio EPO, $h = 3$	-0.256*	0.049	-0.149	-0.081	-3.901**	-2.945**	-1.067	-4.105***	0.091	0.054	0.066
	(0.130)	(0.099)	(0.093)	(0.053)	(1.709)	(1.239)	(1.513)	(1.229)	(0.097)	(0.092)	(0.086)
Observations	10227	10227	10226	9548	11408	11934	11934	8752	8598	8598	8598
Adj. R^2	0.768	0.682	0.531	0.761	0.797	0.793	0.610	0.737	0.624	0.633	0.510
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	0.003	1.461	0.664	0.538
Ind. Variable: STD	0.166	0.166	0.166	0.170	0.150	0.150	0.150	0.144	0.181	0.181	0.181
Economic Effect	0.022	0.005	0.015	0.014	0.024	0.019	0.007	0.044	0.011	0.015	0.022
Panel A.6: $h = 3$ year lagged Energy Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Energy Ratio GPO, $h = 3$	-0.347***	0.156	0.008	0.007	-3.796**	-3.314**	-0.809	-3.357**	0.210	0.125	0.123
	(0.106)	(0.108)	(0.111)	(0.049)	(1.676)	(1.490)	(1.636)	(1.464)	(0.118)	(0.076)	(0.072)
Observations	15036	15036	15035	14156	16201	17334	17334	12638	12757	12757	12757
Adj. R^2	0.776	0.686	0.561	0.778	0.806	0.801	0.618	0.766	0.619	0.592	0.457
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	0.003	1.464	0.682	0.563
Ind. Variable: STD	0.147	0.147	0.147	0.150	0.134	0.133	0.133	0.122	0.158	0.158	0.158
Economic Effect	0.026	0.014	0.001	0.001	0.020	0.018	0.005	0.027	0.023	0.029	0.034
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h = 1$ year lagged Energy Ratio USPTO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio US, $h = 1$	0.041	0.063	-0.038	-0.005	-0.013	-0.096**	0.059	0.001*	0.001***	0.000	-0.000
	(0.185)	(0.175)	(0.089)	(0.082)	(0.046)	(0.044)	(0.180)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R^2	0.957	0.959	0.634	0.814	0.953	0.939	0.74	0.767	0.724	0.47	0.492
Dep. Variable: STD	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.153	0.153	0.153	0.153	0.148	0.148	0.152	0.135	0.135	0.135	0.135
Economic Effect	0.003	0.004	0.004	0.001	0.001	0.007	0.003	0.037	0.053	0.015	0.015
Panel A.2: $h = 1$ year lagged Energy Ratio EPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio EPO, $h = 1$	-0.137	-0.103	0.292	0.056	-0.033	-0.062	0.006	0.000	0.000*	0.000	-0.000
	(0.148)	(0.132)	(0.167)	(0.089)	(0.041)	(0.037)	(0.170)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R^2	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.379
Dep. Variable: STD	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.169	0.169	0.169	0.169	0.163	0.164	0.168	0.150	0.150	0.15	0.15
Economic Effect	0.010	0.008	0.033	0.007	0.002	0.005	0.000	0.022	0.029	0.003	0.004
Panel A.3: $h = 1$ year lagged Energy Ratio GPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio GPO, $h = 1$	0.072	0.101	0.069	-0.027	-0.001	-0.079**	-0.130	0.001	0.000**	-0.000	-0.000
	(0.099)	(0.101)	(0.098)	(0.111)	(0.056)	(0.029)	(0.197)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R^2	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.726	0.48	0.483
Dep. Variable: STD	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.147	0.147	0.147	0.147	0.148	0.148	0.15	0.129	0.129	0.129	0.129
Economic Effect	0.005	0.007	0.007	0.003	0.000	0.005	0.006	0.030	0.044	0.009	0.010
Panel A.4: $h = 3$ year lagged Energy Ratio USPTO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio US, $h = 3$	-0.126	-0.127	0.318*	0.025	-0.072	-0.110*	-0.214	0.001	0.000	0.000	-0.000
	(0.230)	(0.231)	(0.123)	(0.116)	(0.074)	(0.062)	(0.180)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
Adj. R^2	0.957	0.959	0.613	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.157	0.157	0.157	0.157	0.141	0.141	0.148	0.128	0.128	0.128	0.128
Economic Effect	0.009	0.009	0.034	0.003	0.004	0.007	0.010	0.027	0.032	0.025	0.006
Panel A.5: $h = 3$ year lagged Energy Ratio EPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio EPO, $h = 3$	-0.151	-0.152	0.336	0.095	-0.048	-0.063	0.321	0.001	0.000	0.000	0.000
	(0.110)	(0.107)	(0.169)	(0.105)	(0.074)	(0.055)	(0.246)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
Adj. R^2	0.960	0.963	0.598	0.803	0.954	0.938	0.722	0.737	0.657	0.422	0.349
Dep. Variable: STD	2.193	2.19	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.175	0.175	0.175	0.175	0.156	0.157	0.163	0.144	0.144	0.144	0.144
Economic Effect	0.012	0.012	0.039	0.011	0.003	0.005	0.017	0.044	0.046	0.041	0.026
Panel A.6: $h = 3$ year lagged Energy Ratio GPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio GPO, $h = 3$	0.030	0.008	0.178	0.122	-0.028	-0.100	0.181	0.001	0.000	0.000	0.000
	(0.125)	(0.114)	(0.168)	(0.093)	(0.061)	(0.066)	(0.185)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
Adj. R^2	0.949	0.951	0.619	0.811	0.95	0.935	0.738	0.766	0.721	0.437	0.404
Dep. Variable: STD	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.157	0.157	0.157	0.157	0.142	0.142	0.147	0.122	0.122	0.122	0.122
Economic Effect	0.002	0.001	0.019	0.013	0.001	0.007	0.009	0.027	0.036	0.013	0.021
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3.3.5.1 Robustness

I consider four robustness checks. First, conditional on energy patenting firms (Table A.29), most results become insignificant, though the significant prediction of the SDG $overall^{Robeco}$ measure persists. I also find a negative and significant medium-term prediction for MSCI and Refinitiv ESG ratings at EPO. Second, for firms engaged in green patenting at EPO (Table A.30), the negative prediction for ESG ratings at MSCI and Refinitiv continues, potentially due to increased physical shock exposures faced by green innovators in the medium-term. Third, larger firms, often subject to greater scrutiny and higher ESG ratings, may drive the negative prediction of E ratings.[39] In untabulated results, the interaction coefficient between patent ratios and firm size becomes more negative and significant (at the 10% level), suggesting that larger firms are more "*punished*" for higher GI activity. Fourth, I consider alternative specifications – Patent citation ratios and counts. For energy citation ratios (Table A.32), a negative and significant medium-term prediction remains for MSCI E ratings at USPTO. In contrast, Refinitiv E ratings at EPO show similar results, with positive significance for all climate exposure variables, except physical shock. I also find a positive prediction between green citation ratios and direct emissions at USPTO, with most Robeco SDG results remaining robust. For energy patent counts (Table 3.9), all ESG pillars show significant negative coefficients from the short to medium-term across POs, with a 6.5% decrease in E ratings next year following a one-standard-deviation increase in energy patents at USPTO. Similar, though weaker, findings are observed for green patents (Table A.35), with a significant positive prediction for Robeco SDG 7 in the short and medium-term, which remains somewhat robust for green patent counts. These results are of particular interest, as they confirm the negative prediction of E ratings to persist even when considering another measure of firms innovative behavior.

[39] I define and include an indicator variable in Eq. (3.3), equal to one for each market capitalization group, except small- and micro-cap (mkt. cap < \$2 billion), which I use as the basegroup: Mid-cap (mkt. cap > \$2 billion & <\$10 billion), Large-cap (mkt. cap > \$10 billion & <\$200 billion), Mega-cap (mkt. cap > \$200 billion), and zero otherwise.

Table 3.9: Sustainability Metrics On Energy Patent Counts (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A.1: $h=1$ year lagged Energy Counts USPTO	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts US, $h=1$	-0.003***	-0.002	-0.004***	-0.002**	-0.028***	-0.028***	-0.013*	-0.042***	-0.001	0.000*	0.000	-0.001	-0.001	-0.001	0.001	-0.000	-0.000	0.001	0.000**	0.000**	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)	(0.007)	(0.006)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.774	0.684	0.555	0.772	0.791	0.791	0.603	0.711	0.633	0.625	0.481	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.723	0.470	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	40.119	40.119	40.120	40.917	38.284	36.844	36.844	36.844	40.276	40.276	40.276	41.678	41.678	41.678	41.678	33.081	33.082	42.622	35.393	35.393	35.393	35.393
Economic Effect	0.065	0.039	0.099	0.081	0.042	0.042	0.022	0.081	0.015	0.022	0.015	0.019	0.014	0.017	0.018	0.002	0.002	0.010	0.041	0.049	0.016	0.008
Panel A.2: $h=1$ year lagged Energy Counts EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts EPO, $h=1$	-0.006***	-0.003	-0.007***	-0.004**	-0.051***	-0.038**	-0.019	-0.087***	-0.001	0.001**	0.000	-0.005	-0.004	0.004	0.002	-0.001	-0.000	-0.000	0.000**	0.000*	0.000*	-0.000*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.012)	(0.015)	(0.013)	(0.015)	(0.001)	(0.000)	(0.000)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.772	0.691	0.538	0.765	0.783	0.790	0.602	0.695	0.629	0.627	0.490	0.954	0.957	0.609	0.809	0.956	0.940	0.732	0.760	0.698	0.455	0.380
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.660	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	19.779	19.779	19.779	20.403	18.225	17.816	17.816	17.816	18.345	18.345	18.345	23.807	23.807	23.807	23.807	16.598	16.656	20.698	17.562	17.562	17.562	17.562
Economic Effect	0.059	0.040	0.077	0.086	0.038	0.028	0.016	0.084	0.012	0.019	0.017	0.057	0.044	0.070	0.025	0.003	0.003	0.003	0.045	0.042	0.043	0.027
Panel A.3: $h=1$ year lagged Energy Counts GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts GPO, $h=1$	-0.002***	-0.001*	-0.003***	-0.002**	-0.018***	-0.018***	-0.006	-0.029***	-0.000	0.000*	0.000	-0.001	-0.001	0.001	0.001	-0.000	-0.000	0.000	0.000**	0.000**	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.782	0.689	0.574	0.782	0.790	0.791	0.610	0.718	0.624	0.594	0.454	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.769	0.726	0.480	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	59.567	59.567	59.569	60.794	56.897	54.853	54.853	54.853	59.101	59.101	59.101	63.459	63.459	63.459	63.459	48.409	48.453	63.345	52.241	52.241	52.241	52.241
Economic Effect	0.065	0.045	0.098	0.095	0.041	0.039	0.016	0.083	0.013	0.021	0.015	0.033	0.024	0.025	0.026	0.004	0.007	0.005	0.047	0.051	0.024	0.009
Panel A.4: $h=3$ year lagged Energy Counts USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts US, $h=3$	-0.004***	-0.002**	-0.004***	-0.003***	-0.037***	-0.034***	-0.023***	-0.049***	-0.001	0.000*	0.000	0.001	0.000	0.002	0.000	-0.000	-0.000	0.000	0.000**	0.000*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.007)	(0.006)	(0.001)	(0.000)	(0.000)	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.770	0.681	0.545	0.772	0.807	0.802	0.610	0.711	0.624	0.619	0.480	0.957	0.959	0.613	0.807	0.951	0.937	0.731	0.768	0.724	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.940	24.117	21.706	18.670	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	40.044	40.044	40.045	41.294	35.918	34.848	34.848	34.848	41.400	41.400	41.400	48.137	48.137	48.137	48.137	32.838	32.820	42.098	34.942	34.942	34.942	34.942
Economic Effect	0.081	0.057	0.085	0.114	0.053	0.049	0.037	0.092	0.016	0.025	0.011	0.012	0.003	0.065	0.013	0.004	0.005	0.004	0.042	0.050	0.018	0.001
Panel A.5: $h=3$ year lagged Energy Counts EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts EPO, $h=3$	-0.005***	-0.003	-0.006**	-0.003**	-0.072***	-0.042**	-0.037**	-0.106***	-0.002	0.001**	0.001*	-0.001	-0.001	-0.001	0.001	-0.001	-0.001	0.001	0.000**	0.000	0.000**	-0.000
	(0.001)	(0.002)	(0.003)	(0.002)	(0.015)	(0.018)	(0.015)	(0.017)	(0.002)	(0.000)	(0.000)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.769	0.683	0.533	0.762	0.798	0.793	0.610	0.688	0.624	0.634	0.510	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.738	0.657	0.423	0.349
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	19.425	19.425	19.426	20.064	16.269	15.922	15.922	15.922	18.495	18.495	18.495	27.251	27.251	27.251	27.251	16.262	16.300	20.150	16.304	16.304	16.304	16.304
Economic Effect	0.053	0.039	0.069	0.069	0.049	0.029	0.027	0.093	0.022	0.026	0.026	0.018	0.012	0.014	0.027	0.005	0.007	0.008	0.059	0.047	0.073	0.017
Panel A.6: $h=3$ year lagged Energy Counts GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Counts GPO, $h=3$	-0.003***	-0.002**	-0.003***	-0.002**	-0.026***	-0.023***	-0.013**	-0.035***	-0.000	0.000*	0.000	-0.000	-0.000	0.001	0.001	-0.000	-0.000*	0.000	0.000**	0.000**	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.778	0.687	0.563	0.781	0.807	0.802	0.618	0.721	0.619	0.592	0.456	0.949	0.951	0.618	0.811	0.950	0.935	0.738	0.766	0.722	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	59.084	59.084	59.086	60.777	52.956	51.287	51.287	51.287	59.820	59.820	59.820	72.755	72.755	72.755	72.755	47.589	47.597	62.187	50.723	50.723	50.723	50.723
Economic Effect	0.077	0.057	0.086	0.113	0.055	0.049	0.031	0.094	0.013	0.024	0.015	0.007	0.010	0.034	0.032	0.006	0.010	0.008	0.049	0.051	0.034	0.003
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

To conclude, I find that energy, green, and climate patents predict future MSCI and Refinitiv E ratings. However, contrary to expectations, firms appear to be "punished" for higher innovation, whether measured by their patenting intensity, the quality of their patents, or the number of patents. This punishment increases with market capitalization, as larger firms face greater scrutiny than smaller ones. The economic significance suggests that E ratings are influenced more by the total number of patents than by patent ratios, which could be due to data vendors using observed patent counts when updating firms' ratings. Several factors may explain the negative prediction of patenting on E ratings. Firms with higher patenting activity often face greater climate change exposures, regulatory risks, and physical shocks, which could also explain the negative relationship. This is likely to be the case, given my results of positive predictions of climate change exposures. Additionally, patents may take over three years to materialize into a sustainable impact reflected in E ratings. This aligns with the ex-ante expectation of an ambigious effect on E ratings when firms increase their GI, as the financial risks related to climate are not necessarily perceived as lower for innovative firms. This is likely due to information asymmetry, as investors may not fully understand the implications of firms' innovation activities, which is well-documented in the literature (Hirshleifer et al., 2013; Song and Schwarz, 2010). While energy patenting strongly predicts higher Robeco SDG ratings, the evidence is less robust with MSCI SDG ratings. However, it shows more predictability, with green patenting positively influencing $SDG^{Operational}$ 7 ratings in the short term. Nevertheless, I should be cautious in interpreting the results for MSCI due to its relatively short data availability period. As divergences in SDG ratings across vendors have been documented (Bauckloh et al., 2023), further research should investigate the robustness of these relationships as more data becomes available.

While SDGs are harder to quantify, I show that using GI as a complementary sustainability metric can help identify firms with higher future sustainable impact, measured by SDG ratings. Additionally, it would be interesting to examine if other SGC patent classes can predict sustainability metrics, especially within the SDG framework, given that I find firms patenting activity to predict higher ratings in several SDGs, such as SDG 9, 11, and 12 (untabulated). My results are particularly relevant for investors seeking to construct sustainable portfolios. For instance, a Danish pension fund[40] considers four investment categories when constructing its sustainable portfolio. One category consider "*frontrunners*" – firms whose activities drive the world toward a more sustainable future. In this context, GI could be used to identify firms developing new technologies to address global challenges. Another category focuses on ESG-integration, underscoring how institutional investors increasingly rely on complementary metrics to assess sustainability. By evaluating firms across multiple dimensions, investors gain a broader understanding of their sustainability profiles. Notably, firms with high levels of GI predicts lower E ratings, meaning they

[40] https://www.velliv.dk/dk/privat/aftryk

may not be classified as strong E performers despite their innovative contributions. Given that Leippold and Yu (2023) find a long-short portfolio strategy based on GI to generate a significant negative return of 5% per annum, further research should assess whether portfolio sorts based on GI and SDG ratings are rewarded in financial markets. In addition, examining whether GI can serve as a proxy for systematic risk presents an equally interesting avenue for future research.

3.4 Conclusion

In 2015, United Nations member countries adopted a universally shared framework consisting of 17 sustainable development goals to be achieved by 2030 (UN, 2015b). Each SDG targets global sustainability issues, making the framework a strong candidate for a globally agreed-upon sustainability framework. However, substantial investments and innovations are needed to meet these goals. For instance, reaching *net zero* emissions by 2050 requires $4 trillion annually in clean energy investments (IEA, 2021), which would support multiple SDGs, including clean energy (SDG 7), sustainable production (SDG 12), and climate action (SDG 13). However, at current investment levels, only 15% of the SDGs will likely be met, highlighting the need for $5-$7 trillion in annual investments until 2030.

Although firms globally contribute to green and other patenting areas, these innovations are not reflected in E ratings. My findings show that firms with high MSCI E and SDG ratings focus on green innovation, reflecting that existing sustainability metrics interacts with green innovation, positively. However, an increase in patenting intensity is associated with lower E-ratings across both MSCI and Refinitiv vendors. Specifically, a one-standard-deviation increase in sustainable patenting predicts a decrease in MSCI E ratings, equal to a 2% decrease of its standard deviation, in the medium-term. This negative relationship is primarily driven by mid-, large-, and mega-cap firms. While E ratings aim to capture financial risks related to environmental issues, I find no evidence that large firms' innovation activities reduce their financial materiality (risk).

Given the criticism and divergent results in the literature for ESG ratings, I propose using SDG ratings as a measure of sustainable impact. Although existing literature documents discrepancies in SDG ratings across vendors, SDGs cover a broader range of sustainability issues. This granularity allows for a detailed examination of how innovation activities impact specific SDGs. I find that green innovation, particularly in green and energy patents, predicts increases in relevant SDG areas, with robust results using Robeco data. For instance, energy patenting activity predicts higher overall SDG metrics and specific SDGs (7 and 13), with economic effects of up to 4.5% (5.3%) in the short (medium) term.

As institutional investors increasingly rely on complementary metrics to assess sustainability, beyond ESG, incorporating SDGs would align portfolios with sustainable objectives (Van Zanten and Huij, 2024). However, SDGs are hard to quantify, thus using green innovation as a complementary metric for sustainable impact offers a way to fulfill their market and societal roles while remaining accountable to beneficiaries. My findings suggest that green innovation can help identify firms with higher future sustainable impact, positioning them better for the transition to a low-carbon economy, and adding a ”real-world impact" dimension alongside risk and return. Therefore, green innovation should be adopted in creating sustainable products. Further research should explore to what extent green innovation can enhance sustainable investment strategies, specifically by examining its role in portfolios as a hedge against climate risk, as a sorting variable, or as a proxy for systematic risk.

Acknowledgements

I thank the team at Qblue Balanced for their helpful comments and suggestions, not only for their financial expertise but also for giving me access to their data. I especially want to thank Martin Richter for his helpful financial insights and our many exciting discussions on the interlinkages in the sustainable finance domain. I would also like to express my gratitude to my main supervisor, Peter Løchte Jørgensen, for his invaluable insights and feedback. Thanks to Jan Anton Van Zanten at Robeco for providing me access to their SI Open Access Initiative.

3.5 References

Abrams, D. S., Akcigit, U., Grennan, J., 2013. Patent value and citations: Creative destruction or strategic disruption? Tech. rep.

Acs, Z. J., Anselin, L., Varga, A., 2002. Patents and innovation counts as measures of regional production of new knowledge. *Research policy* 31 (7), 1069–1085.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., Van Reenen, J., 2016. Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy* 124 (1), 1–51.

Akgun, O. T., Mudge, T. J., Townsend, B., 2021. How company size bias in ESG scores impacts the small cap investor. *The journal of impact and ESG investing* 1 (4), 31–44.

Avramov, D., Cheng, S., Lioui, A., Tarelli, A., 2022. Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics* 145 (2), 642–664.

Bauckloh, T., Dobrick, J., Höck, A., Utz, S., Wagner, M., 2023. “In Partnership for the Goals”? The (Dis) Agreement of Sdg Ratings. CFR Working Paper, No. 23-02, University of Cologne, Centre for Financial Research (CFR), Cologne.

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.

Bingler, J. A., Kraus, M., Leippold, M., Webersinke, N., 2022. Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures. *Finance Research Letters* 47, 102776.

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.

Bolton, P., Kacperczyk, M. T., Wiedemann, M., 2023. *The co2 question: Technical progress and the climate crisis.* (available at http://dx.doi.org/10.2139/ssrn.4212567).

Cameron, A. C., Trivedi, P. K., 2005. Microeconometrics: methods and applications. Cambridge university press.

Carbon Disclosure Project, 2019. Major Risk or Rosy Opportunity. Are companies ready forclimate change. CDP Climate Change Report 2018, Global edition.

Cepni, O., Demirer, R., Pham, L., Rognone, L., 2023. Climate uncertainty and information transmissions across the conventional and ESG assets. *Journal of International Financial Markets, Institutions and Money* 83, 101730.

Chang, Y.-K., Cheung, W., Chung, M.-H., Tan, H., 2024. The Paris Agreement effect of consumer awareness and sustainable investing: Some international evidence. *Pacific-Basin Finance Journal*, 102394.

Chen, Y.-S., 2008. The positive effect of green intellectual capital on competitive advantages of firms. *Journal of business ethics* 77, 271–286.

Cohen, L., Gurun, U. G., Nguyen, Q. H., 2020. The ESG-innovation disconnect: Evidence from green patenting. Working Paper Harvard Business School.

Cohn, J. B., Liu, Z., Wardlaw, M. I., 2022. Count (and count-like) data in finance. *Journal of Financial Economics* 146 (2), 529–551.

Desheng, L., Jiakui, C., Ning, Z., 2021. Political connections and green technology innovations under an environmental regulation. *Journal of Cleaner Production* 298, 126778.

Dimson, E., Marsh, P., Staunton, M., 2020. Divergent ESG ratings. *The Journal of Portfolio Management* 47 (1), 75–87.

Dobrick, J., Klein, C., Zwergel, B., 2023. Size bias in refinitiv ESG data. *Finance Research Letters* 55, 104014.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging climate change news. *The Review of Financial Studies* 33 (3), 1184–1216.

Favot, M., Vesnic, L., Priore, R., Bincoletto, A., Morea, F., 2023. Green patents and green codes: How different methodologies lead to different results. *Resources, Conservation & Recycling Advances* 18, 200132.

Fiaschi, D., Giuliani, E., Nieri, F., Salvati, N., 2020. How bad is your company? Measuring corporate wrongdoing beyond the magic of ESG metrics. *Business Horizons* 63 (3), 287–299.

Frietsch, R., Neuhäusler, P., Rothengatter, O., Jonkers, K., 2016. Societal Grand Challenges from a technological perspective: Methods and identification of classes of the International Patent Classification IPC. Fraunhofer ISI Discussion Papers Innovation Systems and Policy Analysis; Karlsruhe (Germany): Fraunhofer Gesellschaft; 2016. JRC100598.

Ghisetti, C., Quatraro, F., 2017. Green technologies and environmental productivity: A cross-sectoral analysis of direct and indirect effects in Italian regions. *Ecological Economics* 132, 1–13.

Global Commission on the Economy and Climate, 2018. Unlocking the Inclusive Growth Storyof the 21st Century: Accelerating Climate Action in Urgent Times. The New Climate Economy.

GSIA, 2022. Global Sustainable Investment Review. Accessed 21 June 2024 from: https://www.gsi-alliance.org/wp-content/uploads/2023/12/GSIA-Report-2022.pdf.

Hall, B. H., Griliches, Z., Hausman, J. A., 1984. Patents and R&D: Is there a lag? Tech. rep.

Hart, S. L., 1995. A natural-resource-based view of the firm. *Academy of management review* 20 (4), 986–1014.

He, L., Lohre, H., van Zanten, J. A., 2024. Sustainability Matters: Company SDG Scores Need Not Have Size, Location, and ESG Disclosure Biases. *Available at SSRN: https://ssrn.com/abstract=4886097*.

Hirshleifer, D., Hsu, P.-H., Li, D., 2013. Innovative efficiency and stock returns. *Journal of financial economics* 107 (3), 632–654.

IEA, 2021. Net Zero by 2050. IEA, Paris, available at https://www.iea.org/reports/net-zero-by-2050, Licence: CC BY 4.0.

IEA, 2023. World Energy Outlook 2023. IEA, Paris (available at https://www.iea.org/reports/world-energy-outlook-2023).

Ilhan, E., Sautner, Z., Vilkov, G., 2021. Carbon tail risk. *The Review of Financial Studies* 34 (3), 1540–1571.

Kemp, R., Pearson, P., 2007. Final report MEI project about measuring eco-innovation. UM Merit, Maastricht 10 (2), 1–120.

Khajenouri, D. C., Schmidt, J. H., 2021. Standard or Sustainable-Which Offers Better Performance for the Passive Investor? Forthcoming, Journal of Applied Finance & Banking 11 (1), 61–71.

Khan, M., Serafeim, G., Yoon, A., 2016. Corporate sustainability: First evidence on materiality. *The accounting review* 91 (6), 1697–1724.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132 (2), 665–712.

Kraus, S., Rehman, S. U., García, F. J. S., 2020. Corporate social responsibility and environmental performance: The mediating role of environmental strategy and green innovation. *Technological forecasting and social change* 160, 120262.

Leippold, M., Yu, T., 2023. The Green Innovation Premium. Swiss Finance Institute Research Paper No. 23-21, available at SSRN: https://ssrn.com/abstract=4391444 or http://dx.doi.org/10.2139/ssrn.4391444.

Linnenluecke, M. K., 2022. Environmental, social and governance (ESG) performance in the context of multinational business research. *Multinational Business Review* 30 (1), 1–16.

Madhavan, A., Sobczyk, A., Ang, A., 2021. Toward ESG alpha: Analyzing ESG exposures through a factor lens. *Financial Analysts Journal* 77 (1), 69–88.

Monasterolo, I., De Angelis, L., 2020. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics* 170, 106571.

Pattberg, P., Widerberg, O., 2016. Transnational multistakeholder partnerships for sustainable development: Conditions for success. *Ambio* 45, 42–51.

Peeters, B., Song, X., Callaert, J., Grouwels, J., Van Looy, B., 2010. Harmonizing harmonized patentee names: an exploratory assessment of top patentees. Eurostat Working Paper.

Popescu, I.-S., Hitaj, C., Benetto, E., 2021. Measuring the sustainability of investment funds: A critical review of methods and frameworks in sustainable finance. *Journal of Cleaner Production* 314, 128016.

Popp, D., 2002. Induced innovation and energy prices. *American economic review* 92 (1), 160–180.

Qiu, L., Jie, X., Wang, Y., Zhao, M., 2020. Green product innovation, green dynamic capability, and competitive advantage: Evidence from Chinese manufacturing enterprises. *Corporate Social Responsibility and Environmental Management* 27 (1), 146–165.

Renneboog, L., Ter Horst, J., Zhang, C., 2008. The price of ethics and stakeholder governance: The performance of socially responsible mutual funds. Journal of corporate finance 14 (3), 302–322.

Russo, M. V., Fouts, P. A., 1997. A resource-based perspective on corporate environmental performance and profitability. *Academy of management Journal* 40 (3), 534–559.

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

Scheitza, L., Busch, T., Metzler, J., 2022. The impact of impact funds–A global analysis of funds with impact-claim. *Journal of Financial Transformation.*

Song, H., Schwarz, N., 2010. If it,s easy to read, it,s easy to do, pretty, good, and true. *Psychologist* 23 (2), 108–111.

Stevens, C., Kanie, N., 2016. The transformative potential of the sustainable development goals (SDGs). *International Environmental Agreements: Politics, Law and Economics* 16, 393–396.

TWI2050, 2019. *The Digital Revolution and Sustainable Development: Opportunities andChallenges.* Report prepared by The World In 2050 Initiative. Laxenburg, Austria:International Institute for Applied Systems Analysis (IIASA).

Ulbricht, N., Weiner, C., 2005. Worldscope meets Compustat: A comparison of financial databases. (available at https://dx.doi.org/10.2139/ssrn.871169).

UN, 2015a. Transforming our world: The 2030 agenda for sustainable development. New York: United Nations.

UN, 2015b. Transforming Our World: The 2050 Agenda For Sustainable Development. New York: United Nations.

Van Tulder, R., van Mil, E., 2022. Principles of sustainable business: Frameworks for corporate action on the SDGs. Routledge.

Van Zanten, J. A., Huij, J., 2024. ESG to SDG: Do Sustainable Investing Ratings Align with the Sustainability Preferences of Investors, Regulators, and Scientists? Available at SSRN: https://ssrn.com/abstract=4186680.

van Zanten, J. A., Rein, B., 2023. Who owns (un) sustainable companies? Examining institutional determinants of sustainable investing. *Journal of Cleaner Production* 422, 138542.

Van Zanten, J. A., van Tulder, R., 2021. Improving companies' impacts on sustainable development: A nexus approach to the SDGS. *Business Strategy and the Environment* 30 (8), 3703–3720.

Van Zanten, J. A., Wiersma, T., Whittaker, R., Ruijs, P., Van Lamoen, C., Van Tulder, R., Krosinsky, C., 2023. Beyond Confusion: Principles for Sustainable Investing Ratings and an Open Access SDG Score. (available at https://dx.doi.org/10.2139/ssrn.4589799).

Varini, F. S., Boyd-Graber, J., Ciaramita, M., Leippold, M., 2020. ClimaText: A dataset for climate change topic detection. (available at https://doi.org/10.48550/arXiv.2012.00483).

Webersinke, N., Kraus, M., Bingler, J. A., Leippold, M., 2021. Climatebert: A pretrained language model for climate-related text. (available at https://doi.org/10.48550/arXiv.2110.12010).

Appendix

A.1 Appendix Definition

Table A.1: SGC Patent Classifications

SCG Group	Sub-category
Health	• E-health • Medical Instruments • Pharmaceuticals • Biotech
Bioeconomy	• Agriculture/forestry • Pulp and paper • Machines (cartons, boxes, printing) • Genetic engineering • Landscape management • Food • Proteins • Bio fuels • Bio-materials • Marine • Biotech • Animals/livestock management • Household appliances (food-related)
Transport	• Aeronautics • Automobiles (cars and trucks) • Trains • Trailer and other wheelers • Ships • Logistics/handling • Intelligent transport/navigation • Infrastructure • New power train • Bio fuels for transport • Characteristics of vehicles • CCMTs in transportation
Climate	• Waste management and recycling • Water and wastewater • Air • Air quality management • Soil • Noise • Forests, flora, fauna • Bio-materials
Energy	• Technologies or applications for mitigation or adaptation against climate change • Information or communication technologies having an impact on other technology areas
Security	• Detection • Forensics • Monitoring/Navigation • Access control • Protection • Protective clothing • Equipment • Catastrophe fighting • Public communication • Critical infrastructure • Digital security

Source: Frietsch et al. (2016)

Table A.2: Patent Variables

Variable	Definition
GreenRatio	Is the green patent ratio based on the patenting at either the worldwide, EPO, or USPTO patent office, calculated as the number of granted green patents over the total number of granted patents. Source: GP
HealthRatio	Is the health patent ratio, calculated as the number of granted health patents over the total number of granted patents. Source: GP
BioeconomyRatio	Is the bioeconomy patent ratio, calculated as the number of granted bioeconomy patents over the total number of granted patents. Source: GP
EnergyRatio	Is the energy patent ratio, calculated as the number of granted energy patents over the total number of granted patents. Source: GP
TransportRatio	Is the transport patent ratio, calculated as the number of granted transport patents over the total number of granted patents. Source: GP
ClimateRatio	Is the climate patent ratio, calculated as the number of granted climate patents over the total number of granted patents. Source: GP
SecurityRatio	Is the security patent ratio, calculated as the number of granted security patents over the total number of granted patents. Source: GP
GreenCit	Is the patent citation ratio based on forward citations, i.e., how often a patent has been cited in future work. Similarly to the patent ratio variables, I divide the number of forward citations of green patents by the total number of citations of all patents. Source: GP
HealthCit	Is the patent citation ratio based on forward citations for health patents, calculated as GreenCit. Source: GP
BioeconomyCit	Is the patent citation ratio based on forward citations for bioeconomy patents, calculated as GreenCit. Source: GP
EnergyCit	Is the patent citation ratio based on forward citations for energy patents, calculated as GreenCit. Source: GP
TransportCit	Is the patent citation ratio based on forward citations for transport patents, calculated as GreenCit. Source: GP
ClimateCit	Is the patent citation ratio based on forward citations for climate patents, calculated as GreenCit. Source: GP
SecurityCit	Is the patent citation ratio based on forward citations for security patents, calculated as GreenCit. Source: GP

Table A.3: Financial Variables

Variable	Definition	Control from
LOGS1 (LOGS2 AND LOGS3)	The natural logarithm of firm-level scope 1 (2 and 3) emissions (Worldscope items ENERDP024, ENERDP025, ENERDP096). Source: Worldscope	Bolton et al. (2023)
LOGSIZE	The natural logarithm of market capitalization (in $ million) (Worldscope item 7210). Source: Worldscope	Bolton et al. (2023)
LOGASSETS	The natural logarithm of asses (in $ million) (Worldscope item 2999). Soruce: Worldscope	Sautner et al. (2023)
LOGPPE	The natural logratihm of plant, property & equipment (in $ million) (Worldscope item 2501). Source: Worldscope	Sautner et al. (2023)
Debt / Assets (Leverage)	The book value of debt (Worldscope item 3255) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Sautner et al. (2023)
Cash / Assets	Cash and short-term equivalents (Worldscope item 2005) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Sautner et al. (2023)
PPE / Assets	Plant, Property & Equipment (Worldscope item 2501) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Sautner et al. (2023)
EBIT / Assets	Earnings before interest and taxes (Worldscope item 18191) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Sautner et al. (2023)
R&D / Assets	Research & Development (Worldscope item 1201) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Sautner et al. (2023)
CAPEX / Assets	Capital expenditures (Worldscope item 4601) divided by total assets (World scope item 2999). Winzorized at the 1% level. Source: Worldscope	Bolton et al. (2023)
ROE	The return on equity (Net Income divided by Shareholders Equity, Worldscope items 1706 & 3995). Source: Worldscope & self-constructed	Bolton et al. (2023)
ROA	The return on assets (Worldscope item 8326). Source: Worldscop	Bolton et al. (2023)e
M/B	The market value of equity divided by the book value of equity (Market cap. Divided by Shareholders Equtiy). Source: Self-constructed	Bolton et al. (2023)
Beta	The firm-level market beta estimated over a one-year period. Source: Self-constructed	Bolton et al. (2023)
Volatility	The annual stock return volatility calculated on a monthly frequency. Source: Self-constructed	Bolton et al. (2023)
Cum. return	The cumulative stock return on an annual frequency. Source: Self-constructed	Bolton et al. (2023)
Dec. return	The monthly stock return in December calculated on a daily frequency. Source: Self-constructed	Bolton et al. (2023)
Net, Oper, Prod SDG Ratings	The SDG rating for firms net alignment with any of the 17 SDGs for Net, Operational, and Product alignment. Source: MSCI	
Robeco SDG Ratings	The SDG rating for firms alignment with any of the 17 SDGs under coverage by Robeco. Source: Robeco	
MSCI ind.	An indicator variable equal to one if a firm is part of the MSCI ACWI in a given year and zero otherwise	Bolton et al. (2023)

Table A.4: MSCI SDG Variables

Variable	Definition	Link to SGC
SDG 1: No Poverty	End poverty in all its forms everywhere	
SDG 2: Zero Hunger	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture	Bioeconomy
SDG 3: Good Health & Well-Being	Ensure healthy lives and promote well-being for all at all ages	Health
SDG 4: Quality Education	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all	
SDG 5: Gender Equality	Achieve gender equality and empower all women and girls	
SDG 6: Clean Water and Sanitation	Ensure availability and sustainable management of water and sanitation for all	Climate
SDG 7: Affordable and Clean Energy	Ensure access to affordable, reliable, sustainable and modern energy for all	Bioeconomy, Energy
SDG 8: Decent Work and Economic Growth	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all	
SDG 9: Industry, Innovation and Infrastructure	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation	Transport
SDG 10: Reduced Inequalities	Reduce inequality among and within countries	
SDG 11: Sustainable Cities and Communities	Make cities and human settlements inclusive, safe, resilient and sustainable	
SDG 12: Responsible Consumption and Production	Ensure sustainable consumption and production patterns	
SDG 13: Climate Action	Take urgent action to combat climate change and its impacts	Climate, Energy
SDG 14: Life Below Water	Conserve and sustainably use the oceans, seas and marine resources for sustainable development	Climate
SDG 15: Life on Land	Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss	Climate
SDG 16: Peace, Justice and Strong Institutions	Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels	Security
SDG 17: Partnership for the Goals	Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development	

Source: UN (2015b)

A.2 Appendix Tables - Descriptive

Table A.5: Patent Observations By Country

The sample period is 1995-2023. I report the number of patent observations by firm country for the full sample, including the number of patents observed by firm country for "Public", "Green", and "SGC" categories. Firm country refers to the country of the firm's primary listing. Countries with fewer than 300 patent observations in the full sample are aggregated by region under "Others". "Others South America" includes ECUADOR, JAMAICA, and VENEZUELA. "Others Asia" includes UNITED ARAB EMIRATES, KAZAKHSTAN, PALESTINE, and QATAR. "Others Europe" includes BULGARIA, CZECHIA, ESTONIA, CROATIA, LITHUANIA, LUXEMBOURG, LATVIA, MONTENEGRO, MALTA, PORTUGAL, SERBIA, SLOVENIA and UKRAINE. "Others Africa" includes BOTSWANA, GHANA, MAURITIUS, NIGERIA, TUNISIA, UGANDA, ZAMBIA, and ZIMBABWE. Columns 1 to 3 cover patents granted at any patent office globally. Columns 4 to 6 cover patents granted at the European Patent Office, Columns 7 to 9 cover patents granted at the United States Patent and Trademark Office.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	at USPTO			at EPO			at GPO		
Country	Total	Green	SGC	Total	Green	SGC	Total	Green	SGC
AR	1,158	124	233	188	14	69	2,086	182	456
AT	3,598	415	1,590	4,981	606	1,953	15,716	1,856	6,803
AU	22,209	1,765	11,580	4,807	508	3,112	46,304	4,664	24,850
BE	11,507	1,177	6,032	7,940	741	4,566	35,304	3,523	19,714
BR	11,507	1,185	2,554	1,782	201	734	17,312	1,800	4,614
CA	22,114	2,560	9,772	5,631	858	3,262	41,781	5,417	20,648
CH	53,554	8,382	25,488	35,076	4,356	19,149	157,418	22,036	88,214
CL	504	34	223	209	16	112	1,358	90	665
CN	42,291	3,836	8,885	11,949	934	3,918	67,279	5,963	17,189
CO	144	32	104	40	10	28	332	60	231
CY	797	116	319	174	15	97	1,292	158	584
DE	158,908	22,622	65,798	101,308	12,659	50,731	470,619	65,564	220,554
DK	12,034	2,832	8,199	7,936	2,101	5,833	38,145	8,340	26,064
DUB	628	27	152	77	13	45	999	57	296
EG	147	31	95	66	9	32	438	61	224
ES	3,555	324	1,555	1,931	158	1,039	11,267	1,018	5,815
FI	21,693	1,222	6,854	15,815	704	5,897	64,075	3,407	24,322
FR	105,104	12,285	46,118	71,518	7,065	36,284	350,387	37,724	172,970
GB	132,735	9,322	53,070	41,497	3,453	21,024	262,577	22,028	123,532
GR	1,495	148	724	489	37	311	3,139	297	1,694
HK	49,581	3,168	12,738	12,025	856	3,946	78,008	5,574	23,672
HU	180	17	135	188	17	138	699	71	496
ID	270	7	60	20	1	9	434	19	135
IE	1,045	150	446	380	66	278	2,686	407	1,632
IL	7,375	822	2,805	1,810	208	1,065	13,173	1,575	6,392
IN	36,658	5,905	16,847	18,595	3,763	9,131	108,605	19,189	50,970
IS	219	0	185	235	0	188	973	0	784
IT	15,042	1,433	7,167	11,935	1,315	6,014	56,161	5,831	29,999
JO	168	128	139	34	7	30	335	243	287
JP	872,091	84,209	285,647	254,832	26,456	112,496	1,600,630	160,053	579,636
KE	210	21	121	39	9	27	367	52	233
KR	250,977	28,387	57,263	42,533	6,136	15,836	348,155	39,389	89,235
KW	197	9	75	45	2	24	367	22	154
LK	2,443	409	1,534	666	101	491	3,953	630	2,606
MA	273	21	118	185	11	83	904	60	409
MX	1,220	201	509	582	81	293	3,158	503	1,526
MY	2,174	185	765	498	60	280	7,307	571	2,156
NL	45,179	5,377	15,579	27,233	3,908	10,954	103,159	13,307	38,174
NO	4,336	425	2,176	2,201	247	1,073	12,234	1,394	6,351
NZ	2,793	134	1,652	649	33	490	7,113	416	3,915
OM	362	81	177	54	14	37	550	126	288
PE	215	26	93	141	12	76	675	68	329
PH	5,534	726	2,578	1,023	177	634	8,729	1,179	4,269
PK	665	105	330	204	60	150	1,697	315	1,101
PL	2,011	174	831	777	51	420	7,247	412	2,488
RO	413	48	154	164	26	79	938	121	431
RU	179	36	67	109	15	66	481	75	269
SA	4,633	871	1,934	907	204	447	6,164	1,145	2,646
SE	52,296	2,465	14,714	32,248	1,364	9,588	124,194	6,139	39,830
SG	5,918	758	2,462	1,756	307	1,114	11,278	1,749	5,742
TH	3,434	464	1,373	2,328	158	1,705	8,524	964	4,495
TR	285	9	108	799	35	247	1,762	63	609
TW	170,668	15,448	24,868	11,937	1,188	4,107	269,432	23,994	46,574
US	1,876,626	138,930	652,801	374,650	31,003	185,626	2,985,005	236,084	1,200,653
VN	319	25	146	95	5	40	718	49	326
ZA	16,209	1,542	3,236	2,083	225	725	21,542	2,467	5,811
Others South America	32	3	5	4	0	2	47	3	9
Others Asia	63	6	23	28	2	16	154	22	74
Others Europe	345	41	174	195	11	100	836	83	435
Others Africa	254	19	95	85	7	45	553	47	229
Total	4,038,574	361,224	1,361,475	1,117,686	112,599	526,266	7,386,775	708,656	2,914,809

Table A.6: Firm-Year Observations By Country

The sample period is 1995-2023. I report the number of firm-year observations by country for USPTO, EPO, and GPO. Within each patent office, I report the number of firm-year observations for the total (full sample), green, and SGC samples. A single firm may be granted a patent at any patent office in a given year, therefore columns (1) to (3) represent firm-year observations conditional on a patent grant at USPTO. Consequently, columns (1) and (4) do not sum up to the total in column (7), as they represent different samples. Comparisons of firm-year observations are only valid within patent office.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	at USPTO			at EPO			at GPO		
Country	Total	Green	SGC	Total	Green	SGC	Total	Green	SGC
AT	438	114	347	427	130	335	632	254	534
AU	4,561	960	2,846	2,134	391	1,455	7,204	1,840	4,990
BE	861	308	668	705	262	556	1,135	482	938
BR	659	170	393	392	79	255	907	253	577
CA	4,960	1,133	3,080	1,842	404	1,254	6,810	1,839	4,584
CH	2,188	701	1,608	1,856	602	1,404	2,695	1,040	2,172
CN	6,238	1,163	2,867	2,408	395	1,402	8,179	1,649	4,267
DE	4,163	1,441	3,063	3,686	1,295	2,804	5,692	2,376	4,489
DK	822	288	621	650	224	523	1,075	460	855
ES	684	188	500	577	101	417	1,084	387	858
FI	955	267	657	761	222	575	1,384	499	1,067
FR	3,921	1,364	2,911	3,254	1,102	2,558	5,423	2,185	4,299
GB	7,990	2,164	5,498	4,776	1,201	3,427	10,162	3,486	7,705
GR	522	81	314	262	31	165	777	138	506
HK	5,512	1,107	2,959	2,039	422	1,297	7,333	1,794	4,437
IL	1,167	266	671	555	131	365	1,544	394	982
IN	4,189	903	2,621	2,179	482	1,508	6,148	1,506	4,072
IT	1,305	382	835	1,290	364	881	1,956	654	1,398
JP	26,643	8,907	18,712	17,418	5,390	12,636	33,831	12,223	25,114
KR	8,022	1,907	4,844	3,566	880	2,462	10,798	2,788	7,004
MY	670	132	384	280	49	180	1,015	244	636
NL	994	373	761	804	301	624	1,250	567	1,041
NO	986	238	668	615	144	437	1,344	429	990
NZ	451	85	293	198	22	142	691	165	487
PH	620	153	389	266	58	180	861	234	585
PL	745	109	400	409	44	247	1,231	207	759
SE	3,207	840	2,301	2,358	601	1,723	4,251	1,406	3,313
SG	1,548	278	862	628	99	392	2,262	437	1,404
TH	1,138	267	649	439	115	282	1,634	427	1,035
TW	11,901	3,043	6,196	3,799	712	2,175	15,291	4,530	9,228
US	51,940	17,903	38,092	26,664	8,074	20,236	60,071	23,388	46,404
ZA	876	181	531	441	112	293	1,404	343	937
Others South America	351	69	181	135	21	83	509	105	303
Others Asia	716	164	428	357	85	240	1,042	250	660
Others Europe	934	161	579	638	116	448	1,494	302	1,034
Others Africa	478	100	290	212	36	144	764	168	498
Total	163,355	47,910	109,019	89,020	24,697	64,105	209,883	69,449	150,162

Table A.7: Firm-Year Patent Ratio By Country

The sample period is 2002-2023, conditional on financial data availability. I report the average patent ratios by country for patent grants at USPTO in Panel A for the merged sample. Panel B and C present grants at EPO, and GPO, respectively. Within each patent office, I report the average patent ratio for the green, and all six SGC classes in the samples.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Patent Ratios							
	United States Patent And Trademark Office						
Country	Green	Health	BioEco	Energy	Transport	Climate	Security
AT	0.094	0.070	0.169	0.060	0.255	0.061	0.058
AU	0.122	0.156	0.140	0.057	0.155	0.047	0.100
BE	0.103	0.142	0.199	0.053	0.145	0.053	0.074
BR	0.083	0.051	0.151	0.056	0.176	0.033	0.048
CA	0.127	0.114	0.118	0.079	0.161	0.044	0.097
CH	0.095	0.167	0.170	0.046	0.138	0.028	0.073
CN	0.104	0.099	0.110	0.067	0.109	0.022	0.058
DE	0.107	0.120	0.148	0.067	0.187	0.040	0.079
DK	0.162	0.279	0.265	0.077	0.175	0.047	0.080
ES	0.117	0.210	0.189	0.053	0.154	0.054	0.076
FI	0.094	0.076	0.195	0.051	0.189	0.058	0.081
FR	0.102	0.166	0.171	0.054	0.178	0.033	0.086
GB	0.090	0.119	0.127	0.049	0.143	0.033	0.092
GR	0.102	0.188	0.111	0.063	0.169	0.026	0.109
HK	0.097	0.121	0.105	0.051	0.122	0.033	0.071
IL	0.098	0.140	0.132	0.054	0.134	0.029	0.070
IN	0.118	0.182	0.147	0.067	0.159	0.038	0.083
IT	0.103	0.068	0.120	0.060	0.161	0.034	0.052
JP	0.104	0.115	0.163	0.050	0.157	0.037	0.065
KR	0.112	0.157	0.146	0.073	0.140	0.029	0.069
MY	0.133	0.123	0.144	0.050	0.172	0.073	0.083
NL	0.115	0.108	0.129	0.056	0.171	0.031	0.084
NO	0.105	0.112	0.142	0.065	0.149	0.062	0.152
NZ	0.155	0.241	0.232	0.066	0.133	0.060	0.074
PH	0.103	0.175	0.134	0.082	0.135	0.025	0.095
PL	0.078	0.168	0.157	0.065	0.131	0.027	0.090
SE	0.093	0.161	0.121	0.048	0.138	0.034	0.100
SG	0.106	0.130	0.108	0.050	0.154	0.031	0.082
TH	0.159	0.105	0.104	0.088	0.146	0.054	0.116
TW	0.100	0.082	0.084	0.045	0.097	0.014	0.063
US	0.103	0.148	0.132	0.050	0.150	0.034	0.091
ZA	0.091	0.151	0.112	0.048	0.141	0.026	0.116
Others South America	0.090	0.109	0.099	0.086	0.105	0.082	0.104
Others Asia	0.140	0.109	0.109	0.109	0.109	0.109	0.109
Others Europe	0.078	0.153	0.155	0.155	0.152	0.155	0.160
Others Africa	0.165	0.186	0.186	0.186	0.186	0.186	0.186
Total	0.105	0.131	0.137	0.055	0.146	0.033	0.079

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: Patent Ratios							
	European Patent Office						
Country	Green	Health	BioEco	Energy	Transport	Climate	Security
AT	0.101	0.043	0.225	0.071	0.244	0.078	0.055
AU	0.118	0.242	0.216	0.078	0.175	0.058	0.082
BE	0.107	0.162	0.256	0.056	0.168	0.056	0.059
BR	0.094	0.089	0.197	0.065	0.244	0.039	0.063
CA	0.147	0.173	0.184	0.098	0.195	0.056	0.087
CH	0.087	0.160	0.194	0.052	0.152	0.028	0.058
CN	0.106	0.174	0.179	0.085	0.146	0.021	0.045
DE	0.116	0.117	0.170	0.073	0.221	0.038	0.064
DK	0.163	0.335	0.307	0.080	0.163	0.047	0.056
ES	0.103	0.211	0.223	0.065	0.185	0.040	0.053
FI	0.102	0.069	0.265	0.059	0.233	0.081	0.062
FR	0.105	0.176	0.213	0.064	0.219	0.044	0.079
GB	0.105	0.166	0.190	0.060	0.174	0.046	0.091
GR	0.103	0.268	0.130	0.079	0.203	0.035	0.105
HK	0.134	0.218	0.159	0.078	0.162	0.038	0.070
IL	0.143	0.229	0.224	0.063	0.137	0.027	0.093
IN	0.132	0.249	0.182	0.075	0.188	0.050	0.059
IT	0.120	0.063	0.160	0.078	0.198	0.049	0.061
JP	0.103	0.147	0.213	0.058	0.183	0.042	0.057
KR	0.143	0.236	0.215	0.098	0.198	0.040	0.058
MY	0.140	0.153	0.249	0.055	0.194	0.087	0.072
NL	0.139	0.102	0.190	0.070	0.213	0.045	0.068
NO	0.115	0.094	0.178	0.087	0.162	0.071	0.102
NZ	0.098	0.353	0.318	0.063	0.109	0.044	0.115
PH	0.119	0.315	0.229	0.072	0.153	0.074	0.095
PL	0.080	0.203	0.262	0.081	0.150	0.028	0.068
SE	0.099	0.183	0.155	0.054	0.170	0.035	0.088
SG	0.110	0.193	0.148	0.062	0.225	0.035	0.075
TH	0.178	0.126	0.209	0.123	0.209	0.033	0.059
TW	0.114	0.148	0.156	0.076	0.124	0.026	0.067
US	0.115	0.214	0.195	0.060	0.183	0.037	0.083
ZA	0.147	0.170	0.183	0.076	0.184	0.050	0.094
Others South America	0.125	0.196	0.092	0.075	0.067	0.051	0.093
Others Asia	0.152	0.147	0.147	0.147	0.147	0.147	0.147
Others Europe	0.103	0.196	0.187	0.183	0.184	0.182	0.189
Others Africa	0.149	0.209	0.209	0.209	0.209	0.209	0.209
Total	0.114	0.179	0.198	0.067	0.182	0.041	0.071

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Patent Ratios							
	Global Patent Office						
Country	Green	Health	BioEco	Energy	Transport	Climate	Security
AT	0.103	0.062	0.195	0.060	0.228	0.086	0.051
AU	0.123	0.160	0.153	0.057	0.173	0.049	0.088
BE	0.106	0.139	0.229	0.045	0.163	0.056	0.066
BR	0.088	0.081	0.171	0.053	0.171	0.040	0.049
CA	0.133	0.124	0.142	0.079	0.172	0.051	0.091
CH	0.090	0.164	0.187	0.051	0.142	0.027	0.072
CN	0.109	0.122	0.128	0.072	0.121	0.024	0.054
DE	0.110	0.117	0.153	0.067	0.208	0.036	0.073
DK	0.168	0.277	0.275	0.069	0.177	0.052	0.086
ES	0.130	0.176	0.195	0.063	0.196	0.060	0.068
FI	0.109	0.078	0.227	0.051	0.196	0.080	0.074
FR	0.102	0.155	0.181	0.059	0.202	0.041	0.077
GB	0.099	0.133	0.150	0.053	0.162	0.038	0.086
GR	0.099	0.181	0.130	0.072	0.191	0.035	0.095
HK	0.112	0.143	0.130	0.055	0.143	0.036	0.065
IL	0.115	0.164	0.169	0.056	0.128	0.030	0.087
IN	0.116	0.184	0.151	0.066	0.174	0.046	0.072
IT	0.106	0.079	0.141	0.069	0.169	0.042	0.055
JP	0.103	0.125	0.178	0.050	0.166	0.041	0.063
KR	0.115	0.173	0.161	0.075	0.147	0.035	0.061
MY	0.125	0.128	0.159	0.056	0.178	0.071	0.076
NL	0.119	0.104	0.155	0.052	0.185	0.046	0.072
NO	0.121	0.107	0.164	0.067	0.162	0.064	0.128
NZ	0.128	0.212	0.246	0.060	0.137	0.053	0.069
PH	0.110	0.198	0.159	0.066	0.131	0.049	0.085
PL	0.083	0.159	0.192	0.057	0.152	0.031	0.082
SE	0.107	0.177	0.148	0.052	0.156	0.044	0.092
SG	0.108	0.136	0.123	0.051	0.178	0.037	0.064
TH	0.165	0.114	0.149	0.090	0.163	0.051	0.096
TW	0.105	0.097	0.106	0.050	0.108	0.020	0.062
US	0.109	0.164	0.152	0.051	0.159	0.037	0.086
ZA	0.103	0.148	0.141	0.057	0.158	0.047	0.094
Others South America	0.090	0.116	0.095	0.081	0.097	0.078	0.093
Others Asia	0.128	0.134	0.134	0.134	0.134	0.134	0.134
Others Europe	0.083	0.172	0.171	0.168	0.166	0.166	0.171
Others Africa	0.161	0.201	0.201	0.201	0.201	0.201	0.201
Total	0.109	0.142	0.155	0.057	0.157	0.038	0.073

Table A.8: Firm-Year Patent Ratio By GICS-Industry (6-Digit)

The sample period is 2002-2023, conditional on financial data availability. I report the average patent ratio by green and six SGC classes for each GICS-Industry code (6-digit) for the merged sample. In Panel A, I report the average patent ratio at USPTO, in Panel B at EPO, and in Panel C at GPO.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Patent Ratios							
				USPTO			
Name	Green	Health	Bioeconomy	Energy	Transport	Climate	Security
Advertising (discont. 2018)	0.106	0.129	0.057	0.000	0.216	0.000	0.128
Aerospace & Defense	0.092	0.042	0.084	0.078	0.260	0.027	0.084
Air Freight & Logistics	0.085	0.096	0.086	0.039	0.250	0.029	0.113
Automobile Components	0.076	0.040	0.079	0.050	0.314	0.025	0.039
Automobiles	0.162	0.034	0.028	0.131	0.409	0.029	0.034
Banks	0.084	0.110	0.095	0.043	0.140	0.028	0.110
Beverages	0.106	0.166	0.299	0.041	0.188	0.059	0.047
Biotechnology	0.225	0.654	0.536	0.059	0.180	0.029	0.100
Broadline Retail	0.061	0.068	0.071	0.050	0.129	0.031	0.101
Building Products	0.111	0.052	0.121	0.053	0.114	0.035	0.059
Capital Markets	0.088	0.100	0.105	0.052	0.139	0.038	0.100
Chemicals	0.144	0.095	0.254	0.073	0.129	0.064	0.032
Commercial Services & Supplies	0.099	0.083	0.132	0.053	0.128	0.072	0.092
Communications Equipment	0.059	0.049	0.040	0.027	0.078	0.007	0.079
Construction & Engineering	0.120	0.106	0.127	0.075	0.180	0.065	0.086
Construction Materials	0.138	0.063	0.115	0.102	0.108	0.055	0.048
Consumer Finance	0.047	0.090	0.119	0.021	0.110	0.026	0.140
Consumer Staples Distribution & Retail	0.088	0.133	0.164	0.048	0.135	0.042	0.073
Containers & Packaging	0.052	0.039	0.174	0.030	0.323	0.024	0.041
Distributors	0.065	0.100	0.078	0.042	0.176	0.032	0.065
Diversified Consumer Services	0.086	0.148	0.144	0.043	0.146	0.039	0.100
Diversified REITs	0.130	0.099	0.234	0.068	0.225	0.054	0.059
Diversified Telecommunication Services	0.057	0.066	0.040	0.030	0.089	0.004	0.116
Electric Utilities	0.277	0.081	0.110	0.155	0.191	0.067	0.080
Electrical Equipment	0.182	0.050	0.059	0.149	0.156	0.026	0.048
Electronic Equipment, Instruments & Components	0.098	0.067	0.069	0.048	0.103	0.016	0.090
Energy Equipment & Services	0.106	0.042	0.066	0.059	0.180	0.057	0.106
Entertainment	0.050	0.082	0.078	0.027	0.117	0.026	0.081
Financial Services	0.082	0.123	0.093	0.033	0.137	0.026	0.133
Food Products	0.120	0.184	0.377	0.036	0.154	0.091	0.061
Gas Utilities	0.212	0.078	0.138	0.110	0.173	0.064	0.075
Ground Transportation	0.182	0.083	0.072	0.049	0.273	0.042	0.086
Health Care Equipment & Supplies	0.064	0.536	0.145	0.018	0.060	0.015	0.174
Health Care Providers & Services	0.094	0.334	0.210	0.049	0.133	0.028	0.140
Health Care REITs	0.104	0.186	0.190	0.059	0.081	0.039	0.082
Health Care Technology	0.036	0.233	0.145	0.011	0.074	0.014	0.207
Hotel & Resort REITs	0.003	0.234	0.095	0.048	0.052	0.000	0.030
Hotels, Restaurants & Leisure	0.060	0.100	0.102	0.037	0.119	0.027	0.083
Household Durables	0.058	0.057	0.099	0.030	0.102	0.018	0.051
Household Products	0.065	0.179	0.176	0.018	0.099	0.045	0.037
Independent Power and Renewable Electricity Producers	0.319	0.075	0.063	0.236	0.200	0.024	0.053
Industrial Conglomerates	0.112	0.111	0.144	0.066	0.157	0.034	0.079
Industrial REITs	0.119	0.163	0.066	0.049	0.189	0.033	0.058
Insurance	0.108	0.138	0.113	0.053	0.162	0.029	0.105
Interactive Media & Services	0.045	0.084	0.055	0.021	0.089	0.010	0.105
Internet & Direct Marketing Retail (discont. 2016)	0.000	0.200	0.025	0.000	0.000	0.000	0.225
Internet Software & Services (discont. 2018)	0.079	0.108	0.053	0.029	0.071	0.000	0.331
IT Services	0.074	0.104	0.088	0.044	0.126	0.024	0.116
Leisure Products	0.072	0.050	0.077	0.019	0.202	0.012	0.053
Life Sciences Tools & Services	0.120	0.308	0.351	0.029	0.120	0.028	0.162
Machinery	0.084	0.050	0.144	0.052	0.221	0.044	0.043
Marine Transportation	0.103	0.116	0.096	0.054	0.228	0.019	0.092
Media	0.068	0.090	0.092	0.036	0.111	0.021	0.091
Metals & Mining	0.097	0.073	0.103	0.084	0.139	0.046	0.060
Mortgage Real Estate Investment Trusts (REITs)	0.000	0.000	0.000	0.000	0.250	0.000	0.000
Multi-Utilities	0.228	0.037	0.096	0.133	0.186	0.091	0.065
Office REITs	0.097	0.110	0.114	0.113	0.181	0.051	0.059
Oil, Gas & Consumable Fuels	0.213	0.076	0.103	0.110	0.219	0.066	0.083
Paper & Forest Products	0.117	0.121	0.312	0.071	0.159	0.079	0.029
Passenger Airlines	0.071	0.062	0.055	0.051	0.235	0.010	0.080
Personal Care Products	0.088	0.250	0.205	0.033	0.091	0.027	0.072
Pharmaceuticals	0.120	0.573	0.257	0.038	0.083	0.023	0.059
Professional Services	0.079	0.110	0.098	0.050	0.122	0.026	0.109
Real Estate (discont. 2016)	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Investment Trusts (REITs) (discont. 2016)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Management & Development (discont. 2016)	0.000	0.042	0.083	0.000	0.083	0.028	0.167
Real Estate Management & Development (New code)	0.091	0.121	0.117	0.050	0.133	0.034	0.074
Residential REITs	0.104	0.193	0.244	0.053	0.169	0.016	0.101
Retail REITs	0.074	0.095	0.063	0.055	0.124	0.029	0.048
Semiconductors & Semiconductor Equipment	0.172	0.042	0.049	0.068	0.072	0.008	0.058
Software	0.061	0.076	0.055	0.039	0.108	0.013	0.166
Specialized REITs	0.108	0.130	0.134	0.028	0.125	0.070	0.113
Specialty Retail	0.073	0.093	0.083	0.045	0.133	0.023	0.083
Technology Hardware, Storage & Peripherals	0.058	0.047	0.105	0.030	0.087	0.007	0.078
Textiles, Apparel & Luxury Goods	0.050	0.075	0.116	0.027	0.091	0.018	0.053
Thrifts & Mortgage Finance (discont.)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tobacco	0.084	0.159	0.142	0.020	0.160	0.023	0.046
Trading Companies & Distributors	0.106	0.121	0.136	0.050	0.170	0.039	0.078
Transportation Infrastructure	0.152	0.071	0.073	0.021	0.208	0.017	0.124
Water Utilities	0.154	0.049	0.150	0.082	0.089	0.283	0.118
Wireless Telecommunication Services	0.067	0.081	0.049	0.042	0.111	0.011	0.126
Not Classified	0.139	0.193	0.072	0.082	0.113	0.022	0.127
Total	0.105	0.131	0.137	0.055	0.146	0.033	0.079

Panel B: Patent Ratios	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				EPO			
Name	Green	Health	Bioeconomy	Energy	Transport	Climate	Security
Advertising (discont. 2018)	0.100	0.200	0.200	0.000	0.100	0.000	0.314
Aerospace & Defense	0.094	0.043	0.111	0.095	0.309	0.026	0.072
Air Freight & Logistics	0.092	0.122	0.107	0.068	0.256	0.046	0.125
Automobile Components	0.081	0.042	0.105	0.064	0.400	0.032	0.024
Automobiles	0.204	0.028	0.042	0.175	0.563	0.056	0.034
Banks	0.092	0.123	0.163	0.049	0.193	0.045	0.088
Beverages	0.114	0.260	0.473	0.035	0.234	0.048	0.031
Biotechnology	0.242	0.695	0.555	0.056	0.221	0.030	0.099
Broadline Retail	0.092	0.126	0.144	0.060	0.225	0.031	0.106
Building Products	0.136	0.055	0.149	0.077	0.127	0.051	0.055
Capital Markets	0.109	0.188	0.150	0.077	0.163	0.049	0.077
Chemicals	0.141	0.099	0.311	0.081	0.131	0.070	0.026
Commercial Services & Supplies	0.096	0.094	0.208	0.053	0.166	0.060	0.094
Communications Equipment	0.055	0.075	0.068	0.045	0.087	0.012	0.060
Construction & Engineering	0.144	0.113	0.182	0.094	0.186	0.083	0.077
Construction Materials	0.145	0.078	0.099	0.136	0.109	0.086	0.038
Consumer Finance	0.111	0.242	0.251	0.055	0.253	0.056	0.161
Consumer Staples Distribution & Retail	0.081	0.262	0.288	0.052	0.179	0.039	0.067
Containers & Packaging	0.041	0.057	0.277	0.037	0.482	0.023	0.029
Distributors	0.092	0.228	0.215	0.081	0.159	0.069	0.095
Diversified Consumer Services	0.096	0.260	0.222	0.051	0.162	0.039	0.113
Diversified REITs	0.134	0.125	0.218	0.060	0.345	0.097	0.075
Diversified Telecommunication Services	0.044	0.086	0.059	0.024	0.097	0.012	0.086
Electric Utilities	0.277	0.106	0.163	0.168	0.189	0.093	0.058
Electrical Equipment	0.216	0.068	0.090	0.178	0.182	0.036	0.047
Electronic Equipment, Instruments & Components	0.104	0.093	0.104	0.059	0.133	0.021	0.094
Energy Equipment & Services	0.110	0.064	0.110	0.064	0.161	0.057	0.102
Entertainment	0.051	0.146	0.125	0.059	0.168	0.038	0.062
Financial Services	0.116	0.174	0.127	0.050	0.190	0.022	0.115
Food Products	0.121	0.235	0.512	0.045	0.188	0.089	0.055
Gas Utilities	0.262	0.109	0.225	0.164	0.239	0.100	0.089
Ground Transportation	0.124	0.182	0.108	0.080	0.298	0.033	0.108
Health Care Equipment & Supplies	0.056	0.649	0.168	0.020	0.066	0.015	0.160
Health Care Providers & Services	0.120	0.439	0.283	0.042	0.171	0.028	0.153
Health Care REITs	0.204	0.450	0.343	0.088	0.163	0.045	0.099
Health Care Technology	0.069	0.246	0.194	0.024	0.088	0.018	0.194
Hotel & Resort REITs	0.154	0.231	0.000	0.077	0.000	0.000	0.000
Hotels, Restaurants & Leisure	0.094	0.176	0.204	0.051	0.171	0.028	0.067
Household Durables	0.077	0.065	0.179	0.050	0.152	0.033	0.049
Household Products	0.054	0.297	0.253	0.045	0.119	0.054	0.035
Independent Power and Renewable Electricity Producers	0.410	0.090	0.064	0.290	0.220	0.017	0.063
Industrial Conglomerates	0.123	0.157	0.203	0.090	0.207	0.040	0.059
Industrial REITs	0.130	0.288	0.183	0.053	0.172	0.006	0.048
Insurance	0.104	0.200	0.184	0.053	0.178	0.045	0.066
Interactive Media & Services	0.047	0.156	0.071	0.036	0.072	0.004	0.115
Internet & Direct Marketing Retail (discont. 2016)	0.048	0.143	0.119	0.000	0.000	0.000	0.143
Internet Software & Services (discont. 2018)	0.000	0.000	0.000	0.000	0.100	0.100	0.350
IT Services	0.073	0.166	0.125	0.048	0.157	0.037	0.098
Leisure Products	0.092	0.076	0.140	0.030	0.263	0.013	0.053
Life Sciences Tools & Services	0.159	0.334	0.409	0.022	0.159	0.022	0.190
Machinery	0.078	0.051	0.186	0.062	0.260	0.046	0.034
Marine Transportation	0.099	0.209	0.112	0.035	0.243	0.041	0.054
Media	0.111	0.143	0.190	0.049	0.157	0.037	0.101
Metals & Mining	0.087	0.068	0.128	0.087	0.158	0.051	0.046
Mortgage Real Estate Investment Trusts (REITs)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Multi-Utilities	0.231	0.065	0.167	0.152	0.208	0.131	0.055
Office REITs	0.132	0.228	0.155	0.120	0.165	0.037	0.085
Oil, Gas & Consumable Fuels	0.232	0.087	0.167	0.133	0.240	0.080	0.063
Paper & Forest Products	0.118	0.183	0.460	0.091	0.215	0.132	0.024
Passenger Airlines	0.126	0.047	0.117	0.100	0.439	0.074	0.082
Personal Care Products	0.069	0.359	0.244	0.049	0.091	0.040	0.054
Pharmaceuticals	0.104	0.695	0.249	0.036	0.093	0.024	0.052
Professional Services	0.090	0.159	0.165	0.064	0.151	0.031	0.100
Real Estate (discont. 2016)	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Investment Trusts (REITs) (discont. 2016)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Management & Development (discont. 2016)	0.143	0.286	0.214	0.000	0.143	0.000	0.143
Real Estate Management & Development (New code)	0.124	0.187	0.189	0.073	0.186	0.038	0.066
Residential REITs	0.094	0.388	0.274	0.019	0.184	0.048	0.124
Retail REITs	0.177	0.125	0.137	0.178	0.319	0.014	0.033
Semiconductors & Semiconductor Equipment	0.170	0.078	0.094	0.094	0.096	0.015	0.057
Software	0.080	0.128	0.094	0.050	0.114	0.022	0.160
Specialized REITs	0.168	0.269	0.322	0.082	0.150	0.119	0.169
Specialty Retail	0.081	0.161	0.168	0.051	0.191	0.022	0.054
Technology Hardware, Storage & Peripherals	0.056	0.079	0.203	0.040	0.110	0.009	0.078
Textiles, Apparel & Luxury Goods	0.080	0.122	0.225	0.036	0.138	0.026	0.060
Thrifts & Mortgage Finance (discont.)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tobacco	0.064	0.161	0.147	0.023	0.227	0.057	0.007
Trading Companies & Distributors	0.119	0.152	0.201	0.055	0.209	0.031	0.083
Transportation Infrastructure	0.125	0.120	0.119	0.015	0.318	0.058	0.124
Water Utilities	0.143	0.068	0.108	0.200	0.121	0.275	0.056
Wireless Telecommunication Services	0.080	0.116	0.071	0.062	0.132	0.015	0.079
Not Classified	0.125	0.233	0.167	0.040	0.095	0.068	0.108
Total	0.114	0.179	0.198	0.067	0.182	0.041	0.071

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Patent Ratios							
				GLOBAL			
Name	Green	Health	Bioeconomy	Energy	Transport	Climate	Security
Advertising (discont. 2018)	0.076	0.115	0.052	0.000	0.170	0.000	0.135
Aerospace & Defense	0.097	0.049	0.095	0.073	0.271	0.026	0.085
Air Freight & Logistics	0.089	0.107	0.110	0.047	0.248	0.035	0.096
Automobile Components	0.078	0.044	0.095	0.055	0.332	0.028	0.036
Automobiles	0.179	0.029	0.030	0.135	0.471	0.039	0.028
Banks	0.084	0.114	0.117	0.041	0.155	0.041	0.105
Beverages	0.111	0.187	0.347	0.039	0.197	0.061	0.047
Biotechnology	0.225	0.657	0.537	0.053	0.190	0.030	0.094
Broadline Retail	0.061	0.085	0.080	0.051	0.160	0.049	0.094
Building Products	0.125	0.054	0.126	0.056	0.112	0.047	0.049
Capital Markets	0.101	0.119	0.131	0.060	0.150	0.042	0.090
Chemicals	0.139	0.102	0.272	0.072	0.123	0.064	0.030
Commercial Services & Supplies	0.114	0.084	0.148	0.054	0.147	0.080	0.089
Communications Equipment	0.064	0.066	0.054	0.032	0.088	0.011	0.075
Construction & Engineering	0.128	0.102	0.150	0.078	0.188	0.077	0.075
Construction Materials	0.139	0.063	0.112	0.101	0.122	0.066	0.041
Consumer Finance	0.081	0.151	0.170	0.034	0.145	0.037	0.123
Consumer Staples Distribution & Retail	0.090	0.151	0.196	0.044	0.154	0.042	0.068
Containers & Packaging	0.055	0.044	0.213	0.027	0.368	0.024	0.037
Distributors	0.075	0.143	0.110	0.039	0.174	0.042	0.070
Diversified Consumer Services	0.092	0.154	0.145	0.041	0.147	0.040	0.095
Diversified REITs	0.084	0.167	0.226	0.053	0.235	0.075	0.057
Diversified Telecommunication Services	0.058	0.075	0.055	0.028	0.096	0.012	0.103
Electric Utilities	0.285	0.086	0.129	0.153	0.191	0.073	0.068
Electrical Equipment	0.189	0.063	0.076	0.154	0.166	0.029	0.053
Electronic Equipment, Instruments & Components	0.097	0.077	0.082	0.050	0.115	0.020	0.087
Energy Equipment & Services	0.117	0.049	0.084	0.059	0.171	0.064	0.096
Entertainment	0.055	0.097	0.102	0.035	0.141	0.032	0.076
Financial Services	0.090	0.129	0.120	0.042	0.159	0.034	0.110
Food Products	0.113	0.188	0.405	0.040	0.164	0.084	0.059
Gas Utilities	0.215	0.080	0.173	0.113	0.185	0.084	0.068
Ground Transportation	0.184	0.089	0.087	0.063	0.290	0.043	0.088
Health Care Equipment & Supplies	0.065	0.561	0.164	0.022	0.068	0.018	0.164
Health Care Providers & Services	0.106	0.358	0.234	0.045	0.149	0.030	0.149
Health Care REITs	0.106	0.230	0.183	0.049	0.106	0.034	0.077
Health Care Technology	0.051	0.241	0.141	0.014	0.087	0.012	0.195
Hotel & Resort REITs	0.079	0.210	0.067	0.047	0.074	0.005	0.025
Hotels, Restaurants & Leisure	0.080	0.114	0.129	0.044	0.141	0.030	0.073
Household Durables	0.070	0.068	0.128	0.037	0.110	0.026	0.049
Household Products	0.057	0.207	0.216	0.024	0.106	0.044	0.039
Independent Power and Renewable Electricity Producers	0.330	0.082	0.067	0.236	0.214	0.032	0.055
Industrial Conglomerates	0.115	0.128	0.178	0.071	0.184	0.037	0.067
Industrial REITs	0.112	0.187	0.086	0.034	0.189	0.033	0.035
Insurance	0.111	0.169	0.130	0.044	0.159	0.036	0.099
Interactive Media & Services	0.045	0.101	0.085	0.024	0.100	0.008	0.104
Internet & Direct Marketing Retail (discont. 2016)	0.032	0.124	0.041	0.000	0.000	0.000	0.139
Internet Software & Services (discont. 2018)	0.064	0.105	0.046	0.022	0.061	0.007	0.298
IT Services	0.076	0.117	0.105	0.046	0.145	0.029	0.103
Leisure Products	0.084	0.054	0.104	0.024	0.219	0.013	0.045
Life Sciences Tools & Services	0.139	0.349	0.369	0.031	0.139	0.026	0.171
Machinery	0.084	0.055	0.158	0.053	0.233	0.043	0.039
Marine Transportation	0.110	0.138	0.121	0.047	0.242	0.041	0.084
Media	0.087	0.106	0.124	0.039	0.131	0.028	0.088
Metals & Mining	0.098	0.077	0.115	0.084	0.141	0.051	0.059
Mortgage Real Estate Investment Trusts (REITs)	0.000	0.000	0.000	0.000	0.250	0.000	0.000
Multi-Utilities	0.226	0.049	0.127	0.121	0.178	0.109	0.052
Office REITs	0.122	0.147	0.141	0.100	0.183	0.045	0.061
Oil, Gas & Consumable Fuels	0.201	0.080	0.118	0.111	0.215	0.074	0.071
Paper & Forest Products	0.108	0.133	0.310	0.067	0.174	0.087	0.024
Passenger Airlines	0.077	0.074	0.076	0.055	0.264	0.029	0.066
Personal Care Products	0.083	0.296	0.226	0.039	0.088	0.033	0.063
Pharmaceuticals	0.108	0.612	0.240	0.036	0.086	0.022	0.049
Professional Services	0.087	0.123	0.132	0.054	0.128	0.031	0.097
Real Estate (discont. 2016)	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Investment Trusts (REITs) (discont. 2016)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Real Estate Management & Development (discont. 2016)	0.083	0.244	0.200	0.000	0.089	0.014	0.130
Real Estate Management & Development (New code)	0.104	0.139	0.143	0.056	0.154	0.039	0.069
Residential REITs	0.091	0.215	0.224	0.042	0.224	0.027	0.095
Retail REITs	0.122	0.167	0.135	0.068	0.195	0.029	0.046
Semiconductors & Semiconductor Equipment	0.176	0.050	0.059	0.072	0.078	0.010	0.051
Software	0.070	0.093	0.070	0.042	0.117	0.018	0.156
Specialized REITs	0.119	0.148	0.161	0.030	0.150	0.088	0.118
Specialty Retail	0.084	0.104	0.104	0.049	0.160	0.028	0.075
Technology Hardware, Storage & Peripherals	0.056	0.056	0.118	0.036	0.099	0.008	0.076
Textiles, Apparel & Luxury Goods	0.068	0.100	0.164	0.032	0.115	0.025	0.053
Thrifts & Mortgage Finance (discont.)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tobacco	0.068	0.156	0.127	0.017	0.174	0.028	0.035
Trading Companies & Distributors	0.110	0.118	0.150	0.050	0.195	0.039	0.075
Transportation Infrastructure	0.131	0.076	0.092	0.024	0.228	0.031	0.119
Water Utilities	0.134	0.048	0.182	0.121	0.102	0.239	0.087
Wireless Telecommunication Services	0.066	0.103	0.066	0.042	0.109	0.015	0.107
Not Classified	0.166	0.211	0.137	0.085	0.111	0.030	0.099
Total	0.109	0.142	0.155	0.057	0.157	0.038108	0.073

Table A.9: Firm-Year Patent Ratio By Year

The sample period is 2002-2023, conditional on financial data availability. I report the average patent ratios by green and SGC classes for each year within the merged sample. In Panel A, I report the average patent ratios at USPTO.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Patent Ratios							
	USPTO						
Year	Green	Health	BioEco	Energy	Transport	Climate	Security
2002	0.092	0.121	0.180	NA	0.171	0.048	0.062
2003	0.091	0.131	0.180	NA	0.157	0.042	0.063
2004	0.098	0.132	0.174	NA	0.166	0.043	0.065
2005	0.101	0.139	0.174	NA	0.170	0.045	0.068
2006	0.105	0.144	0.182	NA	0.184	0.046	0.079
2007	0.109	0.141	0.180	NA	0.180	0.048	0.084
2008	0.106	0.139	0.168	NA	0.174	0.049	0.082
2009	0.112	0.146	0.170	NA	0.175	0.041	0.082
2010	0.103	0.144	0.166	0.064	0.169	0.045	0.082
2011	0.099	0.141	0.164	0.070	0.171	0.038	0.077
2012	0.102	0.140	0.153	0.075	0.160	0.039	0.070
2013	0.105	0.146	0.150	0.079	0.151	0.040	0.067
2014	0.109	0.145	0.154	0.084	0.160	0.036	0.075
2015	0.124	0.151	0.164	0.089	0.173	0.042	0.082
2016	0.123	0.152	0.164	0.090	0.174	0.045	0.085
2017	0.124	0.153	0.170	0.088	0.175	0.043	0.087
2018	0.121	0.159	0.176	0.086	0.175	0.040	0.090
2019	0.106	0.152	0.159	0.086	0.159	0.038	0.086
2020	0.118	0.178	0.171	0.087	0.171	0.042	0.102
2021	0.110	0.178	0.170	0.084	0.171	0.038	0.108
2022	0.105	0.109	0.098	0.058	0.102	0.020	0.026
2023	0.106	0.068	0.053	0.032	0.057	0.007	0.003
Total	0.105	0.131	0.137	0.055	0.146	0.033	0.079

Table A.10: Firm-Year Summary Statistics

The table reports sample averages, medians, and standard deviations of several firm-level characteristics for the sample period 2002-2023. Panel A's columns are based on firms' patenting at EPO, Panel B's columns are based on firms' patenting at GPO. Columns (1) to (3) aggregate all firm-years in the sample. Column (4) to (6) aggregate firm-years in the bottom decile based on a firm's average *GreenRatio* across the entire period. All variables are defined in Table A.3.

Panel A.1: Conditioning on patenting at the European Patent Office

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Merged Sample			Bottom decile green ratio			Top decile green ratio		
	Panel B.1: Patent Ratios								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
GreenRatio EP	0.114	0.000	0.257	0.000	0.000	0.000	0.809	1.000	0.225
HealthRatio EP	0.179	0.000	0.345	0.189	0.000	0.363	0.177	0.000	0.348
BioeconomyRatio EP	0.198	0.000	0.337	0.185	0.000	0.344	0.303	0.000	0.421
EnergyRatio EP	0.067	0.000	0.201	0.038	0.000	0.164	0.235	0.000	0.381
TransportRatio EP	0.182	0.000	0.317	0.145	0.000	0.308	0.398	0.250	0.427
ClimateRatio EP	0.041	0.000	0.160	0.030	0.000	0.149	0.105	0.000	0.275
SecurityRatio EP	0.071	0.000	0.209	0.072	0.000	0.226	0.075	0.000	0.229
GreenCit EP	0.045	0.000	0.182	0.000	0.000	0.000	0.207	0.000	0.391
HealthCit EP	0.073	0.000	0.246	0.060	0.000	0.231	0.057	0.000	0.226
BioeconomyCit EP	0.081	0.000	0.248	0.060	0.000	0.225	0.090	0.000	0.278
EnergyCit EP	0.027	0.000	0.143	0.011	0.000	0.096	0.064	0.000	0.238
TransportCit EP	0.086	0.000	0.252	0.056	0.000	0.218	0.118	0.000	0.312
ClimateCit EP	0.017	0.000	0.112	0.010	0.000	0.092	0.029	0.000	0.161
SecurityCit EP	0.030	0.000	0.149	0.024	0.000	0.144	0.024	0.000	0.142
	Panel A.2: Financial & Environmental variables								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
LogS1Tot	10.381	10.226	3.006	9.843	9.644	2.906	10.298	10.168	3.383
LogS2Tot	10.893	10.928	2.322	10.454	10.474	2.230	10.435	10.638	2.496
LogS3Tot	12.698	12.894	3.170	12.161	12.441	2.997	12.559	12.758	3.320
LogSize	6.969	7.000	2.273	6.561	6.565	2.157	6.571	6.602	2.172
LogPPE	9.504	8.479	5.134	9.193	8.217	5.071	9.248	8.331	5.402
LogAssets	11.056	10.052	4.878	10.77	9.81	4.819	10.785	9.891	5.105
Cash/Assets	165,634	119,175	157,247	168,646	121,224	159,916	186,151	126,575	185,603
PPE/Assets	0.291	0.257	0.216	0.291	0.256	0.228	0.308	0.263	0.221
EBIT/Assets	0.085	0.071	0.081	0.085	0.070	0.088	0.081	0.067	0.064
Debt/Assets	0.253	0.225	0.423	0.251	0.221	0.343	0.256	0.223	0.269
R&D/Assets	0.063	0.024	1.832	0.053	0.023	0.241	0.163	0.024	5.835
LogCash	22.617	21.514	5.026	22.333	21.279	4.993	22.397	21.277	5.146
LogR&D	7.928	7.120	4.927	7.588	7.034	4.867	7.797	7.098	5.127
LogCapex	7.336	6.371	5.151	6.993	6.074	5.078	7.038	6.063	5.410
$ESG_{Refinitiv}$	48.374	48.690	19.251	45.704	45.490	19.199	46.337	45.610	18.981
$E_{Refinitiv}$	51.101	53.360	25.896	46.143	46.465	25.812	49.341	51.650	25.252
$S_{Refinitiv}$	51.691	52.270	24.061	48.537	48.350	23.687	48.183	47.230	23.124
$G_{Refinitiv}$	53.848	55.250	22.192	51.850	52.590	22.136	51.983	52.120	21.891
ESG_{MSCI}	4.949	4.900	1.023	4.881	4.900	1.045	4.936	4.900	1.054
E_{MSCI}	5.327	5.100	2.147	5.190	4.900	2.261	5.264	5.100	1.977
S_{MSCI}	4.733	4.700	1.650	4.719	4.700	1.621	4.688	4.700	1.727
G_{MSCI}	5.362	5.400	1.771	5.377	5.400	1.804	5.307	5.300	1.802
SDG Net 7	1.198	1.000	1.465	1.054	1.000	1.403	1.038	1.000	1.461
SDG Net 13	1.420	1.000	1.451	1.289	1.000	1.403	1.260	1.000	1.489
SDG Overall^{Robeco}	0.636	1.000	1.440	0.676	1.000	1.386	0.576	1.000	1.592

Panel B.1: Conditioning on patenting at any patent office globally									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Merged Sample			Bottom decile green ratio			Top decile green ratio		
	Panel C.1: Patent Ratios								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
GreenRatio GPO	0.109	0.000	0.233	0.000	0.000	0.000	0.729	0.667	0.237
HealthRatio GPO	0.142	0.000	0.292	0.142	0.000	0.306	0.151	0.000	0.305
BioeconomyRatio GPO	0.155	0.000	0.286	0.139	0.000	0.292	0.262	0.000	0.382
EnergyRatio GPO	0.057	0.000	0.175	0.031	0.000	0.142	0.204	0.000	0.338
TransportRatio GPO	0.157	0.000	0.276	0.124	0.000	0.273	0.339	0.167	0.384
ClimateRatio GPO	0.038	0.000	0.144	0.027	0.000	0.134	0.107	0.000	0.257
SecurityRatio GPO	0.073	0.000	0.195	0.075	0.000	0.216	0.073	0.000	0.204
GreenCit GPO	0.070	0.000	0.210	0.000	0.000	0.000	0.386	0.097	0.435
HealthCit GPO	0.092	0.000	0.258	0.078	0.000	0.250	0.095	0.000	0.270
BioeconomyCit GPO	0.090	0.000	0.245	0.069	0.000	0.231	0.145	0.000	0.328
EnergyCit GPO	0.037	0.000	0.155	0.017	0.000	0.115	0.114	0.000	0.289
TransportCit GPO	0.111	0.000	0.261	0.077	0.000	0.240	0.202	0.000	0.363
ClimateCit GPO	0.022	0.000	0.122	0.014	0.000	0.107	0.052	0.000	0.198
SecurityCit GPO	0.059	0.000	0.193	0.053	0.000	0.201	0.051	0.000	0.193
	Panel B.2: Financial & Environmental variables								
	Mean	p50	sd	Mean	p50	sd	Mean	p50	sd
LogS1Tot	10.022	9.864	3.090	9.401	9.197	2.996	10.328	10.120	3.569
LogS2Tot	10.535	10.573	2.317	10.006	10.060	2.193	10.234	10.387	2.554
LogS3Tot	12.395	12.593	3.193	11.783	12.109	3.014	12.594	12.859	3.489
LogSize	6.315	6.257	2.274	5.819	5.742	2.091	6.013	5.934	2.200
LogPPE	9.323	8.68	5.119	9.134	8.678	5.124	9.241	8.904	5.304
LogAssets	10.889	10.249	4.881	10.72	10.277	4.895	10.724	10.237	5.035
Cash/Assets	169,045	122,152	160,019	172,765	125,800	161,994	178,617	122,932	178,778
PPE/Assets	0.304	0.263	0.233	0.306	0.266	0.245	0.335	0.289	0.241
EBIT/Assets	0.085	0.069	0.133	0.085	0.068	0.154	0.083	0.065	0.110
Debt/Assets	0.258	0.220	0.484	0.256	0.213	0.499	0.270	0.221	0.426
R&D/Assets	0.057	0.022	1.357	0.050	0.020	0.215	0.063	0.021	0.158
LogCash	22.433	21.761	5.080	22.273	21.849	5.117	22.256	21.674	5.162
LogR&D	7.839	7.546	4.858	7.625	7.686	4.813	7.739	7.544	4.943
LogCapex	7.093	6.483	5.144	6.860	6.434	5.141	6.975	6.576	5.326
Merton Score	5.310	3.786	5.550	5.074	3.610	6.007	4.917	3.600	4.062
$ESG_{Refinitiv}$	45.958	45.730	19.487	42.740	41.530	19.377	45.107	44.730	19.203
$E_{Refinitiv}$	47.482	48.440	26.315	41.923	39.900	25.849	47.092	48.330	25.767
$S_{Refinitiv}$	48.601	48.010	24.012	44.719	43.000	23.333	46.688	46.190	23.009
$G_{Refinitiv}$	52.344	53.200	22.321	49.776	50.015	22.215	51.123	51.490	22.248
ESG_{MSCI}	4.847	4.800	1.062	4.726	4.700	1.085	4.862	4.800	1.142
E_{MSCI}	5.129	4.900	2.186	4.903	4.600	2.263	5.056	5.000	2.006
S_{MSCI}	4.653	4.690	1.656	4.589	4.600	1.637	4.663	4.700	1.764
G_{MSCI}	5.355	5.400	1.814	5.322	5.400	1.851	5.231	5.300	1.841
SDG Net 7	1.039	1.000	1.423	0.843	0.000	1.324	0.855	0.000	1.424
SDG Net 13	1.286	1.000	1.437	1.116	1.000	1.372	1.058	1.000	1.492
SDG Overall^{Robeco}	0.560	1.000	1.440	0.504	1.000	1.412	0.483	1.000	1.618

Table A.11: Top 50 Firms Patenting At USPTO

The sample period is 2002-2023, conditional on financial data availability. I report the average patent ratio by green and SGC classes for each year in the merged sample. In Panel A, I sort firms by their total patent counts for patent grants at USPTO. In Panel B, I sort firms by their MSCI E ratings for patent grants at USPTO.

Panel A: Top 50 firms by USPTO patents

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Firm Name	SortVar: Patents US	Mkt cap	Scope 1	E MSCI Rating	Robeco Overall SDG	Net SDG 7	Net SDG 13	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US	Gics Industry	Country
SAMSUNG ELECTRONICS	6,026	194,254	3,680,042	7	0	NA	NA	0.070	0.015	0.030	0.034	0.039	0.002	0.052	Technology Hardware, Storage & Peripherals	KR
INTERNATIONAL BUS.MCHS.	5,988	149,459	363,730	8	1	1	4	0.045	0.007	0.009	0.021	0.058	0.001	0.092	IT Services	US
BANGO	3,423	135	NA	NA	NA	NA	NA	0.027	0.033	0.110	0.021	0.060	0.001	0.100	Software	GB
MICROSOFT	3,285	934,759	83,365	8	1	1	0	0.013	0.006	0.005	0.022	0.075	0.001	0.131	Software	US
SONY GROUP	2,306	50,341	340,148	6	-1	3	3	0.071	0.017	0.020	0.032	0.076	0.002	0.112	Household Durables	JP
APPLE	2,227	1,194,421	41,551	4	1	2	4	0.039	0.011	0.009	0.055	0.065	0.001	0.084	Technology Hardware, Storage & Peripherals	US
INTEL	2,209	157,446	1,199,243	8	1	1	3	0.062	0.005	0.006	0.065	0.037	NA	0.103	Semiconductors & Semiconductor Equipment	US
ALPHABET A	2,119	772,178	53,984	7	-1	2	3	0.022	0.021	0.010	0.030	0.092	0.003	0.138	Interactive Media & Services	US
DELL TECHNOLOGIES C	1,950	44,879	52,586	6	1	4	3	0.020	0.002	0.003	0.042	0.036	0.001	0.113	Technology Hardware, Storage & Peripherals	US
QUALCOMM	1,676	96,687	68,830	4	0	2	3	0.030	0.003	0.001	0.054	0.075	NA	0.097	Semiconductors & Semiconductor Equipment	US
GENERAL ELECTRIC	1,532	220,143	2,192,360	7	1	2	3	0.188	0.091	0.050	0.171	0.148	0.029	0.123	Industrial Conglomerates	US
FUJITSU	1,464	14,498	227,597	8	1	1	1	0.061	0.008	0.009	0.032	0.057	0.002	0.096	IT Services	JP
TAIWAN SEMICON.MNFG.	1,403	165,325	1,869,416	6	2	3	1	0.104	0.003	0.003	0.013	0.010	0.002	0.009	Semiconductors & Semiconductor Equipment	TW
HEWLETT PACKARD ENTER.	1,403	22,335	79,207	6	1	3	4	0.023	0.003	0.213	0.043	0.045	0.001	0.089	Technology Hardware, Storage & Peripherals	US
PANASONIC HOLDINGS	1,387	28,145	535,378	8	-1	4	1	0.127	0.044	0.055	0.084	0.131	0.010	0.095	Household Durables	JP
SEIKO EPSON	1,358	5,050	128,569	4	1	1	1	0.060	0.017	0.324	0.017	0.088	0.004	0.049	Technology Hardware, Storage & Peripherals	JP
MICRON TECHNOLOGY	1,319	29,705	1,871,384	5	2	1	1	0.090	0.001	0.006	0.027	0.008	0.001	0.019	Semiconductors & Semiconductor Equipment	US
RTX	1,298	84,211	860,127	6	NA	4	2	0.076	0.020	0.062	0.102	0.254	0.024	0.059	Aerospace & Defense	DK
SIEMENS	1,286	8,225	10,610	4	NA	1	1	0.216	0.166	0.036	0.080	0.110	0.017	0.206	Industrial Conglomerates	DE
GENERAL MOTORS	1,272	52,573	1,965,374	6	-2	4	2	0.183	0.004	0.021	0.246	0.545	0.043	0.059	Automobiles	US
SIEMENS	1,222	81,877	1,242,351	8	1	4	4	0.171	0.147	0.026	0.037	0.123	0.020	0.174	Industrial Conglomerates	DE
PHILIPS ELTN.KONINKLIJKE	1,064	30,643	257,800	9	2	4	4	0.137	0.234	0.031	0.035	0.051	0.006	0.205	Health Care Equipment & Supplies	NL
CISCO SYSTEMS	1,045	160,426	46,669	6	1	2	3	0.038	0.003	0.001	0.030	0.036	0.001	0.090	Communications Equipment	US
NEC	1,015	9,177	139,375	7	1	3	3	0.068	0.008	0.010	0.041	0.069	0.002	0.123	IT Services	JP
HON HAI PRECN.IND.	1,012	34,956	84,190	4	-1	2	2	0.054	0.009	0.022	0.038	0.054	0.002	0.044	Electronic Equipment, Instruments & Components	TW
FORD MOTOR	993	40,174	1,581,778	6	-2	2	2	0.140	0.004	0.015	0.181	0.554	0.066	0.039	Automobiles	US
RICOH	988	9,338	157,332	4	1	1	0	0.025	0.005	0.177	0.014	0.091	0.003	0.079	Technology Hardware, Storage & Peripherals	JP
FUJIFILM HOLDINGS	987	17,068	674,129	5	1	4	1	0.055	0.106	0.195	0.019	0.050	0.012	0.116	Technology Hardware, Storage & Peripherals	JP
SAUDI ARABIAN OIL	972	2,003,860	132,382,996	6	-3	NA	NA	0.159	NA	0.019	0.056	0.083	0.036	0.076	Oil, Gas & Consumable Fuels	SA
ERICSSON B	971	33,057	54,728	5	1	4	4	0.024	0.002	0.003	0.032	0.036	NA	0.074	Communications Equipment	SE
HITACHI	967	27,870	1,691,502	6	1	3	2	0.121	0.019	0.085	0.061	0.155	0.020	0.066	Industrial Conglomerates	JP
HP	964	58,593	153,465	6	1	4	4	0.029	0.003	0.130	0.011	0.036	0.001	0.078	Technology Hardware, Storage & Peripherals	US
AMAZON.COM	936	430,779	3,785,189	6	1	2	1	0.014	0.003	0.010	0.014	0.101	0.009	0.104	Broadline Retail	US
HONDA MOTOR	912	52,860	1,292,438	8	-2	2	1	0.177	0.013	0.042	0.116	0.499	0.023	0.038	Automobiles	JP
HONEYWELL INTL.	893	72,994	3,015,651	5	-1	4	4	0.157	0.012	0.046	0.079	0.247	0.031	0.155	Industrial Conglomerates	US
JOHNSON & JOHNSON	889	267,994	398,322	7	-1	3	4	0.039	0.778	0.113	0.011	0.044	0.006	0.100	Pharmaceuticals	US
META PLATFORMS A	888	520,222	30,251	9	-1	1	3	0.031	0.009	0.007	0.014	0.048	NA	0.106	Interactive Media & Services	US
MEDTRONIC	883	82,139	51,847	9	2	4	4	0.026	0.839	0.039	0.012	0.033	0.004	0.209	Health Care Equipment & Supplies	US
TEXAS INSTRUMENTS	849	80,688	1,015,508	7	2	3	2	0.133	0.006	0.006	0.054	0.046	NA	0.046	Semiconductors & Semiconductor Equipment	US
DENSO	846	30,246	586,042	6	NA	2	3	0.142	0.006	0.020	0.083	0.364	0.020	0.082	Automobile Components	JP
NEDBANK GROUP	833	7,586	1,097	7	2	3	2	0.066	0.007	0.012	0.026	0.016	0.001	0.024	Banks	ZA
BOEING	812	89,504	613,812	6	-1	2	3	0.075	0.008	0.090	0.101	0.408	0.021	0.096	Aerospace & Defense	US
INFINEON TECHNOLOGIES	797	17,139	187,382	5	2	2	3	0.130	0.003	0.005	0.038	0.042	0.001	0.042	Semiconductors & Semiconductor Equipment	DE
DINGLONG CULTURE 'A'	788	1,120	NA	NA	NA	NA	NA	0.017	0.001	0.001	0.046	0.022	NA	0.068	Entertainment	CN
MITSUBISHI ELECTRIC	717	21,027	340,299	7	1	1	3	0.108	0.009	0.013	0.065	0.136	0.005	0.097	Electrical Equipment	JP
SK HYNIX	708	28,215	1,881,429	4	2	1	2	0.051	NA	0.001	0.016	0.003	NA	0.005	Semiconductors & Semiconductor Equipment	KR
LG DISPLAY	694	8,081	3,345,322	5	1	1	1	0.117	0.001	0.014	0.044	0.007	NA	0.009	Electronic Equipment, Instruments & Components	KR
XEROX HOLDINGS	688	9,506	123,892	5	1	2	2	0.030	0.017	0.246	0.022	0.086	0.007	0.105	Technology Hardware, Storage & Peripherals	US
RENESAS ELECTRONICS	676	9,997	372,193	6	2	4	2	0.133	0.003	0.005	0.052	0.034	0.001	0.034	Semiconductors & Semiconductor Equipment	JP
TITAN KOGYO	661	61	NA	NA	NA	NA	NA	0.012	0.002	0.384	0.012	0.115	0.006	0.026	Chemicals	JP

Panel B: Top 50 firms by E MSCI score

Firm Name	SortVar - E MSCI Rating	Mkt cap	Patent US	Scope 1	Robeco Overall SDG	Net SDG 7	Net SDG 13	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US	Gics Industry	Country
EXPEDITORS INTL.OF WASH.	10	18,300	4	9,743	-1	3	3	0.500	NA	NA	NA	NA	NA	NA	Air Freight & Logistics	US
FTI CONSULTING	10	5,403	2	21,493	1	NA	1	NA	1.000	NA	0.500	NA	NA	NA	Professional Services	US
KELLY SERVICES 'A'	10	708	2	797	1	2	3	0.100	NA	NA	NA	0.133	NA	0.310	Professional Services	US
STEELCASE 'A'	10	1,734	68	52,692	-1	4	3	0.078	0.008	0.015	0.005	0.024	0.010	0.015	Commercial Services & Supplies	US
ICF INTERNATIONAL	10	1,112	2	386	1	3	3	0.104	0.182	0.225	0.091	0.045	NA	NA	Professional Services	US
TELUS	10	22,286	2	68,079	1	4	4	0.100	0.050	0.020	NA	0.050	NA	0.120	Diversified Telecommunication Services	CA
IGM FINL.	10	6,292	1	34	1	4	4	NA	NA	NA	NA	NA	NA	NA	Capital Markets	CA
STANTEC	10	2,443	1	10,073	2	4	2	0.100	0.100	0.200	NA	0.200	0.200	0.233	Construction & Engineering	CA
BARCLAYS	10	49,924	26	35,918	0	4	4	0.055	0.090	0.098	0.016	0.095	0.025	0.090	Banks	GB
ITV	10	7,296	8	12,873	1	2	3	0.044	0.045	0.201	0.046	0.158	0.026	0.116	Media	GB
ADECCO GROUP	10	9,452	3	51,138	1	NA	3	0.053	0.142	0.202	NA	0.186	NA	0.111	Professional Services	CH
SMITH & NEPHEW	10	11,952	119	10,208	2	3	3	0.017	0.820	0.034	0.004	0.009	0.011	0.046	Health Care Equipment & Supplies	GB
LEGAL & GENERAL	10	21,258	2	13,382	2	3	3	NA	NA	NA	NA	0.062	NA	NA	Insurance	GB
ELEKTA B	10	2,934	16	2,978	2	3	4	0.266	0.768	0.015	0.001	0.022	NA	0.375	Health Care Equipment & Supplies	SE
VODAFONE GROUP	10	102,970	26	314,492	1	2	4	0.069	0.023	0.010	0.039	0.154	0.022	0.214	Wireless Telecommunication Services	GB
ST.JAMES'S PLACE ORD	10	7,769	1	928	1	3	4	NA	NA	NA	NA	0.500	NA	NA	Capital Markets	GB
ROBERT WALTERS	10	341	2	448	NA	NA	NA	0.048	NA	0.262	0.071	0.143	NA	0.071	Professional Services	GB
RELX	10	33,949	16	10,772	1	4	4	0.029	0.032	0.089	0.009	0.103	0.007	0.107	Professional Services	GB
COLOPLAST B	10	12,781	47	11,421	2	2	2	0.022	0.682	0.065	0.001	0.060	0.002	0.011	Health Care Equipment & Supplies	DK
LONDON STOCK EXCHANGE GROUP	10	17,771	16	1,209	1	3	2	0.025	0.352	0.034	0.002	0.092	NA	0.285	Capital Markets	GB
WPP	10	16,675	42	9,537	-1	4	3	0.056	0.057	0.047	0.029	0.167	0.005	0.110	Media	GB
EDP ENERGIAS DE PORTUGAL	10	13,514	1	13,553,192	0	4	4	NA	0.200	NA	0.200	0.200	NA	NA	Electric Utilities	PT
TELECOM ITALIA	10	26,282	28	150,763	1	3	2	0.061	0.009	0.072	0.026	0.059	0.001	0.128	Diversified Telecommunication Services	IT
ELISA	10	4,481	3	425	1	2	3	0.010	0.083	NA	0.024	0.058	NA	0.095	Diversified Telecommunication Services	FI
RANDSTAD	10	8,391	8	44,759	1	1	3	0.048	0.144	0.105	0.048	0.221	0.004	0.087	Professional Services	NL
VANQUIS BANKING GROUP	10	2,752	3	1,922	NA	NA	4	NA	0.154	0.077	NA	NA	NA	0.077	Consumer Finance	GB
BIC	10	3,941	26	9,423	-1	2	1	0.131	0.006	0.070	0.137	0.165	0.012	0.003	Commercial Services & Supplies	FR
SGS 'N'	10	13,501	9	103,445	1	2	2	0.058	0.160	0.204	0.024	0.082	0.008	0.258	Professional Services	CH
IPSOS	10	1,368	5	3,939	NA	3	2	0.038	0.134	0.065	0.004	0.052	0.058	0.061	Media	FR
TF1 (TV.FSE.1)	10	2,403	1	892	NA	3	3	NA	NA	NA	NA	0.077	NA	NA	Media	FR
SARTORIUS STEDIM BIOTECH	10	27,107	12	17,552	2	4	4	0.045	0.045	0.370	NA	0.071	NA	NA	Life Sciences Tools & Services	FR
SWISSCOM 'R'	10	24,629	10	20,339	1	2	4	0.008	0.040	NA	0.003	0.092	NA	0.363	Diversified Telecommunication Services	CH
TELIA COMPANY	10	24,334	11	28,098	0	4	4	0.035	0.011	0.003	0.021	0.042	NA	0.150	Diversified Telecommunication Services	SE
NOS SGPS	10	1,806	1	3,514	1	NA	2	NA	NA	NA	NA	NA	NA	NA	Diversified Telecommunication Services	PT
TELEFONICA	10	66,205	8	169,569	1	2	2	0.022	0.119	0.030	0.024	0.145	0.018	0.136	Diversified Telecommunication Services	ES
TRANSURBAN GROUP STAPLED UNITS	10	7,307	2	166	1	NA	NA	NA	NA	NA	NA	NA	NA	0.083	Transportation Infrastructure	AU
ORANGE	10	48,689	43	343,039	-1	2	3	0.033	0.057	0.041	0.028	0.043	0.001	0.200	Diversified Telecommunication Services	FR
BT GROUP	10	31,139	21	195,133	1	1	4	0.043	0.073	0.035	0.039	0.060	0.010	0.096	Diversified Telecommunication Services	GB
CHINA MOBILE	10	189,302	12	300,847	-1	NA	NA	0.026	NA	NA	0.041	0.048	NA	0.063	Wireless Telecommunication Services	HK
TV ASAHI HOLDINGS	10	1,181	2	167	1	2	2	NA	NA	NA	NA	NA	NA	NA	Media	JP
TELSTRA GROUP	10	41,897	3	69,524	NA	1	1	0.049	NA	0.035	0.026	0.050	0.026	0.060	Diversified Telecommunication Services	AU
EIKEN CHEMICAL	10	316	1	2,918	2	2	2	NA	NA	0.667	NA	NA	0.167	0.167	Health Care Equipment & Supplies	JP
KDDI	10	41,230	20	4,654	1	3	3	0.062	0.026	0.004	0.025	0.092	NA	0.114	Wireless Telecommunication Services	JP
CAPITA	10	5,317	21	12,668	NA	2	3	0.057	0.056	0.047	0.061	0.063	0.002	0.036	Professional Services	GB
DEUTSCHE BOERSE	10	18,677	7	3,913	1	4	3	0.426	0.009	0.017	0.247	0.483	0.022	0.122	Capital Markets	DE
HAYS	10	2,579	4	4,330	1	3	2	NA	0.186	0.053	0.218	0.108	NA	0.184	Professional Services	GB
DEUTSCHE TELEKOM	10	77,524	269	323,204	1	1	1	0.029	0.004	0.009	0.022	0.040	NA	0.065	Diversified Telecommunication Services	DE
VIVENDI	10	24,786	13	13,941	1	4	2	0.024	0.064	0.097	0.013	0.282	0.025	0.220	Media	FR
KOKUYO	10	1,341	11	8,562	-1	4	4	0.005	0.045	0.022	NA	0.067	NA	0.030	Commercial Services & Supplies	JP
ANSELL	10	1,957	8	92,523	2	2	2	0.021	0.126	0.366	0.003	0.075	0.082	0.106	Health Care Equipment & Supplies	AU

A.3 Appendix Tables - Results

Table A.12: Energy Ratio On E Ratings at EPO (GPO)

The observation unit is firm-year. In panel A, the dependent variable is *EnergyRatio EPO*, and in Panel B, *EnergyRatio GPO*. The sample period spans from 2008 to 2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country and year fixed effects. Columns (2) and (5) includes MSCI GICS-industry fixed effects, while columns (3) and (6) include both MSCI GICS-industry fixed effects and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A: EnergyRatio EPO as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
E^{MSCI}	-0.001	0.056***	0.061***	0.022	0.115***	0.126***
	(0.015)	(0.021)	(0.024)	(0.018)	(0.025)	(0.028)
LogAssets				0.083***	0.011	0.006
				(0.022)	(0.024)	(0.024)
Debt/Assets				-0.435*	-0.399*	-0.420*
				(0.244)	(0.208)	(0.215)
Cash/Assets				0.000	0.000**	0.000**
				(0.000)	(0.000)	(0.000)
PPE/Assets				0.844***	0.063	0.123
				(0.264)	(0.279)	(0.284)
EBIT/Assets				-2.501***	-2.193***	-2.357***
				(0.557)	(0.554)	(0.576)
CAPEX/Assets				0.650	2.014	1.583
				(1.466)	(1.293)	(1.287)
R&D/Assets				-1.258	-0.010	-0.048
				(0.799)	(0.796)	(0.814)
Constant	-2.386***	-2.529***	-2.474***	-3.474***	-2.882***	-2.821***
	(0.078)	(0.112)	(0.124)	(0.287)	(0.314)	(0.315)
Controls				✓	✓	✓
Country F.E.	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓
Industry-Year F.E.			✓			✓
Observations	16014	16000	15527	16014	16000	15527
Pseudo R^2	0.020	0.072	0.091	0.032	0.089	0.102
Dep. Variable: STD	0.183	0.183	0.184	0.183	0.183	0.184
Ind. Variable: STD	2.113	2.113	2.109	2.113	2.113	2.109
Economic effect	0.011	0.648	0.699	0.254	1.328	1.444

Panel B: EnergyRatio GPO as dependent variable						
	(1)	(2)	(3)	(4)	(5)	(6)
E^{MSCI}	0.007	0.058***	0.062***	0.024*	0.107***	0.112***
	(0.010)	(0.012)	(0.013)	(0.014)	(0.018)	(0.019)
LogAssets				0.089***	0.022	0.023
				(0.021)	(0.020)	(0.020)
Debt/Assets				-0.488**	-0.413**	-0.446**
				(0.202)	(0.174)	(0.181)
Cash/Assets				0.000	0.000**	0.000**
				(0.000)	(0.000)	(0.000)
PPE/Assets				0.836***	0.161	0.106
				(0.210)	(0.222)	(0.221)
EBIT/Assets				-2.196***	-1.639***	-1.624***
				(0.330)	(0.284)	(0.296)
CAPEX/Assets				0.873	1.553	1.412
				(1.207)	(0.959)	(0.943)
R&D/Assets				-1.499**	-0.415	-0.471
				(0.680)	(0.576)	(0.604)
Constant	-2.568***	-2.678***	-2.651***	-3.702***	-3.134***	-3.106***
	(0.052)	(0.065)	(0.066)	(0.257)	(0.241)	(0.246)
Controls				✓	✓	✓
Country F.E.	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓
Industry-Year F.E.			✓			✓
Observations	28373	28372	28128	28373	28372	28128
Pseudo R^2	0.017	0.064	0.078	0.033	0.086	0.095
Dep. Variable: STD	0.158	0.158	0.158	0.158	0.158	0.158
Ind. Variable: STD	2.159	2.159	2.161	2.159	2.159	2.161
Economic effect	0.096	0.789	0.849	0.328	1.462	1.532

Table A.13: Patent Ratio On E Ratings For All Patent Classes

The observation unit is firm-year. In panel A, I consider all patent ratios as the dependent variable for patents granted at EPO. In Panel B, I condition on patents granted at GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A: Patenting at EPO							
	(1) GreenRatio EPO	(2) HealthRatio EPO	(3) BioeconomyRatio EPO	(4) EnergyRatio EPO	(5) TransportRatio EPO	(6) ClimateRatio EPO	(7) SecurityRatio EPO
E^{MSCI}	0.093***	0.003	-0.022	0.126***	0.021	0.054	0.029
	(0.021)	(0.013)	(0.014)	(0.028)	(0.013)	(0.036)	(0.023)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	15817	15714	15827	15527	15927	14325	15170
Pseudo R^2	0.079	0.314	0.138	0.102	0.123	0.129	0.132
Dep. Variable: STD	0.197	0.309	0.264	0.184	0.261	0.111	0.151
Ind. Variable: STD	1.946	1.945	1.946	2.109	1.960	1.892	1.950
Economic effect	0.914	0.019	0.161	1.444	0.155	0.932	0.378
Panel B: Patenting at GPO							
	(1) GreenRatio GPO	(2) HealthRatio GPO	(3) BioeconomyRatio GPO	(4) EnergyRatio GPO	(5) TransportRatio GPO	(6) ClimateRatio GPO	(7) SecurityRatio GPO
E^{MSCI}	0.059***	-0.003	-0.020	0.112***	0.019	0.003	0.018
	(0.016)	(0.011)	(0.013)	(0.019)	(0.012)	(0.028)	(0.017)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	28601	28481	28602	28128	28615	27770	27814
Pseudo R^2	0.072	0.307	0.150	0.095	0.111	0.124	0.123
Dep. Variable: STD	0.178	0.273	0.233	0.158	0.219	0.095	0.134
Ind. Variable: STD	1.986	1.988	1.986	2.161	1.986	1.966	1.979
Economic effect	0.653	0.020	0.173	1.532	0.170	0.071	0.272

Table A.14: Patent Ratio On E Ratings For All Patent Classes (Robustness: Industry Groups)

The observation unit is firm-year. In panel A, I consider all patent ratios as the dependent variable for patents granted at USPTO. In Panel B, I condition on granted filed at EPO. In Panel C, I condition on patents granted at GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry group, and industry group-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A: Patenting at USPTO							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
E^{MSCI}	0.060***	-0.037***	0.010	0.090***	0.008	-0.003	0.034**
	(0.018)	(0.013)	(0.013)	(0.021)	(0.012)	(0.025)	(0.016)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	14982	14986	15020	14830	15027	14822	14875
Pseudo R^2	0.056	0.287	0.136	0.078	0.088	0.120	0.107
Dep. Variable: STD	0.188	0.267	0.234	0.147	0.222	0.098	0.144
Ind. Variable: STD	1.972	1.974	1.973	1.975	1.974	1.973	1.967
Economic effect	0.632	0.270	0.088	1.214	0.070	0.067	0.463
Panel B: Patenting at EPO							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio EPO	HealthRatio EPO	BioeconomyRatio EPO	EnergyRatio EPO	TransportRatio EPO	ClimateRatio EPO	SecurityRatio EPO
E^{MSCI}	0.097***	-0.042***	0.018	0.103***	0.026*	0.037	0.044**
	(0.020)	(0.014)	(0.014)	(0.025)	(0.014)	(0.029)	(0.022)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	11562	11505	11590	11429	11611	11112	11379
Pseudo R^2	0.051	0.296	0.111	0.078	0.095	0.107	0.114
Dep. Variable: STD	0.196	0.306	0.263	0.170	0.261	0.108	0.149
Ind. Variable: STD	1.955	1.956	1.955	1.959	1.958	1.929	1.957
Economic effect	0.963	0.271	0.132	1.181	0.199	0.671	0.576
Panel C: Patenting at GPO							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio GPO	HealthRatio GPO	BioeconomyRatio GPO	EnergyRatio GPO	TransportRatio GPO	ClimateRatio GPO	SecurityRatio GPO
E^{MSCI}	0.069***	-0.035***	0.019	0.092***	0.023*	-0.001	0.030*
	(0.016)	(0.013)	(0.013)	(0.018)	(0.012)	(0.025)	(0.017)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	16457	16439	16516	16322	16502	16307	16400
Pseudo R^2	0.049	0.290	0.123	0.076	0.089	0.104	0.110
Dep. Variable: STD	0.178	0.272	0.233	0.143	0.219	0.094	0.133
Ind. Variable: STD	1.986	1.987	1.986	1.990	1.986	1.985	1.984
Economic effect	0.765	0.256	0.165	1.287	0.210	0.025	0.452

Table A.15: Patent Ratio On Other Sustainability Metrics (Robustness)

The observation unit is firm-year. In panel A, I consider the Energy ratio as the dependent variable for patents granted at GPO, at EPO, and at USPTO. In Panel B, I use Green ratio as the dependent variable. Panel C use Climate ratio. The sample period is 2002-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable of interest, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A: Energy Ratio

	(1) GPO	(2) EPO	(3) USPTO	(4) GPO	(5) EPO	(6) USPTO	(7) GPO	(8) EPO	(9) USPTO	(10) GPO	(11) EPO	(12) USPTO	(13) GPO	(14) EPO	(15) USPTO
S^{MSCI}	0.013	0.030*	0.026												
	(0.017)	(0.017)	(0.018)												
G^{MSCI}				0.015	0.031**	0.006									
				(0.013)	(0.014)	(0.014)									
ESG^{MSCI}							0.103***	0.138***	0.108***						
							(0.034)	(0.035)	(0.039)						
$E^{Refinitiv}$										0.006***	0.006***	0.005***			
										(0.001)	(0.002)	(0.001)			
$S^{Refinitiv}$													0.002	0.003*	0.002
													(0.001)	(0.002)	(0.001)
$G^{Refinitiv}$															
$ESG^{Refinitiv}$															
LogS1															
LogS2															
LogS3															
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	28128	15527	24227	28128	15527	24227	28128	15527	24227	18612	12971	16842	18612	12971	16842
Pseudo R^2	0.092	0.098	0.096	0.092	0.098	0.096	0.092	0.099	0.096	0.093	0.101	0.098	0.090	0.096	0.096
Dep. Variable: STD	0.142	0.171	0.147	0.142	0.171	0.147	0.144	0.174	0.149	0.147	0.173	0.153	0.146	0.172	0.153
Ind. Variable: STD	1.634	1.639	1.626	1.807	1.755	1.792	1.012	0.971	0.997	25.554	24.677	25.426	24.257	23.496	24.065
Economic effect	0.147	0.292	0.285	0.196	0.321	0.071	0.727	0.775	0.720	0.989	0.801	0.862	0.295	0.386	0.248

	(16) GPO	(17) EPO	(18) USPTO	(19) GPO	(20) EPO	(21) USPTO	(22) GPO	(23) EPO	(24) USPTO	(25) GPO	(26) EPO	(27) USPTO	(28) GPO	(29) EPO	(30) USPTO
S^{MSCI}															
G^{MSCI}															
ESG^{MSCI}															
$E^{Refinitiv}$															
$S^{Refinitiv}$															
$G^{Refinitiv}$	-0.001	-0.001	-0.000												
	(0.001)	(0.001)	(0.001)												
$ESG^{Refinitiv}$				0.003*	0.003	0.002									
				(0.002)	(0.002)	(0.001)									
LogS1							0.033**	0.049***	0.034**						
							(0.016)	(0.016)	(0.017)						
LogS2										0.030*	0.053***	0.027			
										(0.018)	(0.019)	(0.019)			
LogS3													0.001	0.005	0.004
													(0.010)	(0.012)	(0.012)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	18612	12971	16842	18612	12971	16842	26516	16833	23242	26536	16824	23258	15020	10442	13593
Pseudo R^2	0.090	0.096	0.096	0.090	0.096	0.096	0.081	0.091	0.087	0.081	0.091	0.087	0.096	0.099	0.103
Dep. Variable: STD	0.146	0.172	0.153	0.146	0.172	0.153	0.155	0.179	0.158	0.155	0.180	0.159	0.148	0.173	0.153
Ind. Variable: STD	22.071	21.717	21.998	19.246	18.474	19.077	2.965	2.847	2.950	2.270	2.212	2.255	3.077	3.079	3.066
Economic effect	0.083	0.073	0.059	0.359	0.284	0.265	0.636	0.783	0.641	0.436	0.648	0.386	0.015	0.083	0.084

	Panel B: Green Ratio																													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO
S^{MSCI}	-0.004	0.011	-0.015																											
	(0.012)	(0.014)	(0.014)																											
G^{MSCI}				0.012	0.019	0.015																								
				(0.011)	(0.017)	(0.011)																								
ESG^{MSCI}							0.049*	0.111***	0.019																					
							(0.026)	(0.031)	(0.027)																					
$E^{Refinitiv}$										0.003***	0.004***	0.002*																		
										(0.001)	(0.001)	(0.001)																		
$S^{Refinitiv}$													0.000	0.001	-0.000															
													(0.001)	(0.001)	(0.001)															
$G^{Refinitiv}$																-0.001	-0.001	-0.002*												
																(0.001)	(0.001)	(0.001)												
$ESG^{Refinitiv}$																			0.001	-0.000	-0.001									
																			(0.001)	(0.001)	(0.001)									
LogS1																						0.021*	0.033**	0.025**						
																						(0.012)	(0.015)	(0.012)						
LogS2																									0.003	0.023	0.006			
																									(0.013)	(0.015)	(0.014)			
LogS3																												0.002	-0.003	0.006
																												(0.008)	(0.009)	(0.007)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	28601	15817	24618	28601	15817	24618	28601	15817	24618	22012	15625	19873	22012	15625	19873	22012	15625	19873	22012	15625	19873	27995	17896	24525	27872	17775	24433	15218	10606	13735
Pseudo R^2	0.071	0.077	0.076	0.071	0.077	0.076	0.069	0.076	0.073	0.075	0.080	0.079	0.073	0.078	0.077	0.073	0.078	0.078	0.073	0.078	0.077	0.063	0.072	0.069	0.063	0.072	0.069	0.073	0.076	0.078
Dep. Variable: STD	0.178	0.197	0.188	0.178	0.197	0.187	0.181	0.201	0.191	0.172	0.190	0.181	0.173	0.193	0.183	0.173	0.193	0.183	0.173	0.193	0.183	0.188	0.208	0.197	0.188	0.208	0.197	0.178	0.194	0.185
Ind. Variable: STD	1.634	1.641	1.629	1.805	1.756	1.795	1.013	0.970	0.998	25.623	24.959	25.524	24.574	24.203	24.467	22.200	22.004	22.147	19.401	18.881	19.272	2.993	2.867	2.968	2.281	2.218	2.265	3.076	3.077	3.062
Economic effect	0.035	0.091	0.127	0.121	0.167	0.140	0.276	0.535	0.100	0.379	0.478	0.287	0.071	0.123	0.010	0.073	0.086	0.187	0.064	0.012	0.060	0.341	0.449	0.382	0.033	0.245	0.065	0.041	0.043	0.094
	Panel C: Climate Ratio																													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO	GPO	EPO	USPTO
S^{MSCI}	0.030	0.057*	0.027																											
	(0.024)	(0.034)	(0.024)																											
G^{MSCI}				0.040**	0.043*	0.049***																								
				(0.019)	(0.024)	(0.019)																								
ESG^{MSCI}							0.052	0.148**	0.045																					
							(0.041)	(0.061)	(0.053)																					
$E^{Refinitiv}$										0.002	0.006***	0.002																		
										(0.002)	(0.002)	(0.002)																		
$S^{Refinitiv}$													0.001	0.003	0.002															
													(0.002)	(0.002)	(0.002)															
$G^{Refinitiv}$																-0.002	0.000	-0.001												
																(0.001)	(0.002)	(0.001)												
$ESG^{Refinitiv}$																			0.002	0.005**	0.002									
																			(0.002)	(0.002)	(0.002)									
LogS1																						0.068***	0.065*	0.087***						
																						(0.025)	(0.035)	(0.028)						
LogS2																									0.046*	0.063	0.059*			
																									(0.026)	(0.038)	(0.031)			
LogS3																												-0.002	-0.031*	0.021
																												(0.016)	(0.017)	(0.021)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	27770	14325	23265	27770	14325	23265	27770	14325	23265	21173	14411	18841	21173	14411	18841	21173	14411	18841	21173	14411	18841	27220	16759	23543	27110	16639	23450	14624	9686	13043
Pseudo R^2	0.124	0.130	0.142	0.124	0.129	0.142	0.124	0.131	0.143	0.126	0.126	0.140	0.125	0.123	0.138	0.125	0.123	0.138	0.125	0.124	0.138	0.120	0.114	0.138	0.119	0.113	0.137	0.131	0.131	0.150
Dep. Variable: STD	0.095	0.111	0.100	0.095	0.111	0.100	0.097	0.111	0.102	0.101	0.117	0.106	0.099	0.116	0.104	0.099	0.116	0.104	0.099	0.116	0.104	0.105	0.122	0.109	0.105	0.121	0.109	0.092	0.110	0.096
Ind. Variable: STD	1.639	1.639	1.634	1.810	1.739	1.796	1.012	0.962	0.995	25.615	25.024	25.519	24.607	24.203	24.492	22.231	21.903	22.140	19.414	18.858	19.270	2.978	2.854	2.956	2.271	2.207	2.256	3.072	3.078	3.065
Economic effect	0.523	0.839	0.440	0.754	0.672	0.879	0.546	1.285	0.437	0.530	1.362	0.555	0.206	0.529	0.452	0.346	0.040	0.269	0.396	0.852	0.443	1.914	1.518	2.343	0.987	1.148	1.222	0.056	0.859	0.676

Table A.16: Patent Ratio On E Ratings (Robustness: Industry by Industry)

The observation unit is firm-year. The sample period is 2008-2023. I condition on patents granted at USPTO and use the EnergyRatio as the dependent variable, with independent variables as in Table 3.3. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country and year fixed effects. I double-cluster standard errors at the firm and year levels. I report the coefficient for E^{MSCI} in column (1), with the associated standard error in column (2). Column (3) displays the Pseudo R^2, and column (4) shows the number of observations in the regression. Columns (5) and (6) represent the standard deviation of E^{MSCI} and EnergyRatio, respectively. Column (7) reports the industry average E-rating, by which I rank the table. Industries are dropped if there is insufficient observations to estimate the model. ***1% significance, **5% significance, *10% significance.

Panel A: Energy Ratio (USPTO)

Industry	(1) Coef for E^{MSCI}	(2) Std. Err	(3) Pseudo R^2	(4) N	(5) Std. Dev. E^{MSCI}	(6) Std. Dev. EnergyRatio US	(7) Industry E^{MSCI} Rating
Wireless Telecommunication Services	0.124	(0.751)	0.139	44	1.698	0.078	9
Diversified Telecommunication Services	-0.033	(0.091)	0.109	135	2.198	0.085	9
Life Sciences Tools & Services	0.157	(0.123)	0.119	238	1.943	0.082	8
Health Care Providers & Services	-0.125	(0.292)	0.166	88	1.837	0.143	8
Health Care Equipment & Supplies	-0.186*	(0.098)	0.140	666	1.796	0.059	8
Multi-Utilities	-0.613**	(0.312)	0.128	32	0.738	0.163	7
Entertainment	0.324	(0.298)	0.206	114	1.238	0.074	7
Financial Services	0.847	(0.571)	0.542	41	1.805	0.217	7
Commercial Services & Supplies	0.014	(0.108)	0.125	211	2.308	0.108	7
Professional Services	0.238	(0.153)	0.314	93	2.187	0.153	7
Independent Power and Renewable Electricity Producers	0.428***	(0.000)	0.031	10	1.211	0.207	7
Interactive Media & Services	-0.193**	(0.088)	0.343	77	2.221	0.114	7
Media	0.246	(0.178)	0.594	46	2.449	0.207	7
Energy Equipment & Services	0.032	(0.101)	0.262	160	1.747	0.135	6
Broadline Retail	-0.017	(0.070)	0.190	51	3.065	0.049	6
Hotels, Restaurants & Leisure	3.862**	(1.823)	0.431	47	1.995	0.073	6
IT Services	-0.110	(0.189)	0.193	244	1.598	0.093	6
Automobiles	0.003	(0.048)	0.088	238	1.494	0.188	6
Containers & Packaging	0.267**	(0.118)	0.103	175	1.585	0.044	6
Gas Utilities	0.081	(0.214)	0.268	34	1.344	0.333	6
Marine Transportation	-0.812	(1.426)	0.257	12	0.699	0.295	6
Building Products	0.147*	(0.087)	0.056	383	1.299	0.115	6
Electrical Equipment	0.222***	(0.073)	0.112	431	1.498	0.272	6
Personal Care Products	0.093	(0.380)	0.230	135	2.068	0.049	6
Household Products	-0.238	(0.219)	0.092	136	1.688	0.066	6
Paper & Forest Products	-0.626	(0.825)	0.262	55	1.164	0.102	5
Biotechnology	0.007	(0.107)	0.067	597	1.504	0.148	5
Beverages	-1.490**	(0.623)	0.303	74	1.807	0.091	5
Electric Utilities	0.221	(0.278)	0.122	63	1.351	0.318	5
Industrial Conglomerates	-0.045	(0.179)	0.082	167	1.682	0.146	5
Ground Transportation	-0.181	(0.720)	0.177	12	1.915	0.168	5
Software	0.065	(0.048)	0.103	594	1.523	0.105	5
Construction & Engineering	-0.023	(0.221)	0.218	138	1.026	0.240	5
Household Durables	0.037	(0.069)	0.111	292	2.458	0.089	5
Chemicals	0.015	(0.058)	0.090	1123	1.429	0.156	5
Semiconductors & Semiconductor Equipment	0.351***	(0.062)	0.112	830	1.488	0.163	5
Oil, Gas & Consumable Fuels	-0.106	(0.071)	0.070	228	1.331	0.169	5
Machinery	0.157**	(0.064)	0.063	1558	1.133	0.139	5
Trading Companies & Distributors	0.587	(0.591)	0.062	5	1.144	0.079	5
Automobile Components	0.296***	(0.102)	0.054	528	1.382	0.118	4
Textiles, Apparel & Luxury Goods	-0.136	(0.371)	0.277	158	1.956	0.130	4
Pharmaceuticals	0.113	(0.081)	0.053	736	1.573	0.102	4
Electronic Equipment, Instruments & Components	0.377***	(0.056)	0.097	828	1.488	0.129	4
Construction Materials	-0.655*	(0.344)	0.188	66	1.483	0.228	4
Aerospace & Defense	-0.03 4	(0.066)	0.054	435	1.549	0.165	4
Technology Hardware, Storage & Peripherals	0.006	(0.101)	0.057	345	1.414	0.056	4
Passenger Airlines	0.788***	(0.000)	0.297	4	2.313	0.543	4
Food Products	0.022	(0.167)	0.120	421	1.473	0.124	4
Communications Equipment	0.171*	(0.089)	0.057	256	1.613	0.065	4
Metals & Mining	-0.110	(0.160)	0.084	326	1.266	0.172	3
Tobacco	0.808**	(0.358)	0.182	54	1.619	0.062	3
Leisure Products	-0.079	(0.085)	0.143	167	2.123	0.039	3

Panel B: Green Ratio (USPTO)

Industry	(1) Coef for E^{MSCI}	(2) Std. Err	(3) Pseudo R^2	(4) N	(5) Std. Dev. E^{MSCI}	(6) Std. Dev. GreenRatio US	(7) Industry E^{MSCI} Rating
Wireless Telecommunication Services	-0.874	(1.180)	0.187	49	1.640	0.054	9
Diversified Telecommunication Services	0.381***	(0.077)	0.131	124	2.275	0.088	9
Health Care Providers & Services	-0.301	(0.222)	0.188	88	1.837	0.209	8
Life Sciences Tools & Services	-0.017	(0.060)	0.037	242	2.020	0.117	8
Health Care Equipment & Supplies	0.048	(0.044)	0.109	732	1.825	0.122	8
Multi-Utilities	-0.709**	(0.282)	0.094	32	0.738	0.187	7
Entertainment	0.690**	(0.293)	0.290	122	1.275	0.102	7
Financial Services	-1.798	(1.155)	0.385	38	1.796	0.166	7
Commercial Services & Supplies	-0.128**	(0.052)	0.063	206	2.326	0.102	7
Media	0.820*	(0.460)	0.303	67	2.294	0.130	7
Professional Services	-0.154	(0.117)	0.210	93	2.187	0.155	7
Interactive Media & Services	0.125**	(0.061)	0.239	81	2.241	0.124	7
Independent Power and Renewable Electricity Producers	-0.157***	(0.000)	0.061	16	1.373	0.255	7
Energy Equipment & Services	-0.082	(0.145)	0.207	175	1.694	0.159	6
Broadline Retail	-0.036	(0.036)	0.137	49	3.124	0.061	6
Hotels, Restaurants & Leisure	-0.555*	(0.287)	0.327	86	2.001	0.104	6
Marine Transportation	4.314***	(0.569)	0.269	11	1.023	0.364	6
IT Services	0.010	(0.111)	0.196	234	1.531	0.140	6
Containers & Packaging	0.095	(0.069)	0.123	177	1.580	0.073	6
Automobiles	0.104**	(0.049)	0.042	240	1.516	0.175	6
Gas Utilities	-0.004	(0.178)	0.186	39	1.324	0.392	6
Building Products	0.285**	(0.113)	0.072	383	1.295	0.175	6
Electrical Equipment	0.282***	(0.063)	0.097	434	1.494	0.271	6
Personal Care Products	-0.145	(0.258)	0.094	151	2.073	0.103	6
Ground Transportation	-1.140*	(0.586)	0.162	18	1.953	0.343	6
Household Products	-0.236**	(0.103)	0.034	140	1.667	0.067	6
Paper & Forest Products	-0.588	(0.565)	0.190	55	1.164	0.110	5
Beverages	-0.064	(0.147)	0.208	86	1.783	0.160	5
Biotechnology	0.087	(0.063)	0.053	611	1.507	0.269	5
Electric Utilities	0.121	(0.172)	0.103	58	1.287	0.358	5
Industrial Conglomerates	-0.065	(0.114)	0.060	184	1.723	0.179	5
Software	0.057	(0.097)	0.177	589	1.516	0.128	5
Household Durables	0.077	(0.051)	0.113	312	2.491	0.108	5
Construction & Engineering	0.262	(0.232)	0.162	151	1.009	0.258	5
Chemicals	-0.037	(0.049)	0.047	1131	1.430	0.198	5
Semiconductors & Semiconductor Equipment	0.177***	(0.057)	0.080	848	1.498	0.244	5
Oil, Gas & Consumable Fuels	-0.059	(0.124)	0.060	231	1.332	0.259	5
Machinery	-0.080	(0.080)	0.035	1572	1.141	0.164	5
Trading Companies & Distributors	-0.422**	(0.212)	0.066	8	0.936	0.077	5
Automobile Components	-0.035	(0.077)	0.038	539	1.370	0.144	4
Pharmaceuticals	0.072	(0.070)	0.059	766	1.564	0.154	4
Textiles, Apparel & Luxury Goods	0.014	(0.254)	0.251	165	1.987	0.143	4
Construction Materials	-0.469	(0.335)	0.123	70	1.620	0.202	4
Specialty Retail	-1.128*	(0.662)	0.277	25	2.863	0.261	4
Electronic Equipment, Instruments & Components	0.059	(0.063)	0.061	831	1.488	0.153	4
Aerospace & Defense	-0.008	(0.058)	0.069	436	1.558	0.153	4
Technology Hardware, Storage & Peripherals	0.104	(0.097)	0.063	352	1.381	0.072	4
Food Products	-0.023	(0.127)	0.161	441	1.451	0.226	4
Communications Equipment	-0.079	(0.105)	0.135	276	1.608	0.132	3
Metals & Mining	-0.065	(0.121)	0.087	320	1.287	0.161	3
Tobacco	0.230*	(0.122)	0.091	54	1.635	0.091	3
Leisure Products	-0.135**	(0.059)	0.162	177	2.262	0.115	3

Panel C: Climate Ratio (USPTO)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry	Coef for E^{MSCI}	Std. Err	Pseudo R^2	N	Std. Dev. E^{MSCI}	Std. Dev. ClimateRatio US	Industry E^{MSCI} Rating
Diversified Telecommunication Services	0.618	-0.482	0.367	68	2.696	0.032	8
Health Care Providers & Services	-0.085	-0.704	0.445	86	1.717	0.160	8
Life Sciences Tools & Services	-0.042	-0.074	0.130	236	2.021	0.033	8
Health Care Equipment & Supplies	0.098	-0.082	0.118	665	1.842	0.033	8
Gas Utilities	-0.242	-0.551	0.109	10	0.531	0.232	7
Commercial Services & Supplies	-0.061	-0.159	0.164	181	2.061	0.055	7
Interactive Media & Services	-0.307	-0.188	0.290	61	2.108	0.013	7
Multi-Utilities	-33.855***	0.000	0.133	6	0.671	0.090	6
Energy Equipment & Services	0.034	-0.145	0.169	169	1.721	0.084	6
Professional Services	-0.703***	-0.248	0.504	44	2.234	0.155	6
IT Services	-0.009	-0.248	0.182	213	1.511	0.031	6
Automobiles	-0.276***	-0.107	0.124	225	1.474	0.054	6
Containers & Packaging	0.206	-0.134	0.233	157	1.625	0.101	6
Building Products	0.082	-0.156	0.090	372	1.312	0.071	6
Electrical Equipment	-0.162	-0.168	0.148	389	1.508	0.061	6
Broadline Retail	0.205***	0.000	0.013	4	4.892	0.001	6
Personal Care Products	0.944***	-0.288	0.299	143	2.037	0.049	6
Household Products	-0.087	-0.091	0.125	140	1.667	0.055	6
Biotechnology	0.133	-0.126	0.156	444	1.480	0.098	5
Paper & Forest Products	-0.093	-0.560	0.224	55	1.164	0.197	5
Beverages	-0.698	-0.612	0.248	73	1.833	0.070	5
Industrial Conglomerates	-0.231	-0.193	0.186	169	1.672	0.114	5
Electric Utilities	2.043***	-0.680	0.231	43	1.072	0.215	5
Software	-0.193	-0.179	0.502	510	1.416	0.072	5
Household Durables	0.006	-0.085	0.218	276	2.424	0.111	5
Construction & Engineering	-0.464	-0.508	0.189	123	0.941	0.226	5
Semiconductors & Semiconductor Equipment	-0.081	-0.125	0.198	796	1.502	0.028	5
Chemicals	0.121	-0.075	0.105	1136	1.431	0.144	5
Oil, Gas & Consumable Fuels	0.123	-0.120	0.107	227	1.332	0.118	5
Machinery	0.266***	-0.095	0.077	1530	1.145	0.124	5
Textiles, Apparel & Luxury Goods	1.333	-1.073	0.320	118	2.078	0.045	5
Automobile Components	-0.115	-0.142	0.178	523	1.375	0.082	4
Pharmaceuticals	-0.211*	-0.109	0.178	708	1.582	0.067	4
Construction Materials	0.322	-0.330	0.176	55	1.480	0.115	4
Trading Companies & Distributors	0.812	-0.580	0.107	5	0.873	0.078	4
Electronic Equipment, Instruments & Components	0.315	-0.211	0.142	806	1.485	0.049	4
Aerospace & Defense	0.065	-0.121	0.132	436	1.558	0.060	4
Technology Hardware, Storage & Peripherals	0.122	-0.204	0.241	332	1.380	0.034	4
Food Products	-0.082	-0.116	0.179	452	1.442	0.214	4
Communications Equipment	-0.911	-1.039	0.643	194	1.579	0.074	4
Metals & Mining	-0.255	-0.186	0.146	310	1.267	0.118	3
Tobacco	0.074	-0.132	0.149	45	1.623	0.054	3
Leisure Products	-0.136	-0.141	0.140	121	2.102	0.032	3

Table A.17: Forward Citation Ratios On E Ratings (Robustness)

The observation unit is firm-year. In panel A, I consider all forward citation ratios as the dependent variable for patents granted at USPTO. In Panel B, I condition on forward citations for patents granted at EPO. In Panel C, I condition on forward citations for patents granted at GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var}/StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenCitRatio US	HealthCitRatio US	BioeconomyCitRatio US	EnergyCitRatio US	TransportCitRatio US	ClimateCitRatio US	SecurityCitRatio US
E^{MSCI}	0.080***	-0.033**	0.022	0.114***	0.007	-0.013	0.029*
	(0.024)	(0.014)	(0.017)	(0.025)	(0.014)	(0.033)	(0.017)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	14933	14865	14912	14761	14978	14006	14373
Pseudo R^2	0.065	0.288	0.152	0.086	0.086	0.116	0.099
Dep. Variable: STD	0.197	0.271	0.233	0.163	0.245	0.109	0.167
Ind. Variable: STD	1.970	1.971	1.970	1.968	1.971	1.929	1.961
Economic effect	0.800	0.241	0.186	1.373	0.058	0.238	0.340

	Panel B: Patenting at EPO						
	(1) GreenCitRatio EPO	(2) HealthCitRatio EPO	(3) BioeconomyCitRatio EPO	(4) EnergyCitRatio EPO	(5) TransportCitRatio EPO	(6) ClimateCitRatio EPO	(7) SecurityCitRatio EPO
E^{MSCI}	0.116***	0.004	0.065***	0.107***	0.059***	0.039	0.083***
	(0.030)	(0.021)	(0.019)	(0.037)	(0.021)	(0.057)	(0.029)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	10964	10157	10907	10847	11023	7454	9733
Pseudo R^2	0.083	0.289	0.132	0.108	0.132	0.096	0.131
Dep. Variable: STD	0.198	0.286	0.256	0.189	0.271	0.132	0.168
Ind. Variable: STD	1.913	1.933	1.923	1.924	1.921	1.800	1.909
Economic effect	1.119	0.027	0.491	1.090	0.417	0.525	0.946
	Panel C: Patenting at GPO						
	(1) GreenCitRatio GPO	(2) HealthCitRatio GPO	(3) BioeconomyCitRatio GPO	(4) EnergyCitRatio GPO	(5) TransportCitRatio GPO	(6) ClimateCitRatio GPO	(7) SecurityCitRatio GPO
E	0.078***	-0.025*	0.030*	0.116***	0.008	-0.005	0.031*
	(0.023)	(0.013)	(0.017)	(0.024)	(0.015)	(0.031)	(0.018)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	16347	16284	16391	16186	16405	15307	15702
Pseudo R^2	0.064	0.286	0.146	0.084	0.089	0.113	0.105
Dep. Variable: STD	0.194	0.266	0.230	0.161	0.242	0.108	0.163
Ind. Variable: STD	1.982	1.984	1.985	1.981	1.983	1.942	1.973
Economic effect	0.796	0.187	0.256	1.423	0.065	0.098	0.377

Table A.18: Patent Ratios On E Ratings (Robustness: Bolton et al. (2023) Controls)

The observation unit is firm-year. In panel A, I consider all patent ratios as the dependent variable for patents granted at USPTO. In Panel B, I condition on patents granted at EPO. In Panel C, I condition on patents granted at GPO. The sample period is 2008-2023. I apply the control variables from Bolton et al. (2023). All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	(1) GreenRatio US	(2) HealthRatio US	(3) BioeconomyRatio US	(4) EnergyRatio US	(5) TransportRatio US	(6) ClimateRatio US	(7) SecurityRatio US
E^{MSCI}	0.037***	-0.012	-0.009	0.067***	0.008	-0.025	0.017
	(0.013)	(0.012)	(0.011)	(0.016)	(0.010)	(0.019)	(0.011)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	24564	24419	24567	24227	24684	23216	23726
Pseudo R^2	0.067	0.226	0.128	0.088	0.086	0.125	0.103
Dep. Variable: STD	0.2	0.252	0.23	0.159	0.233	0.116	0.169
Ind. Variable: STD	2.145	2.148	2.148	2.149	2.145	2.132	2.14
Economic effect	0.399	0.104	0.080	0.906	0.078	0.455	0.221
	Panel B: Patenting at EPO						
	(1) GreenRatio EPO	(2) HealthRatio EPO	(3) BioeconomyRatio EPO	(4) EnergyRatio EPO	(5) TransportRatio EPO	(6) ClimateRatio EPO	(7) SecurityRatio EPO
E^{MSCI}	0.052***	0.021*	-0.015	0.060**	0.014	0.020	0.037**
	(0.017)	(0.012)	(0.014)	(0.024)	(0.013)	(0.024)	(0.018)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	15773	15682	15795	15527	15894	14294	15138
Pseudo R^2	0.076	0.257	0.122	0.095	0.106	0.131	0.125
Dep. Variable: STD	0.215	0.308	0.276	0.184	0.27	0.129	0.168
Ind. Variable: STD	2.108	2.107	2.107	2.109	2.111	2.06	2.095
Economic effect	0.505	0.146	0.111	0.688	0.109	0.316	0.461
	Panel C: Patenting at GPO						
	(1) GreenRatio GPO	(2) HealthRatio GPO	(3) BioeconomyRatio GPO	(4) EnergyRatio GPO	(5) TransportRatio GPO	(6) ClimateRatio GPO	(7) SecurityRatio GPO
E^{MSCI}	0.039***	-0.007	-0.009	0.064***	0.010	0.006	0.016
	(0.011)	(0.010)	(0.011)	(0.014)	(0.010)	(0.022)	(0.012)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	28601	28481	28602	28128	28615	27770	27814
Pseudo R^2	0.061	0.215	0.111	0.080	0.082	0.107	0.103
Dep. Variable: STD	0.193	0.255	0.232	0.158	0.228	0.112	0.157
Ind. Variable: STD	2.154	2.157	2.155	2.161	2.155	2.154	2.152
Economic effect	0.437	0.06	0.081	0.871	0.099	0.106	0.213

Table A.19: Patent Counts On E Ratings (Robustness)

The observation unit is firm-year. In panel A, I consider all patent counts as the dependent variable for patents granted at USPTO. In Panel B, I condition on patents granted at EPO. In Panel C, I condition on patents granted at GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Green US	Health US	Bioeconomy US	Energy US	Transport US	Climate US	Security US
E^{MSCI}	0.280***	0.161***	0.109***	0.264***	0.155***	0.075	0.203***
	(0.064)	(0.036)	(0.041)	(0.053)	(0.047)	(0.078)	(0.050)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	14982	14986	15020	14830	15027	14822	14875
Pseudo R^2	0.512	0.738	0.479	0.612	0.622	0.468	0.679
Dep. Variable: STD	39.934	56.955	26.738	39.477	65.466	8.98	49.303
Ind. Variable: STD	1.972	1.974	1.973	1.975	1.974	1.973	1.967
Economic effect	0.014	0.006	0.008	0.013	0.005	0.017	0.008
	Panel B: Patenting at EPO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Green EPO	Health EPO	Bioeconomy EPO	Energy EPO	Transport EPO	Climate EPO	Security EP
E^{MSCI}	0.300***	0.161***	0.131***	0.261***	0.137***	0.193***	0.208***
	(0.042)	(0.031)	(0.029)	(0.048)	(0.041)	(0.036)	(0.051)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	11562	11505	11590	11429	11611	11112	11379
Pseudo R^2	0.417	0.717	0.405	0.497	0.503	0.397	0.519
Dep. Variable: STD	14.418	29.657	14.5	19.551	27.057	3.489	11.595
Ind. Variable: STD	1.955	1.956	1.955	1.959	1.958	1.929	1.957
Economic effect	0.041	0.011	0.018	0.026	0.01	0.107	0.035
	Panel C: Patenting at GPO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Green GPO	Health GPO	Bioeconomy GPO	Energy GPO	Transport GPO	Climate GPO	Security GPO
E^{MSCI}	0.283***	0.154***	0.129***	0.258***	0.145***	0.115*	0.209***
	(0.055)	(0.030)	(0.031)	(0.048)	(0.041)	(0.059)	(0.050)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	16457	16439	16516	16322	16502	16307	16400
Pseudo R^2	0.525	0.768	0.526	0.606	0.624	0.516	0.661
Dep. Variable: STD	57.576	105.593	47.961	59.084	95.634	13.591	58.735
Ind. Variable: STD	1.986	1.987	1.986	1.99	1.986	1.985	1.984
Economic effect	0.01	0.003	0.005	0.009	0.003	0.017	0.007

Table A.20: Patent Ratios On E Ratings (Innovating Firms Only)

The observation unit is firm-year. The dependent variable is one of the SGC classes or the green class for patents granted at EPO (GPO) in Panel A (B). The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at EPO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio EPO	HealthRatio EPO	BioeconomyRatio EPO	EnergyRatio EPO	TransportRatio EPO	ClimateRatio EPO	SecurityRatio EPO
E^{MSCI}	0.002	-0.008	-0.011**	0.008*	-0.006*	-0.009**	-0.005*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	7252	5984	7702	6267	8520	3217	5039
Adj. R^2	0.353	0.710	0.462	0.320	0.402	0.342	0.356
Dep. Variable: STD	0.229	0.368	0.289	0.210	0.280	0.179	0.205
Ind. Variable: STD	1.814	2.023	1.865	1.782	1.882	1.648	1.991
Economic effect	0.019	0.043	0.074	0.067	0.042	0.080	0.050
	Panel B: Patenting at GPO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio GPO	HealthRatio GPO	BioeconomyRatio GPO	EnergyRatio GPO	TransportRatio GPO	ClimateRatio GPO	SecurityRatio GPO
E^{MSCI}	0.003	-0.006**	-0.008**	0.008***	-0.004	-0.005**	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	15858	13416	15649	13298	17802	8086	12666
Adj. R^2	0.289	0.728	0.446	0.288	0.374	0.282	0.305
Dep. Variable: STD	0.197	0.323	0.257	0.167	0.232	0.140	0.163
Ind. Variable: STD	1.909	2.002	1.918	1.885	1.940	1.807	1.983
Economic effect	0.025	0.038	0.062	0.085	0.030	0.069	0.007

Table A.21: Patent Ratio On E-ratings (Paris 2015)

The observation unit is firm-year. The dependent variable is *GreenRatio*, *EnergyRatio*, or *ClimateRatio* for patents granted at EPO or GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.2). All regressions includes country, and year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, and the independent variable. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at EPO								
	GreenRatio EPO			EnergyRatio EPO			ClimateRatio EPO		
E^{MSCI}	-0.043*	-0.006	-0.003	-0.013	0.023	0.043	-0.054*	0.029	0.011
	(0.023)	(0.024)	(0.021)	(0.023)	(0.023)	(0.027)	(0.028)	(0.030)	(0.045)
$E^{MSCI} \times I_{2015}$	0.077***	0.098***	0.111***	0.041*	0.111***	0.096***	0.024	0.035	0.053
	(0.023)	(0.026)	(0.024)	(0.023)	(0.026)	(0.032)	(0.030)	(0.040)	(0.054)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	16202	16188	15817	16014	16000	15527	16180	16075	14325
Pseudo R^2	0.015	0.065	0.080	0.033	0.090	0.103	0.065	0.118	0.130
Dep. Variable: STD	0.197	0.197	0.197	0.183	0.183	0.184	0.107	0.107	0.111
Ind. Variable: STD	1.954	1.954	1.946	2.113	2.113	2.109	1.957	1.956	1.892
	Panel B: Patenting at GPO								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GreenRatio GPO			EnergyRatio GPO			ClimateRatio GPO		
E^{MSCI}	-0.048***	-0.004	-0.011	0.029	0.090***	0.100***	-0.076***	0.017	-0.017
	(0.018)	(0.019)	(0.020)	(0.021)	(0.017)	(0.017)	(0.023)	(0.025)	(0.021)
$E^{MSCI} \times I_{2015}$	0.067***	0.067***	0.080***	-0.005	0.021	0.013	0.009	-0.014	0.022
	(0.016)	(0.019)	(0.019)	(0.020)	(0.018)	(0.019)	(0.023)	(0.025)	(0.029)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	28704	28703	28601	28373	28372	28128	28624	28613	27770
Pseudo R^2	0.014	0.063	0.072	0.033	0.086	0.095	0.065	0.111	0.124
Dep. Variable: STD	0.178	0.178	0.178	0.158	0.158	0.158	0.094	0.094	0.095
Ind. Variable: STD	1.985	1.985	1.986	2.159	2.159	2.161	1.987	1.981	1.966

Table A.22: Forward Citation Ratio On E-ratings (Paris 2015)

The observation unit is firm-year. The dependent variable is *GreenCitRatio*, *EnergyCitRatio*, or *ClimateCitRatio* for forward citations on patents granted at USPTO, EPO, or GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.2). All regressions includes country, and year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, and the independent variable. *** 1% significance, ** 5% significance, * 10% significance.

Panel A: Patenting at USPTO									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GreenCitRatio US			EnergyCitRatio US			ClimateCitRatio US		
E^{MSCI}	-0.053*	-0.010	-0.002	0.032*	0.101***	0.104***	-0.166***	-0.076***	-0.109***
	(0.028)	(0.032)	(0.030)	(0.019)	(0.027)	(0.032)	(0.033)	(0.029)	(0.033)
$E^{MSCI} \times I_{2015}$	0.072***	0.083**	0.089**	-0.007	0.044	0.053	0.101***	0.094***	0.136***
	(0.028)	(0.036)	(0.035)	(0.020)	(0.032)	(0.037)	(0.034)	(0.035)	(0.049)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	15051	15020	14933	14922	14920	14761	15040	15038	14006
Pseudo R^2	0.022	0.072	0.088	0.039	0.096	0.109	0.073	0.133	0.145
Dep. Variable: STD	0.197	0.197	0.197	0.163	0.163	0.163	0.105	0.106	0.109
Ind. Variable: STD	1.971	1.971	1.970	1.975	1.975	1.968	1.971	1.966	1.929
Panel B: Patenting at EPO									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GreenCitRatio EPO			EnergyCitRatio EPO			ClimateCitRatio EPO		
E^{MSCI}	-0.022	-0.006	-0.027	0.002	0.029	0.060	-0.038	0.038	0.012
	(0.040)	(0.038)	(0.036)	(0.031)	(0.043)	(0.040)	(0.047)	(0.067)	(0.105)
$E^{MSCI} \times I_{2015}$	0.065	0.092*	0.152***	0.013	0.090*	0.088*	0.006	0.017	0.056
	(0.042)	(0.050)	(0.050)	(0.033)	(0.053)	(0.053)	(0.063)	(0.085)	(0.133)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	11592	11549	10964	11469	11398	10847	9753	9613	7454
Pseudo R^2	0.049	0.088	0.108	0.067	0.118	0.123	0.073	0.134	0.139
Dep. Variable: STD	0.194	0.195	0.198	0.185	0.186	0.189	0.117	0.120	0.132
Ind. Variable: STD	1.954	1.945	1.913	1.960	1.957	1.924	1.929	1.891	1.800
Panel C: Patenting at GPO									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	GreenCitRatio GPO			EnergyCitRatio GPO			ClimateCitRatio GPO		
E^{MSCI}	-0.056**	-0.016	-0.022	0.030	0.090***	0.080***	-0.157***	-0.069**	-0.096***
	(0.028)	(0.030)	(0.030)	(0.019)	(0.022)	(0.022)	(0.031)	(0.028)	(0.035)
$E^{MSCI} \times I_{2015}$	0.077***	0.085**	0.106***	0.004	0.052*	0.075***	0.094***	0.093***	0.133***
	(0.027)	(0.035)	(0.035)	(0.019)	(0.028)	(0.028)	(0.030)	(0.029)	(0.044)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country F.E	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry F.E.		✓	✓		✓	✓		✓	✓
Industry-Year F.E.			✓			✓			✓
Observations	16488	16446	16347	16366	16363	16186	16469	16466	15307
Pseudo R^2	0.022	0.071	0.087	0.039	0.093	0.109	0.071	0.130	0.142
Dep. Variable: STD	0.194	0.194	0.194	0.160	0.160	0.161	0.104	0.105	0.163
Ind. Variable: STD	1.984	1.985	1.982	1.988	1.988	1.981	1.984	1.980	1.973

Table A.23: Patent Ratio On Climate Exposures (Sautner et al. (2023))

The observation unit is firm-year. The dependent variable is one of the SGC classes or the green class for patents granted at USPTO. The sample period is 2002-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry, and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
$\text{Log}(1 + CCExposure_{i,t})$	15.813***	-2.624***	-2.223*	18.268***	12.228***	4.314***	-2.920***
	(2.959)	(0.798)	(1.254)	(2.212)	(3.753)	(1.413)	(0.860)
Adj. R^2	0.191	0.687	0.344	0.276	0.247	0.117	0.137
Ind. Variable: STD	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Economic effect	0.221	0.023	0.024	0.341	0.142	0.109	0.048
$\text{Log}(1 + CCExposure^{Opp}_{i,t})$	28.732***	-3.872**	-1.777	33.062***	22.458***	2.379**	-5.963***
	(6.512)	(1.370)	(2.296)	(5.198)	(7.683)	(0.981)	(1.654)
Adj. R^2	0.185	0.687	0.343	0.263	0.245	0.110	0.137
Ind. Variable: STD	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Economic effect	0.201	0.017	0.009	0.309	0.130	0.030	0.049
$\text{Log}(1 + CCExposure^{Reg}_{i,t})$	49.758**	-8.406*	-7.950	62.142***	49.600*	55.626**	-5.714
	(22.587)	(4.170)	(6.741)	(16.247)	(26.738)	(23.194)	(6.893)
Adj. R^2	0.164	0.687	0.343	0.214	0.237	0.128	0.136
Ind. Variable: STD	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Economic effect	0.073	0.008	0.009	0.121	0.060	0.147	0.010
$\text{Log}(1 + CCExposure^{Phy}_{i,t})$	4.640	0.030	-20.288	0.869	42.266***	-12.697*	-6.907
	(17.387)	(8.977)	(21.722)	(11.651)	(14.488)	(6.850)	(6.475)
Adj. R^2	0.159	0.687	0.344	0.201	0.235	0.110	0.136
Ind. Variable: STD	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Economic effect	0.004	0.000	0.012	0.001	0.026	0.017	0.006
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	14347	14347	14347	14347	14347	14347	14347
Mean dep. Var.	0.108	0.159	0.146	0.059	0.161	0.033	0.085
Dep. Variable: STD	0.179	0.287	0.237	0.134	0.216	0.099	0.152

Table A.24: Patent Ratio On Robeco SDG Ratings – Coefficients Only

The observation unit is firm-year. The dependent variable is one of the seven patent classes. The sample period is 2010-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the coefficient estimates, highlighting in bold the expected SDG links with each SGC and Green class. Due to zero ratings for SDG 5 and 10, these have been discarded. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
SDG Overall	0.008	0.034	-0.024	0.026	0.031	-0.001	-0.013
SDG 1	0.412	0.044	0.102	-0.299*	0.345	-0.161	-0.268*
SDG 2	-0.108	0.199**	**0.156**	-0.017	0.124*	0.036	0.111
SDG 3	0.052	**0.005**	-0.025	0.075	-0.006	-0.018	0.016
SDG 4	0.439	-0.372	0.492*	-0.392	-0.109	-1.385***	-0.015
SDG 6	0.277	0.375**	0.031	0.448***	0.048	**0.536**	-0.240
SDG 7	**0.058**	-0.023	0.071	**0.069**	0.052	-0.095	-0.214***
SDG 8	-0.013	-0.110	-0.089	0.015	0.065	0.133	0.073
SDG 9	-0.065	0.055	-0.530***	-0.003	**-0.157*** **	-0.010	0.002
SDG 11	0.150**	0.291**	-0.125	0.115	0.129***	-0.085	0.080
SDG 12	0.006	0.069	-0.007	0.014	-0.000	0.031	-0.106**
SDG 13	**0.092***	0.136	0.049	**0.088**	0.120***	**-0.000**	-0.113
SDG 14	-0.013	0.299**	-0.134*	0.031	0.102	**0.106**	0.017
SDG 15	-0.065	0.369***	-0.134*	0.011	0.090	**0.073**	-0.006
SDG 16	0.020	0.036	-0.051	-0.030	0.044	0.011	**-0.006**
SDG 17	-0.109	0.098***	1.131***	0.058	0.373***	0.991*	0.256***
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	14064	14030	14020	14016	14183	13355	13666
	Panel B: Patenting at EPO						
	GreenRatio EPO	HealthRatio EPO	BioeconomyRatio EPO	EnergyRatio EPO	TransportRatio EPO	ClimateRatio EPO	SecurityRatio EPO
SDG Overall	-0.010	0.033	0.024	0.027	0.030	0.050	-0.004
SDG 1	-0.348***	0.093	0.059	-0.346***	0.143	-0.100	0.012
SDG 2	-0.376*	0.196*	**0.055**	0.140**	0.050	0.208	-0.403
SDG 3	-0.037	**0.021**	0.021	0.049	0.016	0.045	0.188**
SDG 4	-0.515	0.194	0.552**	-0.179	-0.493*	-1.990***	-0.889***
SDG 6	0.079	0.219	0.026	0.227	0.071	**1.148*** **	-1.058***
SDG 7	**0.068**	-0.014	0.159*	**0.035**	0.065	-0.119	-0.128
SDG 8	-0.059	-0.051	0.089	-0.044	0.123	-0.271*	0.100
SDG 9	-0.070	-0.103	-0.390***	-0.078	**-0.085**	0.099	0.093
SDG 11	0.142**	0.266*	0.062	0.135**	0.094**	0.143	0.097
SDG 12	-0.006	0.061	0.082	0.093*	0.019	0.139	-0.140**
SDG 13	**0.065**	0.158	0.126	**0.032**	0.104*	**-0.020**	-0.123
SDG 14	-0.399*	0.273*	-0.222*	0.178*	0.155	**0.231**	-0.444
SDG 15	-0.450*	0.405**	-0.259**	0.163	0.148	**0.170**	-0.484
SDG 16	-0.031	0.029	-0.051	0.007	-0.025	-0.004	**0.019**
SDG 17	0.005	-0.066	1.023***	-0.384*	0.297***	0.797	0.751**
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	10882	10672	10849	10840	10888	9968	10399
	Panel C: Patenting at GPO						
	GreenRatio GPO	HealthRatio GPO	BioeconomyRatio GPO	EnergyRatio GPO	TransportRatio GPO	ClimateRatio GPO	SecurityRatio GPO
SDG Overall	0.021	0.037*	-0.015	0.034	0.031	0.018	0.009
SDG 1	0.429	-0.005	0.286	-0.186	0.434	-0.107	-0.094
SDG 2	-0.204	0.228***	**0.126**	-0.107	0.123*	0.070	-0.011
SDG 3	-0.004	**0.011**	-0.019	0.066	0.016	0.125	0.046
SDG 4	0.317	-0.228	0.464	-0.055	-0.187	-2.352***	-0.062
SDG 6	0.180	0.333**	0.058	0.034	0.092	**0.578***	-0.403**
SDG 7	**0.092*** **	-0.024	0.072	**0.064**	0.054	-0.174**	-0.182***
SDG 8	0.012	-0.081	-0.096	0.053	0.068	0.093	0.142
SDG 9	-0.027	0.137	-0.412***	-0.012	**-0.125*** **	0.204	0.063
SDG 11	0.151***	0.252**	-0.098	0.119*	0.109**	0.160	0.113
SDG 12	0.028	0.066*	0.012	0.020	0.011	0.099	-0.073
SDG 13	**0.113*** **	0.174*	0.072	**0.066**	0.111**	**-0.091**	-0.113*
SDG 14	-0.092	0.379***	-0.090	-0.047	0.106*	**0.227**	-0.046
SDG 15	-0.128	0.422***	-0.102	-0.051	0.108*	**0.198**	-0.047
SDG 16	-0.004	0.035	-0.053	-0.012	-0.020	-0.053	**0.071**
SDG 17	0.173	-0.115	1.308***	0.087	0.438***	1.026*	0.269***
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	15432	15338	15426	15409	15500	14811	15067

Table A.25: Patent Ratio On MSCI SDG Product Ratings – Coefficients Only

The observation unit is firm-year. The dependent variable is one of the seven patent classes. The sample period is 2020-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the coefficient estimates, highlighting in bold the expected SDG links with each SGC and Green class. Due to insufficient observations for SDG 17, it has been discarded. *** 1% significance, ** 5% significance, * 10% significance.

	Panel A: Patenting at USPTO						
	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
SDG Prod 1	-0.030	0.028**	-0.022	-0.043	0.002	0.014	0.002
SDG Prod 2	-0.109	-0.033	**-0.021**	0.043	0.065**	-0.096	0.072
SDG Prod 3	0.009	**0.020*** **	-0.020	0.029	0.003	0.078	-0.021
SDG Prod 4	0.099	0.345***	-0.143	-1.309*	-0.614	-2.830***	0.201***
SDG Prod 5	0.095	0.021	-0.223**	-0.597***	0.063	-0.194	-0.021
SDG Prod 6	-0.002	0.016	-0.020	0.042	-0.092**	**0.237*** **	-0.076***
SDG Prod 7	**0.070*** **	0.009	-0.015	**0.090*** **	-0.027*	-0.029	0.006
SDG Prod 8	0.035	0.358***	0.167	-0.334***	-0.137	-1.508**	0.168***
SDG Prod 9	0.108***	-0.083	-0.044*	0.138***	**0.012**	0.071	-0.037***
SDG Prod 10	0.012	0.428***	0.183	-0.131	0.029	-1.508**	0.193***
SDG Prod 11	0.072***	-0.032	-0.060**	0.084***	0.008	0.078*	-0.017
SDG Prod 12	0.073***	-0.010	-0.025*	0.095***	0.018**	0.069***	0.002
SDG Prod 13	**0.071*** **	0.010	-0.015	**0.092*** **	-0.027*	**-0.028**	0.008
SDG Prod 14	0.022	0.017	-0.013	0.010	-0.021	**0.162*** **	0.020
SDG Prod 15	0.242*	-0.322	-0.089	0.093	-0.069	**0.551*** **	-0.235**
SDG Prod 16	0.051	-0.038	0.187	0.190*	0.038	-0.152**	**-0.013**
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	5323	5315	5291	5318	5335	4884	4894
	Panel B: Patenting at EPO						
	GreenRatio EPO	HealthRatio EPO	BioeconomyRatio EPO	EnergyRatio EPO	TransportRatio EPO	ClimateRatio EPO	SecurityRatio EPO
SDG Prod 1	-0.009	0.037***	-0.017	0.024	0.006	0.098	0.016
SDG Prod 2	-0.013	-0.044	**-0.005**	0.010	0.036	0.029	0.091*
SDG Prod 3	-0.011	**0.022*** **	-0.019*	0.051	-0.020	0.168***	-0.025
SDG Prod 4	-0.489	0.679	0.504***	0.422***	-0.266***	.	-1.483**
SDG Prod 5	-0.621*	0.104***	-0.157	-0.136**	-0.513***	-0.990**	-0.493***
SDG Prod 6	0.053	0.027	0.007	0.066	-0.038	**0.243*** **	-0.040**
SDG Prod 7	**0.108*** **	0.022	-0.014	**0.124*** **	-0.023	-0.045*	-0.045
SDG Prod 8	-0.062	0.406	0.210	0.093	-0.190	-0.491	0.586***
SDG Prod 9	0.127***	-0.081**	-0.081***	0.146***	**0.039** **	0.141***	-0.011
SDG Prod 10	-0.062	0.406	0.210	0.093	-0.190	-0.491	0.586***
SDG Prod 11	0.081***	-0.091***	-0.086***	0.109***	0.011	0.150***	-0.036
SDG Prod 12	0.094***	-0.012	-0.031**	0.118***	0.022	0.103***	-0.054*
SDG Prod 13	**0.109*** **	0.021	-0.013	**0.127*** **	-0.024	**-0.045***	-0.044
SDG Prod 14	0.037*	0.020	-0.037***	-0.001	-0.008	**0.111***	-0.005
SDG Prod 15	0.285***	-0.345	-0.019	0.051	0.194	**0.829*** **	-0.500
SDG Prod 16	0.124	0.186	0.365	0.068	0.016	0.097	**0.170*** **
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	3868	3803	3840	3853	3837	3277	3508
	Panel C: Patenting at GPO						
	GreenRatio GPO	HealthRatio GPO	BioeconomyRatio GPO	EnergyRatio GPO	TransportRatio GPO	ClimateRatio GPO	SecurityRatio GPO
SDG Prod 1	-0.043	0.027*	-0.017	-0.039	-0.015	0.023	0.030
SDG Prod 2	-0.048	-0.044	**-0.002**	0.073	0.046*	-0.012	0.046
SDG Prod 3	-0.013	**0.022*** **	-0.024**	0.035	-0.016	0.094***	-0.023
SDG Prod 4	-0.124	0.260***	-0.177	-0.899	-0.757	-1.966***	0.126
SDG Prod 5	-0.122	0.123	-0.152**	-0.302**	-0.284	-0.291	-0.106
SDG Prod 6	0.013	0.012	-0.026	0.063**	-0.069*	**0.224*** **	-0.085***
SDG Prod 7	**0.072*** **	0.020	0.002	**0.092*** **	-0.025*	-0.037	-0.022
SDG Prod 8	-0.210	0.259***	0.244	-0.388***	-0.296	-1.823**	0.131*
SDG Prod 9	0.113***	-0.086	-0.038	0.134***	**0.027** **	0.070**	-0.028
SDG Prod 10	-0.005	0.356***	0.254	-0.084	-0.012	-1.823**	0.149***
SDG Prod 11	0.083***	-0.052	-0.072***	0.085***	0.022*	0.086**	-0.012
SDG Prod 12	0.079***	-0.021	-0.028**	0.103***	0.022***	0.068***	-0.019*
SDG Prod 13	**0.072*** **	0.021	0.002	**0.094*** **	-0.025*	**-0.036**	-0.022
SDG Prod 14	0.031*	0.004	-0.027***	0.011	-0.016*	**0.138*** **	0.027
SDG Prod 15	0.111	-0.377*	-0.081	0.087	-0.009	**0.508** **	-0.418***
SDG Prod 16	0.041	-0.049	0.176*	0.066	-0.000	-0.103	**-0.043**
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	5981	5951	5962	5966	5995	5574	5593

Table A.26: Patent Ratio On MSCI SDG Operational Ratings - Coefficients Only

The observation unit is firm-year. The dependent variable is one of the seven patent classes. The sample period is 2020-2023. All variables are defined in Tables A.2 & A.3. The Pseudo Poisson Maximum Likelihood Model is used to estimate Eq. (3.1). All regressions includes country, year, industry and industry-year fixed effects. I double-cluster standard errors at the firm and year levels. I report the coefficient estimates, highlighting in bold the expected SDG links with each SGC and Green class. ***1% significance, **5% significance, *10% significance.

	Panel A: Patenting at USPTO						
	GreenRatio US	HealthRatio US	BioeconomyRatio US	EnergyRatio US	TransportRatio US	ClimateRatio US	SecurityRatio US
SDG Oper 1	0.000	-0.032***	0.020	-0.025	-0.027*	0.016	-0.013
SDG Oper 2	-0.139***	0.067	**-0.054**	-0.059	0.020	-0.061	-0.012
SDG Oper 3	-0.063***	**-0.033*****	-0.010	-0.035	-0.003	-0.090*	-0.040*
SDG Oper 4	-0.020	0.044	0.062*	-0.077	-0.016	0.207**	0.059***
SDG Oper 5	-0.021	0.006	0.039***	-0.031*	-0.013	0.105***	0.038***
SDG Oper 6	-0.076***	0.045***	-0.014	-0.033**	-0.009	**-0.067**	-0.041***
SDG Oper 7	**-0.015**	0.002	0.012	**-0.013**	0.005	0.020	-0.014
SDG Oper 8	-0.026*	-0.011	0.025	-0.017	-0.014	0.007	0.012
SDG Oper 9	0.008	-0.017	0.021	-0.015	**-0.013**	0.002	0.002
SDG Oper 10	-0.014	-0.001	0.023***	-0.012	-0.016	0.049	-0.015
SDG Oper 11	-0.094***	0.072	-0.050*	-0.033	-0.020	-0.178***	-0.072***
SDG Oper 12	-0.089***	0.004	-0.008	-0.046**	-0.012	-0.083**	-0.036***
SDG Oper 13	**-0.024**	-0.000	-0.023	**-0.028**	-0.014	**-0.073**	0.004
SDG Oper 14	-0.140***	0.043	-0.086**	-0.041	-0.006	**-0.146***	-0.082
SDG Oper 15	-0.147***	0.107***	-0.072**	-0.080**	-0.047***	**-0.164****	-0.057
SDG Oper 16	-0.002	-0.012	0.013	-0.002	-0.036**	0.042	**-0.031***
SDG Oper 17	-0.008	0.006	0.029***	-0.004	-0.021*	0.044	-0.021*
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	5323	5315	5291	5318	5335	4884	4894
	Panel B: Patenting at EPO						
	GreenRatio EPO	HealthRatio EPO	BioeconomyRatio EPO	EnergyRatio EPO	TransportRatio EPO	ClimateRatio EPO	SecurityRatio EPO
SDG Oper 1	0.008	-0.030**	0.033*	-0.003	-0.019*	-0.019	0.033**
SDG Oper 2	-0.126*	0.055	**-0.032**	0.000	0.010	0.032	-0.010
SDG Oper 3	-0.018	**-0.053*****	-0.015	-0.001	-0.030	-0.104***	-0.069***
SDG Oper 4	0.001	0.039	0.037	-0.072	-0.030	-0.017	0.251***
SDG Oper 5	-0.017	0.041	0.001	0.004	-0.016	0.128***	0.107***
SDG Oper 6	-0.035*	0.021	-0.002	0.002	-0.001	**-0.031**	-0.012
SDG Oper 7	**0.001**	-0.008	-0.010	**-0.017**	0.011	-0.018	0.014
SDG Oper 8	0.002	0.009	0.028**	0.031**	-0.014	-0.044	0.048***
SDG Oper 9	0.010	-0.033**	0.011	-0.020	**0.005**	0.005	0.037***
SDG Oper 10	-0.013	-0.002	0.032***	0.020	-0.017	0.022	0.039***
SDG Oper 11	-0.068*	0.040	-0.044	0.000	-0.032*	-0.173***	-0.070**
SDG Oper 12	-0.043**	0.021	-0.019	-0.020	-0.002	-0.036	0.008
SDG Oper 13	**-0.016**	0.026	-0.036	**-0.012**	0.004	**-0.037**	0.070
SDG Oper 14	-0.087**	0.031	-0.069***	0.022	0.030	**-0.143*****	-0.069*
SDG Oper 15	-0.098***	0.160***	-0.070***	-0.027	-0.022	**-0.149*****	-0.003
SDG Oper 16	-0.011	-0.007	0.010	0.014	-0.050***	0.020	**0.018**
SDG Oper 17	-0.000	-0.006	0.033*	0.016	-0.020**	0.005	0.048**
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	3868	3803	3840	3853	3837	3277	3508
	Panel C: Patenting at GPO						
	GreenRatio GPO	HealthRatio GPO	BioeconomyRatio GPO	EnergyRatio GPO	TransportRatio GPO	ClimateRatio GPO	SecurityRatio GPO
SDG Oper 1	-0.005	-0.019**	0.017	-0.026	-0.030*	0.008	-0.001
SDG Oper 2	-0.146***	0.080**	**-0.058***	0.016	0.040	-0.023	0.042
SDG Oper 3	-0.061***	**-0.027****	-0.033*	-0.014	-0.019	-0.067**	-0.040**
SDG Oper 4	-0.014	0.049	0.043	-0.071*	-0.052	0.155	0.074***
SDG Oper 5	-0.017	0.019	0.012	-0.020	-0.020	0.074*	0.036**
SDG Oper 6	-0.053**	0.035**	-0.004	0.004	0.003	**-0.072**	-0.050***
SDG Oper 7	**-0.001**	-0.016	-0.007	**-0.004**	-0.002	-0.016	-0.012
SDG Oper 8	-0.019	0.009	0.018	-0.007	-0.027*	0.006	0.007
SDG Oper 9	0.008	-0.017	-0.001	-0.010	**-0.016**	-0.011	0.008
SDG Oper 10	-0.015	-0.003	0.019	0.004	-0.019	0.048*	-0.013
SDG Oper 11	-0.083***	0.066	-0.035	-0.009	-0.025	-0.136***	-0.096***
SDG Oper 12	-0.068***	0.016	-0.006	-0.016	-0.001	-0.082**	-0.025
SDG Oper 13	**-0.007**	0.003	-0.013	**-0.029**	-0.008	**-0.061**	0.025
SDG Oper 14	-0.132***	0.039	-0.086***	0.014	0.000	**-0.131***	-0.075**
SDG Oper 15	-0.139***	0.118***	-0.068**	-0.036	-0.051***	**-0.130*****	-0.055**
SDG Oper 16	-0.005	-0.008	0.006	0.002	-0.040**	0.050	**-0.032*****
SDG Oper 17	-0.002	0.002	0.025**	0.008	-0.014	0.035	-0.013
Controls	✓	✓	✓	✓	✓	✓	✓
All F.E. included	✓	✓	✓	✓	✓	✓	✓
Observations	5981	5951	5962	5966	5995	5574	5593

Table A.27: Sustainability Metrics On Green Patent Ratios

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A.1: $h = 1$ year lagged Green Ratio USPTO	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio US, $h = 1$	-0.016	-0.062	-0.180	-0.036	0.161	-1.165	-1.417	-1.220	0.094	0.099**	0.130**	0.048	0.053	0.185	0.074	-0.004	0.005	-0.107	0.000**	0.000*	0.000	0.000
	(0.054)	(0.071)	(0.172)	(0.041)	(0.909)	(1.013)	(1.171)	(0.770)	(0.101)	(0.042)	(0.052)	(0.090)	(0.093)	(0.132)	(0.145)	(0.040)	(0.037)	(0.174)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	13503	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R^2	0.773	0.684	0.552	0.772	0.790	0.790	0.603	0.767	0.632	0.625	0.483	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.471	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	0.003	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.181	0.181	0.181	0.184	0.174	0.175	0.175	0.176	0.183	0.183	0.183	0.188	0.188	0.188	0.188	0.187	0.188	0.177	0.176	0.176	0.176	0.176
Economic Effect	0.001	0.007	0.019	0.007	0.001	0.008	0.011	0.023	0.012	0.027	0.044	0.004	0.005	0.024	0.010	0.000	0.000	0.006	0.023	0.017	0.026	0.013
Panel A.2: $h = 1$ year lagged Green Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio EPO, $h = 1$	-0.018	0.138*	0.037	0.082**	-0.529	-1.243	0.167	-0.797	0.013	0.114	0.097	-0.098	-0.078	0.426*	0.076	-0.012	-0.007	-0.114	0.000	0.000	-0.000	0.000
	(0.084)	(0.072)	(0.071)	(0.036)	(0.898)	(0.886)	(1.118)	(0.801)	(0.093)	(0.080)	(0.078)	(0.117)	(0.123)	(0.152)	(0.086)	(0.048)	(0.043)	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	10355	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R^2	0.771	0.690	0.535	0.763	0.783	0.789	0.602	0.759	0.629	0.628	0.491	0.954	0.956	0.610	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.380
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	0.003	1.461	0.66	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.187	0.187	0.187	0.189	0.181	0.184	0.184	0.185	0.192	0.192	0.192	0.187	0.187	0.187	0.187	0.195	0.196	0.186	0.185	0.185	0.185	0.185
Economic Effect	0.002	0.015	0.004	0.016	0.004	0.010	0.001	0.011	0.002	0.033	0.035	0.008	0.007	0.054	0.010	0.001	0.001	0.007	0.011	0.015	0.004	0.034
Panel A.3: $h = 1$ year lagged Green Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio GPO, $h = 1$	0.036	0.122	-0.099	0.027	-0.210	-1.720	-2.515**	-1.619	0.101	0.107*	0.132*	-0.019	0.015	0.252	0.067	0.044	-0.004	-0.143	0.000	0.000	0.000	0.000**
	(0.067)	(0.090)	(0.140)	(0.045)	(1.183)	(1.162)	(1.169)	(0.944)	(0.127)	(0.057)	(0.062)	(0.092)	(0.101)	(0.147)	(0.120)	(0.054)	(0.048)	(0.174)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	14806	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R^2	0.781	0.689	0.572	0.781	0.789	0.790	0.610	0.768	0.624	0.594	0.455	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.725	0.479	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	0.003	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.174	0.174	0.174	0.176	0.166	0.167	0.167	0.170	0.176	0.176	0.176	0.179	0.179	0.179	0.179	0.181	0.182	0.172	0.170	0.170	0.170	0.170
Economic Effect	0.003	0.013	0.010	0.005	0.001	0.012	0.019	0.010	0.012	0.028	0.042	0.002	0.001	0.031	0.008	0.003	0.000	0.008	0.010	0.0010	0.006	0.025
Panel A.4: $h = 3$ year lagged Green Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio US, $h = 3$	-0.131	0.044	-0.401***	-0.128**	0.181	-0.462	-1.317	-0.587	0.099	0.094	0.138*	0.014	0.024	-0.071	-0.032	0.051	0.055	-0.297*	0.000	0.000	-0.000	0.000
	(0.080)	(0.081)	(0.082)	(0.051)	(1.091)	(1.003)	(1.101)	(0.926)	(0.108)	(0.055)	(0.068)	(0.140)	(0.141)	(0.090)	(0.095)	(0.047)	(0.043)	(0.142)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	11512	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
Adj. R^2	0.768	0.680	0.543	0.770	0.806	0.801	0.610	0.767	0.624	0.619	0.482	0.957	0.959	0.612	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.94	24.117	21.706	0.003	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.175	0.175	0.175	0.178	0.172	0.173	0.173	0.176	0.179	0.179	0.179	0.190	0.190	0.190	0.190	0.184	0.185	0.176	0.176	0.176	0.176	0.176
Economic Effect	0.012	0.005	0.040	0.023	0.001	0.003	0.011	0.020	0.012	0.025	0.045	0.001	0.002	0.009	0.004	0.003	0.005	0.017	0.020	0.029	0.001	0.01
Panel A.5: $h = 3$ year lagged Green Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio EPO, $h = 3$	-0.077	-0.095	-0.054	-0.097**	-0.802	-0.744	-0.806	-0.693	-0.062	0.041	0.038	-0.038	-0.053	0.074	0.139	0.029	0.035	0.186	0.000*	0.000	0.000	0.000*
	(0.099)	(0.098)	(0.082)	(0.039)	(0.918)	(0.917)	(0.981)	(0.864)	(0.086)	(0.061)	(0.060)	(0.108)	(0.111)	(0.141)	(0.103)	(0.041)	(0.034)	(0.145)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	8752	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
Adj. R^2	0.768	0.682	0.531	0.761	0.797	0.793	0.610	0.736	0.624	0.633	0.510	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.736	0.656	0.421	0.350
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	0.003	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.184	0.184	0.184	0.185	0.180	0.183	0.183	0.177	0.192	0.192	0.192	0.187	0.187	0.187	0.187	0.191	0.192	0.181	0.177	0.177	0.177	0.177
Economic Effect	0.007	0.011	0.006	0.018	0.006	0.006	0.007	0.017	0.008	0.012	0.013	0.003	0.004	0.009	0.018	0.002	0.003	0.011	0.017	0.013	0.015	0.037
Panel A.6: $h = 3$ year lagged Green Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio GPO, $h = 3$	-0.038	0.129	-0.292***	-0.100	-0.661	-1.176	-1.351	-1.205	0.093	0.095	0.127*	-0.103	-0.100	-0.281	0.001	0.032	0.026	-0.326	0.000	0.000	-0.000	0.000
	(0.106)	(0.094)	(0.082)	(0.060)	(1.015)	(1.033)	(1.377)	(0.810)	(0.112)	(0.056)	(0.068)	(0.134)	(0.133)	(0.147)	(0.096)	(0.053)	(0.056)	(0.234)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	12638	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
Adj. R^2	0.776	0.686	0.561	0.778	0.806	0.801	0.618	0.765	0.619	0.592	0.457	0.949	0.951	0.619	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	0.003	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.170	0.170	0.170	0.171	0.165	0.167	0.167	0.169	0.175	0.175	0.175	0.178	0.178	0.178	0.178	0.179	0.180	0.169	0.169	0.169	0.169	0.169
Economic Effect	0.003	0.013	0.028	0.017	0.004	0.008	0.010	0.005	0.011	0.024	0.039	0.008	0.008	0.034	0.000	0.002	0.002	0.018	0.005	0.015	0.007	0.017
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.28: Sustainability Metrics On Climate Patent Ratios

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h = 1$ year lagged Climate Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio US, $h = 1$	-0.009	0.010	-0.070	-0.046	3.500*	1.132	-0.572	1.276	0.060	-0.056	0.026	-0.128	-0.131	0.025	-0.042	0.052	0.052	0.279	0.000*	0.000	0.000	0.000
	(0.103)	(0.113)	(0.188)	(0.051)	(1.876)	(1.520)	(1.547)	(1.316)	(0.177)	(0.078)	(0.102)	(0.182)	(0.187)	(0.190)	(0.096)	(0.055)	(0.057)	(0.232)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	13503	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R^2	0.773	0.684	0.552	0.772	0.791	0.790	0.603	0.767	0.632	0.624	0.481	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.47	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	0.003	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.101	0.101	0.101	0.102	0.105	0.105	0.105	0.102	0.099	0.099	0.099	0.099	0.099	0.099	0.099	0.108	0.108	0.102	0.102	0.102	0.102	0.102
Economic Effect	0.000	0.001	0.004	0.005	0.015	0.005	0.003	0.012	0.004	0.008	0.005	0.006	0.006	0.002	0.003	0.002	0.003	0.009	0.012	0.004	0.017	0.013
Panel A.2: $h = 1$ year lagged Climate Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio EPO, $h = 1$	0.024	-0.167	0.211	-0.032	0.635	0.909	-0.528	1.573	0.185	-0.063	-0.013	-0.156	-0.180	0.176	-0.095	0.034	0.075	0.177	-0.000	0.000	-0.000	0.000***
	(0.114)	(0.172)	(0.164)	(0.073)	(1.429)	(1.607)	(1.721)	(1.245)	(0.121)	(0.070)	(0.094)	(0.109)	(0.110)	(0.382)	(0.151)	(0.062)	(0.078)	(0.248)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	10355	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R^2	0.771	0.690	0.536	0.763	0.783	0.789	0.602	0.759	0.629	0.627	0.490	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.380
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	0.003	1.461	0.660	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.106	0.106	0.106	0.107	0.113	0.112	0.112	0.107	0.110	0.110	0.110	0.098	0.098	0.098	0.098	0.114	0.114	0.106	0.107	0.107	0.107	0.107
Economic Effect	0.001	0.011	0.013	0.004	0.003	0.004	0.003	0.001	0.014	0.011	0.003	0.007	0.008	0.012	0.006	0.001	0.004	0.006	0.001	0.008	0.005	0.022
Panel A.3: $h = 1$ year lagged Climate Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio GPO, $h = 1$	0.078	0.080	0.007	0.027	2.340	2.479	0.056	2.223	0.112	-0.172	-0.066	-0.166	-0.172	0.161	0.002	0.048	0.066	-0.068	0.000	-0.000	0.000	0.000
	(0.092)	(0.159)	(0.191)	(0.065)	(1.497)	(1.458)	(1.642)	(1.359)	(0.210)	(0.122)	(0.140)	(0.152)	(0.151)	(0.240)	(0.140)	(0.070)	(0.059)	(0.209)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	14806	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R^2	0.781	0.688	0.572	0.781	0.789	0.790	0.610	0.768	0.624	0.594	0.454	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.725	0.479	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	0.003	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.097	0.097	0.097	0.098	0.101	0.100	0.100	0.095	0.096	0.096	0.096	0.093	0.093	0.093	0.093	0.104	0.104	0.096	0.095	0.095	0.095	0.095
Economic Effect	0.004	0.005	0.000	0.003	0.009	0.010	0.000	0.002	0.007	0.024	0.011	0.007	0.007	0.010	0.000	0.002	0.003	0.002	0.002	0.0010	0.003	0.019
Panel A.4: $h = 3$ year lagged Climate Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio US, $h = 3$	-0.183*	0.240	-0.002	0.012	-0.132	-0.749	-0.293	0.579	0.123	-0.042	0.048	0.318	0.321	0.386	0.045	-0.033	-0.046	-0.366**	0.000	0.000	-0.000	0.000
	(0.092)	(0.140)	(0.134)	(0.060)	(1.725)	(1.559)	(1.440)	(1.456)	(0.169)	(0.077)	(0.105)	(0.142)	(0.141)	(0.251)	(0.156)	(0.075)	(0.058)	(0.155)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	11512	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
Adj. R^2	0.768	0.680	0.543	0.769	0.806	0.801	0.610	0.767	0.624	0.618	0.48	0.957	0.959	0.613	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.94	24.117	21.706	0.003	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.102	0.102	0.102	0.104	0.107	0.106	0.106	0.102	0.104	0.104	0.104	0.101	0.101	0.101	0.101	0.111	0.111	0.105	0.102	0.102	0.102	0.102
Economic Effect	0.009	0.015	0.000	0.001	0.001	0.003	0.001	0.011	0.009	0.007	0.009	0.014	0.014	0.026	0.003	0.001	0.002	0.012	0.011	0.008	0.006	0.011
Panel A.5: $h = 3$ year lagged Climate Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio EPO, $h = 3$	-0.234*	-0.092	0.081	0.012	-0.399	-0.969	-1.490	-0.541	0.212*	-0.039	0.023	-0.145	-0.166	-0.177	-0.049	-0.000	-0.047	-0.139	0.001***	0.000	-0.000	0.000
	(0.112)	(0.101)	(0.118)	(0.066)	(1.342)	(1.455)	(1.485)	(1.411)	(0.101)	(0.062)	(0.073)	(0.142)	(0.144)	(0.284)	(0.170)	(0.029)	(0.038)	(0.230)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	8752	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
Adj. R^2	0.768	0.682	0.531	0.760	0.797	0.793	0.610	0.737	0.624	0.633	0.509	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.737	0.656	0.421	0.350
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	0.003	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.113	0.113	0.113	0.114	0.120	0.119	0.119	0.108	0.119	0.119	0.119	0.108	0.108	0.108	0.108	0.120	0.120	0.112	0.108	0.108	0.108	0.108
Economic Effect	0.013	0.006	0.005	0.001	0.002	0.005	0.008	0.023	0.017	0.007	0.005	0.007	0.008	0.013	0.004	0.000	0.003	0.005	0.023	0.017	0.005	0.049
Panel A.6: $h = 3$ year lagged Climate Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio GPO, $h = 3$	-0.142	0.096	0.062	-0.052	1.412	1.641	-1.660	1.465	0.273	-0.162	-0.033	0.212	0.206	0.372	-0.096	-0.084	-0.068	-0.643	0.000*	0.000**	-0.000	0.000
	(0.088)	(0.158)	(0.147)	(0.073)	(1.506)	(1.230)	(1.695)	(0.992)	(0.222)	(0.122)	(0.150)	(0.172)	(0.172)	(0.237)	(0.135)	(0.057)	(0.060)	(0.424)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	12638	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
Adj. R^2	0.776	0.686	0.561	0.778	0.806	0.801	0.618	0.765	0.619	0.592	0.456	0.949	0.951	0.619	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	0.003	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.099	0.099	0.099	0.101	0.106	0.105	0.105	0.098	0.099	0.099	0.099	0.098	0.098	0.098	0.098	0.109	0.109	0.100	0.098	0.098	0.098	0.098
Economic Effect	0.007	0.006	0.003	0.005	0.006	0.007	0.008	0.015	0.019	0.024	0.006	0.009	0.009	0.025	0.007	0.003	0.003	0.021	0.015	0.016	0.002	0.019
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.29: Sustainability Metrics On Energy Patent Ratios (Robustness – Innovating Firms)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A.1: $h = 1$ year lagged Energy Ratio USPTO	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio US, $h = 1$	-0.194	-0.083	0.229	0.085	2.718	-0.057	0.257	-0.141	0.277*	0.091	0.143	0.029	0.084	-0.183	0.081	-0.014	-0.031	0.052	0.000	0.000	-0.000	0.000
	(0.152)	(0.133)	(0.190)	(0.077)	(1.910)	(1.796)	(2.131)	(1.559)	(0.142)	(0.110)	(0.106)	(0.301)	(0.270)	(0.175)	(0.154)	(0.066)	(0.072)	(0.226)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	7581	7581	7581	7289	7421	7706	7706	7706	7693	7693	7693	2892	2892	2892	2892	9650	9645	6850	5482	5482	5482	5482
Adj. R^2	0.793	0.711	0.516	0.756	0.834	0.816	0.679	0.696	0.615	0.658	0.495	0.962	0.965	0.600	0.817	0.957	0.945	0.742	0.802	0.770	0.461	0.447
Dep. Variable: STD	1.871	1.68	1.713	0.967	23.263	22.564	21.299	17.706	1.474	0.757	0.589	2.588	2.584	1.500	1.468	2.816	2.054	3.15	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.175	0.175	0.175	0.177	0.173	0.175	0.175	0.175	0.183	0.183	0.183	0.179	0.179	0.179	0.179	0.187	0.187	0.175	0.175	0.175	0.175	0.175
Economic Effect	0.018	0.009	0.023	0.015	0.020	0.000	0.002	0.001	0.034	0.022	0.045	0.002	0.006	0.022	0.010	0.001	0.003	0.003	0.001	0.005	0.005	0.018
Panel A.2: $h = 1$ year lagged Energy Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio EPO, $h = 1$	-0.079	0.134	0.263	0.042	0.088	-0.712	-1.187	-0.792	0.224	0.150	0.184*	-0.631	-0.522	-0.084	-0.183	-0.091	-0.029	-0.049	0.000	-0.000	0.000*	0.000
	(0.129)	(0.178)	(0.235)	(0.090)	(1.780)	(1.715)	(1.818)	(1.322)	(0.160)	(0.095)	(0.096)	(0.328)	(0.279)	(0.418)	(0.143)	(0.055)	(0.059)	(0.246)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5150	5150	5150	4962	5222	5354	5354	5354	5306	5306	5306	1960	1960	1960	1960	6325	6315	4965	3809	3809	3809	3809
Adj. R^2	0.794	0.724	0.525	0.757	0.825	0.817	0.689	0.66	0.623	0.689	0.556	0.943	0.946	0.600	0.827	0.965	0.945	0.745	0.799	0.762	0.458	0.453
Dep. Variable: STD	1.793	1.707	1.655	0.963	21.399	21.542	20.893	16.861	1.518	0.787	0.62	2.709	2.705	1.527	1.467	2.681	1.962	3.153	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.195	0.195	0.195	0.197	0.194	0.194	0.194	0.194	0.207	0.207	0.207	0.193	0.193	0.193	0.193	0.203	0.203	0.193	0.192	0.192	0.192	0.192
Economic Effect	0.009	0.015	0.031	0.009	0.001	0.006	0.011	0.009	0.031	0.039	0.062	0.045	0.037	0.011	0.024	0.007	0.003	0.003	0.001	0.01	0.092	0.067
Panel A.3: $h = 1$ year lagged Energy Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio GPO, $h = 1$	-0.073	0.199	-0.107	0.076	2.533	-0.914	-0.577	-0.504	0.191	0.108	0.118	0.011	0.066	0.013	0.045	-0.027	-0.056	-0.153	-0.000	-0.000	-0.000	0.000
	(0.180)	(0.150)	(0.216)	(0.074)	(2.161)	(2.621)	(2.233)	(1.903)	(0.150)	(0.102)	(0.097)	(0.207)	(0.184)	(0.206)	(0.185)	(0.086)	(0.064)	(0.238)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9408	9408	9408	9072	9161	9557	9557	9557	9429	9429	9429	3717	3717	3717	3717	12419	12410	8515	6772	6772	6772	6772
Adj. R^2	0.796	0.712	0.540	0.769	0.831	0.816	0.680	0.704	0.621	0.630	0.482	0.953	0.956	0.610	0.817	0.956	0.942	0.747	0.793	0.748	0.456	0.417
Dep. Variable: STD	1.899	1.679	1.732	0.992	23.53	22.898	21.371	17.894	1.485	0.748	0.595	2.497	2.493	1.498	1.465	2.855	2.111	3.162	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.164	0.164	0.164	0.165	0.164	0.165	0.165	0.165	0.175	0.175	0.175	0.167	0.167	0.167	0.167	0.182	0.182	0.170	0.161	0.161	0.161	0.161
Economic Effect	0.006	0.019	0.010	0.013	0.018	0.007	0.004	0.005	0.023	0.025	0.035	0.001	0.004	0.001	0.005	0.002	0.005	0.008	0.007	0.0070	0.027	0.006
Panel A.4: $h = 3$ year lagged Energy Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio US, $h = 3$	-0.140	0.029	0.257	0.018	0.510	-2.506	1.620	-1.666	0.240	0.108	0.152	-0.209	-0.212	0.051	-0.071	-0.059	0.024	-0.308	-0.000	-0.000	-0.000	0.000
	(0.102)	(0.166)	(0.181)	(0.089)	(1.839)	(2.027)	(2.120)	(1.695)	(0.155)	(0.139)	(0.132)	(0.229)	(0.231)	(0.314)	(0.190)	(0.083)	(0.104)	(0.256)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	6742	6742	6742	6742	6047	6233	6233	6233	6462	6462	6462	2778	2778	2778	2778	7807	7800	6006	4301	4301	4301	4301
Adj. R^2	0.831	0.737	0.552	0.764	0.844	0.824	0.701	0.700	0.600	0.651	0.501	0.962	0.965	0.603	0.814	0.958	0.942	0.752	0.805	0.767	0.411	0.573
Dep. Variable: STD	1.857	1.679	1.664	0.965	22.728	21.942	20.846	17.255	1.468	0.761	0.591	2.646	2.643	1.516	1.467	2.775	1.998	3.115	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.175	0.175	0.175	0.175	0.170	0.170	0.170	0.170	0.185	0.185	0.185	0.182	0.182	0.182	0.182	0.185	0.185	0.175	0.172	0.172	0.172	0.172
Economic Effect	0.013	0.003	0.027	0.003	0.004	0.019	0.013	0.016	0.03	0.026	0.047	0.014	0.015	0.006	0.009	0.004	0.002	0.017	0.009	0.002	0.009	0.007
Panel B.3: $h = 3$ year lagged Energy Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio EPO, $h = 3$	-0.152	-0.286	-0.138	-0.176*	-2.645	-1.697	-0.632	-2.890*	0.121	0.145	0.174	-0.467	-0.448	0.217	0.343	-0.033	0.010	0.474	0.000	0.000	0.000	0.000
	(0.123)	(0.162)	(0.257)	(0.090)	(2.098)	(1.385)	(1.985)	(1.421)	(0.132)	(0.101)	(0.103)	(0.347)	(0.338)	(0.305)	(0.183)	(0.090)	(0.088)	(0.346)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	4629	4629	4629	4629	4135	4218	4218	4218	4463	4463	4463	2060	2060	2060	2060	5173	5163	4292	2962	2962	2962	2962
Adj. R^2	0.827	0.741	0.559	0.754	0.824	0.819	0.710	0.647	0.606	0.681	0.572	0.956	0.960	0.596	0.826	0.967	0.94	0.745	0.776	0.696	0.419	0.673
Dep. Variable: STD	1.772	1.715	1.622	0.971	20.497	20.687	20.594	16.204	1.532	0.799	0.637	2.710	2.706	1.538	1.483	2.640	1.930	3.106	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.199	0.199	0.199	0.199	0.193	0.193	0.193	0.193	0.212	0.212	0.212	0.198	0.198	0.198	0.198	0.204	0.204	0.193	0.192	0.192	0.192	0.192
Economic Effect	0.017	0.033	0.017	0.036	0.025	0.016	0.006	0.034	0.017	0.038	0.058	0.034	0.033	0.028	0.046	0.003	0.001	0.029	0.022	0.016	0.029	0.038
Panel B.3: $h = 3$ year lagged Energy Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Ratio GPO, $h = 3$	-0.180	0.174	0.069	0.009	0.104	-1.478	0.918	-0.885	0.139	0.097	0.103	-0.863	-0.868	-0.017	0.143	-0.087	-0.066	-0.318	-0.000	-0.000	-0.000	0.000
	(0.123)	(0.144)	(0.235)	(0.095)	(2.460)	(2.390)	(2.118)	(1.698)	(0.141)	(0.119)	(0.111)	(0.448)	(0.448)	(0.434)	(0.185)	(0.065)	(0.058)	(0.295)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8429	8429	8429	8429	7516	7777	7777	7777	7960	7960	7960	3539	3539	3539	3539	10090	10084	7451	5303	5303	5303	5303
Adj. R^2	0.831	0.735	0.567	0.771	0.844	0.824	0.700	0.710	0.610	0.622	0.483	0.950	0.952	0.606	0.811	0.958	0.942	0.754	0.802	0.770	0.427	0.536
Dep. Variable: STD	1.887	1.679	1.684	0.987	23.144	22.287	20.946	17.45	1.486	0.756	0.602	2.567	2.565	1.509	1.464	2.816	2.066	3.124	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.169	0.169	0.169	0.169	0.164	0.165	0.165	0.165	0.180	0.180	0.180	0.174	0.174	0.174	0.174	0.182	0.183	0.170	0.157	0.157	0.157	0.157
Economic Effect	0.016	0.017	0.007	0.001	0.001	0.011	0.007	0.008	0.017	0.023	0.031	0.058	0.059	0.002	0.017	0.006	0.006	0.017	0.014	0.019	0.018	0.047
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.30: Sustainability Metrics On Green Patent Ratios (Robustness – Innovating Firms)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. I condition on innovating firms only. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A.1: $h = 1$ year lagged Green Ratio USPTO	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio US, $h = 1$	-0.067	-0.203*	0.033	-0.069	-0.929	-2.336	-0.314	-1.905	0.079	0.094	0.147**	0.041	0.054	0.212	-0.077	0.054	0.098	-0.064	0.000*	0.000	0.000	0.000
	(0.111)	(0.101)	(0.183)	(0.062)	(1.336)	(1.625)	(1.758)	(1.226)	(0.142)	(0.061)	(0.065)	(0.133)	(0.136)	(0.166)	(0.188)	(0.076)	(0.058)	(0.293)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8997	8997	8997	8348	10557	11180	11180	11180	8568	8568	8568	3318	3318	3318	3318	13087	13006	8267	8398	8398	8398	8398
Adj. R^2	0.757	0.692	0.508	0.760	0.775	0.783	0.597	0.672	0.632	0.657	0.503	0.959	0.961	0.589	0.819	0.953	0.940	0.728	0.778	0.746	0.383	0.378
Dep. Variable: STD	1.896	1.676	1.717	0.972	24.083	23.943	21.796	18.471	1.475	0.733	0.571	2.552	2.550	1.486	1.465	2.799	2.045	3.146	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.197	0.197	0.197	0.201	0.187	0.190	0.190	0.190	0.203	0.203	0.203	0.209	0.209	0.209	0.209	0.209	0.209	0.192	0.193	0.193	0.193	0.193
Economic Effect	0.007	0.024	0.004	0.014	0.007	0.019	0.003	0.020	0.011	0.026	0.052	0.003	0.004	0.030	0.011	0.004	0.010	0.004	0.026	0.013	0.048	0.046
Panel A.2: $h = 1$ year lagged Green Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio EPO, $h = 1$	0.053	-0.041	0.160	0.045	-1.966	-3.383**	-0.909	-2.731**	0.017	0.140	0.142	-0.347	-0.328	0.409	-0.193	-0.075	-0.033	-0.209	0.000*	0.000	0.000	0.000
	(0.133)	(0.124)	(0.138)	(0.065)	(1.357)	(1.566)	(1.694)	(1.249)	(0.143)	(0.081)	(0.088)	(0.212)	(0.212)	(0.237)	(0.230)	(0.071)	(0.065)	(0.240)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5843	5843	5843	5423	7318	7621	7621	7621	5689	5689	5689	2122	2122	2122	2122	8285	8214	5748	5520	5520	5520	5520
Adj. R^2	0.742	0.708	0.519	0.754	0.761	0.782	0.603	0.638	0.625	0.671	0.520	0.950	0.953	0.584	0.831	0.960	0.938	0.734	0.785	0.744	0.447	0.518
Dep. Variable: STD	1.814	1.706	1.688	0.952	22.511	23.342	21.51	17.721	1.529	0.767	0.605	2.739	2.736	1.539	1.493	2.655	1.975	3.157	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.210	0.210	0.210	0.213	0.200	0.205	0.205	0.205	0.218	0.218	0.218	0.211	0.211	0.211	0.211	0.222	0.223	0.203	0.209	0.209	0.209	0.209
Economic Effect	0.006	0.005	0.020	0.010	0.017	0.030	0.009	0.032	0.002	0.04	0.051	0.027	0.025	0.056	0.027	0.006	0.004	0.013	0.023	0.019	0.046	0.048
Panel A.3: $h = 1$ year lagged Green Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio GPO, $h = 1$	0.079	0.212*	-0.068	0.030	0.566	-2.758	-2.534	-2.787*	0.063	0.099	0.133*	0.088	0.101	0.438**	-0.103	0.077	0.031	-0.173	0.000	0.000	0.000	0.000*
	(0.129)	(0.117)	(0.155)	(0.055)	(1.643)	(1.833)	(1.772)	(1.399)	(0.168)	(0.067)	(0.065)	(0.130)	(0.132)	(0.117)	(0.125)	(0.083)	(0.063)	(0.247)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10776	10776	10776	10034	12849	13668	13668	13668	10223	10223	10223	4005	4005	4005	4005	16452	16356	9928	10183	10183	10183	10183
Adj. R^2	0.762	0.683	0.527	0.766	0.775	0.783	0.598	0.681	0.625	0.624	0.473	0.955	0.956	0.595	0.820	0.954	0.938	0.734	0.770	0.738	0.440	0.328
Dep. Variable: STD	1.909	1.672	1.742	0.986	24.384	24.157	21.799	18.571	1.489	0.734	0.583	2.506	2.503	1.493	1.470	2.847	2.106	3.168	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.188	0.188	0.188	0.190	0.176	0.178	0.178	0.178	0.192	0.192	0.192	0.198	0.198	0.198	0.198	0.199	0.199	0.184	0.183	0.183	0.183	0.183
Economic Effect	0.008	0.024	0.007	0.006	0.004	0.020	0.021	0.027	0.008	0.026	0.044	0.007	0.008	0.058	0.014	0.005	0.003	0.010	0.021	0.0070	0.004	0.046
Panel A.4: $h = 3$ year lagged Green Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio US, $h = 3$	-0.062	-0.163	-0.249	-0.156*	1.709	1.043	-1.892	0.101	0.056	0.082	0.128	0.152	0.150	-0.277	0.133	0.176**	0.219***	-0.357	0.001	0.000	-0.000	0.000
	(0.146)	(0.116)	(0.155)	(0.084)	(1.817)	(1.777)	(1.702)	(1.639)	(0.153)	(0.079)	(0.076)	(0.165)	(0.166)	(0.182)	(0.152)	(0.073)	(0.067)	(0.240)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8243	8243	8243	7652	9327	9756	9756	9756	7161	7161	7161	3163	3163	3163	3163	11839	11790	7764	7210	7210	7210	7210
Adj. R^2	0.763	0.695	0.517	0.765	0.787	0.795	0.609	0.670	0.614	0.645	0.492	0.968	0.970	0.592	0.815	0.952	0.935	0.721	0.778	0.743	0.388	0.419
Dep. Variable: STD	1.900	1.683	1.705	0.965	23.677	23.467	21.502	18.045	1.475	0.728	0.570	2.580	2.578	1.507	1.469	2.771	2.012	3.150	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.190	0.190	0.190	0.192	0.185	0.188	0.188	0.188	0.197	0.197	0.197	0.204	0.204	0.204	0.204	0.204	0.205	0.186	0.193	0.193	0.193	0.193
Economic Effect	0.006	0.018	0.028	0.031	0.013	0.008	0.017	0.001	0.008	0.022	0.044	0.012	0.012	0.037	0.018	0.013	0.022	0.021	0.032	0.045	0.025	0.015
Panel A.5: $h = 3$ year lagged Green Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio EPO, $h = 3$	-0.115	-0.248	-0.102	-0.151*	-2.250	-2.264	-1.179	-2.962**	-0.054	0.089	0.099	0.027	0.006	0.112	0.229	-0.009	-0.005	0.315	0.001**	0.000**	0.000	0.000**
	(0.140)	(0.162)	(0.148)	(0.080)	(1.479)	(1.649)	(1.539)	(1.346)	(0.131)	(0.074)	(0.080)	(0.189)	(0.189)	(0.258)	(0.150)	(0.056)	(0.068)	(0.261)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5464	5464	5464	5068	6362	6561	6561	6561	4778	4778	4778	2192	2192	2192	2192	7584	7535	5399	4734	4734	4734	4734
Adj. R^2	0.753	0.703	0.523	0.752	0.781	0.790	0.618	0.634	0.614	0.665	0.540	0.963	0.966	0.579	0.823	0.959	0.934	0.718	0.761	0.695	0.401	0.522
Dep. Variable: STD	1.829	1.722	1.676	0.955	21.793	22.672	21.406	17.227	1.529	0.770	0.613	2.654	2.651	1.541	1.491	2.632	1.958	3.138	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.204	0.204	0.204	0.205	0.199	0.203	0.203	0.203	0.217	0.217	0.217	0.206	0.206	0.206	0.206	0.217	0.218	0.198	0.199	0.199	0.199	0.199
Economic Effect	0.013	0.029	0.012	0.032	0.021	0.020	0.011	0.035	0.008	0.025	0.035	0.002	0.000	0.015	0.032	0.001	0.001	0.020	0.038	0.040	0.030	0.053
Panel A.6: $h = 3$ year lagged Green Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Ratio GPO, $h = 3$	-0.037	0.094	-0.269*	-0.120	-0.716	-0.904	-2.831	-1.953	0.029	0.085	0.114	-0.435	-0.448	-0.292	0.324	0.076	0.163**	-0.468	0.000	0.000	-0.000	0.000
	(0.172)	(0.143)	(0.152)	(0.079)	(1.682)	(1.524)	(1.859)	(1.195)	(0.152)	(0.073)	(0.074)	(0.293)	(0.293)	(0.202)	(0.201)	(0.065)	(0.072)	(0.298)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10016	10016	10016	9344	11507	12076	12076	12076	8642	8642	8642	3861	3861	3861	3861	15092	15035	9370	8807	8807	8807	8807
Adj. R^2	0.764	0.689	0.534	0.770	0.791	0.795	0.608	0.680	0.620	0.624	0.474	0.957	0.959	0.590	0.819	0.953	0.936	0.727	0.770	0.730	0.422	0.383
Dep. Variable: STD	1.909	1.682	1.730	0.981	24.087	23.757	21.556	18.186	1.483	0.725	0.578	2.508	2.506	1.508	1.473	2.817	2.073	3.179	0.003	0.002	0.000	0.000
Ind. Variable: STD	0.182	0.182	0.182	0.184	0.174	0.176	0.176	0.176	0.190	0.190	0.190	0.191	0.191	0.191	0.191	0.195	0.195	0.178	0.181	0.181	0.181	0.181
Economic Effect	0.003	0.01	0.028	0.022	0.005	0.007	0.023	0.019	0.004	0.022	0.038	0.033	0.034	0.037	0.042	0.005	0.015	0.026	0.007	0.017	0.007	0.032
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.31: Sustainability Metrics On Climate Patent Ratios (Robustness – Innovating Firms)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. I condition on innovating firms only. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h=1$ year lagged Climate Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio US, $h=1$	0.035	-0.085	0.097	0.059	3.427	2.755	-0.602	2.056	-0.041	-0.082	0.006	-0.330	-0.323	-0.119	-0.021	-0.103	-0.013	1.064**	0.000	0.000	0.000	0.000
	(0.201)	(0.215)	(0.174)	(0.081)	(2.977)	(2.541)	(3.151)	(2.395)	(0.225)	(0.088)	(0.097)	(0.416)	(0.418)	(0.249)	(0.193)	(0.080)	(0.076)	(0.377)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4709	4709	4709	4290	6000	6239	6239	6239	4514	4514	4514	1554	1554	1554	1554	6597	6525	4541	4686	4686	4686	4686
Adj. R^2	0.738	0.707	0.507	0.762	0.752	0.780	0.576	0.618	0.644	0.696	0.589	0.962	0.966	0.608	0.856	0.968	0.944	0.725	0.737	0.62	0.526	0.343
Dep. Variable: STD	1.777	1.780	1.698	0.979	22.536	23.157	21.321	17.499	1.540	0.725	0.616	2.756	2.758	1.551	1.516	2.587	1.889	3.171	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.149	0.149	0.149	0.152	0.147	0.148	0.148	0.148	0.151	0.151	0.151	0.161	0.161	0.161	0.161	0.166	0.166	0.144	0.144	0.144	0.144	0.144
Economic Effect	0.003	0.007	0.008	0.009	0.022	0.018	0.004	0.017	0.004	0.017	0.001	0.019	0.019	0.012	0.002	0.007	0.001	0.048	0.015	0.002	0.018	0.028
Panel A.2: $h=1$ year lagged Climate Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio EPO, $h=1$	-0.013	-0.042	0.391	-0.085	0.081	0.079	-6.503*	0.729	0.287**	0.018	0.021	-0.789	-0.787	0.658	0.281	-0.024	-0.013	-0.102	0.000	0.000	0.000	0.000**
	(0.167)	(0.303)	(0.484)	(0.140)	(2.037)	(2.277)	(3.152)	(1.605)	(0.128)	(0.085)	(0.080)	(0.426)	(0.425)	(0.451)	(0.277)	(0.074)	(0.103)	(0.588)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2915	2915	2915	2667	4071	4178	4178	4178	2909	2909	2909	938	938	938	938	4243	4177	3077	3068	3068	3068	3068
Adj. R^2	0.717	0.729	0.509	0.769	0.724	0.770	0.589	0.584	0.630	0.723	0.647	0.948	0.954	0.582	0.855	0.975	0.936	0.710	0.739	0.676	0.435	0.350
Dep. Variable: STD	1.649	1.803	1.716	0.969	20.789	22.439	21.269	16.774	1.566	0.767	0.657	3.000	3.000	1.561	1.522	2.47	1.804	3.174	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.162	0.162	0.162	0.165	0.162	0.162	0.162	0.162	0.176	0.176	0.176	0.161	0.161	0.161	0.161	0.175	0.176	0.150	0.153	0.153	0.153	0.153
Economic Effect	0.001	0.004	0.037	0.014	0.001	0.001	0.050	0.007	0.032	0.004	0.006	0.042	0.042	0.068	0.030	0.002	0.001	0.005	0.008	0.020	0.015	0.086
Panel A.3: $h=1$ year lagged Climate Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio GPO, $h=1$	0.313**	-0.037	-0.087	-0.036	4.449*	4.449*	-0.602	4.002**	0.032	-0.163	-0.067	-0.238	-0.239	0.237	-0.373	0.013	-0.047	0.325	0.000	-0.000	0.000	0.000
	(0.143)	(0.225)	(0.256)	(0.094)	(2.496)	(2.324)	(2.511)	(1.861)	(0.223)	(0.102)	(0.099)	(0.000)	(0.000)	(0.470)	(0.274)	(0.077)	(0.069)	(0.414)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6282	6282	6282	5744	8248	8628	8628	8628	5972	5972	5972	2105	2105	2105	2105	9411	9305	6080	6465	6465	6465	6465
Adj. R^2	0.742	0.700	0.511	0.768	0.762	0.784	0.579	0.644	0.635	0.658	0.561	0.957	0.961	0.612	0.849	0.964	0.941	0.730	0.728	0.622	0.522	0.312
Dep. Variable: STD	1.810	1.759	1.728	0.992	23.588	23.752	21.600	17.966	1.551	0.745	0.640	2.601	2.599	1.545	1.491	2.676	1.967	3.198	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.135	0.135	0.135	0.137	0.132	0.132	0.132	0.132	0.137	0.137	0.137	0.136	0.136	0.136	0.136	0.150	0.150	0.127	0.126	0.126	0.126	0.126
Economic Effect	0.023	0.003	0.007	0.005	0.025	0.025	0.004	0.029	0.003	0.030	0.014	0.012	0.013	0.021	0.034	0.001	0.004	0.013	0.001	0.0030	0.002	0.038
Panel A.4: $h=3$ year lagged Climate Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio US, $h=3$	-0.101	-0.033	0.040	0.193	-2.379	-2.279	2.458	-0.634	-0.023	-0.051	0.024	0.500	0.495	0.203	0.101	-0.138	-0.051	-0.287	0.001	0.000*	-0.000	0.000
	(0.188)	(0.173)	(0.244)	(0.142)	(2.270)	(1.978)	(2.668)	(2.050)	(0.223)	(0.091)	(0.103)	(0.282)	(0.283)	(0.442)	(0.296)	(0.081)	(0.083)	(0.453)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4560	4560	4560	4173	5314	5455	5455	5455	3948	3948	3948	1677	1677	1677	1677	6236	6184	4461	4048	4048	4048	4048
Adj. R^2	0.726	0.705	0.516	0.758	0.764	0.788	0.587	0.609	0.618	0.673	0.586	0.962	0.966	0.583	0.837	0.965	0.940	0.710	0.708	0.572	0.408	0.339
Dep. Variable: STD	1.787	1.770	1.703	0.964	21.874	22.218	20.893	16.782	1.536	0.722	0.615	2.696	2.696	1.547	1.499	2.570	1.867	3.170	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.146	0.146	0.146	0.150	0.147	0.147	0.147	0.147	0.155	0.155	0.155	0.142	0.142	0.142	0.142	0.167	0.167	0.144	0.140	0.140	0.140	0.140
Economic Effect	0.008	0.003	0.003	0.030	0.016	0.015	0.017	0.006	0.002	0.011	0.006	0.026	0.026	0.019	0.010	0.009	0.005	0.013	0.028	0.031	0.025	0.036
Panel A.5: $h=3$ year lagged Climate Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio EPO, $h=3$	-0.222	-0.785***	-0.299	-0.306*	-0.608	-3.792	-4.952*	-3.653	0.231**	0.053	0.054	-0.057	-0.146	-0.594	-0.162	-0.034	-0.114	-0.399	0.001***	0.000*	-0.000	0.000
	(0.142)	(0.205)	(0.300)	(0.157)	(1.635)	(2.582)	(2.719)	(2.420)	(0.074)	(0.073)	(0.069)	(0.612)	(0.616)	(0.342)	(0.443)	(0.077)	(0.100)	(0.506)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	2882	2882	2882	2651	3597	3655	3655	3655	2545	2545.000	2545	1118	1118	1118	1118	4069	4022	3003	2689	2689	2689	2689
Adj. R^2	0.717	0.711	0.518	0.749	0.746	0.773	0.598	0.566	0.621	0.730	0.659	0.958	0.962	0.564	0.823	0.971	0.932	0.702	0.719	0.618	0.403	0.446
Dep. Variable: STD	1.656	1.794	1.673	0.964	19.826	21.432	21.079	16.069	1.578	0.759	0.655	2.947	2.947	1.559	1.497	2.443	1.770	3.193	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.164	0.164	0.164	0.165	0.166	0.168	0.168	0.168	0.185	0.185	0.185	0.141	0.141	0.141	0.141	0.179	0.179	0.153	0.153	0.153	0.153	0.153
Economic Effect	0.022	0.072	0.029	0.052	0.005	0.030	0.039	0.038	0.027	0.013	0.015	0.003	0.007	0.054	0.015	0.002	0.012	0.019	0.058	0.044	0.012	0.103
Panel A.6: $h=3$ year lagged Climate Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Ratio GPO, $h=3$	-0.034	0.065	0.355	0.099	-0.426	0.574	-3.868	-1.150	0.167	-0.137	-0.043	0.461	0.444	0.179	-0.070	-0.103	0.052	0.034	0.000	0.000	0.000	0.000
	(0.146)	(0.205)	(0.237)	(0.112)	(2.343)	(2.032)	(2.505)	(1.639)	(0.238)	(0.110)	(0.118)	(0.379)	(0.380)	(0.337)	(0.230)	(0.103)	(0.082)	(0.418)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6161	6161	6161	5661	7484	7731	7731	7731	5225	5225	5225	2267	2267	2267	2267	9033	8970	6020	5680	5680	5680	5680
Adj. R^2	0.736	0.695	0.530	0.765	0.779	0.795	0.597	0.644	0.618	0.645	0.552	0.953	0.956	0.584	0.825	0.962	0.938	0.727	0.728	0.631	0.445	0.313
Dep. Variable: STD	1.816	1.751	1.738	0.985	22.992	23.075	21.267	17.375	1.551	0.741	0.640	2.565	2.561	1.543	1.477	2.661	1.958	3.199	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.136	0.136	0.136	0.140	0.137	0.137	0.137	0.137	0.138	0.138	0.138	0.128	0.128	0.128	0.128	0.152	0.151	0.131	0.126	0.126	0.126	0.126
Economic Effect	0.003	0.005	0.028	0.014	0.003	0.003	0.025	0.009	0.015	0.026	0.009	0.023	0.022	0.015	0.006	0.006	0.004	0.001	0.0200	0.008	0.009	0.051
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.32: Sustainability Metrics On Energy Citation Ratios (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h=1$ year lagged Energy Citation Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio US, $h=1$	-0.024	-0.019	0.095	0.049	-0.399	-0.188	0.001	-0.157	0.219***	0.118*	0.145*	0.012	0.013	0.107	0.072	-0.010	-0.062*	0.034	0.000	0.000	0.000	-0.000
	(0.078)	(0.073)	(0.067)	(0.037)	(0.934)	(0.849)	(1.087)	(0.666)	(0.069)	(0.063)	(0.075)	(0.086)	(0.081)	(0.089)	(0.096)	(0.032)	(0.031)	(0.121)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.773	0.684	0.552	0.772	0.790	0.790	0.603	0.708	0.633	0.625	0.483	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.470	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.167	0.167	0.167	0.170	0.157	0.156	0.156	0.156	0.173	0.173	0.173	0.169	0.169	0.169	0.169	0.163	0.164	0.169	0.152	0.152	0.152	0.152
Economic Effect	0.002	0.002	0.009	0.008	0.003	0.001	0.000	0.001	0.026	0.03	0.046	0.001	0.001	0.012	0.008	0.001	0.005	0.002	0.004	0.016	0.002	0.001
Panel A.2: $h=1$ year lagged Energy Citation Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio EPO, $h=1$	-0.049	-0.106	0.016	-0.039	0.147	0.395	-0.941	-0.622	0.079	0.046	0.039	-0.122	-0.113	-0.007	-0.066	0.012	-0.004	-0.026	0.000**	0.000*	0.000	-0.000
	(0.038)	(0.091)	(0.075)	(0.029)	(0.728)	(0.630)	(1.062)	(0.694)	(0.072)	(0.049)	(0.045)	(0.116)	(0.114)	(0.097)	(0.073)	(0.023)	(0.030)	(0.141)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.771	0.690	0.535	0.763	0.783	0.789	0.602	0.691	0.629	0.627	0.490	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.379
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.66	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.197	0.197	0.197	0.202	0.186	0.184	0.184	0.184	0.204	0.204	0.204	0.194	0.194	0.194	0.194	0.182	0.183	0.195	0.177	0.177	0.177	0.177
Economic Effect	0.005	0.013	0.002	0.008	0.001	0.003	0.008	0.006	0.011	0.014	0.015	0.011	0.01	0.001	0.009	0.001	0.000	0.002	0.020	0.019	0.019	0.016
Panel A.3: $h=1$ year lagged Energy Citation Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio GPO, $h=1$	-0.031	-0.012	0.097	0.048	-0.956	-1.013	-0.975	-0.521	0.194***	0.089	0.102	0.003	0.003	0.124	0.057	-0.009	-0.058*	-0.054	0.000	0.000	0.000	0.000
	(0.079)	(0.069)	(0.070)	(0.031)	(0.917)	(0.775)	(0.804)	(0.620)	(0.058)	(0.051)	(0.059)	(0.059)	(0.055)	(0.066)	(0.075)	(0.029)	(0.030)	(0.100)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.781	0.688	0.572	0.781	0.789	0.790	0.610	0.715	0.624	0.594	0.455	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.725	0.479	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.167	0.167	0.168	0.170	0.159	0.158	0.158	0.158	0.173	0.173	0.173	0.17	0.170	0.170	0.170	0.164	0.165	0.169	0.151	0.151	0.151	0.151
Economic Effect	0.003	0.001	0.009	0.008	0.006	0.007	0.007	0.004	0.023	0.023	0.032	0.000	0.000	0.015	0.007	0.000	0.004	0.003	0.003	0.0150	0.006	0.004
Panel A.4: $h=3$ year lagged Energy Citation Ratio USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio US, $h=3$	-0.159**	0.029	0.010	0.032	-1.874	-0.711	1.124	-0.807	0.242**	0.130*	0.146**	-0.165	-0.147	0.147	-0.021	-0.008	-0.053	0.045	0.000	0.000	0.000	-0.000
	(0.066)	(0.072)	(0.076)	(0.031)	(1.092)	(1.000)	(1.318)	(1.044)	(0.078)	(0.063)	(0.059)	(0.116)	(0.115)	(0.086)	(0.063)	(0.053)	(0.050)	(0.123)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.768	0.68	0.543	0.769	0.806	0.801	0.610	0.707	0.625	0.619	0.482	0.957	0.959	0.613	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.94	24.117	21.706	18.67	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.167	0.167	0.167	0.172	0.152	0.151	0.151	0.151	0.179	0.179	0.179	0.176	0.176	0.176	0.176	0.157	0.158	0.167	0.144	0.144	0.144	0.144
Economic Effect	0.013	0.003	0.001	0.006	0.011	0.004	0.008	0.007	0.030	0.035	0.048	0.013	0.012	0.018	0.003	0.000	0.004	0.002	0.010	0.016	0.016	0.006
Panel A.5: $h=3$ year lagged Energy Citation Ratio EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio EPO, $h=3$	-0.065	0.062	-0.195**	-0.022	-1.868**	-1.409*	-0.243	-1.894**	0.061	0.047	0.078	0.001	0.009	0.119	-0.011	0.018	-0.029	0.200	0.001**	0.000**	0.000*	0.000
	(0.054)	(0.068)	(0.079)	(0.028)	(0.827)	(0.769)	(0.854)	(0.749)	(0.056)	(0.042)	(0.050)	(0.048)	(0.051)	(0.100)	(0.062)	(0.041)	(0.026)	(0.145)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.768	0.682	0.531	0.760	0.797	0.793	0.610	0.682	0.624	0.633	0.510	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.737	0.657	0.423	0.349
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.199	0.199	0.199	0.205	0.179	0.178	0.178	0.178	0.211	0.211	0.211	0.207	0.207	0.207	0.207	0.178	0.178	0.195	0.173	0.173	0.173	0.173
Economic Effect	0.007	0.007	0.023	0.005	0.014	0.011	0.002	0.019	0.009	0.015	0.030	0.000	0.001	0.016	0.002	0.001	0.003	0.013	0.039	0.047	0.051	0.002
Panel A.6: $h=3$ year lagged Energy Citation Ratio GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Energy Cit. Ratio GPO, $h=3$	-0.126*	0.028	0.016	0.031	-2.545**	-1.153	1.099	-1.018	0.225**	0.110	0.126*	-0.149	-0.126	0.172	-0.017	-0.008	-0.049	0.086	0.000	0.000	0.000	0.000
	(0.068)	(0.078)	(0.071)	(0.026)	(1.038)	(0.918)	(1.210)	(0.918)	(0.079)	(0.064)	(0.062)	(0.086)	(0.083)	(0.085)	(0.060)	(0.055)	(0.045)	(0.131)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.776	0.686	0.561	0.778	0.806	0.801	0.618	0.716	0.620	0.592	0.457	0.949	0.951	0.619	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.169	0.169	0.169	0.173	0.155	0.154	0.154	0.154	0.178	0.178	0.178	0.177	0.177	0.177	0.177	0.157	0.157	0.167	0.144	0.144	0.144	0.144
Economic Effect	0.011	0.003	0.002	0.005	0.016	0.007	0.008	0.008	0.027	0.029	0.040	0.012	0.010	0.021	0.002	0.000	0.004	0.005	0.011	0.013	0.009	0.007
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.33: Sustainability Metrics On Green Citation Ratios (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h = 1$ year lagged Green Citation Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio US, $h = 1$	0.081	0.019	-0.078	0.008	-0.311	0.108	-0.697	-0.464	0.031	0.077	0.111*	-0.009	-0.009	0.081	0.035	-0.000	0.000	0.115	0.000	-0.000	0.000	0.000
	(0.047)	(0.048)	(0.098)	(0.029)	(0.765)	(0.696)	(0.761)	(0.558)	(0.072)	(0.053)	(0.062)	(0.079)	(0.078)	(0.085)	(0.103)	(0.036)	(0.027)	(0.103)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.773	0.684	0.552	0.772	0.790	0.790	0.603	0.708	0.632	0.625	0.482	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.470	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.197	0.197	0.197	0.200	0.194	0.195	0.195	0.195	0.195	0.195	0.195	0.204	0.204	0.204	0.204	0.204	0.204	0.196	0.195	0.195	0.195	0.195
Economic Effect	0.008	0.002	0.009	0.002	0.002	0.001	0.006	0.005	0.004	0.023	0.040	0.001	0.001	0.011	0.005	0.000	0.000	0.007	0.000	0.005	0.008	0.014
Panel A.2: $h = 1$ year lagged Green Citation Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio EPO, $h = 1$	-0.026	-0.004	-0.015	-0.005	0.826	0.750	0.071	0.444	0.044	0.048	0.026	0.027	0.020	0.090	-0.028	0.023	0.045	-0.090	0.000	-0.000	0.000	0.000
	(0.044)	(0.041)	(0.053)	(0.024)	(0.494)	(0.606)	(0.731)	(0.463)	(0.047)	(0.035)	(0.028)	(0.112)	(0.109)	(0.097)	(0.080)	(0.028)	(0.029)	(0.094)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.771	0.690	0.535	0.763	0.783	0.789	0.602	0.691	0.629	0.627	0.490	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.379
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.660	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.206	0.206	0.206	0.207	0.212	0.214	0.214	0.214	0.213	0.213	0.213	0.196	0.196	0.196	0.196	0.210	0.211	0.210	0.215	0.215	0.215	0.215
Economic Effect	0.003	0.001	0.002	0.001	0.007	0.007	0.001	0.005	0.006	0.016	0.010	0.002	0.002	0.012	0.004	0.002	0.004	0.006	0.003	0.000	0.002	0.003
Panel A.3: $h = 1$ year lagged Green Citation Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio GPO, $h = 1$	0.066	0.015	-0.052	0.036	-0.624	0.038	-0.993	-0.490	0.040	0.059	0.090	0.031	0.032	0.114	0.083	-0.017	-0.018	0.069	-0.000	-0.000	0.000	0.000
	(0.048)	(0.045)	(0.082)	(0.030)	(0.697)	(0.654)	(0.671)	(0.579)	(0.082)	(0.049)	(0.058)	(0.068)	(0.066)	(0.090)	(0.071)	(0.042)	(0.033)	(0.097)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.781	0.688	0.572	0.781	0.789	0.790	0.610	0.715	0.624	0.594	0.455	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.725	0.479	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.197	0.197	0.197	0.200	0.195	0.196	0.196	0.196	0.196	0.196	0.196	0.200	0.200	0.200	0.200	0.205	0.205	0.196	0.196	0.196	0.196	0.196
Economic Effect	0.007	0.002	0.006	0.007	0.005	0.000	0.009	0.005	0.005	0.017	0.032	0.003	0.003	0.016	0.012	0.001	0.002	0.004	0.007	0.0040	0.003	0.015
Panel A.4: $h = 3$ year lagged Green Citation Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio US, $h = 3$	-0.056	0.070	-0.287***	-0.037	0.064	-0.261	-0.414	0.038	0.042	0.061	0.089	-0.071	-0.060	-0.022	-0.052	0.054*	0.049	-0.184*	0.000	0.000	-0.000	0.000
	(0.057)	(0.065)	(0.090)	(0.035)	(0.813)	(0.710)	(0.824)	(0.602)	(0.086)	(0.047)	(0.056)	(0.103)	(0.104)	(0.116)	(0.065)	(0.029)	(0.031)	(0.106)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.768	0.68	0.543	0.769	0.806	0.801	0.610	0.707	0.624	0.619	0.481	0.957	0.959	0.612	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.940	24.117	21.706	18.67	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.194	0.194	0.194	0.196	0.191	0.193	0.193	0.193	0.197	0.197	0.197	0.210	0.210	0.210	0.210	0.204	0.204	0.197	0.193	0.193	0.193	0.193
Economic Effect	0.006	0.008	0.032	0.007	0.000	0.002	0.004	0.000	0.006	0.018	0.032	0.007	0.006	0.003	0.008	0.004	0.005	0.012	0.004	0.013	0.010	0.002
Panel A.5: $h = 3$ year lagged Green Citation Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio EPO, $h = 3$	-0.009	-0.009	-0.021	-0.047*	0.331	0.501	0.074	0.409	-0.024	0.017	0.019	0.070	0.066	0.165	0.037	0.029	0.014	0.097	0.000	0.000*	-0.000	0.000
	(0.045)	(0.038)	(0.070)	(0.022)	(0.635)	(0.680)	(0.839)	(0.527)	(0.018)	(0.049)	(0.043)	(0.072)	(0.063)	(0.119)	(0.054)	(0.021)	(0.022)	(0.077)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.768	0.682	0.531	0.761	0.797	0.793	0.610	0.682	0.624	0.633	0.509	0.960	0.963	0.598	0.803	0.954	0.938	0.722	0.736	0.656	0.421	0.349
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.212	0.212	0.212	0.213	0.213	0.215	0.215	0.215	0.220	0.220	0.220	0.214	0.214	0.214	0.214	0.216	0.216	0.218	0.215	0.215	0.215	0.215
Economic Effect	0.001	0.001	0.003	0.010	0.003	0.005	0.001	0.005	0.004	0.006	0.008	0.007	0.006	0.024	0.006	0.002	0.001	0.007	0.010	0.018	0.004	0.017
Panel A.6: $h = 3$ year lagged Green Citation Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Cit. Ratio GPO, $h = 3$	-0.010	0.061	-0.202**	-0.015	-0.167	-0.364	0.019	0.020	0.017	0.044	0.064	-0.115	-0.111	0.031	-0.010	0.050	0.036	-0.100	0.000	0.000	-0.000	0.000
	(0.052)	(0.062)	(0.081)	(0.032)	(0.811)	(0.701)	(0.715)	(0.572)	(0.095)	(0.053)	(0.058)	(0.098)	(0.096)	(0.096)	(0.066)	(0.031)	(0.031)	(0.100)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.776	0.686	0.561	0.778	0.806	0.800	0.618	0.716	0.619	0.591	0.456	0.949	0.951	0.618	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.195	0.195	0.195	0.197	0.192	0.194	0.194	0.194	0.196	0.196	0.196	0.205	0.205	0.205	0.205	0.205	0.205	0.197	0.195	0.195	0.195	0.195
Economic Effect	0.001	0.007	0.022	0.003	0.001	0.003	0.000	0.000	0.002	0.013	0.022	0.011	0.010	0.004	0.001	0.004	0.004	0.006	0.003	0.008	0.012	0.004
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.34: Sustainability Metrics On Climate Citation Ratios (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

Panel A.1: $h=1$ year lagged Climate Citation Ratio USPTO	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio US, $h=1$	-0.004	0.018	0.002	0.025	1.631	0.326	0.938	0.928	0.057	-0.005	0.050	-0.215	-0.215	0.046	-0.087	0.017	0.051	0.138	-0.000	-0.000	0.000	0.000
	(0.081)	(0.088)	(0.103)	(0.054)	(1.342)	(1.097)	(1.387)	(0.942)	(0.109)	(0.043)	(0.061)	(0.096)	(0.096)	(0.176)	(0.158)	(0.037)	(0.040)	(0.157)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.773	0.684	0.552	0.772	0.791	0.790	0.603	0.708	0.632	0.624	0.481	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.470	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.112	0.112	0.112	0.113	0.118	0.118	0.118	0.118	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.118	0.118	0.113	0.114	0.114	0.114	0.114
Economic Effect	0.000	0.001	0.000	0.003	0.008	0.002	0.005	0.006	0.004	0.001	0.010	0.011	0.011	0.003	0.007	0.001	0.003	0.005	0.005	0.008	0.013	0.010
Panel A.2: $h=1$ year lagged Climate Citation Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio EPO, $h=1$	0.061	-0.214*	0.240	-0.011	-0.621	0.832	-1.184	-0.476	0.083	0.038	0.041	-0.130	-0.134	-0.240	-0.138	-0.025	0.024	0.091	-0.000	0.000	0.000	0.000
	(0.057)	(0.106)	(0.197)	(0.050)	(0.803)	(0.925)	(0.700)	(0.624)	(0.051)	(0.039)	(0.041)	(0.102)	(0.105)	(0.131)	(0.103)	(0.025)	(0.029)	(0.178)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.771	0.690	0.536	0.763	0.783	0.789	0.602	0.691	0.629	0.627	0.49	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.379
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.66	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.119	0.119	0.119	0.118	0.133	0.132	0.132	0.132	0.122	0.122	0.122	0.100	0.100	0.100	0.100	0.122	0.122	0.119	0.131	0.131	0.131	0.131
Economic Effect	0.004	0.015	0.017	0.001	0.003	0.005	0.007	0.003	0.007	0.007	0.009	0.006	0.006	0.016	0.010	0.001	0.001	0.004	0.001	0.006	0.008	0.002
Panel A.3: $h=1$ year lagged Climate Citation Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio GPO, $h=1$	-0.017	0.061	-0.036	0.014	0.865	-0.132	0.065	0.529	0.069	-0.027	0.040	-0.233*	-0.233*	0.045	-0.113	0.035	0.069*	-0.002	0.000	0.000	0.000	0.000
	(0.071)	(0.092)	(0.107)	(0.058)	(0.963)	(0.976)	(1.269)	(0.800)	(0.107)	(0.038)	(0.065)	(0.085)	(0.084)	(0.124)	(0.174)	(0.034)	(0.040)	(0.147)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.781	0.688	0.572	0.781	0.789	0.790	0.610	0.715	0.624	0.594	0.454	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.725	0.480	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.113	0.113	0.113	0.113	0.120	0.120	0.120	0.120	0.111	0.111	0.111	0.108	0.108	0.108	0.108	0.119	0.119	0.113	0.116	0.116	0.116	0.116
Economic Effect	0.001	0.004	0.002	0.002	0.004	0.001	0.000	0.003	0.005	0.004	0.008	0.012	0.012	0.003	0.009	0.001	0.004	0.000	0.004	0.0000	0.024	0.014
Panel A.4: $h=3$ year lagged Climate Citation Ratio USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio US, $h=3$	-0.132*	0.148	0.038	0.038	0.214	-0.728	0.318	0.887	0.102	-0.019	0.043	0.042	0.042	0.051	-0.003	-0.011	-0.013	-0.285*	-0.000	-0.000	0.000	0.000
	(0.072)	(0.115)	(0.091)	(0.043)	(1.337)	(1.264)	(1.377)	(1.182)	(0.133)	(0.044)	(0.074)	(0.088)	(0.088)	(0.155)	(0.086)	(0.055)	(0.047)	(0.147)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.768	0.680	0.543	0.769	0.806	0.801	0.610	0.707	0.624	0.618	0.480	0.957	0.959	0.612	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.94	24.117	21.706	18.67	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.114	0.114	0.114	0.116	0.120	0.119	0.119	0.119	0.117	0.117	0.117	0.116	0.116	0.116	0.116	0.122	0.121	0.116	0.115	0.115	0.115	0.115
Economic Effect	0.008	0.010	0.002	0.004	0.001	0.004	0.002	0.006	0.008	0.003	0.009	0.002	0.002	0.004	0.000	0.000	0.001	0.011	0.000	0.004	0.002	0.006
Panel A.5: $h=3$ year lagged Climate Citation Ratio EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio EPO, $h=3$	0.051	-0.110	-0.078	-0.029	0.867	0.058	-1.724*	-0.851	0.192**	0.038	0.045	0.019	0.016	-0.023	-0.003	-0.058	-0.011	0.248	0.000	0.000	-0.000	-0.000
	(0.044)	(0.082)	(0.111)	(0.031)	(0.826)	(0.913)	(0.881)	(0.977)	(0.061)	(0.040)	(0.040)	(0.091)	(0.092)	(0.125)	(0.088)	(0.048)	(0.031)	(0.176)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.768	0.682	0.531	0.76	0.797	0.793	0.610	0.682	0.624	0.633	0.509	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.736	0.656	0.421	0.349
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.126	0.126	0.126	0.126	0.140	0.138	0.138	0.138	0.130	0.130	0.130	0.123	0.123	0.123	0.123	0.130	0.130	0.130	0.134	0.134	0.134	0.134
Economic Effect	0.003	0.008	0.006	0.004	0.005	0.000	0.011	0.006	0.017	0.007	0.011	0.001	0.001	0.002	0.000	0.003	0.001	0.010	0.002	0.003	0.002	0.003
Panel A.6: $h=3$ year lagged Climate Citation Ratio GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Cit. Ratio GPO, $h=3$	-0.064	0.155	0.052	0.027	-0.449	0.050	0.816	1.071	0.124	-0.012	0.062	0.019	0.019	-0.081	-0.027	-0.000	-0.006	-0.202	0.000	0.000	-0.000	0.000
	(0.064)	(0.119)	(0.107)	(0.048)	(1.144)	(1.023)	(1.284)	(0.944)	(0.129)	(0.039)	(0.077)	(0.066)	(0.066)	(0.138)	(0.075)	(0.040)	(0.038)	(0.126)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.776	0.686	0.561	0.778	0.806	0.800	0.618	0.716	0.619	0.591	0.456	0.949	0.951	0.618	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	0.115	0.115	0.115	0.117	0.124	0.123	0.123	0.123	0.116	0.116	0.116	0.117	0.117	0.117	0.117	0.124	0.124	0.117	0.119	0.119	0.119	0.119
Economic Effect	0.004	0.011	0.003	0.003	0.002	0.000	0.005	0.007	0.01	0.002	0.013	0.001	0.001	0.006	0.002	0.000	0.000	0.008	0.005	0.005	0.004	0.006
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.35: Sustainability Metrics On Green Counts (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A.1: $h = 1$ year lagged Green Counts USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts US, $h = 1$	-0.003**	-0.001	-0.004***	-0.002**	-0.025***	-0.021**	-0.012	-0.043***	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.008)	(0.010)	(0.007)	(0.001)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807
Adj. R2	0.774	0.684	0.553	0.772	0.791	0.791	0.603	0.711	0.633	0.625	0.481
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542
Ind. Variable: STD	39.853	39.853	39.855	40.524	39.173	37.731	37.731	37.731	40.891	40.891	40.891
Economic Effect	0.051	0.031	0.080	0.083	0.040	0.033	0.020	0.085	0.031	0.020	0.013
Panel A.2: $h = 1$ year lagged Green Counts EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts EPO, $h = 1$	-0.004	-0.006*	-0.012***	-0.006**	-0.082***	-0.060***	-0.027	-0.123***	-0.003	0.001*	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.021)	(0.019)	(0.024)	(0.019)	(0.002)	(0.001)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362
Adj. R2	0.771	0.691	0.538	0.764	0.783	0.790	0.602	0.694	0.629	0.627	0.490
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.660	0.534
Ind. Variable: STD	14.089	14.089	14.089	14.497	13.866	13.573	13.573	13.573	14.726	14.726	14.726
Economic Effect	0.027	0.051	0.096	0.085	0.047	0.034	0.017	0.090	0.025	0.023	0.015
Panel A.3: $h = 1$ year lagged Green Counts GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts GPO, $h = 1$	-0.001*	-0.001	-0.003***	-0.002**	-0.017***	-0.017***	-0.005	-0.029***	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.007)	(0.004)	(0.001)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314
Adj. R2	0.781	0.689	0.573	0.782	0.789	0.790	0.610	0.717	0.624	0.594	0.454
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559
Ind. Variable: STD	57.114	57.114	57.116	57.977	60.053	57.889	57.889	57.889	59.108	59.108	59.108
Economic Effect	0.041	0.045	0.096	0.096	0.041	0.040	0.014	0.088	0.028	0.022	0.013
Panel A.4: $h = 3$ year lagged Green Counts USPTO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts US, $h = 3$	-0.002	-0.002	-0.003**	-0.003**	-0.040***	-0.024***	-0.021*	-0.049***	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.008)	(0.010)	(0.007)	(0.001)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391
R2	0.769	0.680	0.544	0.772	0.807	0.801	0.610	0.710	0.625	0.619	0.480
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.940	24.117	21.706	18.670	1.451	0.669	0.545
Ind. Variable: STD	38.787	38.787	38.788	39.339	36.735	35.679	35.679	35.679	40.592	40.592	40.592
Economic Effect	0.038	0.040	0.075	0.112	0.059	0.036	0.035	0.094	0.034	0.021	0.008
Panel A.5: $h = 3$ year lagged Green Counts EPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts EPO, $h = 3$	-0.004	-0.007*	-0.012***	-0.007***	-0.098***	-0.053**	-0.035	-0.126***	-0.003	0.001*	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.021)	(0.021)	(0.023)	(0.020)	(0.002)	(0.001)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598
R2	0.768	0.683	0.534	0.764	0.798	0.793	0.610	0.685	0.625	0.634	0.510
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538
Ind. Variable: STD	14.007	14.007	14.008	14.396	13.311	13.047	13.047	13.047	14.812	14.812	14.812
Economic Effect	0.025	0.055	0.100	0.109	0.054	0.029	0.021	0.091	0.033	0.026	0.019
Panel A.6: $h = 3$ year lagged Green Counts GPO	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}
Green Counts GPO, $h = 3$	-0.001	-0.002*	-0.003***	-0.003***	-0.027***	-0.018***	-0.011	-0.033***	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.007)	(0.005)	(0.001)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757
R2	0.776	0.687	0.562	0.781	0.806	0.801	0.618	0.719	0.620	0.592	0.456
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563
Ind. Variable: STD	56.486	56.486	56.488	57.187	57.934	56.190	56.190	56.190	58.840	58.840	58.840
Economic Effect	0.036	0.057	0.095	0.143	0.062	0.042	0.028	0.097	0.028	0.021	0.011
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h = 1$ year lagged Green Counts USPTO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts US, $h = 1$	-0.001	-0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.723	0.470	0.492
Dep. Variable: STD	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	41.982	41.982	41.982	41.982	34.171	34.092	43.148	38.181	38.181	38.181	38.181
Economic Effect	0.021	0.014	0.005	0.008	0.002	0.005	0.009	0.035	0.043	0.013	0.004
Panel A.2: $h = 1$ year lagged Green Counts EPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts EPO, $h = 1$	-0.004	-0.002	0.005	0.002	-0.001	-0.002	0.002	0.000	0.000	0.000	-0.000
	(0.004)	(0.003)	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.454	0.379
Dep. Variable: STD	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	14.960	14.960	14.960	14.960	12.513	12.524	15.210	13.097	13.097	13.097	13.097
Economic Effect	0.028	0.016	0.055	0.018	0.006	0.010	0.010	0.027	0.034	0.025	0.019
Panel A.3: $h = 1$ year lagged Green Counts GPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts GPO, $h = 1$	-0.001	-0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.949	0.951	0.630	0.816	0.952	0.938	0.744	0.768	0.726	0.480	0.483
Dep. Variable: STD	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	58.976	58.976	58.976	58.976	50.356	50.209	63.677	58.696	58.696	58.696	58.696
Economic Effect	0.020	0.010	0.029	0.011	0.000	0.001	0.016	0.037	0.044	0.018	0.000
Panel A.4: $h = 3$ year lagged Green Counts USPTO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts US, $h = 3$	0.001	0.000	0.000	-0.001	-0.000	0.000	0.001	0.000	0.000	0.000	-0.000
	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.957	0.959	0.612	0.807	0.951	0.937	0.731	0.767	0.723	0.399	0.416
Dep. Variable: STD	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	45.963	45.963	45.963	45.963	33.451	33.372	41.818	36.461	36.461	36.461	36.461
Economic Effect	0.017	0.007	0.015	0.044	0.000	0.004	0.008	0.027	0.039	0.022	0.005
Panel A.5: $h = 3$ year lagged Green Counts EPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts EPO, $h = 3$	-0.002	-0.002	0.005	0.002	-0.002	-0.003	0.006	0.000	0.000	0.000*	-0.000
	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.960	0.963	0.597	0.803	0.955	0.938	0.722	0.737	0.656	0.422	0.349
Dep. Variable: STD	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	18.057	18.057	18.057	18.057	12.444	12.463	14.964	12.909	12.909	12.909	12.909
Economic Effect	0.015	0.017	0.058	0.025	0.009	0.016	0.027	0.036	0.033	0.057	0.007
Panel A.6: $h = 3$ year lagged Green Counts GPO	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Green Counts GPO, $h = 3$	-0.000	-0.001	0.001	-0.001	-0.000	-0.000	0.001	0.000	0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.949	0.951	0.618	0.811	0.950	0.935	0.738	0.765	0.721	0.437	0.404
Dep. Variable: STD	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	65.380	65.380	65.380	65.380	50.460	50.373	63.373	57.126	57.126	57.126	57.126
Economic Effect	0.007	0.017	0.053	0.023	0.002	0.002	0.026	0.026	0.035	0.031	0.001
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.36: Sustainability Metrics On Climate Counts (Robustness)

The observation unit is firm-year. The dependent variables include MSCI (Refinitiv) ESG ratings, Robeco (MSCI) SDG ratings, Log total emissions, and Climate change exposures. For the SDG ratings, I use 7 and 13. In Panel A.1 (A.4), I report for lag 1 (3) for USPTO. In Panel A.2 (A.5), I report for lag 1 (3) for EPO. In Panel A.3 (A.6), I report for lag 1 (3) for GPO. The sample period is 2008-2023. All variables are defined in Tables A.2 & A.3. The OLS Model is used for model estimation. All regressions includes country, year, and firm fixed effects. I double-cluster standard errors at the firm and year levels. I report the standard deviation of the dependent variable, the independent variable, in combination with the economic significance of a one standard deviation change relative to the standard deviation of the dependent variable (Economic effect), calculated as $|\beta_{ind.var} \times StdDev_{ind.var} / StdDev_{dep.var}|$. ***1% significance, **5% significance, *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
Panel A.1: $h = 1$ year lagged Climate Counts USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts US, $h = 1$	-0.001	0.002	-0.004*	-0.001	-0.025	-0.024	0.030	-0.027	-0.006	0.000	-0.000	-0.002	-0.002	0.003	0.001	-0.001**	-0.001*	0.001	0.000	0.000	0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.001)	(0.018)	(0.023)	(0.020)	(0.025)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14909	14909	14908	13987	16350	17773	17773	17773	13807	13807	13807	6028	6028	6028	6028	23079	22978	13247	13503	13503	13503	13503
Adj. R2	0.773	0.684	0.552	0.772	0.791	0.790	0.603	0.708	0.634	0.624	0.481	0.957	0.959	0.634	0.814	0.953	0.939	0.740	0.767	0.722	0.470	0.492
Dep. Variable: STD	1.980	1.634	1.760	0.996	25.112	24.345	21.888	18.909	1.449	0.668	0.542	2.206	2.202	1.458	1.442	2.903	2.167	3.101	0.003	0.001	0.000	0.000
Ind. Variable: STD	9.185	9.185	9.185	9.365	9.810	9.438	9.438	9.438	9.346	9.346	9.346	10.554	10.554	10.554	10.554	8.460	8.470	10.678	10.316	10.316	10.316	10.316
Economic Effect	0.006	0.013	0.023	0.008	0.010	0.009	0.013	0.014	0.041	0.003	0.001	0.010	0.009	0.024	0.010	0.004	0.005	0.004	0.022	0.018	0.021	0.012
Panel A.2: $h = 1$ year lagged Climate Counts EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts EPO, $h = 1$	-0.006	-0.005	-0.010	-0.007	-0.093	0.023	0.148	-0.023	0.005	0.001	-0.000	-0.006	-0.006	0.020	0.000	-0.005**	-0.002	0.004	0.000	0.000	0.000*	-0.000
	(0.008)	(0.009)	(0.010)	(0.005)	(0.082)	(0.083)	(0.100)	(0.099)	(0.007)	(0.002)	(0.002)	(0.007)	(0.007)	(0.009)	(0.006)	(0.002)	(0.003)	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11248	11248	11248	10506	13025	13849	13849	13849	10362	10362	10362	4477	4477	4477	4477	16664	16537	10389	10355	10355	10355	10355
Adj. R2	0.771	0.690	0.536	0.763	0.783	0.789	0.602	0.691	0.629	0.627	0.490	0.954	0.956	0.609	0.809	0.956	0.940	0.732	0.759	0.698	0.455	0.379
Dep. Variable: STD	1.965	1.656	1.724	0.973	24.431	23.969	21.733	18.512	1.461	0.660	0.534	2.212	2.205	1.478	1.444	2.792	2.114	3.087	0.003	0.001	0.000	0.000
Ind. Variable: STD	3.649	3.649	3.649	3.729	3.834	3.784	3.784	3.784	3.804	3.804	3.804	3.744	3.744	3.744	3.744	3.356	3.357	3.916	3.617	3.617	3.617	3.617
Economic Effect	0.010	0.010	0.020	0.028	0.015	0.004	0.026	0.005	0.012	0.007	0.000	0.009	0.010	0.050	0.001	0.006	0.003	0.005	0.029	0.020	0.064	0.017
Panel A.3: $h = 1$ year lagged Climate Counts GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts GPO, $h = 1$	-0.000	0.002	-0.003	-0.001	0.009	0.003	0.046**	0.020	-0.002	0.000	-0.000	-0.002	-0.002	0.004	0.001	-0.001	-0.000	0.001	0.000	0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.021)	(0.020)	(0.021)	(0.025)	(0.003)	(0.001)	(0.000)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16631	16631	16630	15668	18178	19861	19861	19861	15314	15314	15314	6810	6810	6810	6810	26775	26656	14805	14806	14806	14806	14806
Adj. R2	0.781	0.689	0.572	0.781	0.789	0.790	0.610	0.715	0.624	0.594	0.454	0.949	0.951	0.631	0.816	0.952	0.938	0.744	0.768	0.725	0.480	0.483
Dep. Variable: STD	1.998	1.646	1.781	1.016	25.223	24.473	21.969	19.084	1.463	0.678	0.559	2.191	2.185	1.445	1.442	2.930	2.194	3.117	0.003	0.001	0.000	0.000
Ind. Variable: STD	14.173	14.173	14.174	14.307	15.985	15.409	15.409	15.409	14.461	14.461	14.461	14.488	14.488	14.488	14.488	13.151	13.126	16.403	16.325	16.325	16.325	16.325
Economic Effect	0.002	0.015	0.025	0.011	0.006	0.002	0.032	0.016	0.024	0.002	0.002	0.014	0.014	0.040	0.011	0.003	0.000	0.005	0.022	0.015	0.025	0.020
Panel A.4: $h = 3$ year lagged Climate Counts USPTO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts US, $h = 3$	-0.003	0.001	-0.003	-0.002	-0.082*	-0.036	0.024	-0.068*	-0.005	0.000	-0.000	0.002	0.001	-0.002	-0.001	-0.002*	-0.002*	0.004	0.000	0.000	0.000	-0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.041)	(0.040)	(0.046)	(0.037)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13403	13403	13402	12559	14471	15415	15415	15415	11391	11391	11391	5392	5392	5392	5392	20528	20469	12100	11512	11512	11512	11512
R2	0.768	0.680	0.543	0.770	0.806	0.801	0.610	0.707	0.625	0.618	0.480	0.957	0.959	0.612	0.807	0.951	0.937	0.731	0.768	0.724	0.400	0.416
Dep. Variable: STD	1.981	1.639	1.753	0.987	24.940	24.117	21.706	18.670	1.451	0.669	0.545	2.256	2.255	1.476	1.443	2.840	2.100	3.100	0.003	0.001	0.000	0.000
Ind. Variable: STD	8.900	8.900	8.900	9.095	8.738	8.486	8.486	8.486	9.312	9.312	9.312	11.050	11.050	11.050	11.050	8.347	8.355	10.515	9.286	9.286	9.286	9.286
Economic Effect	0.015	0.008	0.018	0.019	0.029	0.013	0.009	0.031	0.032	0.003	0.003	0.007	0.007	0.016	0.007	0.006	0.007	0.015	0.058	0.051	0.058	0.011
Panel A.5: $h = 3$ year lagged Climate Counts EPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts EPO, $h = 3$	-0.008	-0.008	-0.015	-0.008	-0.260***	0.001	0.102	-0.208**	0.005	0.001	0.000	0.021	0.019	-0.008	0.004	-0.005*	-0.006*	0.019	0.000**	0.000	0.000***	0.000
	(0.009)	(0.011)	(0.009)	(0.006)	(0.080)	(0.096)	(0.086)	(0.083)	(0.009)	(0.002)	(0.002)	(0.010)	(0.009)	(0.017)	(0.007)	(0.002)	(0.003)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	10227	10227	10226	9548	11408	11934	11934	11934	8598	8598	8598	4127	4127	4127	4127	14951	14875	9502	8752	8752	8752	8752
R2	0.768	0.682	0.531	0.761	0.798	0.793	0.610	0.683	0.624	0.633	0.509	0.960	0.963	0.597	0.803	0.954	0.938	0.722	0.739	0.657	0.425	0.349
Dep. Variable: STD	1.967	1.667	1.702	0.973	24.059	23.527	21.541	18.083	1.461	0.664	0.538	2.193	2.190	1.498	1.447	2.729	2.049	3.071	0.003	0.001	0.000	0.000
Ind. Variable: STD	3.761	3.761	3.762	3.827	3.664	3.593	3.593	3.593	3.856	3.856	3.856	4.535	4.535	4.535	4.535	3.425	3.427	3.997	3.541	3.541	3.541	3.541
Economic Effect	0.015	0.017	0.034	0.032	0.040	0.000	0.017	0.041	0.014	0.008	0.003	0.044	0.040	0.024	0.012	0.006	0.010	0.025	0.081	0.062	0.112	0.004
Panel A.6: $h = 3$ year lagged Climate Counts GPO																						
	E^{MSCI}	S^{MSCI}	G^{MSCI}	ESG^{MSCI}	$E^{REFINITIV}$	$S^{REFINITIV}$	$G^{REFINITIV}$	$ESG^{REFINITIV}$	SDG Overall^{Robeco}	SDG 7^{Robeco}	SDG 13^{Robeco}	SDGProd 7	SDGProd 13	SDGOper 7	SDGOper 13	LogS1	LogS2	LogS3	CCExposure	$CCExposure^{Opp}$	$CCExposure^{Reg}$	$CCExposure^{Phy}$
Climate Counts GPO, $h = 3$	-0.002	0.000	-0.003	-0.002	-0.026	-0.002	0.038	-0.018	-0.001	0.000	-0.000	0.001	0.001	-0.001	-0.001	-0.001	-0.001	0.004	0.000*	0.000*	0.000	-0.000
	(0.003)	(0.004)	(0.003)	(0.002)	(0.024)	(0.029)	(0.033)	(0.026)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	15036	15036	15035	14156	16201	17334	17334	17334	12757	12757	12757	6102	6102	6102	6102	24036	23966	13542	12638	12638	12638	12638
R2	0.776	0.686	0.561	0.778	0.806	0.800	0.618	0.716	0.619	0.591	0.456	0.949	0.951	0.618	0.811	0.950	0.935	0.738	0.766	0.721	0.438	0.404
Dep. Variable: STD	1.995	1.652	1.772	1.007	25.087	24.282	21.789	18.851	1.464	0.682	0.563	2.244	2.238	1.471	1.441	2.869	2.121	3.104	0.003	0.001	0.000	0.000
Ind. Variable: STD	14.326	14.326	14.326	14.422	15.150	14.698	14.698	14.698	14.596	14.596	14.596	16.167	16.167	16.167	16.167	13.397	13.393	16.797	15.738	15.738	15.738	15.738
Economic Effect	0.016	0.001	0.020	0.025	0.016	0.001	0.026	0.014	0.012	0.003	0.001	0.011	0.009	0.015	0.011	0.005	0.006	0.020	0.065	0.048	0.072	0.013
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
F.E. Included	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

A.4 Appendix Figures

Figure A.1: Firm-Year Observations Per Year

The figure shows the annual number of firms available in the merged sample. Panel A includes patents at USPTO, with different bars representing the following categories: all patents (Any USPTO - grey bars), green patents (Green USPTO - light green bars), Health patents (Health USPTO - green bars), Bioeconomy patents (Bioeconomy USPTO - orange bars), Energy patents (Energy USPTO - purple bars), Transport patents (Transport USPTO - pink bars), Climate patents (Climate USPTO - yellow bars), and Security patents (Security USPTO - light brown bars). The same labeling applies to Panel B and C, which cover the EPO and GPO samples.

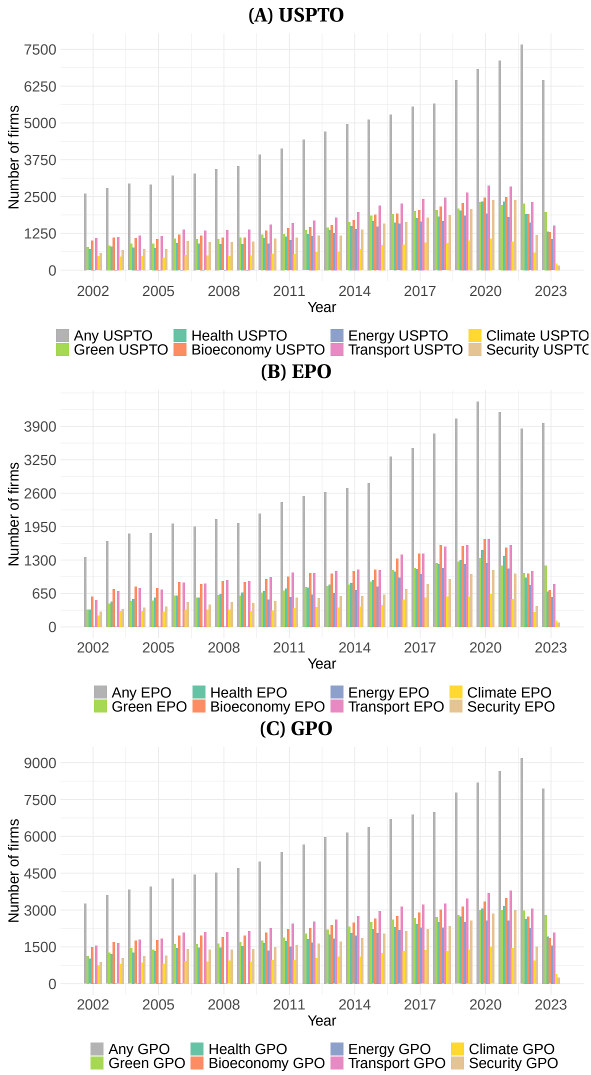
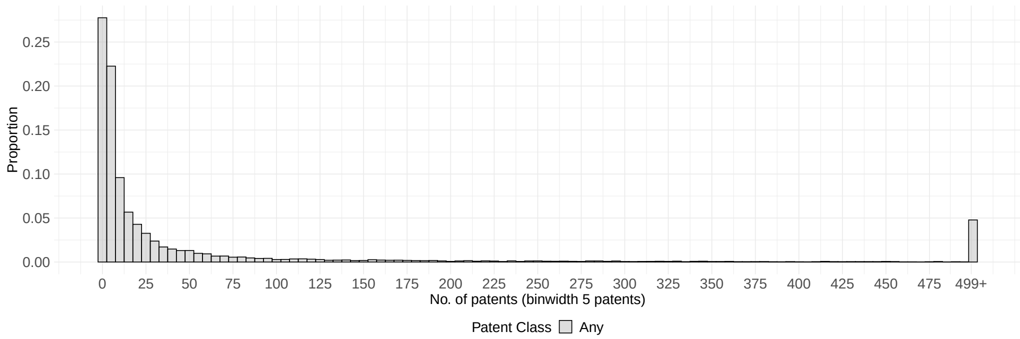


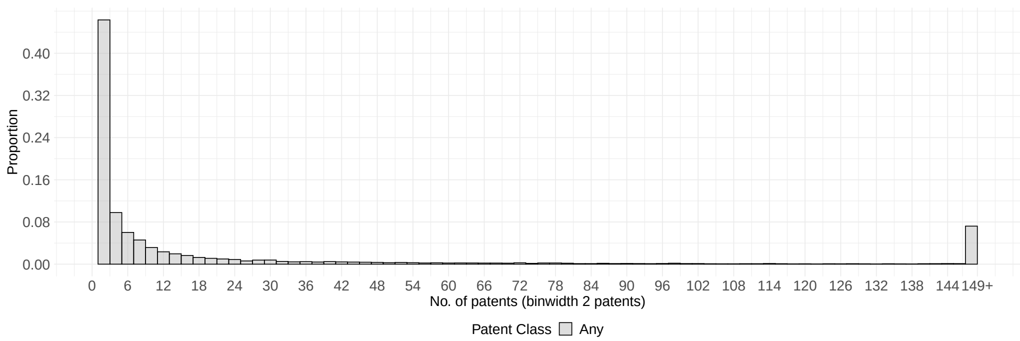
Figure A.2: Histogram Of Patents Counts For Firm-Year Observations

The histograms displays the proportion of firm-year observations grouped by the number of granted patents from 2002 to 2023. In Panel A, the patent count is based on patents granted at USPTO, with a binwidth of 5 patents. The last bin is an overflow bin and includes firms with 499 or more patents. In Panel B, the patent count is based on patents granted at EPO, with a binwidth of 2 patents. The last bin is an overflow bin and includes firms with 149 or more patents. In Panel C, the patent count is based on patents granted at GPO, with a binwidth of 5 patents. The last bin is an overflow bin and includes for,s with 499 or more patents.

(A) USPTO



(B) EPO



(C) GPO

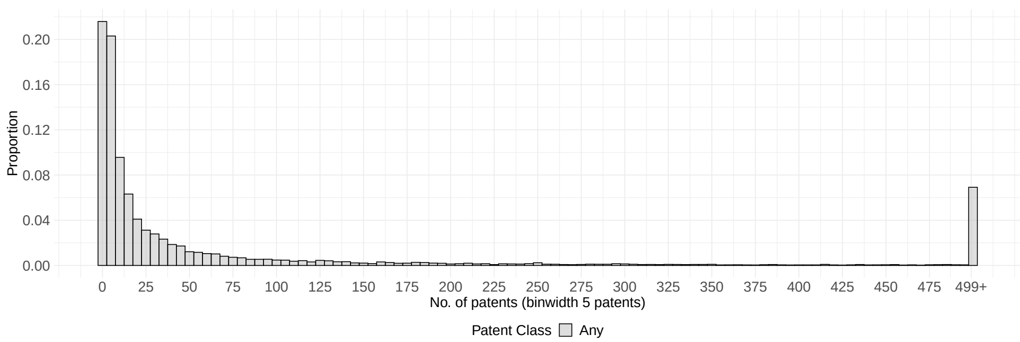
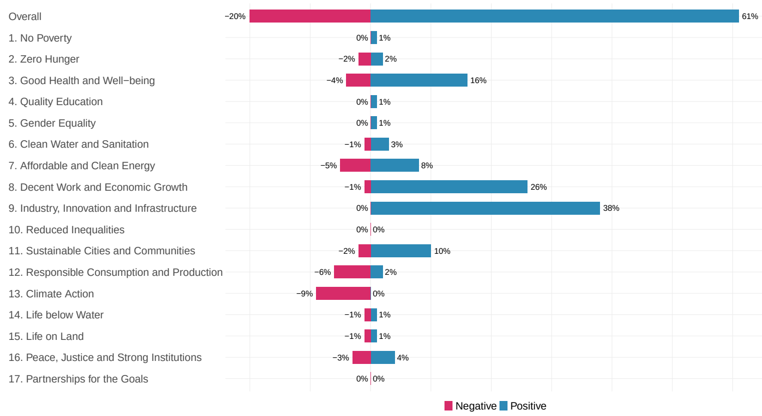


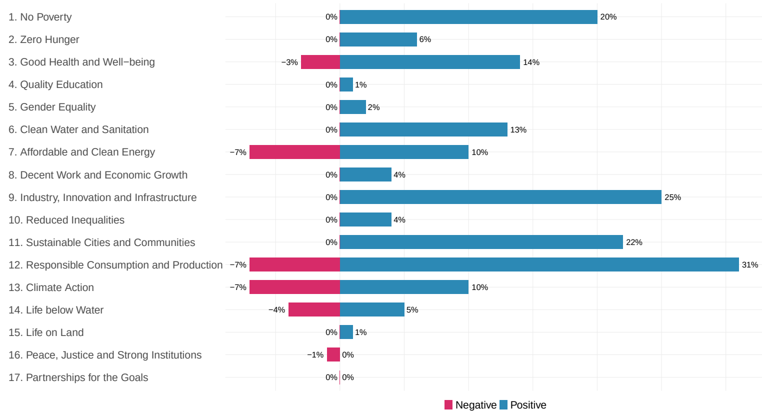
Figure A.3: Distribution Of SDG Ratings By Alignment (USPTO)

The figures plot the cross-sectional distribution of SDG ratings by alignment for firms grants at USPTO between 2010 (2020) and 2023 for Robeco (MSCI). In Panel A, I show the percentage of positive/negative ratings for the SDG alignment with firms in the Robeco Data. In Panel B, I show the percentage of positive/negative ratings for the SDG alignment with firms MSCI Products. In Panel C, I show the SDG alignment with firms MSCI Operations. In Panel D, I show the Net SDG alignment, which is calculated as the simple average of Panels B and C. The percentage of zero SDG ratings, by SDG, constitutes the remaining percentage by SDG.

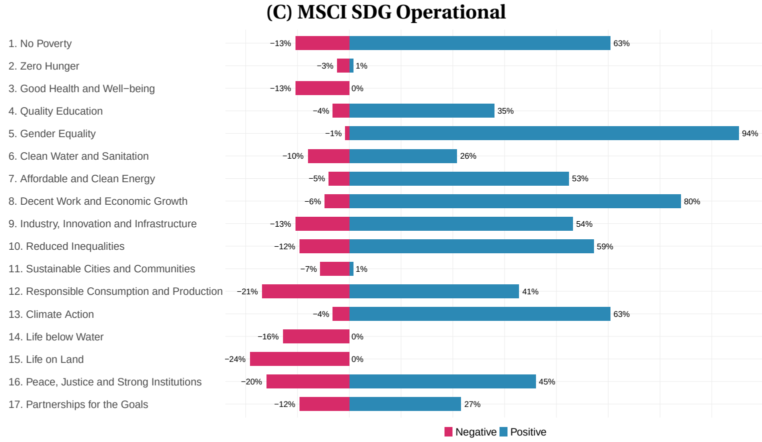
(A) Robeco SDG



(B) MSCI SDG Product



(C) MSCI SDG Operational



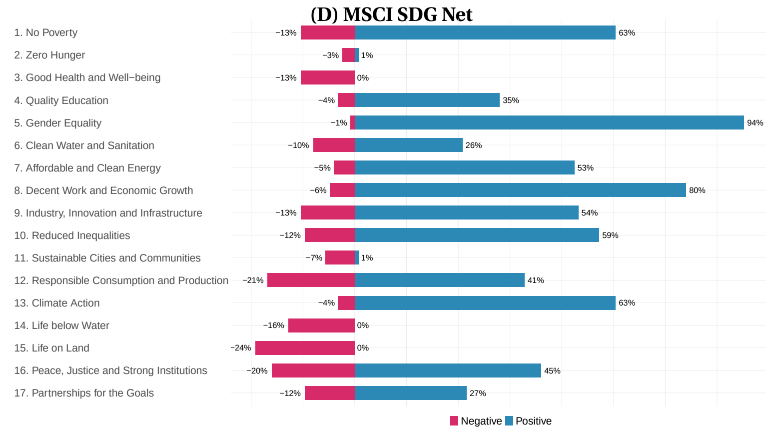


Figure A.5: Correlation Matrix - Patent Ratios

The figure displays a heatmap of Pearson correlation coefficients for the patent ratios, ESG ratings, SDG 7, 13, and overall ratings, and Scope 1-3 variables, using data from firms patenting at USPTO. Light to dark blue colors indicate positive correlations, while light to dark red colors indicate negative correlations.

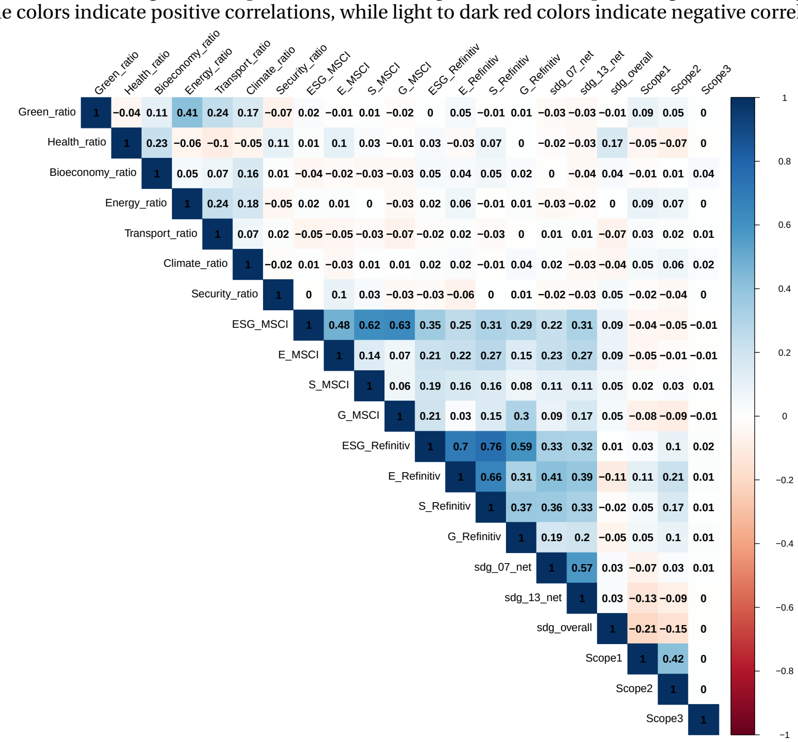


Figure A.6: Correlation Matrix - Patent Counts

The figure displays a heatmap of Pearson correlation coefficients for the patent counts, ESG ratings, SDG 7, 13, and overall ratings, and Scope 1-3, using data from firms patenting at USPTO. Light to dark blue colors indicate positive correlations, while light to dark red colors indicate negative correlations.

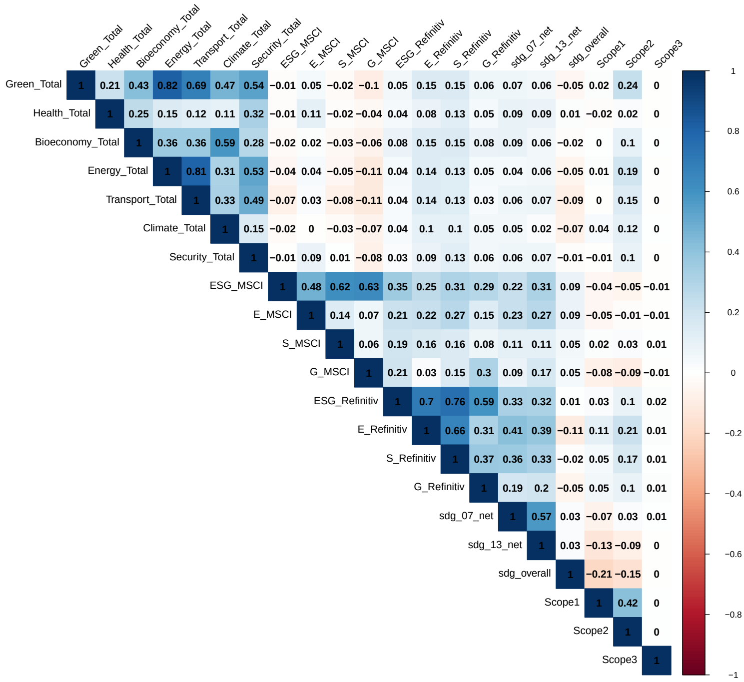
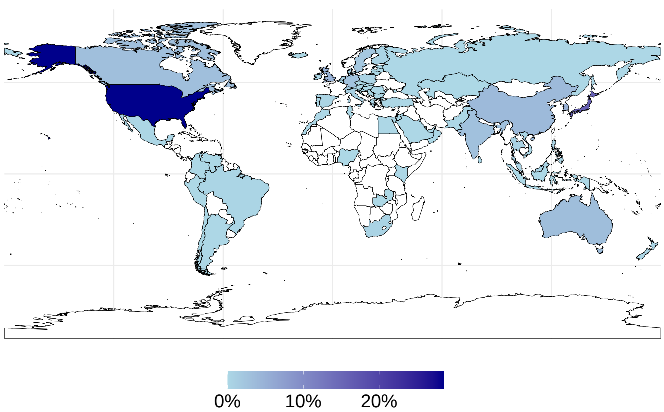


Figure A.7: Country Relevance In Sample

The figure shows the proportion of firm-year observations by country. White indicates no firm-year observations for the country, while light to dark blue colors represent increasing proportions of firm-year observations in the merged sample.



SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Declaration of co-authorship[1] Date: 09-08-2024

This declaration concerns the following article/manuscript:

Title:	The cost of insuring against underperformance of ESG screened index funds
Authors:	Peter Løchte Jørgensen and Mathias Danielsen Plovst

The article/manuscript is:

☒ Published, state full reference: Journal of Sustainable Finance & Investment, 13(4), 1534-1553
☐ Accepted, state journal:
☐ Invited for revision, state journal:
☐ Submitted
☐ In preparation

Date of the current version of the manuscript, if not published or accepted: 06-08-2024

Please fill out Table 1 regarding contribution to the manuscript for all authors. The respective author has contributed to the elements:

A. Research idea: Identifying, developing, specifying, and formulating the overarching research question and aim.
B. Theory: Organizing theoretical perspectives, developing arguments and hypotheses, specifying theoretical model.
C. Research design: Developing and planning design for test or exploration of the research question.
D. Data collection: Preparing and organizing data collection, data collection, preparing data for analysis and storage.
E. Data analysis: Application of empirical techniques to analyze or synthesize study data including providing support for interpretations such as visualizations etc.
F. Writing: Drafting and revising manuscript presenting the research idea and results

of this article/manuscript as follows:

4 Has essentially delivered this part.
3 Major contribution
2 Equal contribution
1 Minor contribution
0 Did not contribute to this part.
N/A Not relevant or not applicable

[1] Attribution of authorship should be based on criteria a-d adopted from the Vancouver guidelines (see also rules and guidelines from Aarhus University) and all individuals who meet these criteria should be recognized as authors. The co-author has contributed:

a) to the conception or design of the work, or the acquisition, analysis, or interpretation of data for the work, *and*
b) drafting the work or revising it critically for important intellectual content, *and*
c) to the final approval of the version to be published, *and*
d) agrees to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Table 1. Individual contributions and signature of each co-author[1]

Author	Extent of contribution (4-0) per element (A.-F.)						Signature of the author[2]
	A. Research Idea	B. Theory	C. Research Design	D. Data Collection	E. Data Analysis	F. Writing	
Peter Løchte Jørgensen	2	2	2	2	2	2	
Mathias Danielsen Plovst	2	2	2	2	2	2	Mathias D. P[illegible]

[1]More rows can be added for additional authors.
[2]All authors must confirm the declaration either by signature or email.

If relevant, you may add more information on the work and collaboration such as open science practices or more detailed specifications of authors' contributions here:

AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES AARHUS UNIVERSITY

Declaration of co-authorship[1] Date: 08-08-2024

This declaration concerns the following article/manuscript:

Title:	Systematic Longevity Risk: The Willingness To Pay
Authors:	Anne G. Balter, Malene Kallestrup-Lamb, Mathias Danielsen Plovst

The article/manuscript is:
- ☐ Published, state full reference:
- ☐ Accepted, state journal:
- ☐ Invited for revision, state journal:
- ☐ Submitted
- ☒ In preparation

Date of the current version of the manuscript, if not published or accepted: 06-08-2024

Please fill out Table 1 regarding contribution to the manuscript for all authors. The respective author has contributed to the elements:

A. Research idea: Identifying, developing, specifying, and formulating the overarching research question and aim.
B. Theory: Organizing theoretical perspectives, developing arguments and hypotheses, specifying theoretical model.
C. Research design: Developing and planning design for test or exploration of the research question.
D. Data collection: Preparing and organizing data collection, data collection, preparing data for analysis and storage.
E. Data analysis: Application of empirical techniques to analyze or synthesize study data including providing support for interpretations such as visualizations etc.
F. Writing: Drafting and revising manuscript presenting the research idea and results

of this article/manuscript as follows:

- 4 Has essentially delivered this part.
- 3 Major contribution
- 2 Equal contribution
- 1 Minor contribution
- 0 Did not contribute to this part.
- N/A Not relevant or not applicable

[1] Attribution of authorship should be based on criteria a-d adopted from the Vancouver guidelines (see also rules and guidelines from Aarhus University) and all individuals who meet these criteria should be recognized as authors. The co-author has contributed:

a) to the conception or design of the work, or the acquisition, analysis, or interpretation of data for the work, *and*
b) drafting the work or revising it critically for important intellectual content, *and*
c) to the final approval of the version to be published, *and*
d) agrees to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

AARHUS BSS
SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Table 1. Individual contributions and signature of each co-author[1]

Author	Extent of contribution (4-0) per element (A.-F.)						Signature of the author[2]
	A. Research Idea	B. Theory	C. Research Design	D. Data Collection	E. Data Analysis	F. Writing	
Anne G. Balter	3	2	2	0	2	2	[illegible]
Malene Kallestrup-Lamb	3	2	2	0	2	2	Malene Kallestrup-Lamb
Mathias Danielsen Plovst	1	2	2	4	2	2	Mathias D. Plovst

[1]More rows can be added for additional authors.
[2]All authors must confirm the declaration either by signature or email.

If relevant, you may add more information on the work and collaboration such as open science practices or more detailed specifications of authors' contributions here: