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ESG INVESTING, POLICY UNCERTAINTY AND BROWN SPINNING

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Dedication

I dedicate my dissertation to all who have made my journey less difficult: to my former supervisor, Roman Kraussl, and my current supervisor, Denitsa Stefanova; to my dissertation committee member, Eric Nowak; to my family - Mr. and Mrs. Oladiran, Titilope, Emmanuel, and Abigail; and to my friends, especially Melanie Kamdem.

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Abstract

Chapter 1 : I examine the recent literature on the expectations, beliefs, and perceptions of investors who incorporate Environmental, Social, Governance (ESG) considerations in investment decisions with the aim to generate superior performance or make a societal impact. Through the lens of equilibrium models of agents with heterogeneous tastes for ESG investments, green assets are expected to generate lower returns in the long run compared to their non-ESG counterparts. However, in the short run, ESG investments can outperform non-ESG investments through various channels. Empirically, results for the relative performance to ESG investment are mixed. I find strong empirical evidence in the literature that investors have a preference for ESG and that their actions can generate positive social impact through engagement. The shift towards more sustainable policies in firms is motivated by the increased market values and the lower cost of capital of green firms driven by investors' choices.

Chapter 2 : I examine whether the uncertainty related to developments in environmental, social and governance (ESG) regulation is reflected in asset prices. I proxy the sensitivity of firms to ESG regulation uncertainty by the disparity between the components of their ESG ratings. Firms with high ESG disparity have a higher option-implied cost of protection against downside tail risk. The impact of the misalignment across the different dimensions of the ESG score is distinct from that of the level of the ESG score itself. Aggregate downside risk bears a negative price for firms with low ESG disparity.

Chapter 3 : I examine the post-divestment environmental implications of brown spinning, where public companies spin off or sell their brown (carbon-intensive) assets to private investors, such as private equity firms or private companies. I focus on the sustainability characteristics of the private buyers to determine whether the post-divestment underlying assets' emissions is different for private investors with a stated sustainability preference compared to those without explicitly stated sustainability preference. First, I find that the emissions of these carbon-intensive assets increase after the change of ownership from public to private hands. Second, private investors with a stated sustainability preference have higher asset-level emissions compared to private players without an explicitly stated sustainability preference.

Chapter 4 : I examine whether financial shocks can limit the brown production activities of a firm. This paper builds on the work of Hartzmark and Shue (2024) who show that brown firms exhibit negative impact elasticity. I decompose the negative impact elasticity and focus on the change in emissions emanating only from the change in output to capture the changes in emissions from firm production activities. I find that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital can limit the brown production activities of the firm. The results are mostly significant for the brown firms.

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Chapter 1

Introduction

Over the recent years, there has been increasing attention of investors towards ESG[1] investments - on whether ESG investment can deliver superior returns while also creating societal impact. Those aspects of ESG investing that encompass investment performance and societal impact can be summarized into three competing hypotheses: (a) doing well by doing good, i.e. investors obtain superior performance while also creating positive societal impact through ESG investment; (b) doing poorly by doing good, i.e., investors obtain inferior performance but create positive societal impact through ESG investment; and (c) doing neutral by doing good, i.e., investors obtain neutral performance or no performance benefit but create positive societal impact through ESG investment.

This dissertation examines questions related to the sustainability preference of investors, the performance of ESG investment, the pricing implication of uncertainty relating to the ESG regulatory development, and the societal impact of ESG investment. This dissertation is divided into four parts. The first part of this dissertation reviews the recent literature on ESG investing to understand the perceptions, beliefs, and expectations of investors in relation to the reality and empirical facts of ESG investments. It begins by examining the theoretical literature to draw insights on

[1] ESG - Environmental, Social, and Governance

the asset pricing implications of incorporating ESG motives in investment decisions. Early studies of sustainable investing consider exclusionary screening applied in portfolio decisions. They attribute the higher cost of capital of brown firms relative to green ones to the reduction in risk-sharing ensuing from such screening (Heinkel et al., 2001). Another channel considered in the literature is that of pricing power of socially responsible firms due to customer loyalty (Albuquerque et al., 2020). Alternatively, another strand of the literature considers that some economic agents derive non-pecuniary benefits from holding green assets (for example, Fama and French, 2007; Baker et al., 2022b). Such investors are willing to pay more to hold green firms, pushing the price of green assets up, thereby leading to lower expected returns.

It examines the empirical literature on whether there is evidence that investors have preference for green assets. It finds a broad consensus in the literature on the sustainability preferences of investors (Bauer et al., 2021; Heeb et al., 2023; Ceccarelli et al., 2023, among others). Empirical studies confirm that there is support for sustainable investments among economic agents, i.e., investors are willing to sacrifice return to engage in ESG investing. Hartzmark and Sussman (2019), Barber et al. (2021), Ceccarelli et al. (2023) document that investors value sustainability. However, in terms of the performance of ESG investment, empirical evidence is mixed. Hong and Kacperczyk (2009), Baker et al. (2022a), Zerbib (2019), Choi et al. (2020), Bolton and Kacperczyk (2021), Faccini et al. (2023), Seltzer et al. (2022), Hsu et al. (2023) all show that green firms underperform relative to brown firms. Gompers et al. (2003), Derwall et al. (2004), Bebchuk et al. (2009), In et al. (2019), Duan et al. (2023), Pastor et al. (2022) document a positive relationship between a firm's ESG profile and its returns, while Hyun et al. (2020), Chava et al. (2025), Ochoa et al. (2022), and Aswani et al. (2024) find no significant relationship. The meta-study of Atz et al. (2021) find that returns from ESG investing documented in the literature are not different on average from returns from conventional investments.

In addition, it examines the empirical literature on whether ESG-motivated investments can generate societal impact. Impact can be achieved through several channels, as argued in recent theoretical studies. Potential channels include search capital frictions (Landier and Lovo, 2020), financing constraints and coordination (Oehmke and Opp, 2024), lower cost of capital and higher valuation (Pastor et al., 2021), and the proportion of ESG investors in the market (Pedersen et al., 2021), among others. Empirical evidence shows that ESG investment can generate societal impact through various channels such as environmental activism (Naaraayanan et al., 2020), shareholder coordination (Crane et al., 2019), institutional commitment (Dyck et al., 2019), divestment (Berk and van Binsbergen, 2025), and two-tier engagement (Dimson et al., 2021). However, the effectiveness of those channels in generating the intended impact is rather varied. Berk and van Binsbergen (2025) argue that ESG divestiture strategies have little impact on the real investment decision of the affected firms. Recent empirical studies (such as Dimson et al., 2021; Krueger et al., 2020; Naaraayanan et al., 2020) provide support for engagement as a way to generate societal impact. Instead of divesting, investors should engage brown firms (firms with low ESG performance) to become green or even encourage green firms to become greener. This action could, in turn, lead to higher valuation and lower cost of capital for the transitory firms.

The second part of this dissertation examines the pricing implications of uncertainty relating to the ESG regulatory development. Specifically, it examines whether the uncertainty related to developments in environmental, social, and governance (ESG) regulation is reflected in asset prices. In the last decade, the volume of ESG topics in US regulatory documents has increased dramatically, especially after the adoption of the Paris agreement in 2015.[2] This surge in regulatory activity has been marked by significant changes and rollbacks, as policy turnarounds have been

[2]See https://eqm.ai/wp-content/uploads/2023/05/2023-05-25-ESG-Regs-Report-2023-2.pdf

prompted by societal pressure, political motives, or short-term economic concerns.[3] As a result, ESG-related regulation has been particularly volatile, reflecting a dynamic and evolving policy landscape. In turn, both firms and investors in their financing or investment decisions are faced with uncertainty about how new, updated, and proposed ESG-related regulation will shape the regulatory framework in the future.

I explore the uncertainty that stems from the development of ESG regulations and the firm's ability to manage its exposure to this regulatory development. I proxy the latter by the observed disparity across the three dimensions of a firm's ESG standing: its environmental, social, and governance performance. I conjecture that the degree of divergence across different aspects of a firm's ESG qualities reflects its ability to adapt to ESG regulatory requirements or its vulnerability to unexpected ESG policy changes, as perceived by the market. Therefore, I consider the deviation in a firm's performance across its "E", "S" and "G" ratings, which I term *ESG disparity*, as a measure of the firm's exposure to unexpected changes in ESG regulation. Although a firm's ESG rating could also be indicative of the firm's ability to address changes in ESG regulation, as arguably higher-rated firms would be less exposed to new or changed regulation compared to lower-rated peers, the level of the ESG rating does not reveal the degree to which a higher rating on one component of the score compensates for a lower rating on another component. Therefore, I argue that it is important to consider the divergence within components of a firm's ESG rating.

As investors cannot fully anticipate the nature or scope of new ESG-related policies, asset prices can be affected as investors learn about the costs of these new policies. I investigate whether ESG policy uncertainty—at the aggregate economy level and at the firm level—is priced in the option market. In the model of Pastor and Veronesi (2013), investors are uncertain whether the current government policy will change or not. Potential new policies are heterogeneous ex ante, as different policies are expected to have different impacts on firms. When choosing a new policy,

[3] For instance, the U.S. withdrew from the Paris Accord in 2017, and rejoined in 2021.

the government maximizes investors' welfare, while also considering non-economic objectives, reflected in the political costs of adopting a new policy. These political costs are uncertain, and as investors learn about them by observing political signals, they revise their expectations about the likelihood that future policies will be chosen. Stock prices are affected because political uncertainty leads investors to demand compensation. In addition, firms that are likely to be impacted more by changes in government policy command an additional premium for investors.

Here, the focus is on the specific case of ESG regulatory policies within the broader set of government regulations. Both investors and firms are uncertain about the choice of new ESG regulations and about the impact of these regulations on the firm. This part of the dissertation examines the impact of ESG regulatory uncertainty on the stock market by investigating whether investors seek option protection when the ESG regulatory uncertainty is higher in the economy. In the cross section, it also examines whether investors demand additional compensation against large price drops from holding firms that are more exposed to changes in ESG regulation.

At the aggregate economy level, the cost of protection against downside risk is higher when the ESG regulatory uncertainty is greater, especially under worse economic conditions. This result is similar to Pastor and Veronesi (2012, 2013) where they find that political uncertainty is priced. At the firm level, firms with high ESG performance have a lower option-implied cost of protection against downside risk compared to firms with low ESG scores. This evidence is in line with the findings of Ilhan et al. (2021) on carbon-intensive firms.

The third and fourth parts of the dissertation focus on the impact of sustainable investors to create real impact. The third part of the dissertation examines whether the sustainability preferences of private investors, as indicated by their status as signatories to the United Nations Principles for Responsible Investment (PRI), influence the emission outcomes of the acquired assets.

The global shift towards sustainability has placed significant pressure on companies to reduce their greenhouse gas (GHG) emissions and adopt more environmentally friendly practices. This has led to an increasing number of public companies divesting their high-emission assets to private players, a process often referred to as "brown spinning." Brown spinning involves the transfer of carbon-intensive assets from public companies, which are potentially subject to stricter regulatory and public scrutiny, to private entities that face less regulatory pressure and public accountability. For example, Berg et al. (2024) show that large emitting firms reduce their carbon emissions mainly through the divestment of their high emitting assets. Although brown spinning can help divesting public companies improve their environmental performance and environmental, social and governance (ESG) ratings, it raises important questions about the overall impact on global or aggregate emissions.

In this part, I examine the post-divestment environmental implications of brown spinning. Specifically, I examine the relationship between the change in ownership from public to private entities and the emission levels of the divested assets. I consider whether the sustainability preferences of private investors, as indicated by their status as signatories to the United Nations Principles for Responsible Investment (PRI), influence the emission outcomes of the acquired assets.

I find that the aggregate direct emissions of the divesting public companies decrease significantly over time. Divesting public companies reduced their scope 1 by 28% between 2014 and 2022 as shown in Table 4.4 and their combined scope 1 and 2 by 26% between 2014 and 2022. This is similar to Berg et al. (2024)'s finding, where they show that large emitters reduced their combined Scope 1 and 2 emissions by 19% after the Paris agreement relative to the period before the Paris agreement. These findings imply that divesting public companies are becoming greener over time and that this transition is mainly driven by divestment (Berg et al., 2024). Second, while divesting public firms are becoming greener, divested assets are not. In contrast, the change in ownership from public to private surprisingly leads to increased GHG emissions. At the plant level, a change in ownership from public to private is associated with a 2.7% increase in GHG emission.

I find that private investors with a stated sustainability preference have higher post-acquisition asset-level emissions compared to private players without an explicitly stated sustainability preference. Assets acquired by private investors with a stated sustainability preference have higher unit-level emissions ranging from 22% to 54% depending on the regression specifications - compared to those without such a stated preference.

The fourth and last parts of the dissertation examine whether financial shocks can limit the brown production activities of a firm. One of the ways investors punish brown companies is by starving them of capital through divestment, i.e. by selling their investment in brown companies and reinvesting in green companies. The divestment strategy is very popular among sustainable investors as it is expected to generate real impact through limiting the brown production activities of the firm and incentivizing the (brown) firms to pursue green production activities. I examine whether these financial shocks induced by investors can limit the brown production activities of the brown firm.

This part builds on the work of Hartzmark and Shue (2024) who show that brown firms exhibit negative impact elasticity. Hartzmark and Shue (2024) develop an impact elasticity measure expressed as the change in environmental impact due to the change in cost of capital. The change in environmental impact is defined as the change in emission intensity. I decompose the change in emission intensity into different activities that can affect it such as change in output, change in methodology, divestment, merger and acquisition, change in boundary, change in renewable energy consumption, among others. I focus on the change in emission emanating only from the change in output to capture the changes in emission from firm production activities.

I find that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital limits the brown production activities of the firm. The results are mostly significant for the brown firms.

Chapter 2

A review on ESG investing: Investors' expectations, beliefs and perceptions

[1]

[1] This is a joint work with Roman Kraussl and Denitsa Stefanova

Abstract

We examine the recent literature on the expectations, beliefs, and perceptions of investors who incorporate Environmental, Social, Governance (ESG) considerations in investment decisions with the aim to generate superior performance or make a societal impact. Through the lens of equilibrium models of agents with heterogeneous tastes for ESG investments, green assets are expected to generate lower returns in the long run compared to their non-ESG counterparts. However, in the short run, ESG investments can outperform non-ESG investments through various channels. Empirically, results for the relative performance to ESG investment are mixed. We find strong empirical evidence in the literature that investors have a preference for ESG and that their actions can generate positive social impact through engagement. The shift towards more sustainable policies in firms is motivated by the increased market values and the lower cost of capital of green firms driven by investors' choices.

2.1 Introduction

Over the last 15 years, there has been a substantial increase in the commitment of institutional investors to responsible investment. United Nations Principles for Responsible Investment (UN PRI), one of the leading proponents of responsible investment in the world, has experienced immense growth in the number of signatories and asset owners committed to responsible investment – from 63 signatories and 32 assets owners with a combined AUM of USD 6.5 trillion in 2006 to 3,826 signatories and 609 assets owners with a combined AUM of USD 121.3 trillion in 2021. This evolution echoes the increasing attention of investors towards ESG investments – a development that has the potential to generate important valuation implications given the role of investor preferences in the determination of risk premia and their term structures.

A first glance at the financial industry indicates that there is no consensus among industry experts on the perceived benefits and performance of ESG investments. To some, ESG investments are seen as a way to generate superior performance. Others perceive them as a means to make social impact that may come at the cost of foregone financial performance. ESG investments might also be seen as an exploitative way to obtain funds from investors which could potentially explain the reason for greenwashing. Those aspects of ESG investing encompassing investment performance and societal impact can be summarized into three competing hypothesis: (a) doing well by doing good, i.e., investors obtain superior performance while also creating positive societal impact through ESG investment; (b) doing poorly by doing good, i.e., investors obtain inferior performance but create positive societal impact through ESG investment; and (c) doing neutral by doing good, i.e., investors obtain neutral performance or no performance benefit but create positive societal impact through ESG investment.

A growing number of academic studies have focused on modeling the preferences of economic agents to investigate the implications of their choices on asset prices, firms' production decisions, and social welfare. There is no single motivation that drives investors' choice of incorporating ESG considerations in their portfolio allocation decisions. Krueger et al. (2020) document in their survey on institutional investors that reputation, moral or ethical considerations, legal/fiduciary duties, as well as financial motives stand behind the decision to incorporate climate risk in portfolio decisions. What mechanism can explain the implications of such investor motives on asset prices? Under what conditions can the decisions of ESG-motivated investors generate real impact by influencing firm behavior in a transition towards clean production technologies? How should ESG capital be allocated across firms to increase aggregate welfare?

In this study, we review the recent literature on ESG investing to understand the perceptions, beliefs and expectations of investors in relation to the reality and empirical facts of ESG investments. We begin by examining the theoretical literature to draw insights on the asset pricing implications of incorporating ESG motives in investment decisions. Early studies of sustainable investing consider exclusionary screening applied in portfolio decisions. They attribute the higher cost of capital of brown firms relative to green ones to the reduction in risk-sharing ensuing from such screening (Heinkel et al., 2001). Another channel considered in the literature is that of pricing power of socially responsible firms due to customer loyalty (Albuquerque et al., 2020). Alternatively, another strand of the literature considers that some economic agents derive non-pecuniary benefits from holding green assets (for example, Fama and French, 2007; Baker et al., 2022b). Such investors are willing to pay more to hold green firms, pushing the price of green assets up, thereby leading to lower expected returns. Green assets thus have negative CAPM alphas, contrary to brown assets. The higher expected returns of brown firms are also obtained due to a hedging motive. Under the assumption that the utility of all economic agents is impaired due to unanticipated realizations of ESG-related risks such as climate change, green assets are expected to underperform relative to brown ones as they can serve as an instrument to hedge against climate risk.

Investing according to ESG criteria also involves a risk as long as there is uncertainty whether assets are truly green according to their ESG scores. Investor uncertainty relative to the ESG profile of an asset can weaken the negative return predictability of the asset's ESG score, as the higher risk due to ESG uncertainty commands a higher risk premium (Avramov et al., 2021). The uncertainty inherent in ESG scores also motivates an information channel to explain how ESG preferences impact firms' cost of capital. Goldstein et al. (2022) show that the cost of capital reflects the average information risk that is faced by investors and is non-monotone in the share of ESG-motivated investors in the market, increasing when both groups of investors are equally represented. As the market becomes less dominated by non-ESG investors, this information channel leads to an increase in the cost of capital. These theoretical models help reconcile the empirical observations of investor willingness to forego financial returns when investing in green assets and the mixed evidence on the cost of capital of green firms.

The performance of ESG investments has been studied in both static and dynamic equilibrium models. For instance, Heinkel et al. (2001), Fama and French (2007), Avramov et al. (2021), and Berk and van Binsbergen (2025) obtain a negative ESG-expected return relationship in a one-period equilibrium model. Nonetheless, ESG investments can outperform in the short run. Pastor et al. (2021) explain the outperformance of ESG investments through a consumers' and an investors' channel, where a positive shift in investors and/or consumers' tastes can lead to outperformance of green assets. In Pedersen et al. (2021), the relative performance of ESG investments is conditioned on the type of investors that is prevalent in the market. In a market where ESG-motivated investors prevail, the latter drive up the prices of green assets, thereby leading to a lower expected return.

A dynamic setup can challenge the negative ESG-alpha relationship through a risk premium channel. As demonstrated in Avramov et al. (2024), the brown-averse agents' willingness to sacrifice expected returns when holding green assets can vary with ESG demand and supply. As positive demand and supply shocks are associated with diminishing marginal utility, a brown-averse investor would require a higher risk premium to hold the market as it becomes greener. Shocks to ESG demand entail a positive risk premium for green stocks, thus dampening or reversing the negative ESG-expected return relationship obtained in a static setting.

We further examine the empirical literature on (i) whether there is evidence that investors have preference for green assets, and (ii) whether holding green assets can serve as a hedge against ESG-related risk. We find a broad consensus in the literature on the sustainability preferences of investors (Bauer et al., 2021; Heeb et al., 2023; Ceccarelli et al., 2023, among others). Empirical studies confirm that there is support for sustainable investments among economic agents, i.e., investors are willing to sacrifice return to engage in ESG investing. Hartzmark and Sussman (2019), Barber et al. (2021), Ceccarelli et al. (2023) document that investors value sustainability. Bauer et al. (2021) provide evidence that the support for sustainable investments is driven by strong social preferences of investors rather than beliefs for better financial outcomes from investments in green assets. They also show that individual investor's social preferences matter in delegated portfolio decisions.

A number of studies have documented evidence that ESG investments serve as a hedge against climate risk. Firms with better ESG performance have lower exposure to climate risk and earn lower returns, consistent with an increased investor demand due to the high potential to hedge against climate risk (Engle et al., 2020; Ardia et al., 2022; Bolton and Kacperczyk, 2021; Huynh and Xia, 2021). There is also evidence of a premium in the option market for hedging climate- or ESG-related uncertainty (Ilhan et al. 2021; Cao et al. 2022). Nofsinger and Varma (2014) find that during the period 2000 and 2011 socially responsible mutual funds outperform convential mutual funds during market prices. Ceccarelli et al. (2023) show that low-carbon mutual funds are exposed less to climate risks and outperform conventional funds in periods with higher salience of such risks.

With these two established facts from the empirical literature, we would expect underperformance of ESG investment. However, the empirical evidence is mixed. Hong and Kacperczyk (2009), Baker et al. (2022a), Zerbib (2019), Choi et al. (2020), Bolton and Kacperczyk (2021), Faccini et al. (2023), Seltzer et al. (2022), Hsu et al. (2023) all show that green firms underperform relative to brown firms. Gompers et al. (2003), Derwall et al. (2004), Bebchuk et al. (2009), In et al. (2019), Duan et al. (2023), Pastor et al. (2022) document a positive relationship between a firm's ESG profile and its returns, while Hyun et al. (2020), Chava et al. (2025), Ochoa et al. (2022), and Aswani et al. (2024) find no significant relationship. Positive ESG demand shocks (Avramov et al., 2024) could help reconcile this evidence. Alternatively, an unexpected increase in environmental or climate concerns (Ardia et al., 2022; Pastor et al., 2022) could also lead to higher realized returns.

We also consider the ability of ESG-motivated investments to generate societal impact. Impact can be achieved through several channels, as argued in recent theoretical studies. Potential channels include search capital frictions (Landier and Lovo, 2020), financing constraints and coordination (Oehmke and Opp, 2024), lower cost of capital and higher valuation (Pastor et al., 2021), and the proportion of ESG investors in the market (Pedersen et al., 2021), among others. Empirical evidence shows that ESG investment can generate societal impact through various channels such as environmental activism (Naaraayanan et al., 2020), shareholder coordination (Crane et al., 2019), institutional commitment (Dyck et al., 2019), divestment (Berk and van Binsbergen, 2025), and two-tier engagement (Dimson et al., 2021). The effectiveness of those channels in generating the intended impact, however, is rather varied. Berk and van Binsbergen (2025) argue that ESG divestiture strategies have little impact on the real investment decision of the affected firms. Recent empirical studies (such as Dimson et al., 2021; Krueger et al., 2020; Naaraayanan et al., 2020) provide support for engagement as a way to generate societal impact. Instead of divesting, investors should engage brown firms (firms with low ESG performance) to become green or even encourage green firms to become greener. This action could, in turn, lead to higher valuation and lower cost of capital for the transitory firms.

The remainder of this paper is organized as follows: In Section 2, we discuss the investors' preferences towards ESG investment. In Section 3, we provide the recent empirical literature on whether investors can "do well by doing good". In Section 4, we discuss whether ESG investment can generate societal impact and through which channels. In Section 5, we conclude by suggesting avenues for future research.

2.2 Investor Preferences for Sustainability

To incorporate investor preferences for sustainable investing, theoretical models typically treat green assets as consumption goods (see, for example, Heinkel et al., 2001; Fama and French, 2007; Avramov et al., 2021, 2024; Berk and van Binsbergen, 2025; Pastor et al., 2021; Pedersen et al., 2021). In these models, investors differ in their preferences for sustainability, where one type of investors has tastes for green assets that are unrelated to their returns. This group of investors derives non-pecuniary benefits from holding green assets: Investors get direct utility from the holdings of green assets, beyond the utility they derive from consumption provided by the payoffs of these assets. This is in contrast with the standard asset pricing assumption where investors are assumed to be concerned solely with the payoffs from the investment and not with the characteristics of the investment itself.

A straightforward (and extreme) way to model investor tastes for green assets is through exclusionary screening based on the characteristics of firms. One type of investors – exclusionary ethical investors – would refuse to hold assets that violate their ethical criteria (e.g., firms with a polluting technology), while another type of investors would be neutral with respect to the greenness of firms (and would consequently not impose restrictions on their asset holdings based on firm characteristics). That is the modeling choice offered in Heinkel et al. (2001), where the presence of exclusionary green investors changes the risk sharing opportunities in the market. As unacceptable firms can be held by fewer investors than green firms, their share prices fall. Given that risk sharing is reduced with the presence of more green investors, the cost of capital of polluting firms rises. An alternative formulation to the exclusionary screening approach to integrate investor tastes is one that also accommodates positive screening. Investor utility is penalized for holding polluting assets, but some utility is gained for holding green stocks. This is the approach introduced in Baker et al. (2022a), where investor utility depends on the holdings of assets and their environmental scores. The additional non-pecuniary preferences of green investors for an asset with high environmental score bid up its price so that green assets have lower expected returns than brown ones. An implication of their model is that investors with tastes for green assets will hold them at higher weights, leading to more concentrated ownership of such assets.

Fama and French (2007) argue that the asset pricing implications in an economy where some investors have tastes for assets as consumption goods are similar to those that arise when some investors trade based on misinformed beliefs. If investors disagree over the probability distributions of future asset payoffs, as markets should clear, informed investors overweigh the assets that are underweight by the misinformed investors and vice versa. The price effects induced by tastes for assets as consumption goods resemble those due to disagreement. However, while price effects of erroneous beliefs would disappear in the long run as misinformed investors eventually learn, such convergence does not hold for investor tastes, as they are assumed to be exogenous.

While some investors may not exhibit preferences for sustainable assets, they may still incorporate the information contained in the ESG scores of firms to update their views on assets' expected risk and return. Pedersen et al. (2021) include such

'ESG-aware' investors in their setup in addition to investors with or without tastes for green assets. Set within a mean-variance framework, the solution to the investor's portfolio problem is characterized by an ESG-efficient frontier. The frontier is hump-shaped, with a lower Sharpe ratio for assets with very high ESG scores. The highest Sharpe ratio is attained by ESG-aware investors who use ESG information in their investment decisions but do not otherwise exhibit ESG preferences. Assets with high ESG scores have lower expected returns due to high demand from ESG-motivated investors.

The size of the ESG industry or the fraction of ESG investors in the economy can impact the performance of ESG investments. Pastor et al. (2021) show that, for the ESG industry to exist, there must be a dispersion in the ESG tastes or preferences. Pedersen et al. (2021) explain that the outperformance of ESG investments is conditioned on the type of investors that is prevalent in the market. If all investors are aware of the value of ESG signals but have no preference for sustainability, ESG scores do not predict abnormal returns, as the information is incorporated in prices. If all investors have preference for sustainability, then higher ESG scores imply lower cost of capital for the firm, which can issue shares at higher prices. The presence of all types of agents in the market leads to a range of possible equilibria that depend on the prevailing type of agents and result in a relationship between ESG scores and expected returns that can be positive, negative, or neutral.

In the models presented so far, investor's utility is modeled as a function that includes (agent-specific) non-pecuniary benefits that a subset of agents derives from holding green assets. However, while concerns about climate change are agent-specific – as are tastes for green assets – the utility of all agents in the economy may be impaired by unanticipated realizations of ESG-related risks, such as climate change. Pastor et al. (2021) accommodate climate risk in their preference specification, so that the utility function of investors is defined over wealth, stock holdings – with the associated non-pecuniary benefits from holding stocks – and climate risk.

Under this preference specification, the expected underperformance of green assets is also driven by the assumption that they serve as a hedge against climate risk that investors care about. Investors are willing to pay more for sustainable assets, and these assets earn lower alphas. ESG investors' portfolio decisions result in a tilt towards green assets and thus generate lower expected returns relative to agents with no preferences for sustainability. The stronger the taste for green holdings, the larger the deviation from the market portfolio (which is held by all agents if there is no dispersion in preferences). Since, in addition, investors dislike unanticipated deteriorations in climate, the higher expected returns from holding brown assets reflect the higher exposure of brown firms to climate risk.

Alternatively, it is plausible to argue that brown firms rather than non-polluting green ones serve as a hedge against climate risk. Under the assumption that the externality is high (i.e., negative climate shocks realize) when polluting firms experience positive shocks to their output, Baker et al. (2022b) argue that the resulting unexpected returns of these firms shoot up, making them climate hedges. Brown-averse investors who suffer the greatest disutility loss in such states have the strongest motive to hedge and thus – counterintuitively – tilt their portfolios more towards polluting firms. The cost of capital for polluting firms falls if the fraction of brown-averse agents in the economy prevails, leading to even more capital being channeled to brown firms. Both mechanisms are plausible, so it ultimately remains an empirical question whether the stocks of clean or polluting stocks hedge climate risk.

In standard asset pricing models such as the CAPM of Sharpe (1964) and Lintner (1965), it is assumed that investors are completely aware of the probability distributions of the future payoffs on assets and optimize their portfolio choice based on the payoffs of these assets under known probability laws. Faced by uncertainty about the true probability law, however, agents would alternatively gradually update their beliefs about the probability distribution of future payoffs based on the arrival of new data. Thus, agents would make investment decisions, compounding the uncertainty that stems from their posterior model weights and the stochastic evolution of the state variables of the model. Arguably, model ambiguity is relevant in the context of ESG preferences. For instance, Giglio et al. (2021) state that "it is implausible that economic agents know with any degree of certainty the precise nature or severity of climate risks that are facing them, a topic of substantial disagreement even within the scientific community". Such disagreement is reflected in the large degree of disparity that exists across ESG ratings of firms issued by different data providers, as documented by Chatterji et al. (2016), Gibson et al. (2021), Berg et al. (2022a), and Christensen et al. (2022). The mixed signals that investors receive on the sustainability profile of a firm could distort the ESG-alpha relationship induced by investor tastes that would otherwise exist if the firm's ESG profile were known with certainty.

Avramov et al. (2024) examine the asset pricing effects of this form of uncertainty. In their model, brown-averse investors derive non-pecuniary benefits from holding assets based on their ESG score. However, the investors observe firms' ESG scores with error. This uncertainty renders firms' stocks to be perceived by investors as riskier. Under these assumptions, the demand for equities is driven by two components: (i) demand for equity in the absence of ESG preferences, and (ii) demand for an asset with a positive payoff when the market is green, and a negative payoff when the market is brown. In this setup, there are two conflicting forces that drive the ESG-alpha relationship: The non-pecuniary benefits that investors extract for holding a green asset (or the green market) drive down the risk premium, while the asset (or the market) is perceived to be riskier due to ESG uncertainty, thus commanding a higher risk premium. The overall result for the ESG-alpha relationship is thus inconclusive. In a setting with multiple assets with different individual levels of ESG uncertainty, alpha increases with ESG uncertainty and the alpha-ESG relation becomes weaker.

The implications of ESG disagreement or uncertainty on the expected performance of ESG investments documented in Berg et al. (2022a,b) and Avramov et al. (2024) highlight the relevance of investors' heterogenous beliefs, learning and ambiguity about the probability distribution of the future payoff, and bring forward potential implications for the survival of ESG investors. According to the market selection hypothesis, agents with relatively inaccurate forecasts are driven out of the market and the price impact of their beliefs is dissipated. To the extent that the behavior of ESG investors mirrors that of misinformed investors (as in Fama and French, 2007), the aspect of long-term survival and impact of such investors becomes of interest. Should we expect that ESG investors perish in the long run or that they learn about the distribution of the future payoffs, and they adjust accordingly? Sandroni (2000), Blume and Easley (2006), and Yan (2008) examine time separable preferences and provide evidence in support of the market selection hypothesis. Borovička (2020) examines the hypothesis under recursive preferences of the Duffie-Epstein-Zin type and shows that it is possible for the agents with incorrect beliefs to survive. Guerdjikova and Sciubba (2015) show that ambiguity-averse agents can survive if the ambiguity vanishes with time or if the economy exhibits no aggregate risk. Kogan et al. (2017) establish necessary and sufficient conditions for agents to survive and to have an impact on prices in the long run. Under the assumption of time-separable preferences, they demonstrate that both components of the market selection hypothesis do not generally hold: Agents with inferior forecasts do not survive in the long run and their price impact is destroyed as they are driven out of the market. Instead, if the forecast errors of these agents accumulate slowly under certain conditions on the curvature of the utility function, the agents can survive and affect prices. The relevance of these findings in the context of ESG investments has not been researched to the best of our knowledge. We note that this opens up an interesting opportunity for future research.

Arguably, investors' interest towards sustainable investment opportunities shifts over time. Such dynamic shifts that we have witnessed over the past decade warrant the accommodation of preference shocks when modelling investor behavior and choices. Non-pecuniary benefits from investing in green assets would vary with the state of the economy, giving rise to models that incorporate dynamics in ESG demand and supply. Preference shocks for sustainable investing arise under such specification, in line with asset pricing models with demand shocks (see Wurgler and Zhuravskaya, 2002; Albuquerque et al., 2014; Koijen and Yogo, 2019). A dynamic equilibrium model that accommodates shocks to investor preferences for ESG can rationalize an ESG-alpha relationship that varies over time and switches sign and magnitude. The empirical evidence that we review in Section 3 brings support for such time variation in the relationship. For example, Bansal et al. (2022) explore the time-variability of abnormal returns of green and brown firms in different states of the economy and highlight the role of countercyclical investor preferences for sustainability in shaping the dynamic ESG-alpha relationship.

Avramov et al. (2024) provide asset pricing implications of such time-varying ESG preferences in a dynamic equilibrium setting. They cast investor preferences in a modified version of Epstein and Zin (1989, 1991) in a two-good economy, where the consumption bundle consists of the physical good and an incremental consumption good that derives from non-monetary benefits from holding green assets. The innovation relative to a setting with standard recursive preferences that allows for an ESG impact in risk premia is that brown-averse agents perceive higher return on wealth than the physical return when the market is green. The willingness of brown-averse agents to accept lower returns for holding green assets (represented as a convenience yield effect) is reflected in a negative ESG-alpha relationship, as obtained in static models. However, in their model, the convenience yield is not fixed but can vary with ESG supply and demand. Brown-averse agents become more sensitive to shocks in ESG supply and demand when the market becomes greener and require a higher risk premium for holding the market. This risk premium channel thus causes the ESG-alpha relationship to fluctuate over time, switching sign and magnitude.

Both the dynamic model of Avramov et al. (2024) and the two-period economy models of Pastor et al. (2021) provide theoretical arguments for the possibility of ESG investment outperformance in terms of realized returns. In their models, ESG demand factors play a key role. A positive shock to investor ESG preferences in the Avramov et al. (2024) model (i.e., higher non-monetary benefits from holding the green asset) leads to an increase in the price of a green asset and hence to a positive unexpected return, while the price of the brown asset drops. Thus, the realized return of a long-short portfolio of green and brown assets respectively would be positive. In the setting of Pastor et al. (2021), ESG preferences can shift unexpectedly over generations of agents which would be associated with positive unexpected returns on green assets. Better than expected performance of green stocks would then be achieved through this investor channel.

Apart from the asset pricing implications, investor tastes for green assets and the resulting willingness to pay more for sustainable investments have the potential to impact firm investment decisions. The cost of capital of a green firm is lowered when investors derive non-pecuniary benefits from holding its equity. Consequently, the valuation of a green firm becomes higher than that of an otherwise identical brown firm. Heinkel et al. (2001) and Pastor et al. (2021) argue that this valuation differential can induce brown firms to become green. This effect, combined with the increased growth rates of green firms due to the lower cost of capital would result in green firms becoming a larger fraction of the overall economy.

The presence on the market of both profit- and ESG-motivated investors could have implications on the cost of capital through an information channel as well, as argued in the model introduced by Goldstein et al. (2022). In a market with investors with heterogeneous preferences over multiple fundamentals, the price informativeness of a security would depend on the trading intensity of any of the types of investors. Its price would reflect the preferences of the investor type that dominates the market. In their setting, two equilibria can coexist: in one, the price is dominated by a financial cash-flow component, while in the other, it loads on the ESG component, also implying the possibility of jumps across equilibria. The information channel allows to reconcile the willingness to pay for green investment with the higher cost of capital for green firms. The cost of capital increases as green firms attract more socially-minded investors, leading to higher information risk for profit-motivated investors who find the price less informative, prompting them to require a higher return.

Given a mechanism for impacting firms' investment decisions, the exclusionary screening criteria applied by (institutional) investors would appear meaningful for increasing the fraction of sustainable firms and achieving a greener economy. Berk and van Binsbergen (2025), however, raise caution against the efficiency of this mechanism. In their study, they investigate the impact of divestiture activities on the firms' cost of capital. They argue that given the current fraction of stock market wealth channeled towards socially responsible investments (SRI), the reduction in the cost of capital due to divestitures is immaterial to the investment decisions of firms. Instead, impact investing or engagement, i.e., exercising the rights of control to change firms' policies and production decisions, would be a more effective strategy to achieve a shift to greener firms. Broccardo et al. (2022) argue that voice (engagement) rather than exit (divestment or boycott) is more effective in pushing firms to become greener.

Under what conditions, however, would the capital of ESG-minded activist investors indeed push firms to adopt green production? And ultimately, what firms should impact investors allocate capital to? Under the theoretical framework of Oehmke and Opp (2024), complementarities emerge between ESG-motivated and profit-motivated investors. Under binding financial constraints, the financing capacity of a firm can be brought beyond the one obtainable under exclusively profit-motivated investors. The underlying condition for this to realize is that ESG investors internalize the counterfactual social costs that would be generated by a firm's brown production if it is financed by financial investors only, i.e., if ESG-minded activist investors follow a broad mandate which spans beyond the firm they invest in. Under this setting, Oehmke and Opp (2024) offer a micro-founded investment criterion that reflects both the social return generated by green production but also the avoided social costs that would have been generated had the ESG investor not provided capital.

Socially responsible investors would fund green firms that profit-motivated investors would not finance if they are willing to forego financial returns. There is a general consensus in the recent literature that investors are willing to pay for sustainable investment. Table 1 summarizes the findings on investors' willingness to pay for sustainability. In an experimental setting, Martin and Moser (2016) demonstrate that both investors and managers are willing to trade off financial and societal benefits. Similar willingness to forego financial benefits to invest according to social preferences is documented in Riedl and Smeets (2017). Bauer et al. (2021) show that the majority of pension fund members have strong support for increasing funds' engagement in sustainability. Social preferences rather than financial beliefs stand behind this choice as investors are willing to forego financial returns to engage in increasing the sustainability of the companies the funds invest in. While the tradeoff of financial and societal preferences is documented in experimental markets, it does not necessarily generalize to a real market setting. Investors on municipal securities markets do not appear to be willing to forego wealth for societal benefits, as documented by Larcker and Watts (2020).

Is investors' willingness to pay for sustainable investments commensurate with the level of impact? Barber et al. (2021), Bonnefon et al. (2025), and Brodback et al. (2022) show that responsible investors care about the magnitude of impact. Contrary to these findings, however, Heeb et al. (2023) find that while dedicated responsible investors are willing to pay for sustainable investment, they are not willing to pay more for impact, i.e., responsible investors' willingness to pay does not scale with the level of impact. In addition, the willingness to pay for sustainable investments can be driven by an emotional rather than a calculative valuation of impact. This satisfaction or "warm glow" represents a pleasure derived from doing good, which is regardless of the actual impact of one's action (Andreoni, 1989, 1990). Heeb et al. (2023) conclude that an average ESG investor is a "warm glow" optimizer rather than a consequentialist who optimizes the impact of her investment. Hartzmark and Sussman (2019) also suggest that emotions may drive investors' valuation of sustainable investments. Brodback et al. (2022) conclude that more egoistic investors avoid responsible investing and that investors exhibit altrustic value. Bauer et al. (2021) argue that investors engage in ESG investments based on non-financial considerations. Ceccarelli et al. (2023) show that, on average, investors have a preference for "climate-friendly" funds and find that there is a "green shift" in the investment community. Baker et al. (2022a) find that investors in the bond market are willing to pursue non-pecuniary benefits, while Zerbib (2019) shows that ESG investors' preferences have a low impact on bond prices.

Riedl and Smeets (2017) examine why investors engage in or hold socially responsible or ESG investments and find that social preferences and social signaling plays a significant role in ESG investment while financial motives are of second order. Dyck et al. (2019) show that institutional investors are motivated by both financial and social returns when addressing firm environmental and social issues. Bolton et al. (2020) evaluate the ideology of institutional investors in terms of whether they are money conscious or whether they are environmentally and socially conscious. They show that most pension funds are more environmentally and socially conscious while most of the largest mutual funds are money conscious. The large index funds are also more leaning towards the money conscious camp. Bauer et al. (2021) show that for pension funds, social preferences rather than financial beliefs or confusion drive the choice for more sustainability.

The literature on modeling preferences in the context of ESG investing has focused predominantly on treating ESG-minded investors as a homogenous group.

While the preferences of socially responsible investors may be aligned in terms of direction, they may disagree, however, on the relative importance of the different aspects of the sustainability profile of a firm. As well, the objectives of responsible investors may not be aligned. For instance, while investors may dislike firms with high carbon emissions, they may disagree on the social cost of the technologies in place to reduce them. Modeling the heterogeneity in preferences of ESG investors is a promising avenue for future research.

Table 2.1: **Investor Preferences for Sustainability**

This table summarizes the evidence documented in recent studies on investors' willingness to pay for sustainability.

Studies	**Focus**	**Period**	**Main Findings**
Riedl and Smeets (2017)	Investors' motives for holding socially responsible mutual funds.	2006 – 2012	Social preferences and social signaling explain socially responsible investment decisions. Financial motives play a minor role.
Hartzmark and Sussman (2019)	The value investors attach to sustainability	2016 – 2017	Mutual fund investors value sustainability. Market-wide demand for funds depends on their sustainability rating.
Zerbib (2019)	Effect of ESG investors' preferences on bond market prices	2013 – 2017	Low impact of investors' pro-environmental preferences on bond prices.
Larcker and Watts (2020)	Willingness-to-pay in the municipal securities market	2013 – 2018	Investors appear unwilling to forgo wealth to invest in environmentally sustainable projects.
Bauer et al. (2021)	Sustainable investment behavior and drivers behind investors' willingness-to-pay	2018, 2020	67.9% of participants favor increasing pension funds' engagement to increase sustainability of portfolio companies. Social preferences rather than financial beliefs or confusion drive choice for more sustainability.
Baker et al. (2022a)	Willingness-to-pay in the municipal bonds market	2010 – 2016	Investors in the bond market are willing to pursue nonpecuniary benefits.
Brodback et al. (2022)	Investors' willingness-to-pay for socially responsible assets and magnitude of impact	Experimental	Investors attribute a positive value to social responsibility at an increasing rate and are willing to pay a higher price for more responsible companies, even if they cannot expect a higher return.
Heeb et al. (2023)	Impact investors' willingness-to-pay for sustainable investments	2020	While investors have substantial willingness-to-pay for sustainable investments, their allocation decisions are not sensitive to impact.
Ceccarelli et al. (2023)	Willingness to pay for sustainable investment	2017 – 2019	Substantial increase in the monthly net flows of low-carbon funds relative to conventional funds after being labeled as "low carbon".

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2.3 Sustainability and Investment Performance

This section reviews the recent empirical literature on whether investors can "do well by doing good", i.e., whether investors can earn superior returns by investing in sustainability. At the firm level, Hong and Kacperczyk (2009), Baker et al. (2022a), Zerbib (2019), Bolton and Kacperczyk (2021), Garel et al. (2024) and Hsu et al. (2023) show that green firms generate lower returns relative to brown firms. Gompers et al. (2003), Derwall et al. (2004), Bebchuk et al. (2009), In et al. (2019), and Pastor et al. (2022) document a positive relationship between a firm's ESG profile and its equity returns, while Aswani et al. (2023) find no significant relationship. The meta-study of Atz et al. (2021) find that returns from ESG investing documented in the literature are not different on average from returns from conventional investments.

There is, however, overwhelming evidence that corporate sustainability improves corporate financial performance. Atz et al. (2021) document that twelve out of thirteen recent meta-analyses find a positive relationship between sustainability and corporate financial performance. Disaggregating corporate sustainability into an environmental, social and governance component leads to further insights in the ESG-performance relationship. There is overwhelming and robust evidence that better governance is associated with better financial performance and higher firm value (see Core et al., 1999; La Porta et al., 2002; Gompers et al., 2003; Bebchuk et al., 2009, 2013). The environmental and social components which reflect the "doing well by doing good" argument find more mixed empirical support. There is still a positive but weak relationship with firm value (see the meta-study by Margolis et al., 2011, or Ferrell et al., 2016).

It seems puzzling that, while firm value and corporate financial performance are positively related with ESG, investors are not generally able to extract superior performance from their ESG investment strategies. Atz et al. (2021) offer potential explanations: Investor performance is strategy-related, so ultimately a performance result mirrors the extent to which an investment strategy truly reflects the information contained in the ESG profile of a firm. In addition, benefits from ESG investing are state-dependent and are mainly realized during crisis periods. Further, ESG metrics are of inconsistent quality, widely dispersed across data providers. Alternatively, the market could be pricing ESG strategies correctly, so that no abnormal returns are realized ex post.

We argue in addition that the documented empirical findings on ESG investment performance could be rooted in a risk-based argument or that they can be explained through the lens of models on investor preferences and beliefs. From a risk perspective, there are conflicting views in the seminal literature on whether investments in green or brown firms serve as a hedge against risk (along different ESG dimensions). On the one hand, investing in non-ESG firms introduces additional risk such as carbon emission risk, environmental regulation risk, biodiversity risk, physical risk, transition risk or litigation risk heightened by social norms (see Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2021; Garel et al., 2024; Hsu et al., 2023). Investors' demand for compensation for the exposure to these additional risks leads to a higher risk premium for holding brown assets. Therefore, non-ESG investments require higher expected returns compared to ESG investments. Alternatively, one could argue as well that it is polluting firms instead that provide a hedge against climate risk, as positive shocks to their output may tend to occur when negative climate shocks realize, so that they would pay off when pollution is high. Baker et al. (2022b) argue that investors who suffer the greatest disutility from the occurrence of such adverse climate shocks would have the strongest motive to hedge and would hence increase their holdings of polluting stocks.

From the investor preference perspective, under the assumption that some investors have a preference for sustainable investments and derive non-pecuniary utility from holding green assets, such investors would be willing to sacrifice returns to hold

ESG investments, implying a negative ESG-performance relationship. This argument follows the lines of the convenience yield effect from holding liquid safe assets, introduced by Krishnamurthy and Vissing-Jorgensen (2012). The prevalence on the market of investors with preference for green assets leads to the underperformance of ESG investments. However, the shift in customer or investor tastes for green assets can lead instead to the outperformance of ESG investments (Pastor et al., 2021). In addition, the convenience yield of holding green assets can vary over time, off-setting the negative ESG-expected return relationship (Avramov et al., 2024). In a greener market, brown-averse agents become more sensitive to ESG demand and supply shocks and require a higher risk premium implying positive ESG-expected return relationship. Finally, Avramov et al. (2021) show that ESG uncertainty can change the ESG-performance relation, contributing further to the arguments put forward in Atz et al. (2021) that green firms could underperform in expectation.

Empirical studies reach largely opposing conclusions on the relationship between ESG performance and investment returns. In Table 2, we summarize the evidence documented in the recent literature on the relationship between sustainability and investment performance. Focusing on a specific aspect of the ESG profile of a firm – its carbon emissions – In et al. (2019), Bolton and Kacperczyk (2021), Azar et al. (2021), Aswani et al. (2024), and Hsu et al. (2023) document diverging findings. Based on a sample of publicly traded U.S. firms, Hsu et al. (2023) find a positive relationship between the toxic emission intensity of firms and their corresponding stock returns over the period 1991 to 2016. For a more recent sample, however, In et al. (2019) find that the stocks of high carbon emission firms earn lower returns relative to their low emission counterparts. A negative relationship between firms' carbon emissions and stock returns is documented in Bolton and Kacperczyk (2021) for a global sample of firms. Aswani et al. (2024), on the other hand, find no relationship, raising caution about carbon emissions being priced in equity markets. In addition, they argue that the wedge between vendor-estimated and firm-disclosed emissions could potentially explain divergent findings, as the former tend to reflect firm growth, for which investors are rewarded.

Hartzmark and Sussman (2019) focus in their analysis on ESG and mutual funds performance. They do not find evidence that mutual funds with a high sustainability rating outperform their peers that rank low on the ESG dimension after adjusting for well-known risk factors. Their study exploits the introduction of the Morningstar sustainability ratings in 2016. Contrary to this evidence, Ammann et al. (2019) document better performance for sustainable funds evaluated over a longer period. Both studies, however, show that funds with higher sustainability ratings receive greater fund inflows compared to lower-ranked funds, highlighting the finding that in general, investors have preference for sustainable investments. The empirical evidence brought forward in Ammann et al. (2019) suggests that sustainable investments are driven by future performance expectations of sustainable funds and that non-pecuniary motives for sustainable investments play a role.

Studies of the ESG performance of funds investing in private equity or that employ alternative investment strategies document a significant degree of underperformance of funds focused on ESG vs. their peers without such stated objective. For venture capital funds, Barber et al. (2021) find that impact funds underperform traditional venture capital funds. For endowment funds, Aragon et al. (2021) show that responsible investment endowments generate lower portfolio performance compared to non-responsible investment endowments. The two papers relate the ESG investment underperformance to investor's willingness to pay for sustainability. For hedge funds, Liang et al. (2022) show that a substantial fraction of hedge funds that are signatories to the UN PRI engage in greenwashing. Further, investors do not appear to be able to identify such funds. These funds are found to underperform both truly green and truly brown funds. Liang et al. (2022) relate the evidence of greenwashing and underperformance to agency problems.

The ESG-performance relationship can also be state-dependent and vary over time. Empirical studies have considered the performance of green firms or funds that rate high on the sustainability dimension during crisis periods. Lins et al. (2017) show that firms with high social capital have higher returns than firms with low social capital during the 2008–2009 financial crisis. Pastor and Vorsatz (2020) show that during the Covid19 crisis of 2020, funds with high sustainability ratings perform well and investors remain focused on sustainability during this major crisis.

One of the arguments that has been brought forward to explain the underperformance of ESG investments is risk-based. Investors who hold non-ESG investments are exposed to additional sources of risk and would consequently demand a risk premium. While empirical studies demonstrate a positive relation between sustainability and reduced risk exposure, the evidence for underperformance of ESG investments is less prevalent. Lopez de Silanes et al. (2020) find that ESG firm engagement is correlated with decreased risk (as measured by the volatility of equity prices), the latter being attributable to firms disclosing more information. However, they show that ESG scores have little or no impact on risk-adjusted financial performance. Ceccarelli et al. (2023) find that low-carbon funds are likely to have lower exposure to future potential realizations of climate change risks. However, in months with higher salience of climate change risks, low-carbon mutual funds outperform conventional funds but possess higher idiosyncratic volatility. Liang et al. (2022) show that low-ESG signatories exhibit greater operational risk. Ilhan et al. (2021) show that firms with higher carbon emissions exhibit more tail risk and more variance risk. Hsu et al. (2023) find that highly polluting firms are more exposed to environmental regulation risks. Hoepner et al. (2021) demonstrate that investors' ESG engagement leads to a reduction in portfolio firms' downside risk, where engagement over environmental topics has first-order importance.

The uncertainty emanating from ESG related regulatory policies has the potential to impact the investment decisions of economic agents. Ilhan et al. (2021) show that carbon risks are priced in the options market, while Cao et al. (2022) provide evidence that investors pay a premium to hedge against ESG related uncertainty: Options of low ESG-rated stocks are more expensive compared to high-ESG stocks. Focusing on extreme events on the downside, the evidence of higher cost of option protection against tail risk for carbon intense firms brought forward by Ilhan et al. (2021) is relevant for the broader spectrum of ESG-related risks. The regulatory uncertainty related to different aspects of ESG policies could be reflected in the hedging behavior of investors. Kräussl et al. (2023) examine the disparity across different aspects of ESG policies and find that firms with a high disparity in ESG ratings across the different components have a higher cost of option protection against downside risk. Investigating the implications of the demand for hedging against ESG-related uncertainty on higher-order moments of asset returns is an important avenue for future research.

Table 2.2: **ESG Investment Performance** This table summarizes the findings of recent studies on ESG investment performance.

Studies	**Focus**	**Period**	**Main Findings**
Panel A. Equity Market			
Higher Returns of ESG Investments			
In et al. (2019)	Carbon efficient firms and stock returns	2005 – 2015	Carbon-efficient firms outperform carbon-inefficient firms.
Choi et al. (2020)	Global warming, carbon intensity and stock return	2001 – 2017	High carbon-intensive firms underperform low carbon-intensive firms in abnormally warm weather.
Ardia et al. (2022)	Green premium and climate change concern	2010 – 2018	Green (brown) firms' stock prices tend to increase (decrease) with unexpected increase in climate change concerns.
Pastor et al. (2022)	Green premium in equity markets	2012 – 2020	Green stocks outperform brown stocks, driven by an unexpected increase in environmental concerns.
Lower Returns of ESG Investments			

Studies	Focus	Period	Main Findings
Bolton and Kacperczyk (2021)	Carbon emissions and stock returns	2005 – 2017	Stocks of firms with higher total CO2 emissions (and changes in emissions) earn higher returns. Investors demand compensation for exposure to carbon emission risk.
Faccini et al. (2023)	Climate risks reflected in stock prices	2000 – 2018	Stocks with high climate beta outperform those with low climate beta.
Garel et al. (2024)	Biodiversity premium	2018 – 2022	Firms with larger biodiversity footprint earn higher returns following a major biodiversity-related policy event; investors demand compensation for exposure to biodiversity risk.
Hsu et al. (2023)	Pollution premium	1991 – 2016	Firms with high toxic emission intensity generate higher return compared to firms with low toxic emission intensity within the same industry. Exposure to environmental-related risks.
Neutral Returns of ESG Investments			

Studies	Focus	Period	Main Findings
Chava et al. (2025)	Risk, return and ES ratings	1991 – 2016	No significant relationship between ES ratings and average stock returns.
Ochoa et al. (2022)	Sustainable investment strategies and climate change risks	2018 – 2019	Performance of stocks with high environmental performance is not different from that of stocks with low environmental performance.
Aswani et al. (2024)	Carbon emissions and stock returns	2005 – 2019	Unscaled raw emissions estimated by vendors are correlated with stock returns, unlike unscaled emissions disclosed by the firms. Carbon emission intensity is not correlated with stock returns.
Panel B. Bond Market			
Higher Returns of ESG Investments			
Duan et al. (2023)	Carbon risk pricing in corporate bond markets	2006 – 2019	Bonds of more carbon intensive firms earn lower returns.

Studies	Focus	Period	Main Findings
Pastor et al. (2022)	Green premium in bond markets	2020 – 2021	German green bonds outperform non-green twins' bonds, driven by an unexpected increase in environmental concerns. Negative yield spread between green bond and twin bond.
Lower Returns of ESG Investments			
Zerbib (2019)	Bond pricing	2013 – 2017	The yield of a green bond is lower than that of a conventional bond.
Baker et al. (2022a)	Pricing and ownership of U.S. green bonds	2010 – 2016	Green bonds are issued at a premium (lower yield) compared to conventional bonds
Seltzer et al. (2022)	Climate regulatory risks and corporate bonds	2009 – 2017	Firms with poor environmental profiles have higher yield spreads and lower credit rating compared to firms with good environmental profiles.
Neutral Returns of ESG Investments			
Hyun et al. (2020)	The price of going green	2010 – 2017	No robust evidence of yield premium or discount on green bonds
Panel C. Funds			

Studies	Focus	Period	Main Findings
Higher Returns of ESG Investments			
Nofsinger and Varma (2014)	Socially responsible funds vs. conventional funds' performance during market crises	2000 – 2011	Socially responsible mutual funds outperform conventional mutual funds during market crises.
Ceccarelli et al. (2023)	Benefits and costs of low carbon mutual funds	2017 – 2019	Low carbon funds have a lower exposure to climate change risk at the cost of lower sectoral diversification; they outperform conventional funds in months with higher salience of climate change risks.
Lower Returns of ESG Investments			
Riedl and Smeets (2017)	Return and fee performance of socially responsible mutual fund	2006 – 2012	Socially responsible funds (SRI) funds generate lower returns and request higher management fees compared to conventional funds.
Barber et al. (2021)	Investor's willingness to accept trade-off between financial returns and non-pecuniary benefits	1995 – 2014	Impact funds earn lower internal rates of return (IRRs) ex-post than traditional VC funds. Willingness-to-pay: Investors accept lower IRRs ex ante for impact funds.

Studies	Focus	Period	Main Findings
Liang et al. (2022)	Investment performance of hedge funds management companies that are committed to UN PRIs	2006 – 2019	Hedge funds managed by PRI signatories underperform other hedge funds, driven by those hedge funds that engage in greenwashing.
Neutral Returns of ESG Investments			
Hartzmark and Sussman (2019)	Investor perception of sustainable investment and willingness to pay	2016 – 2017	Investors perceive sustainability as a positive attribute of a company. High sustainability funds do not outperform low sustainability funds.

2.4 Sustainability and Societal Impact

ESG investments may not necessarily result in higher returns but they may generate positive social impact. Impact can be achieved through a number of channels, as argued in recent theoretical studies. Potential channels include search capital frictions (Landier and Lovo, 2020), financing constraints and coordination (Oehmke and Opp, 2024), lower cost of capital and higher valuation (Pastor et al., 2021), and the proportion of ESG investors in the market (Pedersen et al., 2021), among others. Within the framework of Pedersen et al., 2021, as the number of ESG investors grows in the financial market, the expected returns of ESG firms drop. Thus, as the fraction of ESG investors grows, green firms can raise capital at a lower cost and enjoy high valuation, forcing brown firms to become green and green firms to become greener. Alternatively, under search capital frictions, Landier and Lovo (2020) demonstrate that a larger presence of ESG investors lowers the probability of brown firms getting financed, forcing firms to internalize the externalities of their choices, thereby creating impact.

Oehmke and Opp (2024) show that coordination among socially responsible and financial investors can lead to impact. When ESG investors have a broad mandate, they internalize the counterfactual social costs that would be generated by firms if they seek to be financed by non-ESG investors. Under financing constraints, impact is achieved as responsible investors raise the financing capacity of green firms beyond the levels that could be achieved solely by financial investors. There is a large body of empirical literature documenting the channels through which ESG investments can create societal impact, ranging from divestment strategies to engagement. Table 3 summarizes the major findings in recent studies on the ability of ESG investments to generate social impact. Among the channels for generating impact, studies consider environmental activism (Naaraayanan et al., 2020), shareholder coordination (Crane et al., 2019), institutional commitment (Dyck et al., 2019), divestment (Berk and van Binsbergen, 2025), and two-tier engagement (Dimson et al., 2021).

Elaborating on the environmental activism channel, Naaraayanan et al. (2020) examine the real effect of environmental activist investment choices on targeted firms. While they find that there is a negative relationship between the financial performance of firms and their ESG performance, they find evidence of social impact. Firms targeted by environmental activist investors with shareholder propositions reduce their toxic releases, greenhouse gas emissions, and cancer-causing pollution. They argue that local economies benefit from the effect of the environmental activist. Their results suggest that engagement is an effective tool for long-term investors in achieving socially desirable outcomes.

Institutional commitments to sustainable investment strategies can lead to a positive social impact. For instance, Dyck et al. (2019) show that investors who are signatories to the UN PRI generate a higher impact on firm' environmental and social performance than the average investor. However, the institutional commitment channel can be distorted or blurred by the act of greenwashing. Gibson et al. (2022) connect the commitment of responsible institutional investors to their actions and performance to provide understanding on whether these investors indeed "walk the talk". They find that non-US institutional investors that publicly commit to responsible investing exhibit better ESG portfolio-level scores, while for US institutional investors it is not the case. The disparity between commitment and actions for the latter seems to be driven by the incentive for underperforming investors to engage in greenwashing to attract flows. Liang et al. (2022) find that a non-trivial number of hedge funds that endorse the UN PRI similarly do not "walk the talk" and greenwash their funds instead. The act of greenwashing impacts negatively on the ability of the institutional commitment channel to create real societal impact by effectively reallocating capital from brown to truly sustainable firms.

Shareholders may also coordinate to influence the firms they own. The trend of less concentrated institutional ownership that we have witnessed over the past decades has given way to investor coordination aimed at influencing corporate policies. In line with the theoretical predictions of Edmans and Manso (2011), Crane et al. (2019) find empirical support that shareholder coordination strengthens corporate governance. However, ownership cliques can also coordinate to minimize the price impact of their trades, leading to weaker governance via the threat of exit. Dyck et al. (2019) find the same result for environmental and social issues but argue that private engagement could be the most effective instrument for intended change, while public engagement might just be a tool to increase leverage in private engagement.

The divestment channel is one of the most popular channels to generate societal impact. However, recent empirical studies caution against its effectiveness in generating the intended impact. For instance, Berk and van Binsbergen (2025) find that ESG divestiture strategies have little impact on the real investment decision of the affected firms. They document no detectable change in value when firms are either included or excluded from the leading socially conscious US index FTSE USA 4Good. Divestment strategies have been shown to have relatively small stock price effects around the announcement date and an insignificant one after the announcement date (Nguyen et al., 2020). In line with this evidence, Krueger et al. (2020) find that institutional investors consider ESG engagement as a more effective way to deal with externalities rather than divestment. Naaraayanan et al. (2020) find support to the hypothesis that engagements are an effective tool for long-term shareholders to address climate change risks.

Engagement strategies involve influencing the production choice of brown firms, forcing them to become green. Dimson et al. (2021) find that a two-tier engagement strategy that combines lead investors with supporting investors, is effective in successfully achieving the stated engagement goals and is followed by improved target performance. Their findings suggest that coordinated engagements are value-enhancing for shareholders, especially when engagements are headed by a lead investor and/or are successful. Krueger et al. (2020) find that long-term, larger, and ESG-oriented institutional investors, consider risk management and engagement, rather than divestment, to be the better approach for addressing climate risks. Dyck et al. (2019) also rule out screening (both negative and positive) as a driver for the improvement of environmental and social issues.

Shareholder ESG initiatives may be driven by monetary objectives or do aim at value maximization, but they could similarly be motivated by non-pecuniary outcomes, sometimes harming shareholder value (Krueger, 2015). He et al. (2023) focus on the differences in incentives among shareholders to disentangle these two opposing hypotheses. They document that the majority of shareholders oppose environmental and social (ES) proposals. Consistent with the view that ES engagement activities are value-enhancing, they find that ES proposals decrease the probability of value destroying incidents. Due to agency issues, value-relevant proposals do not pass and higher support to those failed ES proposals predicts a greater number of ES incidents and higher probability of future negative tail returns. What type of investors drive these changes in firm choices? Institutional investors are deemed to be more sophisticated and have access to quantitatively more or qualitatively superior information than retail investors. Retail investors predominantly react to simple signals such as past return measures in their investment decisions (see, for example, Del Guercio and Tkac, 2002; Evans and Fahlenbrach, 2012; Salganik-Shoshan, 2016). Households seem to act as simple decision-makers and invest using readily available information. Sustainability-related information might also be too costly for the retail investors to obtain as compared to institutional investors. This might suggest that the real sustainability change is driven by institutional investors.

The current literature is divided on whether institutional investors and retail investors differ along their preferences for sustainability. Hartzmark and Sussman (2019) and Ammann et al. (2019) argue that both institutional and retail investors show a preference for sustainability. In reaction to the exogenous shock caused by the introduction of Morningstar sustainability ratings, Hartzmark and Sussman (2019) find that institutional investors have a similar response to non-institutional investors. Contrary to these findings, Ammann et al. (2019) find strong evidence that retail investors move money away from low sustainable funds into high sustainable funds, whereas the evidence is weaker for institutional investors. One possible explanation of this result could be that institutional investors possess superior information about the sustainability profile of the funds that is already incorporated in the Morningstar sustainability ratings, so that these investors react less strongly to the exogenous shock once these ratings become public, compared to retail investors. There is only limited research that focuses exclusively on retail investors and the extent to which their investment decisions are linked to ESG considerations: Moss et al. (2024) find that ESG disclosures are irrelevant to retail investors' portfolio allocation decisions. Based on a survey about climate risk perceptions, Krueger et al. (2020) document that institutional investors consider climate and environmental risks as having lower relative importance compared to traditional financial risks for their portfolio decisions, while at the same time having significant financial implications for the portfolio firms. Further, there is no dominating motive behind investors' perspectives on incorporating environmental concerns in their portfolio decisions. They argue that institutional investors appear to be guided by reputation protection incentives, moral or ethical considerations, and their fiduciary duties. Gibson et al. (2020) attribute the outperformance of institutional investors with better ESG footprints to the growing investor preference for ESG investment and the demand-driven price pressure exerted by the institutional investors on stocks with good environmental scores.

Institutional investors that engage in ESG appear to have distinct characteristics relative to their peers that do not incorporate sustainability considerations in their investment decisions. Kim et al. (2019) find that CSR activities are mainly promoted by the presence of active rather than passive long-term institutions. Long-term institutional investors are also associated with lower portfolio turnover and benefit more from the price pressure channel of ESG investment outperformance (Gibson et al., 2020). Funds with longer horizons and funds that are less management-friendly are significantly more likely to support ES shareholder proposals (He et al., 2023). Glossner (2019) finds that firms held by short-term investors have significantly more ESG incidents as compared to firms held by long-term investors which experience significantly less costly ESG incidents.

Higher institutional ownership (Crane et al., 2019; Dyck et al., 2019; Chen et al., 2020), stronger investors' social norm or strong community belief (Dyck et al., 2019), EU regional concentration (Crane et al., 2019), longer investor horizon (Glossner, 2019; Kim et al., 2019), and public commitments (Gibson et al. 2022) are all institutional investor characteristics that have been found to contribute to the improvement of firm's ESG performance. This empirical result further strengthens the importance of considering the presence of heterogenous investors to better understand the ESG implications of their investment decisions. Crane et al. (2019) show that only European institutional investors impact firms' environmental and social performance. Glossner (2019) and Kim et al. (2019) find that investors with longer investment horizons improve firms' ESG performance. Chen et al. (2020) show that an exogenous increase in institutional holdings caused by the Russell index reconstitutions improves the portfolio firms' CSR performance.

Delving deeper in the implications of investment choices of socially motivated investors for total social welfare, Green and Roth (2021) offer a framework to investigate the equilibrium and optimal allocation of social capital, where investors differ not only in their motivation (being socially or financially motivated), but also in the degree of their sophistication. The latter distinction is made based on whether economic agents take into account the effects of their investment choices. Naïve socially-motivated investors do not consider the displacement effects that their investment choices may have on other investors. Such 'values-aligned' investors form their portfolios based on the social returns of the firms they invest in. They place high intrinsic value in investing in green firms and the competition among these investors drives prices of such firms upwards. In that case, the willingness to pay for green investments is inefficient with respect to generating impact. Contrary to them, sophisticated or ‘impact-aligned’ investors are concerned with the total social output or the aggregate externality level. They invest in firms that would not attract capital from financially motivated investors. The willingness to pay to subsidize such firms is efficient in that it creates social value.

Moisson (2022) also investigates the implications of investors’ degree of sophistication. In his model, sophistication reflects investors’ capacity to assess the consequences of their investment choices on the common good – and anticipate the investment choices of other investors of similar type. Within that framework, socially-minded investors can be naïve consequentialists concerned with the direct impact of their investment choices or investors concerned with the aggregate externality level. Under direct consequentialism, a higher level of sophistication generates a lower perceived induced externality and higher equilibrium levels of pollution.

Do socially motivated institutional investors behave like ‘values-aligned’ or ‘impact-aligned’ investors? The results in Green and Roth (2021) suggest that socially minded investors could achieve higher impact and financial returns if they shift capital to firms that require a subsidy to be viable. The empirical evidence they provide demonstrates that the portfolio allocation decisions of sustainable mutual funds are consistent with values alignment. Sustainable mutual funds do not appear to invest in less profitable firms that would not have attracted capital from financially minded investors. Whether other institutional investors display similar investment patterns or whether they take into consideration the ability of firms to raise capital from investors with no ESG concerns remains an avenue for future research. Understanding investment patterns in private markets in particular is relevant for evaluating social impact and exploring displacement effects and the financing of deals that do not attract socially neutral capital.

Table 2.3: **Societal Impact of ESG Investment**

This table summarizes the findings of recent studies on the ability of ESG investments to generate societal impact.

Studies	**Focus**	**Period**	**Main Findings**
Chen et al. (2020)	Institutional shareholders and CSR	2003 – 2006	Exogenous increase in institutional holding improves portfolio firms' CSR performance.
Krueger et al. (2020)	Investor's perception and engagement	2017 – 2018	Institutional investors consider engagement rather than divestment as an effective approach to address climate risk.
Naaraayanan et al. (2020)	Real effects of environmental activist investing	2010 – 2018	Targeted firms reduce their toxic releases, greenhouse gas emissions, and cancer-causing pollution. Negative relationship between financial performance and environmental activism.
Azar et al. (2021)	Big Three and carbon emissions reduction	2005 – 2018	Importance of engagement efforts: negative relationship between the Big Three ownership and subsequent carbon emissions.
Berk and van Binsbergen (2025)	Quantitative impact of ESG divestitures	2002 – 2020	The impact of ESG divestitures on the cost of capital is too small to meaningfully affect real investment decisions.
Dimson et al. (2021)	Coordinated engagements and ESG risks	2007 – 2015	A two-tier engagement strategy, combining lead investors with supporting investors, is effective in successfully achieving stated engagement goals and is followed by improved target performance. Target firms have higher overall ESG ratings.
Hoepner et al. (2023)	Shareholder engagement and downside risk	2005 – 2018	Successful ESG engagements reduce the firm's exposure to downside risk.
He et al. (2023)	Shareholder voice and ES risks	2004 – 2019	Higher support in failed ES proposals predicts subsequent ES incidents. Negative relation between fund support in ES proposals and subsequent abnormal returns.

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2.5 Conclusion

Climate change and sustainability will remain defining issues for our society. Understanding the role of investor capital in fueling the transition to a sustainable economy has attracted the efforts of an increasing number of financial economists over the past years. A lot has already been achieved in modeling investor preferences for sustainability and understanding how these preferences drive investment choices and impact firm financial performance as well as firm behavior and production decisions.

Theoretical studies offering frameworks for modeling ESG investor preferences have so far primarily considered ESG investors as a homogenous group. Socially responsible investors, however, may differ in their preferences along different aspects of sustainability, e.g., along environmental, governance or social dimensions, or they may have heterogeneous priors and differ in their beliefs about the sustainability performance of a firm along these dimensions. Given the documented divergence in how firms fare across different aspects of sustainability, exploring the implications of such heterogeneity in preferences or beliefs on the investment choices of economic agents is a promising avenue for future research. To enable empirically well-grounded models of investor beliefs, research should advance towards measuring investors' subjective perceptions of firms' sustainability performance and their expectations about future cash flows relative to firms' ESG standing. A step in that direction is the retail investor survey on ESG beliefs and perceptions by Giglio et al. (2025) eliciting investors' long-run expectations about the return from ESG investing. Investors' beliefs about higher order moments are also highly relevant for understanding the asset pricing implications of ESG investing. Collecting data on beliefs about risk or investor perceptions about downside tail events in relation to firms' sustainability standing would bring further progress. In addition, gathering beliefs data in private markets is particularly interesting, as the lack of transparent information relative to public markets leaves much more room for subjective judgments. Further, empirical work towards unveiling the dynamics of beliefs about firms' ESG performance would be especially important, as theoretical studies have established that ESG preference shocks are a relevant risk source (Avramov et al. (2024)).

Another important issue is whether ESG investors are misinformed and whether they do act on inaccurate expectations rather than tastes for sustainability. Previous studies have argued that the behavior of ESG investors is closely related to that of misinformed ones (Fama and French, 2007). Agents with inferior forecasts face either the prospect of being driven out of the market by agents with correct beliefs and have their price impact destroyed, or they survive by improving their forecasts through learning. Arguably, one could apply this market selection hypothesis in the context of sustainable investing. Investors' heterogenous beliefs about the probability distribution of future payoffs conditioned on sustainability performance could have relevant implications for the long-term survival of ESG investors. However, while the price effects of erroneous beliefs and disagreement are temporary under the assumption that investors learn, investor tastes for sustainable assets are not similarly likely to disappear due to learning. In addition, the conditions for price impact and for survival are not the same in general (Kogan et al., 2017). It can be that investors who see their market share disappearing still provide risk-sharing opportunities for the dominant type of (well-informed) investors, therefore maintaining price impact. Future research would establish whether this mechanism remains relevant in the context of ESG investing.

Stated beliefs may diverge from actual investor allocations decisions. Investors may claim their investment choices are guided by considerations for sustainability, but their portfolios might not reflect these claims (Heeb et al., 2023). Exploring the actual behavior of economic agents and eliciting their truthful preferences is central for understanding what drives economic decisions and why investors may be willing to sacrifice financial returns to increase social welfare. The field surveys explored in Bauer et al. (2021) shed light on the willingness of pension fund investors to support engagement in sustainable actions in portfolio companies. Further studies should explore the integration of individual investors' social preferences in delegated portfolio decisions. More broadly, however, it remains an open question whether individual investors are motivated by the prospect of achieving societal impact or simply by warm glow (Andreoni, 1989, 1990). Future research should be directed towards investigating those issues. In addition, further empirical work should cast more light on disentangling the implications on companies' practices of investors' choices driven by exclusionary screening and those guided by engagement motives. Theoretical work by Oehmke and Opp (2024) and Green and Roth (2021) indicates that impact is achieved if investors take in consideration the acrions of other market participants. Future empirical studies should investigate whether green capital indeed flows to underfunded companies implementing or targeting the implementation of sustainable processes that would not have otherwise attracted funding from financially-motivated investors.

The ability of investors to correctly identify green firms has implications on the allocation of capital in the economy towards sustainable practices. ESG ratings are largely inconsistent across sustainability rating providers. Such uncertainty over the ESG profile of investments is priced (Avramov et al., 2021). If reflected in the portfolio decisions of agents, ESG uncertainty leads to an ESG-alpha relationship that can be nonlinear and ambiguous. Apart from asset pricing implications, the extent that such uncertainty is reduced as economic agents uncover the true ESG profile of firms may have important societal implications, mitigating the cost of uncertainty and decreasing the cost of equity for green firms. Investigating the implications of the demand for hedging against ESG-related uncertainty on higher-order moments of asset returns is an important avenue for future research.

While investors show a preference for sustainability and are willing to forgo returns to create societal impact, they are faced with the problem of greenwashing which impedes effective reallocating capital from brown assets to truly green investments. Future research should focus on ways to effectively detect greenwashing and on the design of an effective mechanism to penalize firms or funds that engage in greenwashing. Studies in that direction would inform policy decision makers on the effectiveness of ESG-focused regulations such as the proposed amendment to the unfair commercial practices directives (UCPD) and the consumer rights directive by the European Commission (or SFDR article 8 and 9) to curb greenwashing.

Chapter 3

ESG Policy Uncertainty

[1]

[1] This is a joint work Roman Kraussl and Denitsa Stefanova.

Abstract

We examine whether the uncertainty related to developments in environmental, social and governance (ESG) regulation is reflected in asset prices. We proxy the sensitivity of firms to ESG regulation uncertainty by the disparity between the components of their ESG ratings. Firms with high ESG disparity have a higher option-implied cost of protection against downside tail risk. The impact of the misalignment across the different dimensions of the ESG score is distinct from that of the level of the ESG score itself. Aggregate downside risk bears a negative price for firms with low ESG disparity.

3.1 Introduction

There has been an increasing number of environmental, social and governance (ESG) related regulatory developments around the world.[2] In the last decade, the volume of ESG topics in US regulatory documents has increased dramatically, especially after the adoption of the Paris agreement in 2015.[3] This surge in regulatory activity has been marked by significant changes and rollbacks, as policy turnarounds have been prompted by societal pressure, political motives or short-term economic concerns.[4] As a result, ESG-related regulation has been particularly volatile, reflecting a dynamic and evolving policy landscape. In turn, both firms and investors in their financing or investment decisions are faced with uncertainty about how new, updated, and proposed ESG-related regulation will shape the regulatory framework in the future.

In this paper, we explore the uncertainty that stems from the development of ESG regulations and the firm's ability to manage its exposure to this regulatory development. We proxy the latter by the observed disparity across the three dimensions of a firm's ESG standing: its environmental, social and governance performance. We conjecture that the degree of divergence across different aspects of a firm's ESG qualities reflects its ability to adapt to ESG regulatory requirements or its vulnera-

[2]At the global level, there exist the International Sustainability Standards Board (ISSB), the Carbon Disclosure Project (CDP), the Climate Disclosure Standard Board (CDSB), the Global Reporting Initiative (GRI), the Task Force on Climate-related Financial Disclosures, and the Value Reporting Foundation, among others. In Europe, there is the Corporate Sustainability Reporting Directive (CSRD), the Sustainable Finance Disclosure Regulations (SFDR), and the Green/EU taxonomy, among others. In mainland China, there is the EU-China Common Ground Taxonomy (CGT), and the China Securities Regulatory Commission (CSRC) ESG risk disclosure rules. In the US, there are the following proposed regulations related to ESG: the SEC climate-related disclosure rules, the Climate Risk Disclosure Act, and the ESG Disclosure Simplification Act. For example, the European Commission has delayed the implementation of the SFDR several times, contributing to the uncertainty with respect to the final regulation. Once in place as of January 2023, the SFDR has outlined a set of 14 core indicators comprising Level 2's mandatory reporting template with a focus on adverse environmental and social impacts. However, the implementation of Level 2 requirements has raised confusion among investors, leading the European Supervisory Authorities to call for the European Commission to clarify what defines a sustainable investment. See https://www.esginvestor.net/sfdr-level-2-uncertainty-unnerves-managers/

[3]See https://eqm.ai/wp-content/uploads/2023/05/2023-05-25-ESG-Regs-Report-2023-2.pdf

[4]For instance, the U.S. withdrew from the Paris Accord in 2017, and rejoined in 2021.

bility to unexpected ESG policy changes, as perceived by the market. We therefore consider the deviation in a firm's performance across its "E", "S" and "G" ratings, which we term *ESG disparity*, as a measure of the firm's exposure to unexpected changes in ESG regulation. Although a firm's ESG rating could also be indicative of the firm's ability to address changes in ESG regulation, as arguably higher-rated firms would be less exposed to new or changed regulation compared to lower-rated peers, the level of the ESG rating does not reveal the degree to which a higher rating on one component of the score compensates for a lower rating on another component. Therefore, we argue that it is important to consider the divergence within components of a firm's ESG rating.

As investors cannot fully anticipate the nature or scope of new ESG-related policies, asset prices can be affected as investors learn about the costs of these new policies. In this paper, we investigate whether ESG policy uncertainty—at the aggregate economy level and at the firm level—is priced in the option market. Specifically, we explore whether the aggregate cost of protection against downside tail risk that investors require on the market varies with the ESG regulatory uncertainty they face. At the firm level, we examine the relationship between the degree of firms' exposure to ESG regulatory uncertainty and the cost of option protection against the occurrence of tail events on the downside. We also study the pricing of the uncertainty related to a firm's ESG performance to determine whether investors pay a premium to hedge against this risk.

In a first step, we examine whether uncertainty related to ESG regulation developments is reflected in the options market. In the model of Pastor and Veronesi (2013), investors are uncertain whether the current government policy will change or not. Potential new policies are heterogeneous ex ante, as different policies are expected to have different impacts on firms. When choosing a new policy, the government maximizes investors' welfare, while also considering non-economic objectives, reflected in the political costs of adopting a new policy. These political costs are uncertain, and as investors learn about them by observing political signals, they revise their expectations about the likelihood that future policies will be chosen. Stock prices are affected because political uncertainty leads investors to demand compensation. In addition, firms that are likely to be impacted more by changes in government policy command an additional premium for investors.

We focus here on the specific case of ESG regulatory policies within the broader set of government regulations. Both investors and firms are uncertain about the choice of new ESG regulations and about the impact of these regulations on the firm. We examine the impact of ESG regulatory uncertainty on the stock market by investigating whether investors seek option protection when the ESG regulatory uncertainty is higher in the economy. In the cross-section, we also examine whether investors demand additional compensation against large price drops from holding firms that are more exposed to changes in ESG regulation.

Ilhan et al. (2021) and Cao et al. (2022) consider firms' ESG ratings to proxy for the sensitivity of firms to ESG regulation. Arguably, firms with high ESG performance are less sensitive to ESG regulatory developments compared to firms with low ESG performance. However, the combined ESG score of a firm hides any potential disparity between its environmental, social or governance performance. A high disparity in the different dimensions that make up the sustainability footprint of a firm would reflect an increased operational or regulatory uncertainty facing the firm. Therefore, in addition to the level of a firm's ESG rating, we consider the disparity across the firm's environmental, social, and governance performance to proxy for its sensitivity to unexpected changes in ESG regulation. We interpret ESG disparity as a signal of the management's ability to manage its ESG regulatory development. Firms may struggle to identify the ESG regulatory standards to follow and align their reports with various ESG-related reporting frameworks, resulting in disparity in their reported environmental, social and governance performance.[5]

[5] For instance, Coca-Cola claims to align its 2021's ESG report to the following reporting framework

We focus on the options market to investigate whether investors account for the ESG uncertainty reflected in the disparity across the different components of a firm's ESG rating and whether investors are willing to pay in order to hedge it. Options are a natural asset class to study pricing and hedging of downside tail risk, as their prices reflect the forward expectations of investors and do not require a realization of the state. Considering that investors may care more about downside losses than upside gains (Roy, 1952; Kahneman and Tversky, 1979; Gul, 1991), we focus on downside risk. We estimate the cost of protection against downside risk for each US firm following Ilhan et al. (2021) and Kelly et al. (2016).

At the aggregate economy level, the cost of protection against downside risk is higher when the ESG regulatory uncertainty is greater, especially under worse economic conditions. This result is similar to Pastor and Veronesi (2012, 2013) where they find that political uncertainty is priced. At the firm level, firms with high ESG performance have a lower option-implied cost of protection against downside risk compared to firms with low ESG scores. This evidence is in line with Ilhan et al. (2021)'s findings on carbon-intense firms. Interestingly, while all three components of the ESG score contribute significantly to the price of downside risk, the implications of the governance score have the opposite sign. Firms that score highly on governance also have a higher option protection against downside tail risk. However, regardless of their level of ESG performance, firms with high ESG disparity, or as we conjecture, with a low ability to manage ESG regulatory developments, have a consistently higher cost of option protection against downside risk.

Second, we investigate the effect of ESG treatment (or labeling) on the cost

and standards: Global Reporting Initiative (GRI), Task Force on Climate-related Financial Disclosures, Sustainability Accounting Standards Board (SASB), United Nations Global Compact (UNGC), UN Guiding Principles Reporting Framework (UNGPRF), and United Nations Sustainable Development Goals (SDGs). Pepsico, on the other hand, claims to align its 2021's ESG report to Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), Task Force on Climate-related Financial Disclosures (TCFD), and Carbon Disclosure Project (CDP). Of course, while there are some similarities in their reporting framework and standards, any difference therein could impact their environmental, social, and governance performance assigned by third-party ESG raters such as Thomson Reuters or MSCI.

of option protection against downside tail risk. We find that the cost is lower for firms that receive ESG scores in a given year relative to firms without a score and with similar fundamental characteristics. In addition, to further address endogeneity concerns, we exploit the introduction of an ESG-based equity index. In April 2019, SPGlobal launched the S&P 500 ESG Index which includes only firms that are ESG top performers. This event presents a unique opportunity to estimate the effect of the inclusion of a firm in ESG membership on its associated cost of protection against downside risk. We find that index inclusion significantly lowers the firm's cost of protection against downside tail risk. As uncertainty in relation to the ability of a firm to manage ESG regulation is reduced for investors with the publication of an ESG rating or inclusion in an ESG-based equity index, the cost of protection against tail risk reflected in the options market is reduced.

Third, we examine the pricing of aggregate downside risk conditioned on the two aspects of firms' ESG performance: the level of a firm's overall ESG score and the disparity across its components. We extract both the firm-specific and aggregate downside risk measures from the option market which captures the forward expectation of all future events (including rare events). We estimate each US firm's downside risk (FDR) following Gao et al. (2018) and extract an aggregate downside risk measure using principal component analysis (PCA) based on the correlation of monthly estimates of firm downside risk measures (Siriwardane, 2015). We find that there is a one-factor structure driving the time series variation in FDR across all firms. This single factor represents the aggregate downside risk (ADR) measure in our study. Given this aggregate option-implied measure of tail risk, we investigate whether downside risk is priced in the cross-section of stock returns conditional on the level of the ESG score of firms or on the disparity across the different components of the score. We find that aggregate downside risk bears a negative price of risk for firms with high or low levels of ESG performance. When we condition on the disparity across the E, S and G dimension of sustainability scores, we find that the cross-sectional relationship between expected stock returns and downside risk betas is significant in the cross-section of firms with low ESG disparity.

To the best of our knowledge, this is the first paper to examine ESG uncertainty as captured by the disparity between the different components of the ESG profile of a firm and to relate it to downside risk in the options market. Focusing on a specific ESG aspect—that of carbon emission performance—Ilhan et al. (2021) find that climate policy uncertainty is priced in the options market. More carbon-intense firms are associated with a higher cost of protection against downside risk. Our results corroborate these findings, documenting that firms with high emission reduction scores have lower downside tail risk. Cao et al. (2022) is the closest to our paper. They examine whether firms' ESG scores are related to the expensiveness of their options, as captured by implied volatility. Our paper is in line with their baseline result in that firms' ESG performance is reflected in options prices. However, we focus on the disparity across the different components of firms' ESG performance and find that it is reflected in firms' downside tail risk.

Other studies have attempted to study the relationship between ESG-related performance and risk in other markets other than the options market. Glossner (2017) examines the relationship between ESG risks and long-run stock returns. He finds that the portfolio of firms with high ESG risk generates a negative alpha and attributes the negative alpha to unexpected costly ESG incidents and negative earnings surprises. He et al. (2023) examine the implications of shareholder votes in environmental and social (ES) proposals and find that higher support in failed ES proposals predicts subsequent ES incidents. They also document a negative relation between ES incidents and risk-adjusted performance. Hoepner et al. (2023) find that ESG engagement reduces a firm's exposure to downside risk.

Previous literature examines the divergence in ESG ratings across different ESG raters, the cause of the divergence across raters (Christensen et al., 2022; Berg et al., 2022a; Gibson et al., 2021; Eccles et al., 2020), and whether rating divergence is priced in the cross-section of stock returns ((Gibson et al., 2021)). Christensen et al. (2022) document that greater ESG disclosure leads to greater disagreement between ESG rating agencies. They observe that rating disagreement is greater when firms have relatively high or low average ESG ratings. They also find that the environmental and social pillars of ESG, rather than governance, drive more of the positive relationship between ESG disclosures and ESG disagreement. Berg et al. (2022a) investigate the sources of divergence in environmental, social and governance (ESG) ratings. Gibson et al. (2021) analyze the level and nature of disagreement about a firm's ESG rating and study the impact of ESG rating disagreement on stock returns. They find a positive relationship between environmental rating disagreement and stock returns, and a negative one for social and governance rating disagreement.

We contribute to this literature by considering a different dimension of disagreement: the uncertainty in the ESG performance of a firm as captured by the divergence across its different environmental, social and governance scores. We find that the uncertainty in the ESG performance related to such disagreement is priced in the options market. Although there is literature on the pricing of aggregate downside risk, little is understood about the pricing of downside risk in relation to the ESG performance or profile of the firm. Ang et al. (2006) show that the cross-section of stock returns reflect a risk premium for bearing downside risk. Huang et al. (2012) estimate the firm-specific extreme downside risk and document that there is a positive premium on firm-specific extreme downside risk. They find that high extreme downside risk stocks outperform low extreme downside risk stocks. Siriwardane (2015) also finds that downside risk obtained from the option market is priced in the cross-section of equity returns. Kelly and Jiang (2014) show that tail risk has strong predictive power for aggregate market returns. We contribute to this stream of literature by relating the pricing of the aggregate downside risk to the firms' ESG performance.

The remainder of this paper is organized as follows. Section 2 describes the data and the different option-implied risk measures. Section 3 presents empirical analyses of the relationship between ESG uncertainty and the cost of protection against downside tail risk. Section 4 examines ESG uncertainty and aggregate downside risk. Section 5 concludes.

3.2 Data

We obtain ESG ratings for the sample of US firms covered by Thomson Reuters for the period from December 2002 (the earliest year in the database) to December 2021. Sustainability scores are provided at an annual frequency. The ESG scores of individual firms incorporate ratings along three dimensions: environmental (E), social (S) and governance (G). The overall ESG combined score is discounted for significant ESG controversies that impact the company being rated. Thomson Reuters provides a second level of disaggregation of the sustainability scores along the E, S and G dimensions: Resource Use, Emissions, and Innovation scores for the environmental category; Workforce, Human Rights, Community, and Product responsibility for the social category; Management, Shareholders, and Corporate Social Responsibility (CSR) strategy for the governance category. The ESG metrics are reported as percentile rank scores. Scores in the environmental and social categories, as well as the controversies score are benchmarked against industry groups according to the Thomson Reuters Business Classifications (TRBC). The scores in the governance categories are measured against the country of incorporation of the firm.

In Panel A of Table 3.1, we report descriptive statistics of the firms' ESG scores, as well as of the individual components of the aggregate score. The average ESG score across firms is 42. The governance component generally attains higher levels relative to E and S, with a G score of 53.4 for the average firm; it is also the least volatile of the three. Over the years, the number of US firms' ESG scores in our sample has grown significantly from 59 firms with ESG scores in 2002 to 3,113 US

Table 3.1: Descriptive Statistics

This table reports descriptive statistics covering the period from 2002 to 2021. Panel A reports descriptives of the sustainability metrics of the firms in the sample. ESG is the firm's environmental (E), social (S) and governance (G) combined score which incorporates ESG controversies. The ten category scores are also reported. Panel B reports descriptives of the risk measures used in the analysis. IVSDn represents the firm's cost of protection against downside risk. It relates the left-tail implied volatility to the moneyness measured by the option's Black Scholes delta for the out-of-the-money (OTM) standardized put options with a 30-day maturity. The remaining risk measures in Panel B are defined in Table A1 in the Appendix. Panel C provides descriptives of firms' monthly returns and a number of controls. The CAPM beta and volatility are estimated over a 12-month period. For the CAPM beta, the firms' monthly returns are regressed on the S&P 500 returns and a constant. *logassets* measures firm size and is computed as the natural logarithm of firm's assets. *divnetinc* is the ratio of the firm's gross dividend to net income. *ebitassets* is the ratio of the firm's earnings before interest and tax (EBIT) to assets. *capexassets* is the ratio of the firm's capital expenditure (capex) to assets. *booktomar* is the ratio of the firm's equity book value to the market value. *debtassets* is the ratio of total debt to total assets. *N* states the number of firm-month observations.

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: Sustainability Measures					
ESG	119,406	41.979	17.873	0.869	92.516
E	119,406	32.755	28.620	0.000	98.546
S	119,406	45.804	21.726	0.741	97.963
G	119,406	53.417	21.722	0.292	98.599
Resource use	119,070	35.010	34.747	0.000	99.884
Emissions reduction	119,070	33.763	33.591	0.000	99.807
Innovation	119,070	21.267	30.017	0.000	99.367
Workforce	119,070	49.165	26.737	0.162	99.835
Human rights	119,070	21.701	30.953	0.000	99.206
Community	119,070	68.124	23.363	0.362	99.900
Product responsibility	119,070	40.423	30.413	0.000	99.780
Management	119,070	57.773	27.436	0.052	99.983
Shareholders	119,070	55.924	27.484	0.051	99.969
CSR strategy	119,070	28.278	34.151	0.000	99.804
Panel B: Risk Measures					
IVSDn	119,406	0.444	0.436	−2.112	4.308
smfiv	119,406	0.201	0.286	0.012	8.059
mfiv_bkm	119,406	0.213	0.296	0.012	7.535
mfiv_bjn	119,406	0.204	0.273	0.012	6.779
smfivd	119,406	0.091	0.105	0.006	2.110
mfivd_bkm	119,406	0.137	0.211	0.007	5.651
mfivd_bjn	119,406	0.119	0.165	0.006	4.042
mfis	119,406	−0.617	0.498	−3.786	4.200
mfik	119,406	5.281	2.024	1.832	29.022
cvix_sigma2	119,406	0.206	0.294	0.011	7.543
cvix_sigma5	119,406	0.213	0.296	0.012	7.542
cvix_mnes20	119,406	0.163	0.158	0.012	2.574
cvix_mnes25	119,406	0.178	0.185	0.012	3.149
rix	119,406	0.018	0.047	0.0002	1.609
rixnorm	119,406	0.081	0.037	0.021	0.288
Panel C: Controls					
return	119,111	1.225	10.767	−84.353	305.691
volatility	119,028	8.903	5.720	1.310	96.651
beta	117,147	1.199	1.010	−9.380	12.198
logassets	119,394	22.941	1.582	17.766	28.620
divnetinc	118,206	0.792	43.731	−162.716	4,300.375
ebitassets	106,927	0.100	0.090	−0.843	0.917
capexassets	115,722	0.044	0.052	0.000	0.865
booktomar	119,096	1.025	48.868	−5.945	4,868.352
debtassets	119,370	0.264	0.211	0.000	3.892

firms in 2021. The average firm's ESG performance has also increased over the years. From 2002 to 2013, the ESG combined score increased from 26.21 in 2002 to 40.42 in 2013. Thereafter, the average ESG performance decreased slightly. A similar pattern is observed for the environmental, social and governance scores, where the environmental ratings have increased almost threefold over the entire period. In general, the governance pillar score has the highest average performance over time.

We extract daily options data on U.S. individual stocks from OptionMetrics over the period from January 2001 to December 2021. Specifically, we obtain volatility surface data for standardized options with an expiration of 30 calendar days, the zero-coupon yield curve, and the forward and spot rates. We use the filtered options data to compute different measures of downside risk.

The measure of downside risk that we use for our baseline analysis is the implied volatility slope (IVSDn), obtained following Kelly et al. (2016) and Ilhan et al. (2021). The IVSDn relates the left-tail implied volatility to the moneyness measured by the Black Scholes delta of out-of-the-money (OTM) standardized put options with a 30-day maturity. We also process the surface data to make it less discrete in moneyness and interpolate the observed implied volatilities as a function of moneyness.[6] We regress the implied volatility of OTM standardized put options on the corresponding delta (ranging between -0.5 and -0.1) and a constant to extract the IVSDn for each individual firm in our sample. The slope of the function that relates implied volatility to moneyness quantifies the relative cost of option protection against downside tail risk. It is a relative measure as it captures the cost of protection against extreme downside events relative to the cost of protection against less extreme events on the downside.

Panel B of Table 3.1 presents the descriptive statistics of the measures of option-implied (downside) risk estimated over the period 2002-2021. In line with Ilhan et

[6]See Kelly et al. (2016) and Ilhan et al. (2021) for more information on the computation procedures.

al. (2021), the IVSDn estimate is typically positive, which indicates that deeper OTM puts are more expensive. The average cost of protection against downside risk among firms is 0.44. For robustness, we also estimate an array of different measures of option-implied downside risk offered in the literature. We obtain the model-free implied volatility measures of Britten-Jones and Neuberger (2000), Bakshi et al. (2003), and Martin (2011, 2017), including measures of implied volatility on the downside. We also consider the model-free implied skewness and kurtosis measures of Bakshi et al. (2003), the corridor volatility index of Andersen and Bondarenko (2007) and Andersen et al. (2015), and the rare disaster concern index (RIX) of Gao et al. (2018). The descriptions of these measures can be found in Table A.1 in the Appendix.

We obtain monthly returns for the firms and the S&P 500 index, as well as firm characteristics from Thomson Reuters for the period from 2002 to 2021. Specifically, we obtain total assets, total debt, normalized EBIT, net income after taxes, gross dividends on common stocks, capital expenditure, company market capitalization, book value per share, and total common shares outstanding. For each firm, we also obtain 12-month rolling window CAPM betas and return volatility. Descriptive statistics of these control variables are reported in Panel C of Table 3.1.

3.3 ESG Policy Uncertainty and Downside Tail Risk

In this section, we examine the relationship between ESG policy uncertainty and the value of option protection against downside risk. First, we investigate whether ESG policy uncertainty is reflected in the option market. We interpret policy uncertainty as the inability to predict how the regulation on environmental, social and governance issues will evolve in the future. Second, we examine the relationship between individual firms' sustainability performance and the value of option protection against downside risk. We consider two aspects of firm ESG performance: the level of a firm's ESG score and the disparity across the E, S and G scores within each firm. Firms with low ESG scores, as well as firms with diverging performance along the environmental, social and governance dimensions are more likely to be affected by unanticipated changes in ESG regulation. We incorporate both measures of firm-level ESG performance to evaluate the expensiveness of protection against left-tail events for firms with high or low levels of sensitivity to ESG policy uncertainty captured by those measures. Third, we investigate the implications of receiving an ESG score on the cost of option protection against downside tail risk. The uncertainty relative to a firm's ability to adapt to unanticipated changes in ESG regulation is reduced for investors with the publication of ESG ratings. We therefore investigate the effects of ESG labeling on the cost that investors pay in order to hedge against downside risk.

3.3.1 ESG Policy Uncertainty

We examine the aggregate ESG regulatory uncertainty within the framework of Pastor and Veronesi (2012, 2013) which explains why political uncertainty about regulation may have an impact on asset prices. Within that framework, regulatory uncertainty is viewed as the uncertainty whether the current government policy will change. It derives from the political costs of a given policy that are unknown to investors and who as a result cannot fully anticipate which policy the government will choose. A second source of uncertainty in their framework is related to the uncertain impact of any given policy on firm profitability. As investors learn about the costs of the new policy by observing political signals, they revise their beliefs about expected future policies, generating an effect on asset prices.

In this study, we narrow down to a specific subset of government policies: those related to ESG aspects of economic activity. We seek to determine whether uncertainty associated with ESG regulation is priced in the option market. An implication of the Pastor and Veronesi (2013) model also exploited in Kelly et al. (2016) is that the option protection against downside tail risk becomes more valuable when regulatory uncertainty is higher.

We proxy aggregate ESG regulatory uncertainty with the US environmental and climate policy uncertainty index of Noailly et al. (2022), the US environmental and Renewable energy policy uncertainty index of Noailly et al. (2022), and the US climate policy uncertainty index of Gavriilidis (2021). Our measure of the aggregate cost of protection against downside risk is obtained as the implied volatility slope (IVSDn), relating volatility to moneyness for standardized OTM put options with 30 days to expiration, aggregated across the firms in our sample. In order to investigate whether the effects of ESG policy uncertainty are more pronounced when the economy is weaker, we also account for aggregate economic conditions. In particular, we use the following variables: the National Bureau of Economic Research (NBER) recession dummy, the cyclically adjusted PE ratio (CAPE ratio) of Bob Shiller, the Chicago Fed National Activity Index (CFNAI), the industrial production growth (IPG) in percent, and the real gross domestic product (GDP) growth in percent.

Table 3.2 shows the result of the regression of aggregate IVSDn—which represents the aggregate cost of protection against downside tail risk—on ESG regulatory uncertainty. Across all specifications, the aggregate cost of protection against downside risk increases with ESG regulatory uncertainty, especially when the economic conditions are weak.

3.3.2 ESG Performance and Firm's Downside Tail Risk

The evidence in Table 3.2 suggests that an increase in the ESG regulatory uncertainty (as proxied by its environmental component) is associated with more valuable option protection against downside risk in the aggregate. In the following, we exam-

Table 3.2: Aggregate Environmental Policy Uncertainty Indices and Cost of Protection Against Downside Risk

The dependent variable is the aggregate of the firms' Implied Volatility Slope(IVSDn) which relates the implied volatility to the moneyness (measured by delta) for the standardized OTM put options with 30 days to expiration; this captures the cost of protection against downside risk. The main independent variable is the aggregate US Environmental Policy Uncertainty Indices. Panel A reports results for the aggregate US Climate Policy Uncertainty (measured by Gavriilidis (2021)), multiplied by 100. Panel B reports results for the aggregate US Environmental and Climate Policy Uncertainty (measured by Noailly et al. (2022)), multiplied by 100. Panel C reports results for the aggregate US Environmental and Renewable Energy Policy Uncertainty (measured by Noailly et al. (2022)), multiplied by 100. We use the following measures of aggregate economic conditions: the National Bureau of Economic Research (NBER) recession dummy, equal to one during recession months and zero otherwise, the cyclically adjusted PE (CAPE) ratio of Bob Shiller, the Chicago Fed National Activity Index (CFNAI), the industrial production growth (in percentage), and the real Gross Domestic Product (GDP) growth (in percentage). Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	(1)	(2)	(3)	(4)	(5)
Panel A: Climate Policy Uncertainty					
CPU Index	0.076***	0.070***	0.075***	0.071***	0.078***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
NBER recession	0.068***				
	(0.026)				
CAPE		0.005***			
		(0.002)			
CFNAI			−0.009		
			(0.006)		
Industrial Production Growth (%)				−0.005**	
				(0.002)	
Real GDP Growth (%))					0.001
					(0.004)
Constant	0.236***	0.115**	0.242***	0.250***	0.239***
	(0.013)	(0.046)	(0.013)	(0.014)	(0.017)
Observations	252	252	252	252	252
Adjusted R^2	0.215	0.219	0.201	0.213	0.194
Panel B: Environmental and Climate Policy Uncertainty					
EnvPolicy Uncertainty Index	0.030**	0.031**	0.013	0.025*	0.012
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
NBER recession	0.084***				
	(0.018)				
CAPE		−0.006***			
		(0.001)			
CFNAI			−0.083***		
			(0.011)		
Industrial Production Growth				−0.008***	
				(0.001)	
Real GDP Growth					−0.021***
					(0.004)
Constant	0.237***	0.393***	0.256***	0.258***	0.313***
	(0.018)	(0.044)	(0.017)	(0.018)	(0.023)
Observations	219	219	219	219	219
Adjusted R^2	0.116	0.098	0.240	0.169	0.145
Panel C: Environmental and Renewable Energy Policy Uncertainty					
EREPU Index	0.021***	0.016***	0.014***	0.018***	0.013**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
NBER recession	0.085***				
	(0.018)				
CAPE		−0.005***			
		(0.002)			
CFNAI			−0.079***		
			(0.010)		
Industrial Production Growth (%)				−0.008***	
				(0.001)	
Real GDP Growth (%))					−0.019***
					(0.004)
Constant	0.235***	0.376***	0.246***	0.257***	0.299***
	(0.011)	(0.045)	(0.011)	(0.011)	(0.016)
Observations	219	219	219	219	219
Adjusted R^2	0.160	0.108	0.265	0.201	0.165

ine the cross-sectional implications of ESG policy uncertainty. The effect could be differentiated depending on the firm's level of exposure to ESG regulations.

A first proxy for such firm-level sensitivity towards ESG regulation is the level of the ESG score of the firm. Arguably, firms with high ESG scores are expected to be impacted by unexpected changes in ESG regulation to a lesser extent than their peers that fare worse on ESG. To investigate the relationship between a firm's ESG score and its cost of protection against downside risk, we estimate the following baseline regression:

$$IVSDn_{i,m,t+1} = \alpha_0 + \beta_1 ESGrating_{i,t} + \delta X_{i,t} + \epsilon_{i,m,t+1}, \tag{3.1}$$

where $IVSDn_{i,m,t+1}$ denotes the implied volatility slope of firm i in month m of year $t+1$, $ESGrating_{i,t}$ is the $ESG_{i,t}$, $E_{i,t}$, $S_{i,t}$ or $G_{i,t}$ of firm i sustainability score in year t, and $X_{i,t}$ is a vector of controls for firm i at time t. We average on a monthly basis the daily implied volatility slope for each firm. We match the firm's IVSDn in year $t+1$ to the firm's sustainability score in year t since Thomson Reuters updates its sustainability score when they receive the firm's annual report, therefore, resulting in a delay in ESG score update. As controls, we include firm's monthly return, CAPM *beta*, *volatility*, based on a 12-month rolling estimate, *logassets*, the natural logarithm of total assets, *divnetinc*, gross dividends divided by net income after taxes, *ebitaseets*, normalized earnings before interest and taxes, standardized by total assets, *capexaseets*, obtained as capital expenditure divided by total assets, *debtassets*, total debt divided by total assets, and *booktomar*, book value of equity divided by firm's market capitalization. Beta, volatility, and return are measured at a monthly level while the sustainability scores and the rest of the control variables are available at annual frequency.

Table 3.3 presents the result of the firm-month level regression of the implied volatility slope (IVSDn)—our option-implied measure of the cost of protection against

Table 3.3: Firm's ESG Performance and the Cost of Protection Against Downside Risk

This table reports the regression output corresponding to the model in Equation (3.1). The main dependent variable is the Implied Volatility Slope on the downside (IVSDn) which relates the implied volatility to the moneyness (measured by delta) for the standardized OTM put options with 30 days to expiration. Column (1) presents the specification in which $ESGrating_{i,t}$ corresponds to the ESG score of firm i at time t. Columns (2) through (4) have the E, S and G pillar scores as the $ESGrating_{i,t}$ measure. All specifications include the same set of control variables. Those include firms' monthly return, the CAPM beta, obtained by regressing the firm's monthly return on the S&P 500 Index return, a constant using a 12-month rolling period, and volatility, estimated over a 12-month period. *logassets* measures firm size and is computed as the natural logarithm of a firm's assets. *divnetinc* is the ratio of the firm's gross dividend to net income. *ebitassets* is the ratio of the firm's earnings before interest and tax (EBIT) to assets. *capexassets* is the ratio of the firm's capital expenditure (capex) to assets. *booktomar* is the ratio of the firm's equity book value to the market value. *debtassets* is the ratio of total debt to total assets. All specifications include year fixed effects. The sample includes all US firms with ESG scores from Thomson Reuters and covers the period from 2002 to 2022. Standard errors, clustered by firm and year, are reported in brackets. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	(1)	(2)	(3)	(4)
ESG	−0.00117***			
	(0.0001)			
Environmental		−0.00103***		
		(0.0001)		
Social			−0.00141***	
			(0.0001)	
Governance				0.0002***
				(0.0001)
beta	0.008***	0.007***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
volatility	−0.011***	−0.011***	−0.011***	−0.011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
return	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
logassets	−0.077***	−0.071***	−0.072***	−0.084***
	(0.001)	(0.001)	(0.001)	(0.001)
divnetinc	0.0001**	0.0001***	0.0001**	0.0001**
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
ebitassets	−0.374***	−0.365***	−0.355***	−0.399***
	(0.014)	(0.014)	(0.014)	(0.013)
capexassets	−0.091***	−0.081***	−0.109***	−0.075***
	(0.023)	(0.023)	(0.023)	(0.023)
debtassets	0.078***	0.073***	0.076***	0.084***
	(0.006)	(0.006)	(0.006)	(0.006)
booktomar	0.00001	0.00001	0.00001	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	2.146***	1.980***	2.035***	2.258***
	(0.024)	(0.027)	(0.025)	(0.023)
Year FE	Yes	Yes	Yes	Yes
Observations	103,051	103,051	103,051	103,051
Adjusted R^2	0.257	0.258	0.259	0.256

downside risk—on firms' overall ESG score as well as its three components reflecting firms' environmental (E), social (S) and governance (G) performance. The findings show that there is a negative and significant relationship between the cost of protection against downside tail risk and the overall sustainability performance of the firms. This result becomes more nuanced when we narrow down to the three pillar scores. The higher the firm's E and S performance, the lower the cost of protection against downside risk. However, governance performance exhibits a negative relationship, which implies that firms with higher governance performance have a higher cost of protection against downside risk. The coefficients of the control variables have the expected signs: the higher the CAPM beta, the higher the cost of protection against downside risk. Larger, more profitable, high capital expenditure and lower financial leverage firms have lower cost of protection against downside risk.

We also consider the second level of ESG score disaggregation through the category scores along the following dimensions: Resource Use, Emissions, and Innovation scores which constitute the environmental pillar score; Workforce, Human Rights, Community, and Product Responsibility, contributing towards the social score; and Management, Shareholders, and CSR Strategy for the governance dimension. Table 3.4 reports the firm-month level regression to examine the relationship between each of the category scores and the cost of option protection against downside tail risk.

The findings in Table 3.4 indicate that for the category scores along the environmental and social dimensions, all underlying components have a negative and significant relationship with the cost of protection against downside risk. Firms with better efficient use of resources, lower emissions, and better innovation to reduce environmental costs and burdens have a lower cost of protection against downside risk. The same holds for firms with a better workforce, human rights, community, and product responsibility score. The pattern is more nuanced along the governance components. There, higher shareholder and CSR strategy scores are associated with a lower cost of option protection. However, higher management scores imply the op-

Table 3.4: Firm's ESG Performance and the Cost of Protection Against Downside Risk: Second Level of Disaggregation

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVSDn) on the sustainability performance based on Equation (3.1). This table reports only the parameter estimates of β_1 on sustainability performance. The control variables are CAPM beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets, and booktomar. All specifications control for fixed-year effects. Panel A reports the parameter estimates along the environmental dimension: where $ESGrating$ corresponds to firm's scores on Resource use, Emission reduction, and Innovation. Panel B reports the parameter estimates along the social dimension: Workforce, Human rights, Community, and Product responsibility. Panel C reports the parameter estimates along the governance dimension: Management, Shareholder, and CSR strategy. Standard errors, clustered by firm and year, are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Dimension	Environmental	Social	Governance
Panel A: Environmental			
Resource use	-0.001^{***}		
	(0.00004)		
Emissions reduction	-0.001^{***}		
	(0.00004)		
Innovation	-0.0001^{***}		
	(0.00004)		
Panel B: Social			
Workforce		-0.001^{***}	
		(0.0001)	
Human rights		-0.001^{***}	
		(0.00004)	
Community		-0.001^{***}	
		(0.0001)	
Product responsibility		-0.0004^{***}	
		(0.00004)	
Panel C: Governance			
Management			0.0004^{***}
			(0.00004)
Shareholder			-0.0001^{***}
			(0.00004)
CSR strategy			-0.001^{***}
			(0.00004)

posite. Firms with better board structure, compensation policy, and board functions have a higher cost of protection against downside risk. Given that the weighting methodology of Thomson Reuters attributes substantially higher weight to management in their governance score, the positive association with a firm's downside risk is also reflected in the governance dimension of a firm's score.

3.3.3 ESG Disparity and Firm's Downside Tail Risk

In the following, we examine the relationship between the disparity across a firm's sustainability profile (i.e., environmental, social and governance performance) and its cost of option protection against downside risk. We conjecture that the observed disparity across the components of a firm's sustainability metric proxies for its ability to manage ESG regulatory developments. A firm with high ESG disparity signals a low ability to manage ESG regulatory requirements.

For each firm in our sample, we compute the disparity across its E, S and G scores as the mean absolute deviation (MAD) between the different components and sort firms into deciles. We estimate the baseline regression in Equation (3.1) for firms within each MAD decile. Table 3.5 presents the β_1 estimates for firms in the 10th decile (representing those with the highest disparity) and in the 1st decile (representing those with the lowest disparity). We find that both high- and low-disparity firms associate a higher cost of downside option protection with low ESG scores. However, when the disparity is low, the individual components of the sustainability score are not significantly associated with the cost of option protection.

We introduce the ESG disparity as an independent continuous variable to the baseline regression. The (augmented) baseline regression equation is as follows:

$$IVSDn_{i,m,t+1} = \alpha_0 + \beta_1 ESGrating_{i,t} + \lambda_1 ESGdisparity_{i,t} + \delta X_{i,t} + \epsilon_{i,m,t+1}. \quad (3.2)$$

Table 3.5: The Cost of Protection Against Downside Risk and Firms' ESG Ratings: Across Deciles of ESG Disparity

For each firm in our sample, we compute the mean absolute deviation (MAD) for the E, S and G scores. Next, we sort the firms into deciles based on the computed mean absolute deviation and extract those that belong to the 10th decile (highest disparity) and 1st decile (lowest disparity). Regressions are estimated at the firm-month level. The main dependent variable is the Implied Volatility Slope on the downside (IVSDn) which relates the implied volatility to the moneyness (measured by delta) for the standardized OTM put options with 30 days to expiration. The row "ESG" reports parameter estimates for β_1 from a regression of IVSDn on the ESG score with controls and year fixed effects for the firms in the 90th and the 10th deciles. The rows "E", "S" and "G" report parameter estimates for β_1, where the variable $ESGrating$ is represented by the environmental, social and governance scores, respectively. The "High Disparity" column denotes the regression result column for firms' in the 10th decile based on the mean absolute deviation (MAD). The "Low Disparity" column denotes the regression result column for firms' in the 1st decile based on the MAD. The sample includes all US firms with E, S and G scores and covers the period from 2002 to 2022. The t-statistics are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	High Disparity		Low Disparity	
ESG	-0,00379	***	-0,00044	***
	(-8,93974)		(-2,80907)	
E	-0,00198	***	-0,00009	
	(-6,84420)		(-0,57762)	
S	-0,00162	***	-0,00008	
	(-7,72468)		(-0,47048)	
G	0,00070	***	-0,00006	
	(2,49038)		(-0,40209)	

$IVSDn_{i,m,t+1}$ is the implied volatility slope of firm i at month m in year $t+1$, and $ESGrating_{i,t}$ is the $ESG_{i,t}$, $E_{i,t}$, $S_{i,t}$, or $G_{i,t}$ of firm i sustainability score in year t. $X_{i,t}$ is a vector of controls for firm i at time t. The ESG disparity is the firm's mean absolute deviation across its environmental, social and governance performance which captures the ability of the firm to manage its ESG regulatory development.

Table 3.6 presents the estimates of a firm-month level regression of IVSDn on the sustainability performance and the ESG disparity of firms based on Equation (3.2). The model is estimated for the overall ESG score as well as its various components. Throughout all specifications and for all levels of disaggregation of the ESG score, we find that a high ESG disparity is consistently and significantly associated with a higher cost of option protection against left-tail risk. Investors in firms with poor ESG performance (in the aggregate or along most of the different dimensions of the score) would typically pay a higher cost to protect against extreme left-tail events in the option market. However, they would do so consistently when the uncertainty associated with the firm's ability to manage its exposure to ESG regulation is high.

Table 3.6: ESG Disparity

This table summarizes the results of regressions of the monthly cost of protection against downside risk (IVSDn) on firm's ESG ratings and its individual components, and the ESG disparity measure based on Equation (3.2). The table reports only the coefficient estimates on the ESG rating variable (β_1) and on ESG disparity (λ_1). The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. All specifications include year fixed effects. Panel A reports parameter estimates where the ESG rating variable is the firm's ESG score. Panel B reports estimates for specifications in which the ESG rating variable is the E, S or the G score. Panel C reports estimates for specifications where the ESG rating variable is either one of the category scores: Resource use, Emission reduction, Innovation, Workforce, Human rights, Community, Product responsibility, Management, Shareholder, or CSR strategy. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Coefficients	ESG rating - β_1	ESG disparity - λ_1
Panel A: Aggregate		
ESG	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Panel B: First level:		
Environmental	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Social	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Governance	0.0001	0.001^{***}
	(0.0001)	(0.0001)
Panel C: Second level:		
Environmental:		
Resource use	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)
Emissions reduction	-0.001^{***}	0.001^{***}
	(0.00005)	(0.0001)
Innovation	-0.00001	0.001^{***}
	(0.00004)	(0.0001)
Social:		
Workforce	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Human rights	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)
Community	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Product responsibility	-0.0004^{***}	0.001^{***}
	(0.00004)	(0.0001)
Governance:		
Management	0.0003^{***}	0.001^{***}
	(0.00004)	(0.0001)
Shareholder	-0.0002^{***}	0.002^{***}
	(0.00004)	(0.0001)
CSR strategy	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)

Next, we examine whether the ability of companies to manage the ESG disparity differs between sectors. We link the firms in our sample to their various sectors based on the Global Industry Classification Standard (GICS). The GICS classifies firms into 12 sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate. Table A.2 presents the results of the regressions of the monthly cost of protection against downside risk (IVSDn) on the sustainability performance and ESG disparity based on Equation (3.2) for each sector. For most of the industry sectors, the relationship between $IVSDn$ and ESG performance that we document for the overall sample still holds and remains significant. Exceptions are Materials, Utilities, and Communication Services, where the direction of the relationship reverses or becomes insignificant. The option value of protection against downside tail risk is higher for firms with large ESG disparity for all industries but two: Communication Services and Real Estate. For Materials and Utilities, the λ_1 estimate is not discernible from zero. The pattern persists across the E, S and G dimensions of sustainability.

3.3.4 ESG Labeling and Downside Risk

In our analyses so far, we have established a relationship between a firm's ESG profile and the costs that investors face to protect themselves against extreme events on the downside. In this section, we consider the implications for a firm receiving an ESG score in the first place, regardless of its level, relative to a firm that has not yet been rated on its sustainability performance. To estimate the causal effect of the availability of a sustainability score on the cost of protection against downside risk, we consider two groups of firms: firms with ESG scores (treated firms) and firms without ESG scores that are otherwise comparable to the treated firms based on a set of firms' observed characteristics (our control group). We apply the matching technique for panel data developed by Imai et al. (2023), which allows simple diagnostics to check covariates' balance and to estimate the short-term and long-term causal effects or the average treatment effect.

For each treated observation, we find a set of control observations that have identical treatment histories over a 12-month period.[7] We apply the covariate balancing propensity score (CBPS) weighting technique to ensure that the treated and control observations have similar covariate values. The observed confounders we consider are the quick ratio, firm size, financial leverage, hard spending, intangibles, growth, cash ratio, profitability, and dividend yield. We also consider several other weighting and matching techniques. For matching techniques, we apply 'up-to-five matching', where each treated firm can only match a maximum of five control firms. We then apply the difference-in-difference estimator to estimate the causal effect of ESG treatment on the cost of protection against downside risk.

Figure A1 presents the distribution of the treatment across firms and time. At the beginning of our sample period, most of the companies were not assigned ESG scores. The number of companies treated with a score increases with time. We note that it is also very rare that a firm switches treatment status, facilitating the estimation of long-term causal effects of ESG treatment. In addition, we have a reasonably high number of matched control firms to estimate the average effects of treatment and therefore make causal inferences (see Figure A2). Next, we refine the matched set of Figure A2 to adjust for confounders. We apply two refinement weighting methods, the CBPS and the Propensity Score weighting method. Figure A3 plots the standardized mean difference between the treated observations and the matched control group over a 12-month pre-treatment period based on both weighting methods. The standardized mean difference is close to zero and reasonably constant during the pretreatment period. This suggests that there is no imbalance

[7] The length of the treatment histories period represents a bias-variance trade-off. Increasing its length improves the credibility of the unconfoundedness assumption but reduces the efficiency of the estimates (Imai et al. (2023).

in confounders and that the parallel trend assumption for the difference-in-difference estimator used to estimate the average treatment effect seems appropriate.

We estimate the causal effect of ESG treatment on the cost of protection against downside risk. For any two firms that are the same in their fundamental characteristics but one receives ESG treatment (ESG score) and the other does not, we estimate the impact of the treatment on the value of option protection against the tail risk. Figure 3.1 presents the estimated average treatment effect based on the two matching and weighting methods. For the immediate effect, the average treatment is negative, which implies that the cost of protection is lower for firms that receive ESG scores compared to firms with the same fundamental characteristics that have not been assessed. For the long-term (cumulative) effect over the next four months, the average effect of the treatment remains negative. The results are statistically significant at the 95% confidence level, where we use the bootstrap method to obtain standard errors. Overall, we find that ESG treatment lowers the cost of protection against downside risk for the firm.

We also consider an alternative empirical strategy to estimate the causal effect of ESG treatment on the value of option protection against tail risk by exploiting a quasi-natural experiment setting. In April 2019, SPGlobal launched the S&P 500 ESG Index. The index comprises more than 300 of the original S&P 500 companies, included on the basis of their ESG score. According to SPGlobal, the S&P 500 ESG Index is a broad-based market cap-weighted index that is designed to measure the performance of securities that meet sustainability criteria, while maintaining similar overall industry group weights as the S&P 500. Inclusion in the index is a signal of the good ESG performance of a firm. We use a difference-in-difference (DiD) approach to compare changes in the cost of protection against downside risk between firms that are included in the S&P 500 ESG Index (treatment group) and those that are not included (control group). Table 3.7 presents the results.

Table 3.7: Average ESG Treatment Effect on the Cost of Protection Against Downside Risk

This table presents the result of the DiD estimates of the effect of the inclusion of a S&P 500 company in the S&P 500 ESG Index on the cost of protection against downside risk, proxied by the IVSDn. *Treated* is a dummy variable that is equal to 1 if a firm is included in the S&P 500 ESG Index. *Post* is a dummy variable that takes the value of 1 for the period after the launch of the S&P 500 ESG Index in April 2019. Controls include firm's market beta, volatility, return, log assets, dividends standardized by net income, EBIT, CAPEX, and debt, all standardized by total assets, as well as its book-to-market ratio. The main variable of interest is the interaction term of *Treated* * *Post* that indicates the average effect of ESG membership treatment on the cost of protection against downside risk. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:		
	IVSDn		
	(1)	(2)	(3)
Treated	−0.159***	−0.092***	−0.064***
	(0.003)	(0.003)	(0.003)
Post	0.355***	0.345***	0.103***
	(0.004)	(0.004)	(0.006)
Treated * Post	−0.144***	−0.117***	−0.145***
	(0.006)	(0.006)	(0.006)
Year FE	No	No	Yes
Controls	No	Yes	Yes
Observations	118,855	102,799	102,799
R^2	0.132	0.179	0.269
Adjusted R^2	0.132	0.179	0.268
Residual Std. Error	0.406	0.387	0.366
	(df = 118851)	(df = 102786)	(df = 102769)
F Statistic	6,012.186***	1,863.433***	1,301.243***
	(df = 3; 118851)	(df = 12; 102786)	(df = 29; 102769)

We find that in all specifications, the coefficient of the interaction term ($Treated * Post$) is negative and statistically significant. Our results show that the inclusion into 'ESG membership' as represented by inclusion in the S&P 500 ESG Index lowers the firm's cost of protection against downside risk. We note that the result remains robust to replacing IVSDn by other option-implied measures of risk (see Table A.8).

3.3.5 Robustness

We first address the concern that ESG scores are available only for a small proportion of the firms in our sample at the beginning of the sample period. While all our regression specifications include year fixed effects, we alternatively consider a subsample restricted to observations from 2010 to 2022. We perform our baseline regression based on Equation (3.1) on that subsample. The results in panel A of Table A.3 show that the relatively low number of firms with ESG scores at the beginning of the sample period does not appear to be driving our results. The subsample results remain consistent with those obtained over the entire period.

Another characteristic of the ESG dataset is the appearance of zero E scores for some firms in the sample, while the ESG, G and S scores for those firms have nonzero values at the same time. To alleviate concerns that zero pillar scores may be attributable to missing data, we also exclude firms with zero environmental scores. We perform our baseline regression based on the model in Equation (3.1). Panel B in Table A.3 displays the results. Estimates for coefficients on ESG level and disparity remain consistent with those obtained without imposing the nonzero restriction on E scores in Table 3.6.

One major concern with the use of ESG scores is the low correlation of ESG data among ESG data providers (Berg et al., 2022a). To verify the robustness of our findings to the ESG data of other providers, we consider the MSCI ESG sustainability scores. Table A.4 presents the results of the regressions of the monthly cost of protection against downside risk (IVSDn) on the MSCI sustainability performance and the ESG disparity based on the augmented model in Equation (3.2). The direction of the IVSDn—sustainability relationship remains consistent with our results based on Thomson Reuters ESG data.

We further examine the robustness of our results to using alternative option-implied risk measures. We consider three model-free measures of downside risk as captured by the implied volatility on the downside extracted from OTM puts: the *smfivd* measure of Martin (2011, 2017), the *mfivd bkm* measure of Bakshi et al. (2003), and the *mfivd bjn* measure of Britten-Jones and Neuberger (2000). Panel A of Table A.5 presents the results of the regressions based on the model in Equation (3.1) using these alternative downside risk measures. We find strong evidence that the different downside risk measures have a negative and statistically significant relationship with firms' ESG, environmental and social performance. As with our IVSDn measure, the relationship between downside risk measures and the firm governance score remains inconclusive and statistically insignificant.

We also consider option-implied risk measures that do not focus exclusively on downside tail events. We compute the simple model-free implied volatility (*smfiv*) of Martin (2011, 2017), the model-free implied volatility (*mfiv bkm*) of Bakshi et al. (2003), the model-free implied volatility (*mfiv bjn*) of Britten-Jones and Neuberger (2000), the model-free implied skewness (*mfis*) and kurtosis (*mfik*) based on Bakshi et al. (2003), the corridor volatility index (*cvix*) of Andersen and Bondarenko (2007) and Andersen et al. (2015) measured on the relative deviation of 2 standard deviations from the at-the-money (ATM) moneyness of 1, and the rare disaster concern index (*rix*) of Gao et al. (2018). The findings in Panel B of Table A.5 indicate that, except for *mfis*, all option-implied risk measures exhibit the relationship with ESG performance documented for our baseline measure, the implied volatility slope on the downside (IVSDn). For the model-free implied skewness that quantifies the asymmetry in the risk-neutral distribution, there is no significant relationship with the overall firm ESG performance. The relationship becomes positive and significant for the E and S scores.

All the risk measures that we have considered so far have been computed on the basis of options data. To examine the general validity of our results outside the option market, we alternatively consider credit default swaps (CDS). CDS provide insurance protection to the buyer against default of the reference entity. We therefore take the CDS spread as an alternative measure of the cost of protection against extreme downside events. We obtain daily CDS spreads based on 5-year senior bonds—which are the most liquid CDS contracts traded on the US market. Data is obtained from S&P Global and covers the period from January 2004 to December 2021. For each firm, we compute the monthly average CDS spread. We match firms with CDS data to the availability of Thomson Reuters ESG scores, resulting in a sample of 205 US firms. Table A.6 presents the regressions of the monthly CDS on the sustainability performance and ESG disparity based on the model in Equation (3.2).

Our findings based on CDS spreads confirm the results obtained for the option-implied measure of the relative cost of protection against downside tail risk. Firms with higher ESG scores and lower ESG disparity have lower CDS spreads. The results are similar for the three pillar scores, although in some cases coefficient estimates lose significance. For the category scores, while the results for the level of each individual score are somewhat mixed, we document a consistent and significant relationship between the CDS spread and firms' ESG disparity. Overall, we find consistent support that firms with low ESG disparity have low cost of protection against downside tail risk, regardless on whether it is captured on the option market or implied from CDS spreads.

Finally, we consider different variants of the regression model in Equation (3.2) that include year of sector fixed effects and clustered standard errors. Table A.7 shows the results. Different model specifications yield the same robust relationship between the overall ESG performance of a firm and the cost of option-implied protection against extreme downside events. Firms with low ESG scores and high disparity across the E, S and G dimensions of their score have consistently higher costs for downside risks protection.

3.4 Aggregate Downside Risk

We have established that better ESG performance or lower divergence across the E, S and G dimensions of a firm's sustainability score is associated with lower cost of protection against downside tail risk for that firm. In this section, we investigate whether investments built following ESG criteria can serve as a hedge against downside risk. We estimate the risk-neutral probability of downside events in the economy which we term 'aggregate downside risk'. It reflects the price of insurance against extreme future downside movements of the financial market (similar to the definition of Gao et al. (2018) for the rare disaster index (RIX)). It captures the ex-ante market expectations about future disasters or downside events.

We begin by constructing each firm's downside risk (FDR) measure following the procedure in Gao et al. (2018). Details on how we obtain the FDR measure are outlined in the Appendix. We extract our measure of aggregate downside risk (ADR) via principal component analysis following Siriwardane (2015):

$$FDR_{it}(\tau) = \Psi_i * ADR_t(\tau), \tag{3.3}$$

where Ψ_i is a firm-specific constant and $ADR_t(\tau)$ is the aggregate downside risk measure at time t which depends on the time to maturity τ. $ADR_t(\tau)$ is the risk-neutral probability of downside events from time t to $t+\tau$ and is common to all firms. All cross-sectional variation in $FDR_{it}(\tau)$ is driven by variation in Ψ_i and $ADR_t(\tau)$ is common to all firms. This implies that $FDR_{it}(\tau)$ is governed by a single factor.

We use daily data on OTM options of US firms from OptionMetrics covering the period from 2001 to 2021 to construct the firm downside risk (FDR) and aggregate downside risk (ADR). Our approach is similar to that in Gao et al. (2018) used to obtain a market-wide rare disaster index. We use out-of-the-money (OTM) put options with 30 days to expiration. We interpolate the implied volatilities across a range of observed moneyness levels and fill in the implied volatilities beyond the observed moneyness bounds with the volatilities on the bounds. We generate 1,001 implied volatility data points over the moneyness range from 1/3 to 3. We use the implied volatility curves to compute the Black Scholes (1973) OTM option prices and then apply Equation (A4) to obtain daily FDR for each US firm in our sample.

We proceed to obtain ADR through principal component analysis. We only consider firms with at least 18 daily estimates of FDR in a month. PCA is performed on the correlation matrix of the monthly FDR_i. In our subsequent analyses, we consider firms with at least 192 monthly FDR_i estimates. This leaves us with a total of 1,191 US firms for the computation of the ADR measure. Figure 3.2 shows the first 10 principal components from a PCA on the correlation matrix of the firm's downside risk measures FDR_i. We observe that the first principal component explains about 45% of the variation across the firm downside risk measures, while the variation explained by the remaining principal components is very low – ranging from 9% for the second component to 1% for the tenth component. This indicates that a single major factor drives the time series variation in FDR_i across firms. This single major factor represents the aggregate downside risk (ADR) that is common to all firms.

Figure 3.3 visualizes the time series of the ADR measure representing the aggregate risk-neutral probability of downside events. The evidence is in line with the results documented in Siriwardane (2015). Consistent with the interpretation of ADR as the risk-neutral probability of downside events common to all firms, we see that ADR experienced the highest spike during the Covid-19 pandemic followed by the spike during the global financial crisis.

3.4.1 Sustainability Scores and Aggregate Downside Risk

In the following, we focus on investigating whether ESG-based investments can serve as a hedge against downside market events. We verify whether investing in firms with high ESG ratings can protect investors against aggregate downside risk. We first determine each firm's exposure to ADR by running the following 12-month rolling regression for each time $t \in [m-12; m]$ and month m:

$$R_{i,t} = \alpha_{i,m} + \beta_{i,m} ADR_t + \epsilon_{i,t}, \tag{3.4}$$

where $R_{i,t}$ is the monthly return of firm i at time t, ADR_t is the aggregate downside risk for time t, and $\beta_{i,m}$ is the downside beta for firm i in month m. The monthly returns are filtered to exclude penny stocks which are defined as stocks with less than a share price of \$5. We also include firms with ESG scores but without individual options data. After obtaining 12-month rolling downside betas for each firm, we group the firms in high, medium and low sustainability performance terciles according to their ESG scores as observed at the end of the previous year and compute the average beta in each tercile across companies and over the sample period.

Table 3.8: Sustainability Scores and Firms' Exposure to Aggregate Downside Risk (ADR)

This table reports estimates of the sensitivity of firms' returns to aggregate downside risk (ADR). For each firm i at each time t, we perform a 12-month moving-window regression based on the regression model in Equation (3.4). Reported are the average parameter estimates $\beta_{i,m}$ across firms in high, medium and low terciles, formed according to the level of sustainability scores observed at the end of the previous year. Firms are grouped into terciles at the end of each year and average $\beta_{i,m}$ estimates are calculated for the months m of the current year. Then, the average $\beta_{i,m}$ between firms is obtained throughout the sample period from 2003 to 2021. Panel A reports time series and cross-sectional $\beta_{i,m}$ estimate averages for the following sustainability score terciles: the ESG score, and the Environmental, Social and Governance pillar scores. Panel B reports time series and cross-sectional $\beta_{i,m}$ estimate averages for terciles formed according to our ESG disparity measure.

Sustainability terciles	High	Medium	Low
		$\beta_{i,m}$	
Panel A: ESG performance			
ESG	$-0,026$	$-0,034$	$-0,052$
Environmental	$-0,022$	$-0,041$	$-0,047$
Social	$-0,028$	$-0,041$	$-0,042$
Governance	$-0,034$	$-0,037$	$-0,040$
Panel B: ESG disparity			
ESG disparity	$-0,045$	$-0,033$	$-0,033$

Panel A of Table 3.8 presents the average downside risk betas for firms with low, medium and high overall ESG, E, S and G scores. Since downside risk is decreasing in downside beta, the most negative downside risk betas connote the highest downside risk. We observe that irrespective of their ESG performance, firms are negatively exposed to ADR on average. However, firms with high ESG scores have lower exposure to ADR as compared to firms with low ESG performance. This implies that investing directly in high ESG firms does not provide an insurance against downside risk but an investment strategy of longing high ESG firms and shorting low ESG firms might protect investor portfolios against downside risk. The results remain similar in magnitude when we consider separately the E, S and G components of firms' sustainability scores. Panel B reports the ADR betas for firms sorted according to ESG disparity. Firms with low disparity across their E, S and G scores have the lowest exposure (in absolute terms) to ADR.

3.4.2 The Price of Aggregate Downside Risk

In the following, we determine the pricing of ADR conditioned on the ESG performance of firms. We categorize firms into low, medium and high ESG performance terciles at the end of each month m. For each sample of firms, the overall sample and the three ESG performance tercile samples, we perform Fama and MacBeth (1973) regressions of month $m+1$ excess stock returns on month m firms' downside betas and the risk factor loadings of standard asset pricing models.

The downside betas of individual firms and the factor loadings corresponding to the CAPM, the 3-factor Fama-French model and the 5-factor Fama-French model, are obtained by running 12-month rolling regressions of monthly excess stock returns on month m ADR and the set of standard risk factors. For each sample of firms and for each month m, we perform the following cross-sectional regression:

$$R_{i,m+1} = \alpha + \lambda_m^{ADR} \beta_{i,m}^{ADR} + \Omega_m^{riskfactors} X_{i,m}^{riskfactors} + \epsilon_{i,m}, \tag{3.5}$$

where $R_{i,m+1}$ is the month $m+1$ excess return of stock i, $\beta_{i,m}^{ADR}$ is the aggregate downside risk beta of stock i in month m, and $X_{i,m}^{riskfactors}$ is the vector of standard risk factor betas estimated in month m for firm i. Table 3.9 reports the time-series average of monthly λ^{ADR} estimates from the cross-sectional regression in Equation (3.5) for the entire sample of firms. We find that regardless of the risk specification, ADR is priced in the cross-section and commands a significant negative risk premium.

In a next step, we perform the cross-sectional regression in Equation (3.5) on three samples conditional on the ESG performance of firms. Table 3.10 presents the results for a model where ADR is the only risk factor (Panel A), a model where

Table 3.9: The Price of Aggregate Downside Risk (ADR)

This table presents the results of Fama and MacBeth (1973) regressions of month $m+1$ excess stock returns on month m ADR betas $\beta^{ADR}_{i,m}$ and risk factors betas for the CAPM, the Fama-French 3-factor model, and the Fama-French 5-factor model. The table reports the intercept of each regression (α) and the market prices of risk corresponding to aggregate downside risk (λ^{ADR}), and the three factor models: the CAPM (λ^{MKT}, for the market factor), the Fama-French 3-factor model (adding λ^{SMB} and λ^{HML}, corresponding to the size and value factors, respectively), and the Fama-French 5-factor model (adding λ^{RMW} and λ^{CMA} for the profitability and investment factors, respectively). Newey West t-stats are reported in parentheses.

Portfolio	α	λ^{ADR}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}
ADR	0.010	−0.116					
	(2.980)	(-2.121)					
CAPM + ADR	0.007	−0.087	0.004				
	(2.932)	(-2.059)	(2.059)				
3-Factor + ADR	0.007	−0.084	0.003	0.002	0.0006		
	(2.891)	(-2.284)	(2.079)	(0.355)	(0.400)		
5-Factor + ADR	0.008	−0.084	0.003	0.002	0.0007	−0.0005	−0.0006
	(3.091)	(-1.870)	(1.746)	(2.943)	(0.661)	(-0.975)	(-1.135)

ADR is augmented by the market factor (Panel B), a model augmented with the 3-factor Fama-French model (Panel C), and a model augmented by the Fama-French 5-factor risk model (Panel D). We note that the expected return – β^{ADR} relationship is negative irrespective of the firms' ESG performance. However, it is statistically significant only in the cross-section of firms that belong to either the top or the bottom ESG score terciles. ADR does not appear to be priced in the cross-section of firms with medium ESG scores. That pattern is confirmed across the different risk specifications considered.

We further condition our sample on the observed disparity between the E, S and G scores of each firm. We consider three samples of firms according to their ESG disparity observed at the end of each month m: high, medium and low disparity firms. We repeat the cross-sectional regressions for the three samples of firms and report the results in Panel A of Table 3.11. We find that for the low ESG disparity sample, ADR remains significantly and consistently priced across all risk model specifications.

Table 3.10: Pricing of Aggregate Downside Risk (ADR) Conditioned on Firms' ESG Performance.

This table presents the results of Fama and MacBeth (1973) regressions of month $m+1$ excess stock returns on month m ADR betas $\beta_{i,m}^{ADR}$ and risk factor betas for the CAPM, the Fama-French 3-factor model, and the Fama-French 5-factor model. Estimates are reported for three samples of firms, formed conditional on their ESG performance observed at the end of month m. 'Low ESG Score', 'Medium ESG Score' and 'High ESG Score' refer to the estimates for firms in the low, medium or high ESG score tercile. The table reports the intercept of each regression (α) and the market prices of risk corresponding to aggregate downside risk (λ^{ADR}), and the three factor models: the CAPM (λ^{MKT}, for the market factor), the Fama-French 3-factor model (adding λ^{SMB} and λ^{HML}, corresponding to the size and value factors, respectively), and the Fama-French 5-factor model (adding λ^{RMW} and λ^{CMA} for the profitability and investment factors, respectively). Newey West t-stats are reported in parentheses.

Portfolio	α	λ^{ADR}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}
ADR:							
Low ESG Score	0.010	-0.124					
	(2.838)	(-2.220)					
Medium ESG Score	0.010	-0.090					
	(2.945)	(-1.589)					
High ESG Score	0.0092	-0.140					
	(3.119)	(-2.199)					
CAPM + ADR:							
Low ESG Score	0.0079	-0.0997	0.0031				
	(2.757)	(-2.176)	(1.443)				
Medium ESG Score	0.0064	-0.0743	0.0041				
	(2.361)	(-1.548)	(2.291)				
High ESG Score	0.0063	-0.0900	0.0045				
	(2.779)	(-2.200)	(2.066)				
3-Factor + ADR:							
Low ESG Score	0.0072	-0.09292	0.00272	0.0031	0.0009		
	(2.816)	(-2.186)	(1.313)	(4.494)	(0.759)		
Medium ESG Score	0.0071	-0.0734	0.0030	0.0022	0.0003		
	(2.546)	(-1.614)	(1.795)	(3.0247)	(0.269)		
High ESG Score	0.0066	-0.0875	0.0044	0.0003	0.0004		
	(2.891)	(-2.284)	(2.079)	(0.355)	(0.400)		
5-Factor + ADR:							
Low ESG Score	0.0077	-0.1002	0.0025	0.0035	0.0011	0.0003	-0.0009
	(2.923)	(-2.139)	(1.165)	(4.086)	(0.897)	(0.338)	(-1.888)
Medium ESG Score	0.0078	-0.0698	0.0021	0.0022	-0.00002	-0.0003	-0.0003
	(2.623)	(-1.55)	(1.104)	(2.495)	(-0.018)	(-0.607)	(-0.505)
High ESG Score	0.0066	-0.0785	0.0041	0.0002	0.0005	0.0002	-0.0009
	(2.926)	(-2.080)	(1.974)	(0.193)	(0.434)	(0.258)	(-1.390)

The exposure to ADR maintains a strong relation with expected stock returns for firms with mostly aligned E, S and G metrics. However, when we consider the sample of firms for which the E, S and G metrics deviate the most (the high ESG disparity sample), λ^{ADR} declines in both absolute magnitude and significance. The relationship between expected stock returns and ADR betas is no longer significant for the high ESG disparity sample.

In order to understand the relative importance of the level of ESG scores and their disparity in pricing ADR, we further condition both terciles of poorly and best performing firms in terms of ESG scores on the degree of disparity between the E, S and G components of the score. Results from the cross-sectional regression in Equation (3.5) are reported in Panels B and C of Table 3.11 for firms belonging to the bottom tercile of ESG performance and those belonging to the top tercile of ESG performance, respectively. Interestingly, for both sets of firms, we confirm the pattern observed in Panel A of Table 3.11: ADR is priced only in the cross-section of stocks for which the three components of their ESG score are mostly aligned. Regardless of overall ESG scores, it is only for firms with low ESG disparity that we observe a consistent and strong negative relationship between expected returns and ADR exposure.

3.5 Conclusion

With the increasing abundance of ESG-related regulation, firms are faced with a growing uncertainty with respect to the adoption and scope of new regulation, as well as their ability to manage future regulatory developments. In this paper, we explore three main areas: (1) the ESG uncertainty emanating from the development of ESG regulations, (2) the firm's ability to manage regulatory development, and (3) the pricing of ESG exposure to aggregate downside risk.

First, we find that uncertainty related to environmental, social and governance

Table 3.11: Pricing of Aggregate Downside Risk (ADR) Conditioned on Firms' ESG Disparity.

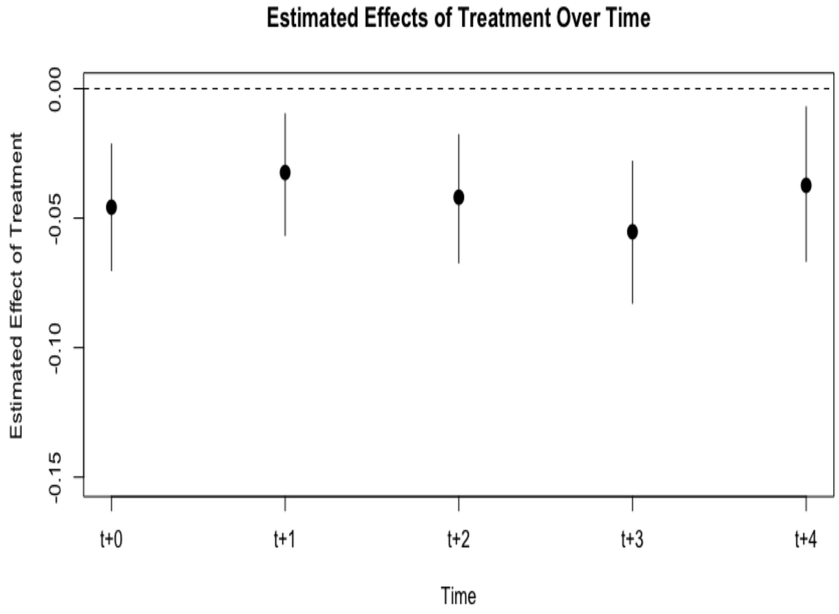
This table presents the results of Fama and MacBeth (1973) regressions of month $m+1$ excess stock returns on month m ADR betas $\beta_{i,m}^{ADR}$ and risk factors betas for the Fama-French 5-factor model. Firms are allocated to a low, medium or high ESG score tercile according to their ESG score at the end of month m. Within each one of these terciles, as well as for all firms, firms are further split in terciles according to their ESG disparity observed in month m. 'Low ESG Disparity', 'Medium ESG Disparity' and 'High ESG Disparity' refer to the estimates for firms in the low, medium or high ESG disparity tercile. The table reports the intercept of each regression (α) and the market prices of risk corresponding to aggregate downside risk (λ^{ADR}), the market risk factor (λ^{MKT}), the size (λ^{SMB}), value (λ^{HML}), profitability (λ^{RMW}), and investment (λ^{CMA}) factors. Panel A reports the regression results on all firms in our sample. Panel B reports the regression results conditioned on firms with low ESG performance. Panel C reports the regression results conditioned on firms with high ESG performance. Newey West t-stats are reported in parentheses.

Portfolio	α	λ^{ADR}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}
Panel A: All firms							
Low ESG Disparity	0.008	-0.123	0.002	0.003	0.001	0.0006	-0.0008
	(3.136)	(-2.068)	(1.105)	(3.470)	(1.254)	(0.783)	(-1.602)
Medium ESG Disparity	0.007	-0.078	0.003	0.002	0.0009	-0.0004	-0.0009
	(2.786)	(-1.944)	(1.662)	(2.313)	(0.978)	(-0.509)	(-1.603)
High ESG Disparity	0.008	-0.065	0.004	0.002	0.0002	-0.001	-0.0002
	(2.863)	(-1.440)	(2.034)	(2.255)	(0.205)	(-1.815)	(-0.338)
Panel B: Low ESG performance							
Low ESG Disparity	0.006	-0.178	0.008	0.004	0.002	0.004	-0.0001
	(1.710)	(-2.297)	(1.956)	(4.041)	(0.986)	(-1.359)	(-0.182)
Medium ESG Disparity	-0.029	0.220	0.023	0.006	0.016	-0.002	-0.002
	(0.785)	(-0.865)	(1.127)	(1.463)	(0.976)	(-2.007)	(-2.748)
High ESG Disparity	0.012	-0.050	-0.001	0.002	0.004	-0.0009	-0.0004
	(3.276)	(-1.208)	(-0.377)	(0.446)	(1.080)	(-1.565)	(-0.538)
Panel C: High ESG performance							
Low ESG Disparity	-0.016	-0.096	0.040	-0.012	-0.041	-0.024	-0.0003
	(-0.836)	(-2.374)	(1.150)	(-0.705)	(-0.929)	(-1.043)	(-0.462)
Medium ESG Disparity	0.005	-0.157	0.008	0.001	0.0003	0.0003	-0.0011
	(1.607)	(-2.353)	(1.736)	(0.770)	(0.103)	(0.380)	(-1.598)
High ESG Disparity	0.009	-0.053	0.005	-0.005	-0.005	0.0002	-0.0009
	(2.570)	(-0.053)	(2.186)	(-0.414)	(-0.620)	(0.297)	(-1.224)

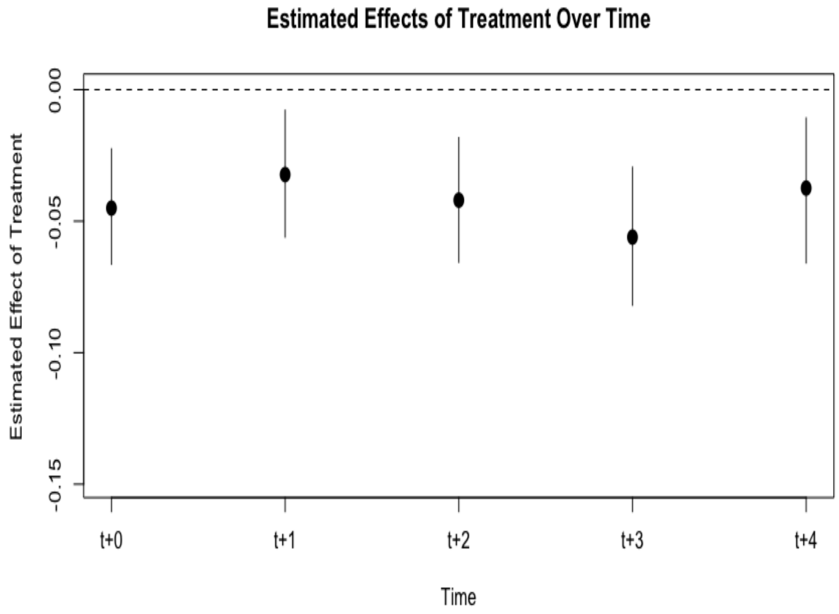
(ESG) regulatory developments is reflected in asset prices. At the aggregate or at the economy level, the cost of protection against downside risk is higher when the ESG regulatory uncertainty is higher, and even more so when the economic conditions are worse. At the firm level, firms with high ESG scores have a lower cost of protection against downside tail risk compared to firms with low ESG performance. However, more granular scores show a nuanced pattern, as firms with higher governance ratings or better management scores are also associated with an increased cost of protection against downside tail events.

Second, we account for the possibility that a firm's ESG standing may include divergent ratings along the environmental, social and governance dimensions of its sustainability profile. We find that firms with high ESG disparity have a higher cost of protection against downside risk. This implies that firms with a low ability to manage ESG regulatory development command a higher cost of protection against downside risk.

Third, we find a negative price of aggregate downside risk for firms with either high or low ESG performance. Firms with high ESG performance command a lower negative price of aggregate downside risk. Both high and low ESG firms have negative exposure to downside risk. However, high ESG firms have lower exposure to downside risk compared to low ESG firms. Investing directly in high ESG firms does not provide insurance against downside risk as they have negative exposure to downside risk. However, an investment strategy of longing high ESG firms and shorting low ESG firms might provide insurance against downside risk.



(a) CBPS Weighting



(b) PS Weighting

Figure 3.1: Estimated Average Treatment Effect of ESG Status (Treatment) on the Cost of Protection Against Downside Risk.

The estimates are based on the Covariates Balance Propensity Score (CBPS) weighting method (Panel (a)) and the Propensity Score weighting method (Panel (b)) that adjusts for treatment and covariates histories during the 12-month period prior to the treatment. Estimates for the average effects of ESG treatment are shown for the four-month period after the immediate effect, with 95% asymptotic confidence intervals as vertical bars. The bootstrap method is used for the standard error calculation.

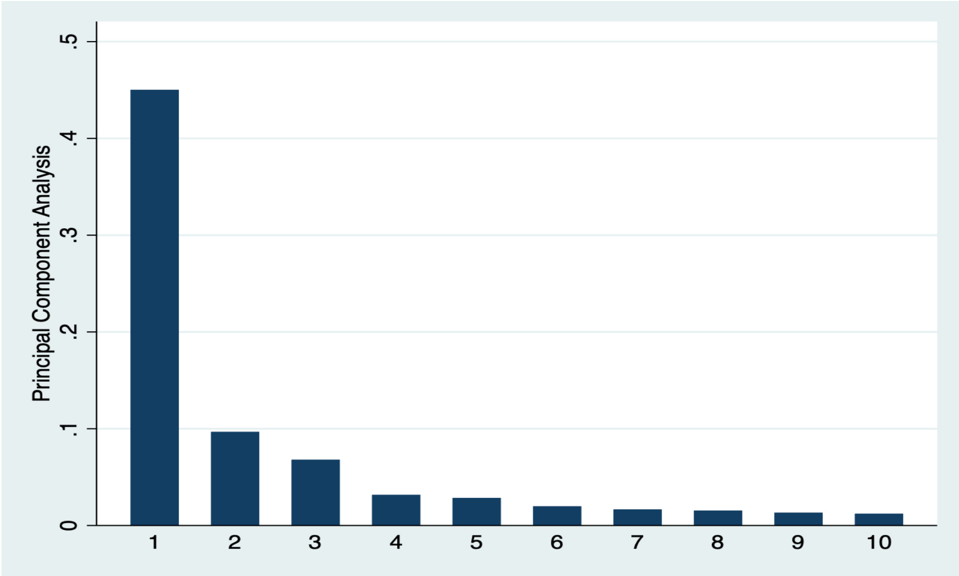


Figure 3.2: Principal Component Analysis (PCA) on Firms' Downside Risk (FDR).

The figure reports the first 10 principal components based on the correlation matrix of the firm downside risk measure, FDR_i, extracted from option prices. For the computation of the principal components, a firm must have at least 18 daily observations per month to be included. This analysis applies to a set of firms with at least 192 monthly observations. The data range is from January 2001 to December 2021.

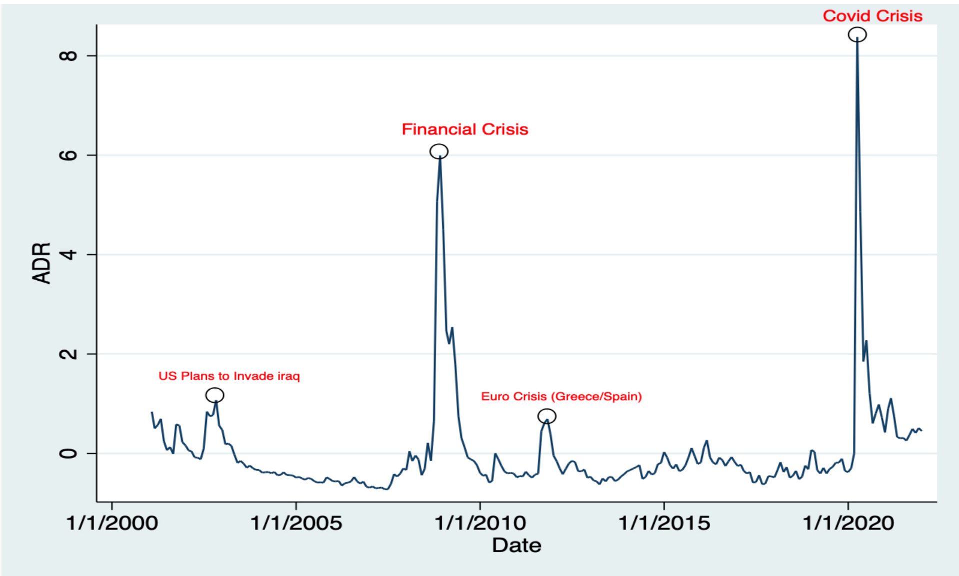


Figure 3.3: Aggregate Downside Risk (ADR).

The figure plots a monthly time series of the risk-neutral probability of downside events, defined as the first principal component extracted from the panel of firm downside risk measures, FDR_i, and estimated from option prices. The risk-neutral probability of downside events is constructed following Siriwardane (2015). A firm must have at least 18 daily observations in a month to be included. PCA is conducted on the correlation matrix of the monthly FDR_i. We discard firms with less than 192 monthly observations. The data range is from January 2001 to December 2021.

Chapter 4

Brown Spinning

Abstract

I examine the post-divestment environmental implications of brown spinning, where public companies spin off or sell their brown (carbon-intensive) assets to private investors, such as private equity firms or private companies. I focus on the sustainability characteristics of the private buyers to determine whether the post-divestment underlying assets' emissions is different for private investors with a stated sustainability preference compared to those without explicitly stated sustainability preference. First, I find that the emissions of these carbon-intensive assets increase after the change of ownership from public to private hands. Second, private investors with a stated sustainability preference have higher asset-level emissions compared to private players without an explicitly stated sustainability preference.

4.1 Introduction

In recent years, the global shift towards sustainability has placed significant pressure on companies to reduce their greenhouse gas (GHG) emissions and adopt more environmentally friendly practices. This has led to an increasing number of public companies divesting their high-emission assets to private players, a process often referred to as "brown spinning." Brown spinning involves the transfer of carbon-intensive assets from public companies, which are potentially subject to stricter regulatory and public scrutiny, to private entities that face less regulatory pressure and public accountability. For example, Berg et al. (2024) show that large emitting firms reduce their carbon emissions mainly through the divestment of their high emitting assets.

Although brown spinning can help divesting public companies improve their environmental performance and environmental, social, and governance (ESG) ratings, it raises important questions about the overall impact on global or aggregate emissions. For example, in 2020, BP Plc sold all of its Alaska upstream business to Hilcorp Energy (a private player) for $5.6 billion. After the sale, BP Plc reported a significant reduction of 33.33 MtCO2e in its scope 3 upstream emissions. However, the underlying assets transferred to Hilcorp Energy did not show improvement in their emissions post-acquisition. In this paper, I examine the post-divestment environmental implications of brown spinning. Specifically, I examine the relationship between the change in ownership from public to private entities and the emission levels of the divested assets.

To examine the post-divestment environmental implications of brown spinning, I consider all the completed asset spin-off transactions in the Energy and Utilities sectors. I obtain the Public to Private Entities (PPE) transactions data from S&P Global, one of the leading financial data providers. I filter PPE transactions based on the following criteria: transaction type (acquisition of asset or branch, spinoff, or splitoff); transaction industry (energy and utilities, unclassified[1]); completed transaction status; company geography of the issuer (United States); completion date (between 01/01/2020 and 12/31/2022); company type of the buyer or investor (private company or private fund); and company type of the seller (public company).

One main concern of brown spinning is that when the assets are sold or spun off to the private players, it becomes difficult to (publicly) observe the carbon emissions of the divested assets because private players stop reporting on them [2]. To address this issue, I link the filtered PPE transactions to the plant-level emission data made publicly available by the US Environmental Protection Agency (EPA). The US EPA provides detailed plant-level data, particularly on the emission level and the ownership status.

However, there is an issue with the ownership data provided by the EPA. Some underlying assets still retain the name of the operating companies even after the change of ownership. For example, the Alyeska pipeline service plants in Figure 4.3 still retain the name of the operating company as the parent company even after the change of ownership from BP Plc to Hilcorp Energy. To address this, I examine the PPE transactions one by one to determine the ultimate parent company. After this mapping and cleaning, I end up with 41 unique public companies, 60 unique private investors, and 201 unique underlying assets.

These public companies are predominantly large, with a combined asset value of $4.7 trillion [3] and total Scope 1 emissions of 810 million metric tons of CO2 equivalent as of 2022. 51% of the public companies - representing 82% of the total emissions of Scope 1 - are part of Climate 100+ firms. The Climate 100+ firms consists of 170 firms with the largest GHG emissions globally. The underlying assets of the PPE transactions are high carbon-intensive assets; and to put it in perspective,

[1]Some energy and utilities transactions are located in the unclassified segment of the industry classification.

[2]This is the main limitation of Berg et al. (2024)'s study

[3]combined market capitalization of $3.3 trillion as of July 31, 2024

the average emissions of the underlying assets involved in the PPE transactions are twice those of the average US plant.

The following are the key findings. First, the aggregate direct emissions of the divesting public companies, that is, the public companies involved in PPE transactions, decrease significantly over time. Divesting public companies reduced their scope 1 by 28% between 2014 and 2022 as shown in Table 4.4 and their combined scope 1 and 2 by 26% between 2014 and 2022. This is similar to Berg et al. (2024)'s finding, where they show that large emitters reduced their combined Scope 1 and 2 emissions by 19% after the Paris agreement relative to the period before the Paris agreement. These findings imply that divesting public companies are becoming greener over time and that this transition is mainly driven by divestment (Berg et al., 2024).

Second, while divesting public firms are becoming greener, divested assets are not. In contrast, the change in ownership from public to private surprisingly leads to increased GHG emissions. At the plant level, a change in ownership from public to private is associated with a 2.7% increase in GHG emissions.

Third, I consider whether the sustainability preferences of the private investors, as indicated by their status as signatories to the United Nations Principles for Responsible Investment (PRI), influence the emissions outcomes of the acquired assets. I find that private investors with a stated sustainability preference have higher post-acquisition asset-level emissions compared to private players without an explicitly stated sustainability preference. Assets acquired by private investors with a stated sustainability preference have higher unit-level emissions ranging from 22% to 54% compared to those without such a stated preference.

Higher post-acquisition asset-level emissions of private investors with a stated sustainability preference, compared to those without, could have several interpretations. An interpretation is that these private investors publicly commit to responsible practices to attract inflows (Hartzmark and Sussman, 2019) but lack a real commitment to responsible investing (Brandon et al., 2022), thus engaging in greenwashing

(Liang et al., 2022). Another interpretation is that these sustainable private investors undertake ambitious transition projects that take longer to reform, leading to higher immediate emissions compared to their non-sustainable peers[4]. In the future, I plan to explore the channels that drive the higher post-acquisition emissions of sustainable private investors compared to their non-sustainable counterparts.

The closest paper to this study is by Berg et al. (2024), which examines how large emitters reduce their carbon emissions. They show that divestment is the main activity that contributes to the reduction of emissions from large emitters. However, the main limitation in Berg et al. (2024), as clearly stated in their paper, is that they are unable to track the emissions of the assets post-divestment. My paper complements theirs by tracking the post-divestment emissions of the assets and providing insight into the environmental implications of the divested assets after the change in ownership. Most of my sample of public companies in PPE transactions also intersects with the sample of large emitters in Berg et al. (2024). To the best of my knowledge, this is the first paper to consider the post-divestment environmental footprint (and implications) of the assets divested to private players, specifically in the energy and utilities sector.

This paper contributes to the discussion on the unintended consequence of environmental policies. Although Berg et al. (2024) show that divestment is a key factor driving emission reductions after the Paris Agreement, I demonstrate that the emissions of divested assets do not decrease post-divestment, casting doubt on the overall greenness of the economy. Other studies, such as Bartram et al. (2022) and Ben-David et al. (2021), have also highlighted the unintended consequences of environmental (climate) policies. For example, Bartram et al. (2022) examines the real effect of the California cap-and-trade program on firm behavior. They show that financially constrained firms respond to the cap-and-trade program by reallocating

[4]The main limitation to testing this interpretation is that it requires longer horizon of project or asset-level emissions data of the private investors

their emissions and production activities to other less regulated states. Ben-David et al. (2021) shows that tightened environmental policies in the home countries incentivize multinational firms to shift their emissions abroad[5].

This paper also contributes to the literature on whether investors' sustainability preferences translate into real impact. As mentioned above, I find that private investors with sustainability preferences have higher asset-level emissions compared to those without explicitly stated sustainability preferences. This result aligns with some recent studies on the real impact of sustainability investments. For example, Brandon et al. (2022) shows that institutional investors in the US publicly committed to sustainable or responsible investment do not improve the sustainability performance of their portfolio companies compared to their uncommitted peers. Similarly, Kim and Yoon (2021) finds that US mutual fund managers that publicly commit to responsible investing do not improve the sustainability performance of their funds, while Liang et al. (2022) shows that hedge funds that publicly commit to sustainable investing do not "walk the talk" and only commit to sustainable investing to increase their fund inflows.

The remainder of the paper is organized as follows. Section 4.2 describes the data and the source. Section 4.3 presents empirical analyses of the relationship between the change in ownership and the emission levels of the assets. Section 4.4 examines whether the sustainability preferences of private investors matter for the assets' emission levels. Section 4.5 concludes.

[5]Other related papers: Eskeland and Harrison (2003); Cole (2004); Wagner and Timmins (2009); Dam and Scholtens (2012); Bento et al. (2015)

4.2 Data Source and Description

4.2.1 US Plant and Unit Level Data

I obtain aggregate US greenhouse gas emissions data, along with plant and unit level emissions data, from the US Environmental Protection Agency (EPA) for the period 2010-2022. The aggregate US greenhouse gas emissions include carbon dioxide, methane, nitrous oxide, and fluorinated gases. The EPA provides detailed plant-level data, including facility names, reported addresses, latitude and longitude, city names, and parent companies, among other information. In addition, it provides unit-level data on plants, such as unit names, unit types, unit reporting methods, and a breakdown of GHG emissions into non-biogenic CO2, methane, nitrous oxide, and biogenic CO2[6]. The main component of the GHG emissions is non-biogenic CO2.

4.2.2 Public to Private Entities (PPE) Transactions

I obtain Public to Private Entities (PPE) transactions data from S&P Global, one of the leading financial data providers. I filtered the PPE transactions based on the following criteria: *transaction type* (acquisition of asset or branch, spinoff, or splitoff); *transaction industry* (energy and utilities, unclassified[7]); *completed transaction status*; *company geography of the issuer* (United States); *completion date* (between 01/01/2010 and 12/31/2022); *company type of the buyer or investor* (either private company or private fund); and *company type of the seller* (public company).

Next, I examined these transactions one by one to determine the ultimate parent company, as I noticed that some private companies had public companies as their ultimate parent. After this cleaning, I ended up with 49 unique public companies, 60 unique private investors, and 201 unique underlying assets. These underlying assets

[6] Fuel type data is also provided.

[7] Some energy and utilities transactions are located in the unclassified segment of the industry classification.

of the PPE transactions are high carbon-intensive assets; for instance, the average emissions of the PPE underlying assets is 0.716 compared to 0.393 for overall US plant-level emissions.

Emissions of Public Companies. I also obtain the emissions data of the public companies involved in the PPE transactions from S&P Global, covering the period from 2010 to 2022[8]. S&P Global acquired a controlling stake in Trucost plc, effective on October 1, 2016, integrating Trucost's environmental data into its products. Trucost is a leader in environmental (and carbon) data. I specifically obtained scope 1, scope 2, scope 3 upstream, and scope 3 downstream emissions. S&P Global defines scope 1 emissions as emissions from directly emitting sources owned or controlled by a company; scope 2 location-based emissions as emissions from the consumption of purchased electricity or steam by the company; scope 3 upstream emissions as emissions from other upstream activities not covered in scope 2; and scope 3 downstream emissions as emissions associated with the use of sold goods and services.

Mapping of Plant Ownership for PPE Transactions. The US Environmental Protection Agency (EPA) provides data on the parent companies of the underlying plants. However, some plants list their operating name as the parent company name, which does not reflect the real parent company name. This implies that any change in ownership from one parent company to another will not be reflected in this case. For example, Alyeska Pipeline Service plants list their parent company name as Alyeska Pipeline Service. In 2020, there was a change in ownership of Alyeska Pipeline Service plants from BP plc to Hilcorp Energy, but the plants still retained their parent company name as Alyeska Pipeline Service. To address this issue for PPE transactions, I consider each filtered PPE transaction individually to determine the ultimate parent companies. I obtain data on the ultimate parent companies from S&P Global and the plant-level (and unit-level) data from the US EPA. I consider the filtered PPE transaction data to be the cleanest in this study, as I reviewed the

[8] These are S&P-generated emission values.

transactions one by one.

Descriptive Statistics. Table 4.1 shows the descriptive statistics of all the main emissions variables used in this study. Panel A of Table 4.1 reports the summary statistics of the emissions of the public companies involved in the Public-Private (Asset Spinoff) transactions and the underlying assets (plants) transferred. The public emissions section of the PPE transactions presents the scope 1, scope 2, scope 3 upstream, and scope 3 downstream emissions of all public companies involved in the PPE transactions. While scope 1, scope 2, and scope 3 upstream cover the period from 2010 to 2022, scope 3 downstream starts from 2017 to 2022. All emissions values are divided by 100 million metric tons.

The average emissions of scope 1, scope 2, scope 3 upstream and scope 3 downstream of the public companies involved in the PPE transactions is 36, 2, 15 and 110 million metric tons of CO2, respectively. Scope 3 emissions constitute the largest emissions, with the maximum emission reaching 772.101 million metric tons of CO2e. The plant-level section of the PPE transactions presents the summary statistics of the direct emissions of the underlying plants transferred, further broken down into unit levels. At the plant level, the average aggregate emissions is 0.716 million metric tons, with a maximum of 15.739 million metric tons. At the unit level, the average emission levels for non-biogenic CO2, methane CH4, nitrous oxide N2O, and biogenic emissions are 0.166, 0.0004, 0.001, and 0.005 million metric tons, respectively. The main emissions at the unit level is the non-biogenic CO2 emission.

Panel B of Table 4.1 reports the summary statistics of the overall US plant emissions. At the plant level, the average aggregate emissions is 0.393 million metric tons, with a maximum of 22.985 million metric tons. At the unit level, the average emission levels for non-biogenic CO2, methane CH4, nitrous oxide N2O, and biogenic emissions are 0.114, 0.0002, 0.0004, and 0.003 million metric tons, respectively. The main takeaway is that the average emissions of the plants transferred under the PPE transactions is twice that of the average emissions of all US plants.

Table 4.1: Descriptive Statistics

The table reports descriptive statistics of the variables of interest covering the period from 2010 to 2022 (in 100 million metric tons). Where the period differs, it is stated in front of the variable involved. Panel A reports descriptive statistics for assets spun off from public entities to private players (PPE transactions). The scope 1, 2, and 3 GHG emissions refer to the scope 1, 2, and 3 emissions of the public entities involved in the transaction (public entities where the changes in emissions are greater than 500% are excluded[9]). Panel B reports descriptive statistics for overall US plants at both the plant level and the unit level.

Statistic	N	Mean	St. Dev.	Min	Max
Panel A: PPE (Asset Spinoff) transactions					
Public Emission:					
Scope 1	364	35.534	35.935	0.014	296
Scope 2	369	2.004	2.891	0.002	15.739
Scope 3 upstream	385	14.694	30.393	0.023	165.645
Scope 3 downstream - from 2017	142	110.203	188.095	0.001	772.101
Plant level:					
Aggregate	1,841	0.716	1.777	0.000	17.655
Unit level:					
Non-biogenic CO2 emissions	8,774	0.166	0.638	0.000	8.773
Methane CH4 emissions	8,774	0.0004	0.002	0.000	0.025
Nitrous Oxide N2O emissions	8,774	0.001	0.003	0.000	0.045
Biogenic CO2 emissions	8,774	0.005	0.027	0.000	0.544
Panel B: All US Plants					
Plant level:					
Aggregate	99,045	0.393	1.258	0	22.985
Unit level:					
Non-biogenic CO2 emissions	249,428	0.114	0.462	0	17.749
Methane CH4 emissions	249,428	0.0002	0.001	0	0.051
Nitrous Oxide N2O emissions	249,428	0.0004	0.002	0	0.141
Biogenic CO2 emissions	245,758	0.003	0.028	0	0.872

4.2.3 BP Plc vs Hilcorp Energy Case Study

BP Plc is a multi-national oil and gas **public** company headquartered in London. BP's purpose is to help reimagine energy for people and the planet, aiming to reach net zero and improve people's lives[10]. Over the years, BP Plc has been reducing its carbon emissions, including scope 1, scope 2, and even scope 3. Figure 4.1 reports the scope 1, scope 2, and scope 3 emissions of BP Plc over the years, showing a decrease in emissions. However, BP's current approach to achieving its net zero goal or reducing its carbon emissions is through divestment of its high-polluting assets and investing in renewable energy.

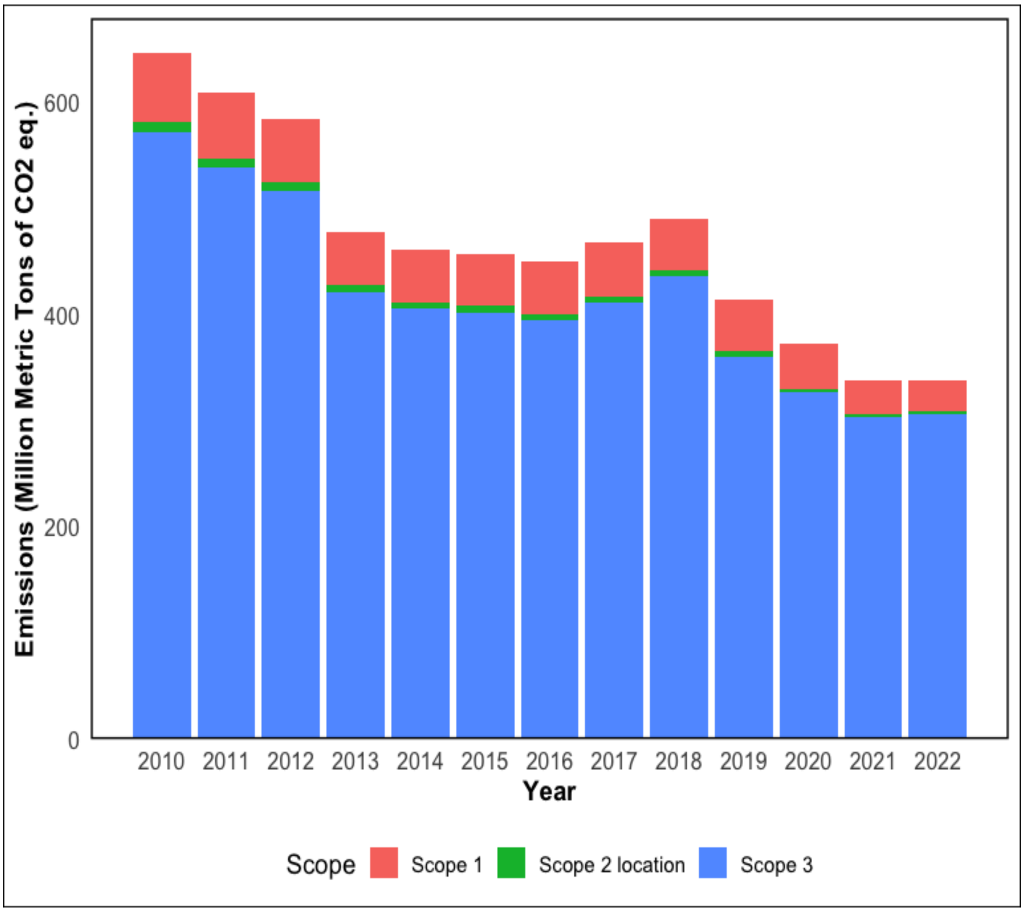


Figure 4.1: BP Scope 1, 2, and 3 Emissions Combined.
The figure reports the total Scope 1, 2, and 3 emissions of BP covering the period from 2010 to 2022.

Each year, the Carbon Disclosure Project (CDP) requests carbon-related information from firms such as BP, including a breakdown of how they are reducing their

[10] https://www.bp.com/en/global/corporate/who-we-are/our-purpose.html

scope 1 and 2 emissions. The breakdown of emissions reduction is categorized into divestment, change in production, change in methodology, other emission reduction activities, acquisitions, other operational changes, change in renewable energy consumption and change in boundary. Firms must state the amount of (positive or negative) changes from each category[11]. This is a voluntary disclosure to the CDP.

Table 4.2 shows the year-on-year emission reduction path of BP Plc, illustrating how BP Plc has been reducing its scope 1 and 2 emissions year-by-year[12]. Divestment is the main reduction pathway employed by BP Plc, with reductions in carbon emissions from divestment reaching as high as 20.4% in 2021. To put this in perspective, the average emission reduction from the "divestment" category is 7 times the average emission reduction from the "other emission reduction activities" category and nearly 7 times the average emission reduction from the "other operational changes" category. Other categories, except for the change in renewable energy consumption, are on average positive.

Table 4.2: BP Plc's CDP Information on Changes in Gross Global Scope 1 and 2 Emissions

This table reports BP Plc's CDP information on changes in gross global Scope 1 and 2 emissions for the years 2010 to 2022. Note that BP did not report to CDP for 2017, 2018, and 2019. This table provides a breakdown of BP's emission reduction path.

Year	Divestment	Change in output	Change in methodology	Emissions reduction activities	Acquisitions	Other: Operational changes	Change in renewable energy consumption	Change in boundary
2010	-2.4	2.5	0.5	-0.2				
2011	-4.8		-0.2	-0.3	3	-3.2		
2012	-2.4		-0.6	-0.4	1.3	-1.2		
2013	-19.23			-0.33	0.7	1.67		
2014	-5.96			-0.22	1.59	-1.19		
2015	-1.8		1.1	-0.2	0.5	0.7		
2016	-0.8			-0.5	0.5	2.8		
2017								
2018								
2019								
2020	-9.9	0.2	-0.2	-1.8	0.6	-5.1	0	
2021	-20.4	-0.5	0.2	-3		-0.6	0	
2022	-3.4	-0.3	-0.1	-2.3	0	-3.1	-1.9	
Average	-7.11	0.48	0.10	-0.93	1.02	-1.08	-0.83	0.00
Sum	-71.09	1.90	0.70	-9.25	8.19	-8.62	-2.50	0.00

[11]For instance, if a firm reduces its emissions by -2% from the previous year, it must show the breakdown, e.g., -1.8% from divestment, 0.2% from change in boundary.

[12]BP did not submit reports to CDP for 2017, 2018, and 2019.

It is evident that BP engages in divestment as part of its emission reduction strategy, which is not an issue. The central issue is "Who are the buyers?", "Do they care about sustainability?" and "Do the emissions of the divested assets increase after the sale?" One major buyer of BP Plc's divested assets is Hilcorp Energy, the largest privately owned oil and natural gas company in the US[13]. In 2014, BP Plc sold all its interests in four oil fields on the Alaska North Slope to Hilcorp Energy for $1.5 billion. In 2020, BP Plc sold all its Alaska operations to Hilcorp Energy for $5.6 billion. Table 4.3 provides the details of these transactions, including the details of the assets involved. I track the emissions of the divested assets to see what happens to the emission levels when ownership changes hands from BP Plc to Hilcorp Energy. Figure 4.2 presents the asset (plant)-level emissions of the assets transferred from BP Plc to Hilcorp Energy in 2014, while Figure 4.3 presents the asset (plant)-level emissions of the assets divested from BP Plc to Hilcorp Energy in 2020. The conclusion is that there is no significant reduction in the emissions of the assets divested when ownership changes hands from BP Plc to Hilcorp Energy.

[13] https://www.hartenergy.com/companies/hilcorp-energy-co

Table 4.3: BP Plc (Public Company) vs Hilcorp Energy (Private Company)

This table presents an example of transactions between BP Plc, a public entity, and Hilcorp Energy, a private player.

	Details	Ann. Date	Complet. Date	Amount
1.	Interests in four oil fields on Alaska North Slope (a) All interest in Endicott (b) All interest in Northstar (c) 50% interest in Liberty (d) 50% interest in Milne Point	04/22/2014	11/30/2014	$1.5 billion
2.	All Alaska operations of BP Plc & BP pipeline (Alaska) inc (a) 49% in Alyeska Pipeline Service Company (b) 49% in Trans alaska pipeline system (c) 32% in Point Thomson Export Pipeline (d) 50% in Milne Point Pipeline (e) 25% in Prince William Oil Spill Response Corp.	08/27/2019	12/18/2020	$5.6 billion

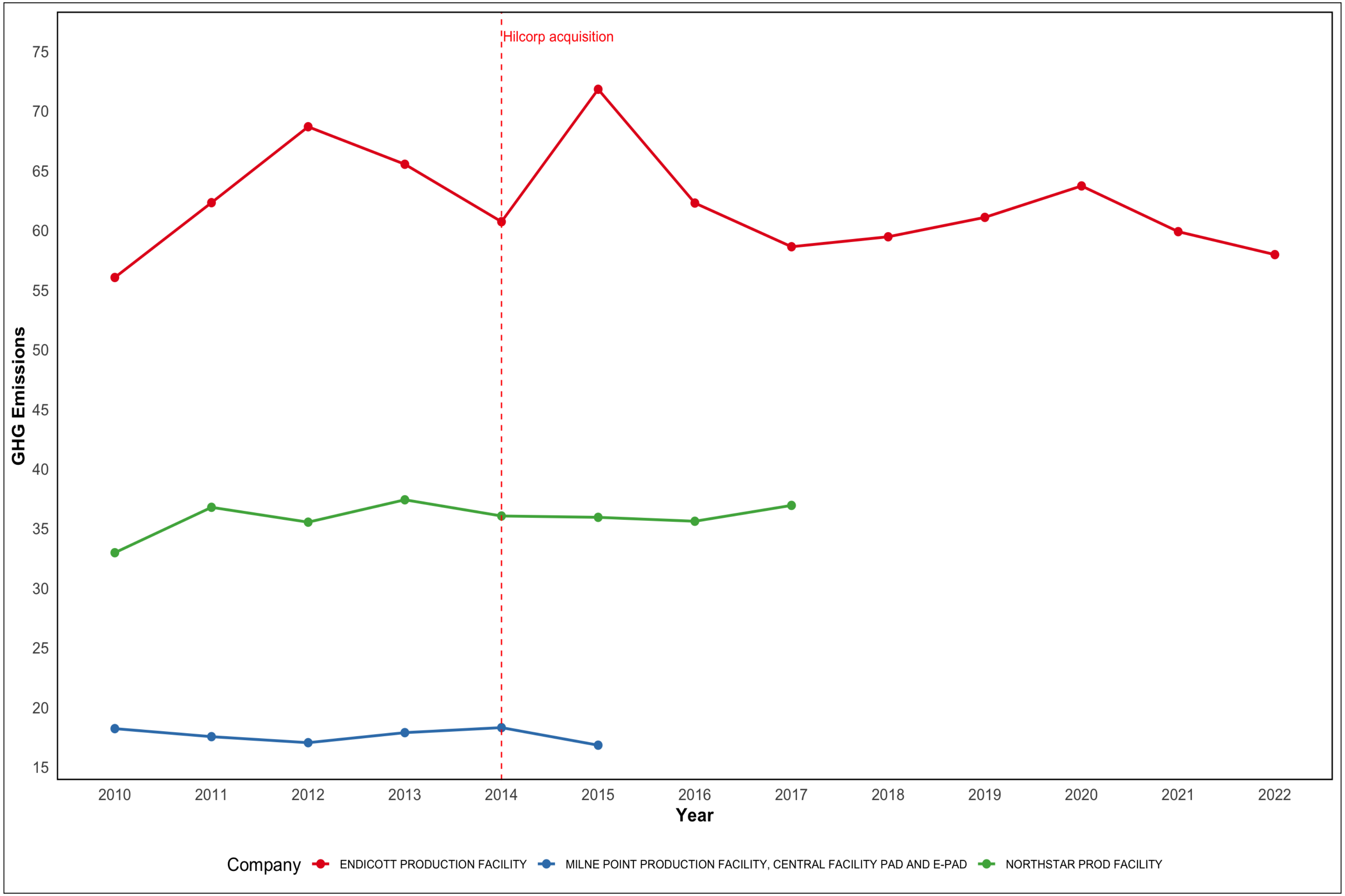


Figure 4.2: Asset Spin-Off: From BP to Hilcorp Energy in 2014.

The figure reports the asset sales from BP plc to Hilcorp Energy in 2014. The red dotted vertical line indicates the acquisition of BP's share by Hilcorp Energy.

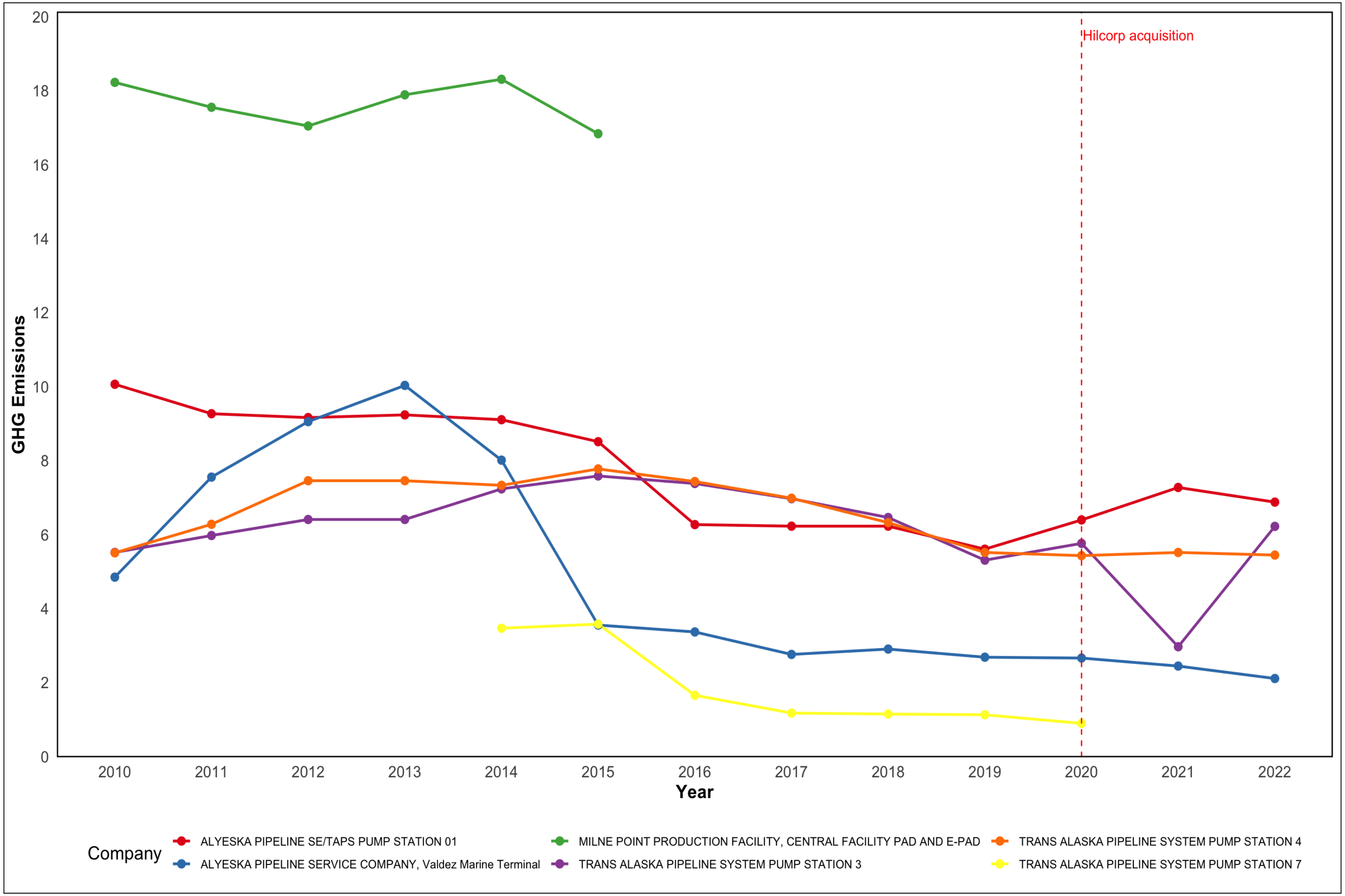


Figure 4.3: Asset Spin-Off: From BP to Hilcorp Energy in 2020.

The figure reports the asset sales from BP plc to Hilcorp Energy in 2020. The red dotted vertical line indicates the acquisition of BP's share by Hilcorp Energy.

4.2.4 PPE Transactions

Here, I extend the analysis from the BP Plc vs. Hilcorp Energy case study to all public-to-private entity (PPE) transactions in the energy and utilities sector. I consider all completed asset spinoff transactions in energy and utilities from public companies to private companies (either private companies or private funds) covering the period between 2010 and 2022. The reason for this period is that the emissions data for the underlying assets from the US EPA data set begin from 2010. Direct emissions (scope 1 emissions) of the public entities involved in the PPE transactions have been significantly reduced over the years, as reported in Figure 4.4, while the divested assets have not experienced similar significant emission reductions, as shown in Figure 4.5. Next, I examine the relationship between the change in plant ownership-from public to private players-and the plant's emission levels. Specifically, I examine what happens to the emission levels of the assets divested in the PPE transactions after the change in ownership.

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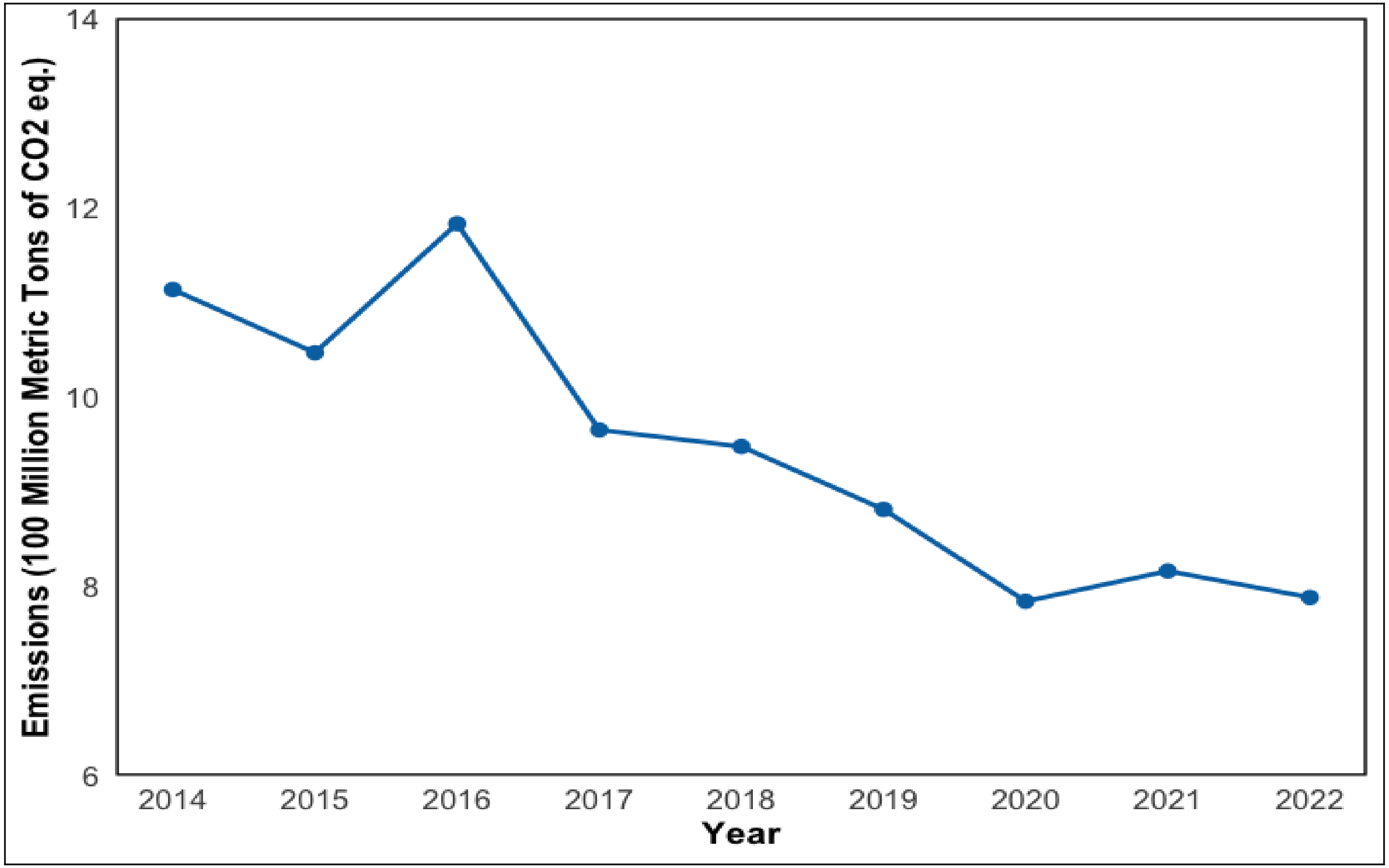

Figure 4.4: PPE Transaction (Balanced): Scope 1 Emission of the Public Entities

The figure reports the Scope 1 emission for a balanced sample of the public entities involved in the PPE transaction, measured in 100 million metric tons of CO2 equivalent (mt CO2e).

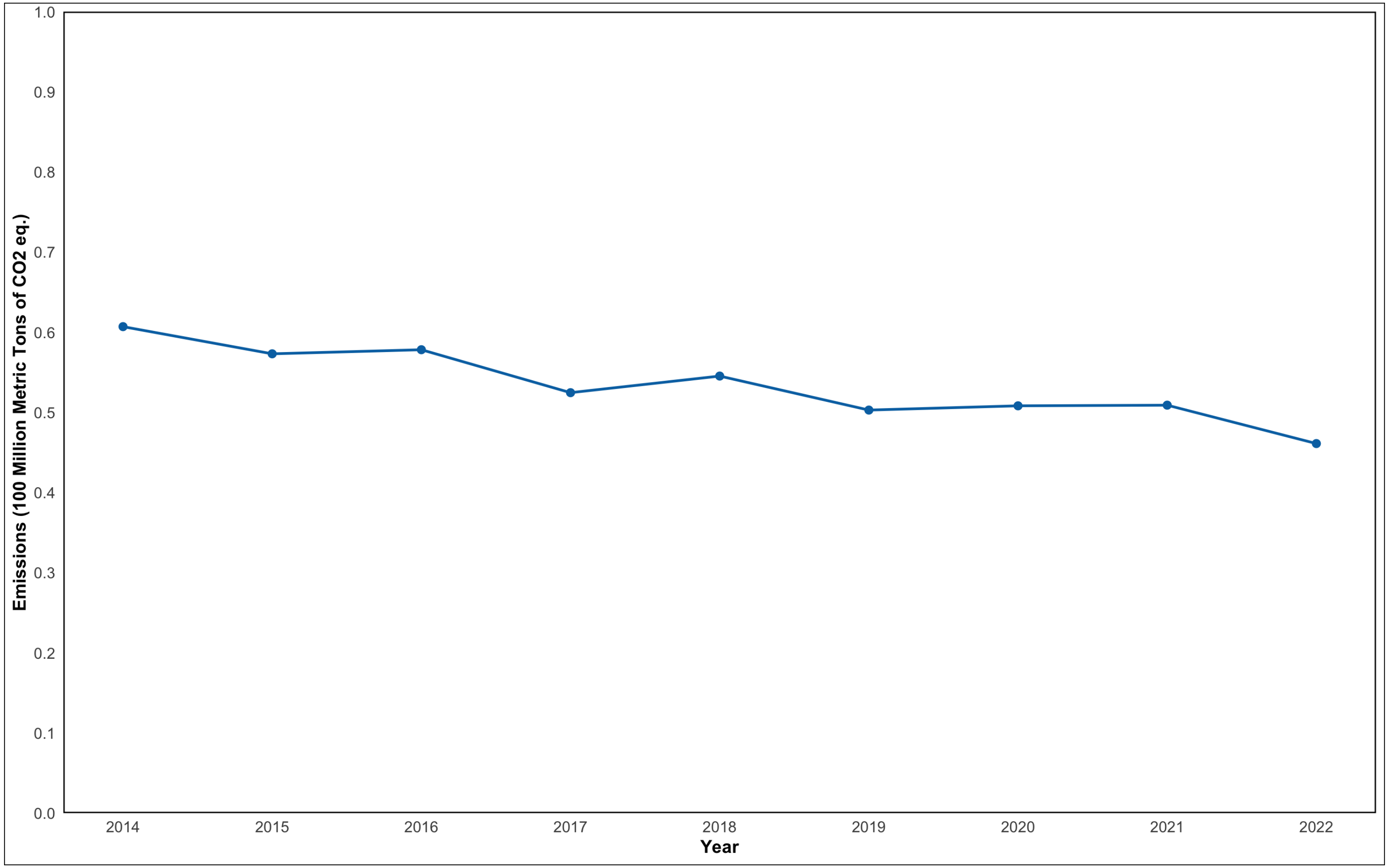

Figure 4.5: PPE Plant-Level Emission Over Time (Balanced Panel).

The figure reports the plant-level emission for a balanced sample of the underlying assets involved in the PPE transaction, measured in 100 million metric tons of CO2 equivalent (mt CO2e).

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Empirical Strategy

To examine the relationship between the change in plant ownership - from public to private players - and the plant's emission levels, the following (baseline) standard regression specification is performed.

$$\ln(Y_{i,t}) = \beta_0 + \beta_1(\text{Change in Ownership}_{i,t}) + \alpha_i^{\text{state}} + \alpha_i + \alpha_t + \epsilon_{i,t}, \tag{4.1}$$

where Y is a measure of greenhouse gas emissions (GHG) at the plant level (and unit level) in metric tons of CO2e in the reporting year t. Change in Ownership is an indicator variable equal to one if the plant i is owned (or controlled) by private players and zero otherwise. α_i^{state}, α_i, and α_t are fixed effects of the state (location), plant, and reporting year, respectively.

4.3 Result

The analysis begins by considering the relationship between the change in ownership and the emission levels of the plants disposed of in the PPE transactions. Specifically, I estimate the baseline regression specification of Equation 4.1, where the main variable of interest is the indicator variable 'Change in Ownership'. The variable 'Change in Ownership' is equal to one (1) when the plant is owned or controlled by a private company or private fund, and zero (0) otherwise. Table 4.4 presents the results of the plant-level regression of the log of greenhouse gas (GHG) emissions on the change in ownership. The main coefficient of interest, "Change in Ownership," is positive across different regression specifications. This means that the emissions levels of the plants increase when ownership changes hands from public to private owners.

I also perform unit-level regressions on the change of ownership, where the ag-

Table 4.4: Plant-Level Regression on Change in Ownership

This table examines the relationship between a change in ownership from public to private owners and asset-level emissions. The unit of observation is the plant reporting year level and the sample period spans 2010 to 2022. The independent variable is the natural logarithm of plant-level emissions. "Change in Ownership" is an indicator variable equal to one if the plant is owned (or controlled) by private players, and zero otherwise. Regressions include fixed effects for the plant, reporting year and location, as indicated. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:			
	log of GHG			
	(1)	(2)	(3)	(4)
Change in Ownership	0.281***	0.705***	0.027	0.833***
	(0.084)	(0.095)	(0.046)	(0.093)
Constant	11.665***	12.248***	11.847***	11.520***
	(0.056)	(0.188)	(0.232)	(0.200)
Year FE		Yes	Yes	Yes
Plant FE			Yes	
State FE				Yes
Observations	1,841	1,841	1,841	1,841
Adjusted R^2	0.006	0.043	0.896	0.206

gregate emissions are further broken down into four components: non-biogenic CO2 emissions, methane CH4 emissions, nitrous oxide N2O emissions, and biogenic CO2 emissions. The main component of these four is the non-biogenic CO2 emissions. Biogenic CO2 emissions are excluded from the regression analysis because they include many zeros and our dependent variable is the natural logarithm of the emissions variables. Panel A of Table 4.5 presents the unit-level regression results of the log of non-biogenic CO2 emissions on the change in ownership. The results indicate a positive relationship between the change in ownership and the unit-level emissions. Panel B of Table 4.5 presents the unit-level regression results of the log of methane CH4 emissions on the change in ownership, while panel C of Table 4.5 presents the unit-level regression results of the log of nitrous oxide N2O emissions on the change in ownership. The conclusion remains the same.

Overall, the results show that plant-level emissions increase after the change of ownership from public to private owners.

Table 4.5: Unit-Level Regression on Change in Ownership

This table examines the relationship between a change in ownership from public to private owners and unit-level emissions. The unit of observation is the unit reporting year level and the sample period spans from 2010 to 2022. The independent variable is the natural logarithm of unit-level emissions. Panels A, B, and C report the regression results where the independent variable is the natural logarithm of non-biogenic CO_2 emission, methane (CH_4) emission, and nitrous oxide (N_2O) emission, respectively. "Change in Ownership" is an indicator variable equal to one if the unit is owned (or controlled) by private players, and zero otherwise. Regressions include fixed effects for the plant, reporting year and location, as indicated. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:			
	(1)	(2)	(3)	(4)
Panel A	log of non biogenic co2 emission			
Change in Ownership	0.630***	0.752***	0.544***	0.673***
	(0.084)	(0.105)	(0.059)	(0.103)
Constant	8.147***	8.767***	8.168***	9.199***
	(0.057)	(0.171)	(0.445)	(0.235)
Observations	6,827	6,827	6,827	6,827
Adjusted R^2	0.008	0.013	0.809	0.167
Panel B	log of methane ch4 emission			
Change in Ownership	0.682***	1.178***	0.824***	1.175***
	(0.072)	(0.087)	(0.063)	(0.086)
Constant	2.033***	2.623***	0.820*	2.084***
	(0.049)	(0.142)	(0.435)	(0.192)
Observations	5,651	5,651	5,651	5,651
Adjusted R^2	0.015	0.038	0.703	0.183
Panel C	log of nitrous oxide n20 emission			
Change in Ownership	0.543***	1.117***	0.740***	1.068***
	(0.073)	(0.089)	(0.061)	(0.086)
Constant	2.502***	3.185***	1.678***	2.346***
	(0.050)	(0.146)	(0.435)	(0.190)
Observations	5,513	5,513	5,513	5,513
Adjusted R^2	0.010	0.038	0.731	0.205
Year FE		Yes	Yes	Yes
Plant FE			Yes	
State FE				Yes

4.4 Sustainability Preference of the Private Investors

Here, I examine whether the sustainability preference of the private owners matters for the emission level of the underlying or divested asset after the change in ownership. I use the United Nations Principles for Responsible Investment (PRI) signatories to identify the sustainability preferences of investors. PRI involves a network of investors (both asset managers and owners) that works to promote sustainable or responsible investment through the incorporation of sustainability into their investment decisions. Investors signal their public commitment to responsible investing by joining or becoming PRI signatories.

First, I separate the PPE transaction sample into two: the first sample is where the private buyers are PRI signatories (PRI signatories sample) and the second sample is where the private buyers are non-PRI signatories (Non-PRI signatories sample). Then, I perform the baseline regression of Equation 4.1 on the two samples. Panel A of Table 4.6 presents the unit-level regression result of the log of non-biogenic CO2 emissions on the change in ownership for the PRI signatories sample, and Panel B of Table 4.6 presents the unit-level regression result of the log of non-biogenic CO2 emissions on the change in ownership for the Non-PRI signatories sample. Both results show a positive relationship between the change in ownership and the emission level. This means that the emission level of the divested assets is higher for both PRI and Non-PRI signatories post-divestment. However, the coefficient of the change in ownership is higher for PRI signatories compared to the Non-PRI signatories. This implies that the emission level of assets acquired by the PRI signatories is higher post-acquisition.

Second, I augment the baseline regression specification as follows:

Table 4.6: Unit-Level Regression on Change in Ownership and PRI Signatories

This table examines whether there is a difference in the post-divestment unit-level emissions of assets acquired by private investors with a preference for sustainability compared to those acquired by investors without such a preference. If an investor is a PRI signatory, it signals a public commitment to responsible and sustainable investments. The sample is divided into two groups: the first group includes assets acquired by private investors who are PRI signatories, and the second group includes assets acquired by private investors who are non-PRI signatories. Panel A reports the results for PRI signatories, while panel B reports for non-PRI signatories. The unit of observation is the unit reporting year level and the sample period spans from 2010 to 2022. The independent variable is the natural logarithm of the emissions of non-biogenic CO_2 at the unit level. "Change in Ownership" is an indicator variable equal to one if the unit is owned (or controlled) by private players, and zero otherwise. Regressions include fixed effects for the plant, reporting year and location, as indicated. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:			
	(1)	(2)	(3)	(4)
Panel A: PRI signatories		Log of non biogenic co2 emission		
Change in Ownership	1.110***	2.131***	1.098***	1.414***
	(0.212)	(0.297)	(0.155)	(0.316)
Constant	8.202***	9.370***	12.581***	10.898***
	(0.126)	(0.474)	(0.283)	(0.557)
Observations	992	992	992	992
Adjusted R^2	0.026	0.053	0.818	0.193
Panel B: Non PRI signatories				
Change in Ownership	0.400***	0.560***	0.592***	0.507***
	(0.099)	(0.130)	(0.066)	(0.124)
Constant	8.336***	8.661***	8.135***	9.118***
	(0.072)	(0.186)	(0.458)	(0.248)
Observations	5,358	5,358	5,358	5,358
R^2	0.003	0.005	0.829	0.181
Adjusted R^2	0.003	0.002	0.813	0.175
Year FE		Yes	Yes	Yes
Plant FE			Yes	
State FE				Yes

$$\begin{aligned}\ln(Y_{i,t}) = \beta_0 + \beta_1(\text{Change in Ownership}_{i,t}) + \beta_2(\text{PRI}_{i,t}) \\ + \beta_3(\text{Change in Ownership}_{i,t} * \text{PRI}_{i,t}) + \alpha_i^{\text{state}} + \alpha_i + \alpha_t + \epsilon_{i,t},\end{aligned} \tag{4.2}$$

where PRI is an indicator variable equal to one if the asset i is later acquired by a PRI signatory and zero otherwise. The main parameter of interest is β_3, which captures the differential emission level between PRI signatories and Non-PRI signatories.

Table 4.7 presents the unit-level (augmented) regression result of the log of non-biogenic CO2 emissions on the change in ownership and PRI. The results show that private investors with a preference for sustainability have higher emissions post-acquisition compared to those private investors without explicitly stated sustainability preferences. In the appendix to this chapter, I theoretically motivate why sustainable private investors may have or purchase higher asset-level emissions compared to non-sustainable private investors, simply by observing the differential transaction price (DTP).

Table 4.7: Unit-Level Regression on Change in Ownership and PRI Signatories

This table examines whether there is a difference in the post-divestment unit-level emissions of assets acquired by private investors with a preference for sustainability compared to those acquired by private investors without such a preference. If an investor is a PRI signatory, it signals a public commitment to responsible and sustainable investments. The unit of observation is the unit reporting year level and the sample period spans from 2010 to 2022. The independent variable is the natural logarithm of unit-level non-biogenic CO_2 emissions. "Change in Ownership" is an indicator variable equal to one if the unit is owned (or controlled) by private players, and zero otherwise. "PRI" is an indicator variable equal to one if the asset is acquired by a PRI signatory, and zero otherwise. Regressions include fixed effects for the plant, reporting year and location, as indicated. Standard errors are reported in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:			
	Log of non biogenic co2 emission			
	(1)	(2)	(3)	(4)
Change in Ownership	0.572***	0.735***	0.487***	0.656***
	(0.091)	(0.111)	(0.063)	(0.110)
PRI	0.067	0.137	−0.559***	0.128
	(0.150)	(0.152)	(0.111)	(0.168)
Change in Ownership * PRI	0.538**	0.480*	0.222*	0.283
	(0.247)	(0.252)	(0.121)	(0.240)
Constant	8.135***	8.755***	8.188***	9.215***
	(0.062)	(0.172)	(0.444)	(0.236)
Observations	6,827	6,827	6,827	6,827
R^2	0.010	0.016	0.829	0.173
Adjusted R^2	0.009	0.014	0.810	0.167
Year FE		Yes	Yes	Yes
Plant FE			Yes	
State FE				Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

4.5 Conclusion

In this paper, I examine the environmental implications of brown spinning, where public companies spin off or sell their brown (carbon-intensive) assets to private investors, either private equity firms or private companies. Specifically, I examine the relationship between the change in ownership from public to private entities and the emission levels of the divested assets. I document that while divesting public firms are becoming greener, divested assets are not. The change in ownership from public to private leads to increased GHG emissions. At the plant level, a change in ownership from public to private is associated with higher GHG emissions ranging from 2.7% increase in GHG emissions.

I consider whether the environmental or sustainability preference of the private owners matters for the emission level of the underlying asset after the change in ownership. I find that private investors with a stated sustainability preference have higher post-acquisition asset-level emissions compared to private players without an explicitly stated sustainability preference. Assets acquired by private investors with a stated sustainability preference have higher unit-level emissions ranging from 22% to 54% compared to those without such a stated preference.

Chapter 5

Real Impact: Firm's Production Response to Financial Shocks

Abstract

I examine whether financial shocks can limit the brown production activities of a firm. This paper builds on the work of Hartzmark and Shue (2024) who show that brown firms exhibit negative impact elasticity. I decompose the negative impact elasticity and focus on the change in emissions emanating only from the change in output to capture the changes in emissions from firm production activities. I find that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital limits the brown production activities of the firm. The results are mostly significant for the brown firms.

5.1 Introduction

> *"Companies and industries that are not moving towards zero-carbon emissions will be punished by investors and go bankrupt."*
>
> – Mark Carney, Former Governor of the Bank of England

One of the ways investors punish brown companies is by starving them of capital through divestment, i.e. by selling their investment in brown companies and reinvesting in green companies. The divestment strategy is very popular among sustainable investors as it is expected to generate real impact through limiting the brown production activities of the firm and incentivizing the (brown) firms to pursue green production activities. This divestment strategy is expected to create a cost of capital differential between brown firms and green firms, that is, to increase the cost of capital for brown firms and lower the cost of capital for green firms. If a mass number of investors divest their investment from a brown firm, this creates a financial shock to the brown firm. In this paper, I examine the (brown) firm's production response to such financial shocks. I examine whether these financial shocks induced by investors can limit the brown production activities of the brown firm.

This paper builds on the work of Hartzmark and Shue (2024) who show that brown firms exhibit negative impact elasticity. Hartzmark and Shue (2024) develop an impact elasticity measure expressed as the change in environmental impact due to the change in cost of capital. The change in environmental impact is defined as the change in emissions intensity. I decompose the change in emissions intensity into different activities that can affect it such as change in output, change in methodology, divestment, merger and acquisition, change in boundary, change in renewable energy consumption, among others. I focus on the change in emissions emanating only from the change in output to capture the changes in emissions from firm production activities. I measure financial shocks, similar to Hartzmark and Shue (2024), through changes in the annual return of the firm. A positive (negative) annual return or positive (negative) financial shock indicates a lower (higher) cost of capital.

First, I replicate the main results of Hartzmark and Shue (2024) showing that brown firms exhibit a negative impact elasticity, while green firms exhibit a near-zero impact elasticity. I use the definition of brown and green firms as defined by Hartzmark and Shue (2024) for my analysis. I divide the firms into quintiles based on the previous year emissions value. The firms in the 1st (top) quintile represent the brown firms, while the firm in the 5th (bottom) quintile represents the green firms. I find that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital limits the brown production activities of the firm.

Another important work relevant to this paper is Berg et al. (2024)'s paper. They show that large emitters reduce their emissions mainly through divestment. In their paper, large emitters are defined as firms that are targeted by Climate 100+ (CA100+), a global climate initiative that puts pressure on these targeted firms to reduce their carbon emissions. These targeted firms are among the largest emitters in the world that emit approximately 80% industrial GHG emissions and are more exposed to investor pressure. I use the same criteria to identify large emitters and attempt to reconcile the reason why large emitters might exhibit negative impact elasticity but also have reduced their emissions over time through divestment of brown assets.

I obtain the most comprehensive global data set on the carbon emissions of publicly listed firms from the Carbon Disclosure Project (CDP) dataset covering the period from 2011 to 2023. The CDP data set provides a breakdown of the year-on-year changes in combined global emissions (scope 1 and scope 2) of firms. The breakdown is into the following categories[1]: divestment, change in output, change in methodology, emission reduction activities, acquisitions, other operational changes,

[1] even though some headings have changed over the years

change in renewable energy consumption, change in boundary [2] of firms. The year-on-year emission breakdown allows me to isolate the emissions reduction or increase emanating from the change in output or production. This is a similar data used by Berg et al. (2024) to identify the activity driving the reduction in the emissions of the large emitter.

I replicate the main result of Berg et al. (2024) to show that large emitters have significantly reduced their absolute global emissions (scope 1 and scope 2) after the Paris 2015 agreement but no change in emissions intensity between the pre- and post-Paris agreement period. This exercise both serves as a quality check on my cleaned CDP dataset but, more importantly, highlights that observing the change in emissions intensity could be due to many activities other than the change in production. I find that these large emitters also exhibit negative impact elasticity, similar to the brown firms defined based on Hartzmark and Shue (2024). These large emitters are a subset of the brown firms.

I examine the production response of these large emitters to financial shock, to see whether they exhibit a similar pattern compared to the broader brown firms. I find that the impact of financial shock on brown production activities for large emitters is weaker compared to the broader brown firms, where I observe a strong (or significant) impact of financial shock on brown production activities. One possible explanation is that these large emitters are more exposed to environment pressure, and the first response to positive (negative) financial shock is not to increase (decrease) production. This could also be a story that large emitters are less financial constraints compared to broader brown firms. In my future work, I plan to explore why the impact of the financial shock on brown production activities is less significant for large emitters and also to consider other possible responses other than just production. However, the main takeaway is that positive financial shocks increase

[2] I also refer you to Table 4.2 to see an example of the breakdown of year-on-year changes in combined global emissions (scope 1 and scope 2)

brown production activities of the firm.

This paper contributes mainly to the literature on the impact of sustainable investor action on firm activities. Empirical evidence shows that the actions of investors can generate societal impact through various channels such as environmental activism (Naaraayanan et al., 2020), shareholder coordination (Crane et al., 2019), institutional commitment (Dyck et al., 2019), divestment (Berk and van Binsbergen, 2025) and two-tier engagement (Dimson et al., 2021). Berk and van Binsbergen (2025) argue that ESG divestiture strategies have little impact on the real investment decision of the affected firms. Dimson et al. (2021), Krueger et al. (2020), and Naaraayanan et al. (2020) provide support for engagement as a way to generate societal impact. My paper fits into this strand of literature by showing that financial shock induced by sustainable investors can create impact on the production activities of the brown firms.

The rest of the paper proceeds as follows. In Section 5.1, I provide a detailed description of the data. Section 5.2 presents my main results and Section 5.3 concludes.

5.2 Data source and data descriptive

Emissions data. I obtain the global emissions data for publicly listed firms from the Carbon Disclosure Project (CDP) dataset for the period from 2011 to 2023. CDP is the most comprehensive data source on emissions data for publicly listed firms. I obtain the global emissions scope 1 and scope 2 data and the breakdown of the year-on-year changes in the combined firms' global emissions (scope 1 and scope 2) data. The breakdown is into the following categories[3]: divestment, change in output, change in methodology, emission reduction activities, acquisitions, other operational changes, change in renewable energy consumption, change in boundary

[3]even though some headings have changed over the years

[4]. I also obtain data from S&P Global Trucost on scope 1 and scope 2 emissions covering the period from 2011 to 2023 to perform a robustness check because the result of Hartzmark and Shue (2024) is based on emissions data from S&P Global Trucost. However, there are many publicly listed firms that I observe in the CDP emissions data set but not in S&P Global Trucost dataset.

Annual return and Revenue. I obtain the yearly annual return from the global accounting factor of Jensen et al. (2023) in Wharton Research Data Services (WRDS) covering the period from 2010 to 2023. I also obtain the annual revenue from the global accounting factor of Jensen et al. (2023) to be able to calculate the global emissions intensity of each firm.

Descriptive statistics. Table 5.1 presents the descriptive statistics of the variables of interest covering the period 2011 to 2023. Emissions intensity is defined as the combined scope 1 and scope 2 divided by revenue. Large emitters, brown firms, and green firms have an average emissions intensity of 0.589, 0.687, and 0.020 respectively. Brown firms have higher emissions intensity compared to large emitters. There is a large significant difference between emissions intensity of brown firms and green firms. The "Increased output" is an indicator variable equal to 1 if a firm reports an increase in emissions from the output and zero otherwise, while the "Decreased output" is an indicator variable equal to 1 if a firm reports a decrease in the emission from the output and zero otherwise. The "Increased output" represents about 20% of the emissions breakdown, while the "Decreased output" represents about 15% of the emissions breakdown.

[4] I also refer you to Table 4.2 to see an example of the breakdown of year-on-year changes in combined global emissions (scope 1 and scope 2) of firms

Table 5.1: Descriptive Statistics

The table reports descriptive statistics of the variables of interest covering the period from 2011 to 2023. Panel A presents the summary statistics for the overall sample. Emissions intensity is defined as the combined scope 1 and scope 2 divided by revenue. Panel B presents the emission intensity for each type of firm. Panel C presents the fraction of the sample where the emission increase or decrease is due to change in output.

Statistic	N	Mean	SD	p10	p50	p90
A. Overall						
Emissions intensity	23,354	0.206	0.381	0.003	0.036	0.718
Change in emissions intensity	19,831	-0.004	0.103	-0.032	-0.0004	0.019
Annual return	23,312	0.012	0.031	-0.022	0.011	0.044
B. Firm type						
Emissions Intensity						
Large emitters	1,294	0.589	0.561	0.026	0.380	1.461
Brown firms	4,225	0.687	0.535	0.049	0.542	1.461
Green firms	3,987	0.020	0.084	0.001	0.006	0.034
C. Emissions breakdown (0/1)						
Output						
Increased output	24,829	0.284				
Decreased output	24,829	0.148				

5.3 Results

I begin by replicating the result of Hartzmark and Shue (2024) to set the foundation for the main question, which is to examine whether the financial shocks induced by investors can limit the brown production activities of firms. Brown firms are defined exactly as in Hartzmark and Shue (2024), that is, firms are divided into quintiles based on the emissions value of the previous year. The firms in the 1st (top) quintile represent the brown firms, while the firm in the 5th (bottom) quintile represents the green firms. The large emitters are included in the analysis. The large emitters are those firms that are targeted by Climate 100+ (CA100+), a global climate initiative that puts pressure on these targeted firms to reduce their carbon emissions. These targeted firms are among the largest emitters in the world that emit approximately 80% industrial GHG emissions.

Table 5.2 shows that both large emitters and brown firms have a significant negative impact elasticity indicating that negative financial shocks lead to an increase in emissions, while green firms exhibit a close to zero impact elasticity. When the financial performance of both large emitters and brown firms improves, they increase their emissions intensity. This is similar to the result of Hartzmark and Shue (2024)) and a similar coefficient magnitude can be obtained by multiplying the coefficients in table 5.2 by 100.

I perform a replication exercise to generate the main result of Berg et al. (2024) for two reasons: (1) for data quality check - to compare my year-on-year changes in the combined firms' global emissions (scope 1 and scope 2) results with those reported in Berg et al. (2024)'s paper. (2) to show that the observed changes in emissions intensity might be due to many activities other than a change in production.

Table 5.3 reports the result on the emission activity of both large emitters and brown firms around the 2015 Paris agreement. Column 1 of Table 5.3 confirms the result of Berg et al. (2024) that large emitters reduce their emissions significantly

Table 5.2: Change in emissions intensity and Financial Shocks

The dependent variable is the change in emissions intensity from year t to t+1. The emissions intensity is measured as the total of global scope 1 and scope 2 divided by revenue. The main independent variable is the interaction between the firm-level return in the period year and an indicator whether the firm is a large emitter, brown or green. The sample covers the period 2011 to 2013. All columns include year-fixed effects and type-fixed effects for whether the firm is large emitter, brown, or green. Standard errors are reported in parentheses and clustered at the firm level. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:		
	Change in Emission Intensity		
	(1)	(2)	(3)
Large Emitter x Annual Return	-0.461***		
	(0.123)		
Brown firm x Annual return		-0.674***	
		(0.060)	
Green firm x Annual return			-0.074
			(0.057)
Type FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	19,808	19808	19808
Adj. R^2	0.022	0.027	0.021

post 2015 Paris Agreement. However, brown firms significantly increase their emissions after the 2015 Paris Agreement, as shown in column 2 of Table 5.3. When the dependent variable is replaced with emission intensity. The significance of large emitters vanished but still significant for the brown firm. One significant difference between large emitters and brown firms is that large emitters are more exposed to environmental/investors' pressure compared to brown firms. This could potentially explain the difference observed in the result.

Table 5.3: Emissions of large emitters and brown firms around the 2015 Paris Agreement

This table report the emission activity of both large emitters and brown firms around the 2015 Paris Agreement. The main independent is the interaction between Post 2015 which equals 1 for firm reporting period after 2015 and indicator whether the firm is large emitter or brown firm. Columns 1 and 2 report the result for combined scope 1 and 2 emissions while columns 3 and 4 report the emissions intensity. All columns include fixed effects for the firm and the year. Standard errors are reported in parentheses and clustered at the firm level. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:			
	Log of scope 1 + 2		Emissions Intensity	
	(1)	(2)	(3)	(4)
Large Emitter x Post 2015	-0.130***		0.006	
	(0.033)		(0.006)	
Brown firm x Post 2015		0.088***		0.014***
		(0.018)		(0.003)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	23,354	20,956	23,354	20,956
Adj. R^2	0.96	0.96	0.93	0.94

I examine whether financial shocks can limit the brown production activities of the firm, that is, do firm's emissions from production increase or decrease following negative or positive financial shocks. I examine the emissions response from production following a financial shock of three types of firms: large emitters, brown firms, and green firms. Brown and green companies are defined exactly as in Hartzmark and Shue (2024), that is, the firms are divided into quintiles based on the value of the emissions of the previous year. The firms in the 1st (top) quintile represent the brown firms, while the firms in the 5th (bottom) quintile represent the green firms. The largest emitters are those firms that are targeted by Climate 100+ (CA100+), a global climate initiative that puts pressure on these targeted firms to reduce their carbon emissions.

Firms report to CDP whether their combined scope 1 and 2 emissions have increased or decreased relative to the previous reporting year, and they also state the reasons why their emissions have increased or decreased relative to the previous reporting year. The reasons are into the following categories: change in output, change in methodology, divestment, merger and acquisition, change in boundary, change in renewable energy consumption, and others. More interesting, firms have to state the percentages changes in each category and in which direction they increased or decreased. The change in output category is the focus of my analysis. I define a *decrease in emissions from production* indicator variable to be equal to 1 if a firm reports a decrease in emissions from output and zero otherwise, and I also define a *decrease in emissions from production* indicator variable to be equal to 1 if a firm reports an increase in emissions from output and zero otherwise.

Panel A of Table 5.4 reports the impact of financial shocks on the firm's decrease in emissions from production activities. I find that large emitters, brown and green firms, are more likely to decrease (increase) their emissions after a negative (positive) financial shock. However, brown firms are significantly more likely to reduce their emissions following a negative financial shock. The results are weaker for large emitters and green firms. The large emitters are a subset of the brown firms. I excluded the large emitters from the sample and performed the regression again, just for the brown and green firm. Panel B of table 5.4 shows that the result is the same for the brown and green firms. The reason for panel B analysis will be much clearer in the next paragraph.

Panel A of Table 5.5 reports the impact of financial shocks on the firm's increase in emissions from production activities. Brown firms are more likely to decrease (increase) their emissions following a negative (positive) financial shock. However, the results are not significant for large emitters and green firms. Large emitters are a subset of the brown firms and the results are not significant. Therefore, I exclude them from the sample and perform the regression again. Panel B of table 5.4 reports these results. The results for brown firms are more significant. The main takeaway is that brown firms are more likely to decrease (increase) their emissions following a negative (positive) financial shock.

Table 5.4: Emissions decrease from production and financial shocks

The dependent variable is the *decrease in emissions from production* indicator variable to be equal to 1 if a firm reports a decrease in emissions from the output and zero otherwise. The main independent variable is the interaction between the firm-level return in the period year and an indicator whether the firm is a large emitter, brown or green. The sample covers the period 2011 to 2013. All columns include year-fixed effects and type-fixed effects for whether the firm is large emitter, brown, or green. Panel B excludes the large emitters from the sample. Standard errors are reported in parentheses and clustered at the firm level. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:		
	Decrease in Emission (from output)		
	(1)	(2)	(3)
Panel A			
Large Emitter x Annual Return	-0.630*		
	(0.371)		
Brown firm x Annual return		-0.893***	
		(0.178)	
Green firm x Annual return			-0.340*
			(0.180)
Type FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	20,623	20,623	20,623
Adj. R^2	0.053	0.054	0.053
Panel B			
Ex Large Emitter :			
Brown firm x Annual return		-0.859***	
		(0.193)	
Green firm x Annual return			-0.357**
			(0.178)
Type FE		Yes	Yes
Year FE		Yes	Yes
Observations		19,360	19,360
Adj. R^2		0.050	0.049

Table 5.5: Emissions increase from production and Financial Shocks

The dependent variable is the *increase in emissions from production* indicator variable to be equal to 1 if a firm reports decrease in emissions from output and zero otherwise. The main independent variable is the interaction between the firm-level return in the period year and an indicator whether the firm is a large emitter, brown or green. The sample covers the period 2011 to 2013. All columns include year-fixed effects and type-fixed effects for whether the firm is large emitter, brown, or green. Panel B excludes the large emitters from the sample. Standard errors are reported in parentheses and clustered at the firm level. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:		
	Increase in Emission (from output)		
	(1)	(2)	(3)
Panel A			
Large Emitter x Annual Return	0.747		
	(0.034)		
Brown firm x Annual return		0.572**	
		(0.228)	
Green firm x Annual return			0.249
			(0.230)
Type FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	20,623	20,623	20,623
Adj. R^2	0.034	0.034	0.034
Panel B			
Ex - large Emitter:			
Brown firm x Annual return		0.704***	
		(0.249)	
Green firm x Annual return			0.275
			(0.229)
Type FE		Yes	Yes
Year FE		Yes	Yes
Observations		19,360	19,360
Adj. R^2		0.031	0.030

5.4 Conclusion

In this chapter, I examine whether financial shocks can limit the brown production activities of a firm. It builds on the work of Hartzmark and Shue (2024) where they show that brown firms exhibit negative impact elasticity. I decompose the negative impact elasticity and focus on the change in emission emanating only from the change in output to capture the changes in emissions from firm production activities.

I examine the emissions response from production following financial shocks of three types of firms: large emitters, brown firms, and green firms. Brown and green firms are defined exactly as in Hartzmark and Shue (2024), that is, the firms are divided into quintiles based on the emissions value of the previous year. The firms in the 1st (top) quintile represent the brown firms, while the firm in the 5th (bottom) quintile represents the green firms. The largest emitters are those firms that are targeted by Climate 100+ (CA100+), a global climate initiative that puts pressure on these targeted firms to reduce their carbon emissions. I find that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital can limit the brown production activities of the firm. The results are mostly significant for the brown firms. In future research, I plan to consider other decompositions of the negative impact elasticity and the first-best response of the firm. I also plan to explore why the impact of the financial shock on brown production activities is less significant for large emitters and also to consider other possible responses other than just production.

Chapter 6

Conclusion

Climate change and sustainability will remain the defining issues for our society. This dissertation is an important piece of work, as it contributes to the discussion on sustainable investment and improves our understanding of the behavior of sustainable investors. The dissertation is divided into four parts. The first part reviews the existing literature on the preference of sustainable investors, the performance of sustainable investment, and the real impact of sustainable investment. The findings of the first part are summarized as follows: (1) There is strong empirical evidence in the literature that investors have a preference for ESG and that their actions can generate positive social impact through engagement. (2) There is mixed empirical evidence for the relative performance to ESG investment. (3) The shift to more sustainable policies in firms is motivated by increased market values and lower capital costs of green firms driven by investors' choices.

The remaining parts of the dissertation build on the research gap identified in the first part of the thesis. Specifically, the second part of the dissertation examines the pricing implications of ESG uncertainty. It explores three main areas: (1) the ESG uncertainty emanating from the development of ESG regulations, (2) the firm's ability to manage regulatory development, and (3) the pricing of ESG exposure to aggregate downside risk. It finds that uncertainty related to environmental, social, and governance (ESG) regulatory developments is reflected in asset prices. At the aggregate or at the economy level, the cost of protection against downside risk is higher when the ESG regulatory uncertainty is higher, and even more so when the economic conditions are worse. At the firm level, firms with high ESG scores have a lower cost of protection against downside tail risk compared to firms with low ESG performance. It also finds that firms with high ESG disparity have a higher cost of protection against downside risk. This implies that firms with a low ability to manage ESG regulatory development command a higher cost of protection against downside risk. It finds a negative price of aggregate downside risk for firms with either high or low ESG performance. Firms with high ESG performance command a lower negative price of aggregate downside risk. Both high and low ESG firms have negative exposure to downside risk.

The third part of the dissertation examines the sustainability characteristics of the private buyers to determine whether the post-divestment underlying assets' emissions is different for private investors with a stated sustainability preference compared to those without explicitly stated sustainability preference. It finds that private investors with a stated sustainability preference have higher post-acquisition asset-level emissions compared to private players without an explicitly stated sustainability preference. Assets acquired by private investors with a stated sustainability preference have higher unit-level emissions ranging from 22% to 54% compared to those without such a stated preference.

The last part of the dissertation examines whether financial shocks can limit the brown production activities of a firm. It builds on the work of Harztmark and Shue (2024) where they show that brown firms exhibit negative impact elasticity. It decomposes the negative impact elasticity and focuses on the change in emission emanating only from the change in output to capture the changes in emission from firm production activities. It finds that a negative (positive) financial shock leads to a decrease (increase) in emissions related to output. This implies that a higher cost of capital limits the brown production activities of the firm. The results are mostly significant for the brown firms.

Although this dissertation provides insight into key questions, it also opens avenues for further research. In particular, a critical examination of the channels driving the higher post-acquisition emissions of sustainable private investors compared to their non-sustainable counterparts would be valuable. Additionally, further examination of the other decompositions of the negative impact elasticity such as change in methodology, divestment, merger and acquisition, change in boundary, change in renewable energy consumption; and an analysis of the firm's first-best response to financial shocks present promising directions. Another important area for exploration is understanding why the effect of financial shocks on brown production is less pronounced for large emitters, as well as investigating alternative firm responses beyond production activities.

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Appendix A

Appendix to Chapter 3

Firm downside risk (FDR) is the firm's price of a downside insurance contract. To understand the foundation for the construction of the FDR, please refer to Gao et al. (2018). The computation to extract the FDR is as follows:

$$IV_{it} = \frac{2e^{r\tau}}{\tau}\{\int_{K>S_{it}} \frac{1}{K^2} C_{it}(S_{it}; K, T)dK + \int_{K<S_{it}} \frac{1}{K^2} P_{it}(S_{it}; K, T)dK\} \qquad \text{(A1)}$$

$$\mathrm{V}_{it} = \tfrac{2e^{r\tau}}{\tau}\{\textstyle\int_{K>S_{it}} \tfrac{1-In(K/S_{it})}{K^2} C_{it}(S_{it}; K, T)dK + \textstyle\int_{K<S_{it}} \tfrac{1-In(K/S_{it})}{K^2} P_{it}(S_{it}; K, T)dK\},$$

where r is the constant interest rate, τ is the time to maturity or time to expiration, and $C_{it}(S_{it}; K, T)$ is the price of firm's i call options with strike price T and $maturity K$. $P_{it}(S_{it}; K, T)$ is the price of firm's i put options with strike price T and maturity K. The difference between V_{it} and IV_{it} is $-In(K/S_{it})$ in V_{it} which implies that larger (smaller) weights are assigned to more deeply OTM put(call) options. This allows us to extract extreme price deviation. The difference between the V_{it} and IV_{it} captures investors' expectations about the distribution of large price variation (Gao et al. (2018)).

Next, we obtain only the downside measures of the firm's IV and V which leaves us with only the OTM put options:

$$IV_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{1}{K^2} P_{it}(S_{it}; K, T) dK. \tag{A2}$$

$$V_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{1 - ln(K/S_{it})}{K^2} P_{it}(S_{it}; K, T) dK. \tag{A3}$$

$$FDR_{it} = V_{it}^{-} - IV_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{ln(K/S_{it})}{K^2} P_{it}(S_{it}; K, T) dK. \tag{A4}$$

FDR_{it} is the difference between V_{it}^{-} and IV_{it}^{-} which captures investors' expectation of extreme downside price movement of firm's i. It can also be interpreted as the risk-neutral probability of firm's i extreme downside movement. FDR_{it} can also be seen as the value of a simple portfolio of put options on firm i and form at date t to extract extreme downside movement.

Table A.1: Variable definitions for risk measures, sustainability measures and controls.

Variable	Definitions
Panel A: Risk Measures	
smfiv	Simple model-free implied volatility from Martin (2011, 2017).
mfiv_bkm	Model-free implied volatility from Bakshi et al. (2003). This is equation A in our paper.
mfiv_bjn	Model-free implied volatility from Britten-Jones and Neuberger (2000). This is equation A1 in our paper.
smfivd	Simple model-free implied volatility for OTM puts (downside) from Martin (2011, 2017)
mfivd_bkm	Model-free implied volatility for OTM puts (downside) from Bakshi et al. (2003). This is equation A3 in our paper.
mfivd_bjn	Model-free implied volatility for OTM puts (downside) from Britten-Jones and Neuberger (2000). This is equation A2 in our paper.
mfis	Model-free implied skewness based on Bakshi et al. (2003).
mfik	Model-free implied kurtosis based on Bakshi et al. (2003).
cvix_sigma2	Corridor volatility index from Andersen and Bondarenko (2007), Andersen et al. (2015) measured on the relative deviation of 2 sigmas from the At-the-Money (ATM) moneyness of 1.
rix	Rare disaster concern index (rix) from Gao et al. (2018). This is the difference between mfivd_bjn and mfivd_bkm. This is equation A4 in our paper.
Panel B: Sustainability Measures	

Continued on next page

Table A.1 – continued from previous page

Variable	Definitions
Environmental, Social and Governance (ESG) score	The term ESG used in this study is the ESG combined (ESGC) score which takes into consideration the ESG controversies. ESGC overlays the ESG score with ESG controversies to provide a comprehensive evaluation of the company's sustainability impact and conduct over time. ESGC scores provide a rounded and comprehensive scoring of a company's ESG performance, based on the reported information pertaining to the ESG pillars, with the ESG controversies overlay captured from global media sources.
Environmental (E) score	Resource use score, Emissions reduction score, and Innovation score are aggregated to form the Environmental Score.
Social (S) score	Workforce score, Human rights score, Community score, and Product responsibility score are aggregated to form the Social score.
Governance (G) score	Management score, Shareholders score, and CSR strategy score are aggregated to form the Governance score.
Resource use score	The resource use score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management.
Emissions reduction score	The emission reduction score measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes.
Innovation score	The innovation score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed products.
Workforce score	The workforce score measures a company's effectiveness in terms of providing job satisfaction, a healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce.
Human rights score	The human rights score measures a company's effectiveness in terms of respecting fundamental human rights conventions.

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Table A.1 – continued from previous page

Variable	Definitions
Community score	The community score measures the company's commitment to being a good citizen, protecting public health and respecting business ethics.
Product responsibility score	The product responsibility score reflects a company's capacity to produce quality goods and services, integrating the customer's health and safety, integrity and data privacy.
Management score	The management score measures a company's commitment and effectiveness towards following best practice corporate governance principles.
Shareholders score	The shareholders score measures a company's effectiveness towards equal treatment of shareholders and the use of anti-takeover devices.
CSR strategy score	The CSR strategy score reflects a company's practices to communicate that it integrates economic (financial), social and environmental dimensions into its day-to-day decision-making processes.
Panel C: Controls	
Return	Monthly return for the individual US firms
Volatility	12-month rolling window of the firm standard deviation based on the firm's return.
Beta	12-month rolling window of the firm beta based on the regression of the firm's return on S&P 500 return (market return).
Logassets	Natural logarithms of total assets
Divnetinc	Gross dividends-common stocks divided by net income after taxes
Ebitassets	Normalized Earnings before interest and taxes (EBIT) divided by total assets
Capexassets	Capital expenditure (Capex) divided by total assets
Booktomar	Book value(computed as book value per share multiply by total common shares outstanding) divided by market capitalization

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Table A.1 – continued from previous page

Variable	Definitions
Debtassets	Total debt divided by total assets

Table A.2: ESG Performance and Disparity Across Sectors.

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVSDn) on the sustainability performance and the ESG disparity based on Equation (3.2). This table reports only the coefficients on sustainability performance (β) and on ESG disparity (λ) for each sector. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. We classify firms into sectors based on the Global Industry Classification Standard (GICS). The GICS classifies firms into 12 sectors: Energy, Material, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate. We label firms that we could not match to any sector as 'No sector identified'. Standard errors are reported in parentheses. Conventional significance levels apply. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

	ESG		Environmental		Social		Governance	
Coefficients	β_1	λ_1	β_1	λ_1	β_1	λ_1	β_1	λ_1
Industry:								
Energy	-0.001^{***}	0.003^{***}	-0.002^{***}	0.002^{***}	-0.001^{***}	0.003^{***}	-0.00001	0.003^{***}
	(0.0003)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Material	0.001^{***}	0.001	0.001^{***}	0.001^{**}	0.001^{***}	0.001^{*}	0.0003^{*}	0.0003
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Industrials	-0.001^{***}	0.001^{**}	-0.0004^{**}	0.001^{*}	-0.001^{***}	0.001^{**}	0.001^{***}	0.001^{**}
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Consumer Discretionary	-0.001^{***}	0.002^{***}	-0.001^{***}	0.001^{***}	-0.001^{***}	0.002^{***}	-0.0004^{***}	0.002^{***}
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Consumer Staples	-0.0004^{*}	0.002^{***}	-0.0001	0.002^{***}	-0.001^{***}	0.002^{***}	0.0003	0.002^{***}
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Health Care	-0.002^{***}	0.001^{***}	-0.001^{***}	0.0003	-0.002^{***}	0.001^{**}	-0.0001	0.001^{***}
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Financials	-0.0002	0.004^{***}	-0.001^{**}	0.004^{***}	0.001^{**}	0.005^{***}	-0.00002	0.004^{***}
	(0.001)	(0.001)	(0.0003)	(0.001)	(0.0005)	(0.001)	(0.0003)	(0.001)
Information Technology	-0.001^{***}	0.003^{***}	-0.001^{***}	0.002^{***}	-0.001^{***}	0.003^{***}	0.0002	0.003^{***}
	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Communication Services	0.004^{***}	-0.001^{**}	-0.001^{***}	-0.001	-0.002^{***}	-0.0003	0.002^{***}	-0.001^{**}
	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.0003)	(0.001)
Utilities	0.0005	0.0001	0.002^{***}	0.001	0.001^{**}	0.0002	0.001^{**}	-0.0003
	(0.0004)	(0.001)	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.0003)	(0.001)
Real Estate	-0.001^{***}	-0.001^{**}	-0.001^{***}	-0.002^{***}	0.00001	-0.001^{**}	-0.0004^{*}	-0.001^{*}
	(0.0003)	(0.0004)	(0.0002)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0005)
No sector identified	0.006^{***}	0.001	0.001^{**}	0.003^{**}	0.005^{***}	0.002^{*}	0.002^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

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Table A.3: Sub-Sample Regressions

This table presents the results of the sub-sample regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (3.2). Only the coefficients on sustainability performance and on ESG disparity are reported. The control variables are firms' CAPM beta and volatility, estimated over a 12-month period, return, *logassets* (measuring firm size and is computed as the natural logarithm of firm's assets), *divnetinc* (the ratio of the firm's gross dividend to net income), *ebitassets* (the ratio of the firm's earnings before interest and tax (EBIT) to assets), *capexassets* (the ratio of the firm's capital expenditure (capex) to assets), *debtassets* (the ratio of total debt to total assets), and *booktomar* (the ratio of the firm's equity book value to the market value). All specifications include year fixed effects. Panel A runs a regression of the sample from January 2010 to December 2021. Panel B reports results for a sample that covers the period from 2002 to 2022 and excludes firms with zero environmental scores. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
Panel A: Sample from 2010 to 2022				
ESG	−0.001***			
	(0.0001)			
E		−0.001***		
		(0.0001)		
S			−0.001***	
			(0.0001)	
G				0.0002***
				(0.0001)
ESG disparity	0.002***	0.001***	0.002***	0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed Effects	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Observations	82,528	82,528	82,528	82,528
R^2	0.224	0.224	0.225	0.223
Adjusted R^2	0.224	0.224	0.225	0.223
Residual Std. Error (df = 82505)	0.401	0.401	0.401	0.401
F Statistic (df = 22; 82505)	1,081.669***	1,082.779***	1,091.286***	1,075.681***
Panel B: Excluding firms with zero E score				
ESG	−0.001***			
	(0.0001)			
E		−0.001***		
		(0.0001)		
S			−0.001***	
			(0.0001)	
G				0.00004
				(0.0001)
ESG disparity	0.001***	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed Effects	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Observations	80,395	80,395	80,395	80,395
R^2	0.275	0.275	0.275	0.274
Adjusted R^2	0.275	0.275	0.275	0.274
Residual Std. Error (df = 80366)	0.364	0.364	0.364	0.365
F Statistic (df = 28; 80366)	1,091.023***	1,089.241***	1,091.353***	1,082.686***

Table A.4: MSCI ESG Scores

This table presents the results of the regressions of the monthly cost of protection against downside risk (IVS) on the MSCI sustainability ESG, E, S, and G scores and ESG disparity based on Equation (3.2). This table reports only the coefficients on sustainability performance and on ESG disparity. All specifications include the control variables in Table 3.3. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
ESG	−0.021***			
	(0.002)			
E		−0.018***		
		(0.001)		
S			−0.004***	
			(0.001)	
G				0.005***
				(0.001)
ESG disparity	0.006***	0.008***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Observations	79,167	79,167	79,167	79,167
R^2	0.185	0.187	0.184	0.184
Adjusted R^2	0.184	0.186	0.183	0.184
Residual Std. Error (df = 79146)	0.457	0.457	0.458	0.457
F Statistic (df = 20; 79146)	896.532***	907.718***	889.728***	891.151***

Table A.5: Other Option-Implied Risk Measures

This table displays the results of the regressions of the option-implied risk measures outlined in Panel A of Table A.1 on the sustainability performance based on the model in Equation (3.1). Only the coefficients on sustainability performance are reported for brevity. All specifications include the control variables in Table 3.3, as well as year fixed effects. Panel A reports results for model-free implied volatility measures on the downside. Panel B has the results for other option-implied measures. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

Dimension	ESG	Environmental	Social	Governance
Panel A: Model-free implied volatility measures on the downside				
smfivd	−0.0002***	−0.0002***	−0.0001***	−0.00001
	(0.00002)	(0.00001)	(0.00001)	(0.00001)
mfivd_bkm	−0.0004***	−0.0003***	−0.0001***	0.00003
	(0.00003)	(0.00002)	(0.00003)	(0.00003)
mfivd_bjn	−0.0003***	−0.0002***	−0.0001***	0.00001
	(0.00003)	(0.00002)	(0.00002)	(0.00002)
Panel B: Other option-implied measures				
smfiv	−0.001***	−0.0003***	−0.0001	0.0001**
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
mfiv_bkm	−0.001***	−0.0004***	−0.0001***	0.00004
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
mfiv_bjn	−0.001***	−0.0004***	−0.0001***	0.00004
	(0.00004)	(0.00003)	(0.00004)	(0.00003)
mfis	0.00004	0.0003***	0.001***	−0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
mfik	−0.001***	−0.003***	−0.005***	0.002***
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
cvix_sigma2	−0.001***	−0.0004***	−0.0001***	0.00004
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
rix	−0.0001***	−0.0001***	−0.00001*	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)

Table A.6: Credit Default Swap (CDS) Spreads

The table reports the results of the regression of monthly credit default swap spreads on firms' ESG rating and ESG disparity based on the model in Equation (3.2). Only the coefficients on sustainability performance and ESG disparity are reported for brevity. All specifications include the control variables in Table 3.3, as well as year fixed effects. Panel A reports results for the overall ESG score. Panel B reports estimates for the Environmental, Social and Governance pillar scores. Panel C reports results for the category scores. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable : Credit Default Swap	
Coefficients	ESG rating - β_1	ESG disparity - λ_1
Panel A: Overall ESG Score		
ESG	-0.276^{***}	0.179^{**}
	(0.055)	(0.088)
Panel B: Pillar Scores		
Environmental	-0.145^{***}	0.136
	(0.041)	(0.091)
Social	-0.032	0.217^{**}
	(0.047)	(0.088)
Governance	-0.038	0.230^{***}
	(0.042)	(0.088)
Panel C: Category Scores		
Environmental:		
Resource use	-0.001	0.222^{**}
	(0.032)	(0.090)
Emissions reduction	-0.103^{***}	0.158^{*}
	(0.033)	(0.090)
Innovation	-0.047	0.206^{**}
	(0.029)	(0.088)
Social:		
Workforce	-0.011	0.220^{**}
	(0.038)	(0.088)
Human rights	0.251^{***}	0.305^{***}
	(0.029)	(0.088)
Community	-0.087^{*}	0.216^{**}
	(0.045)	(0.087)
Product responsibility	-0.143^{***}	0.207^{**}
	(0.030)	(0.087)
Governance:		
Management	-0.035	0.235^{***}
	(0.033)	(0.088)
Shareholder	0.188^{***}	0.190^{**}
	(0.032)	(0.087)
CSR strategy	-0.171^{***}	0.141
	(0.029)	(0.088)

Table A.7: Alternative Regression Specifications

This table presents the results of the different regression models of the monthly cost of protection against downside risk (IVS) on firm's ESG rating and ESG disparity based on the model in Equation (3.2). Only the coefficients on sustainability performance and ESG disparity are reported for brevity. All specifications include the control variables in Table 3.3. Column(1) provides regression results that incorporate year fixed effects but no clustered standard errors. Column(2) provides regression results that incorporate year-sector fixed effect but no clustered standard errors. Column(3) provides regression results that incorporate year-sector fixed effect and year-clustered standard errors. Column(4) provides regression results that incorporate year-sector fixed effect and year-sector clustered standard errors. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:			
	IVS			
	(1)	(2)	(3)	(4)
Panel A : Thomson ESG Data				
ESG rating	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ESG disparity	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant and controls	Yes	Yes	Yes	Yes
Fixed effect	Year	Year + Sector	Year + Sector	Year + Sector
Clustered SD error	No	No	Year	Year + Sector

Table A.8: Average Treatment Effect of ESG membership on Different Measures of Risk

The table presents the result of the DiD estimates of the effect of the inclusion of a S&P 500 company in the S&P 500 ESG Index on the cost of protection against downside risk, proxied by the IVS, as well as alternative measures of risk: the simple model-free implied volatility (*smfiv*) and its version focusing on the downside (*smfivd*) of Martin (2011, 2017), the model-free implied volatility (*mfiv bkm*) of Bakshi et al. (2003), and the rare disaster concern index (*rix*) of Gao et al. (2018). *Treated* is a dummy variable that is equal to 1 if a firm is included in the S&P 500 ESG Index. *Post* is a dummy variable taking the value of 1 for the period after the launch of the S&P 500 ESG Index which in April 2019. Controls include firm's market beta, volatility, return, log assets, dividends standardized by net income, EBIT, CAPEX, and debt, all standardized by total assets, as well as its book-to-market ratio. The main variable of interest is the interaction term of *Treated* * *Post* which indicates the average treatment effect of ESG membership on the cost of protection against downside risk. *p<0.1; **p<0.05; ***p<0.01.

	Dependent variable:				
	IVS	smfiv	smfivd	mfiv_bkm	rix
	(1)	(2)	(3)	(4)	(5)
Treated	-0.064^{***}	-0.020^{***}	-0.011^{***}	-0.024^{***}	-0.002^{***}
	(0.003)	(0.002)	(0.001)	(0.002)	(0.0003)
Post	0.103^{***}	-0.034^{***}	-0.012^{***}	-0.036^{***}	-0.006^{***}
	(0.006)	(0.003)	(0.001)	(0.004)	(0.001)
Treated * Post	-0.145^{***}	-0.113^{***}	-0.036^{***}	-0.114^{***}	-0.018^{***}
	(0.006)	(0.004)	(0.001)	(0.004)	(0.001)
Fixed Year Effect	Yes	Yes	Yes	Yes	Yes
Controls and constant	Yes	Yes	Yes	Yes	Yes
Observations	102,799	102,799	102,799	102,799	102,799
R^2	0.269	0.353	0.400	0.358	0.230
Adjusted R^2	0.268	0.352	0.399	0.358	0.230
Residual Std. Error (df = 102769)	0.366	0.221	0.077	0.225	0.038
F Statistic (df = 29; 102769)	$1,301.243^{***}$	$1,930.319^{***}$	$2,358.373^{***}$	$1,979.511^{***}$	$1,057.269^{***}$

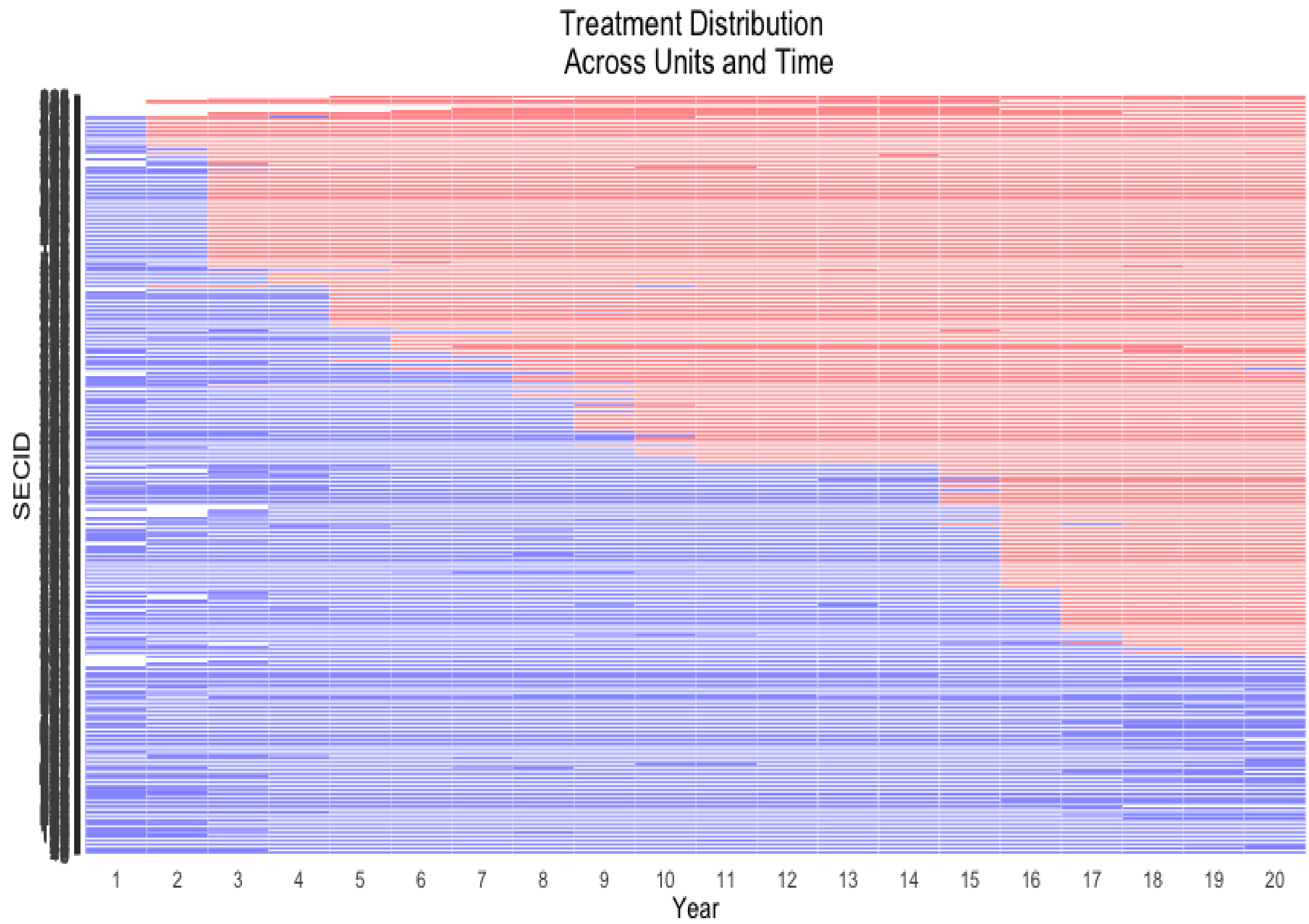
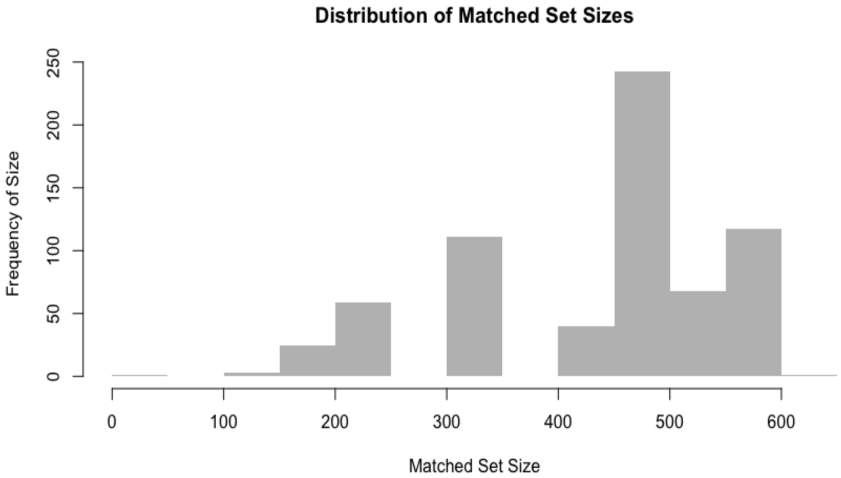
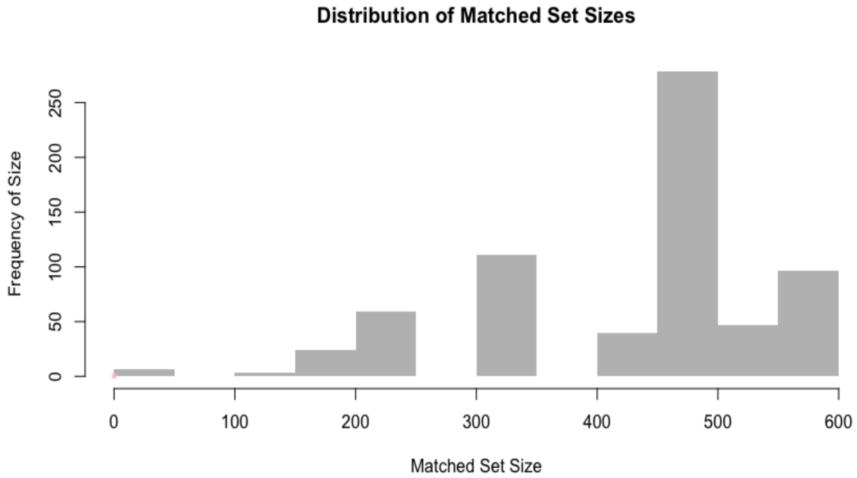


Figure A1: Treatment Variation Plot for the Distribution of ESG Treatment Across Firms and Time.

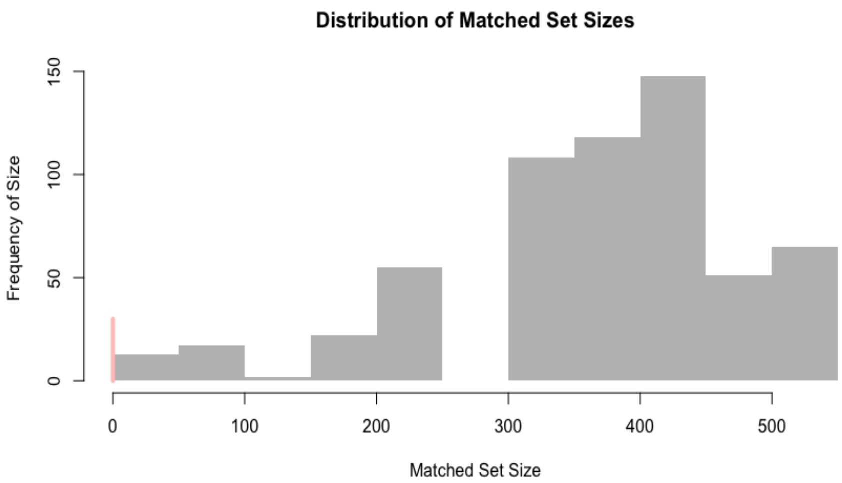
Each bar corresponds to a firm (identified by its security ID, SECID, on the vertical axis). The red (blue) bars represent the ESG treatment (control) firm-year observations. Year 1 corresponds to 2001 and year 20 corresponds to 2020.



(a) Up to 6 identical treatment periods



(b) Up to 12 identical treatment periods



(c) Up to 24 identical treatment periods

Figure A2: Frequency Distribution of the Number of Matched Control Firms.

This figure plots the distribution of matched set sizes, i.e. the number of control matched firms that share the same treatment history as the treated firm prior to the treatment period. Panels (a) through (c) correspond to treatment periods of 6, 12 and 24 months. The thinner red vertical bars at zero represent the number of treated observations that have no matched control units.

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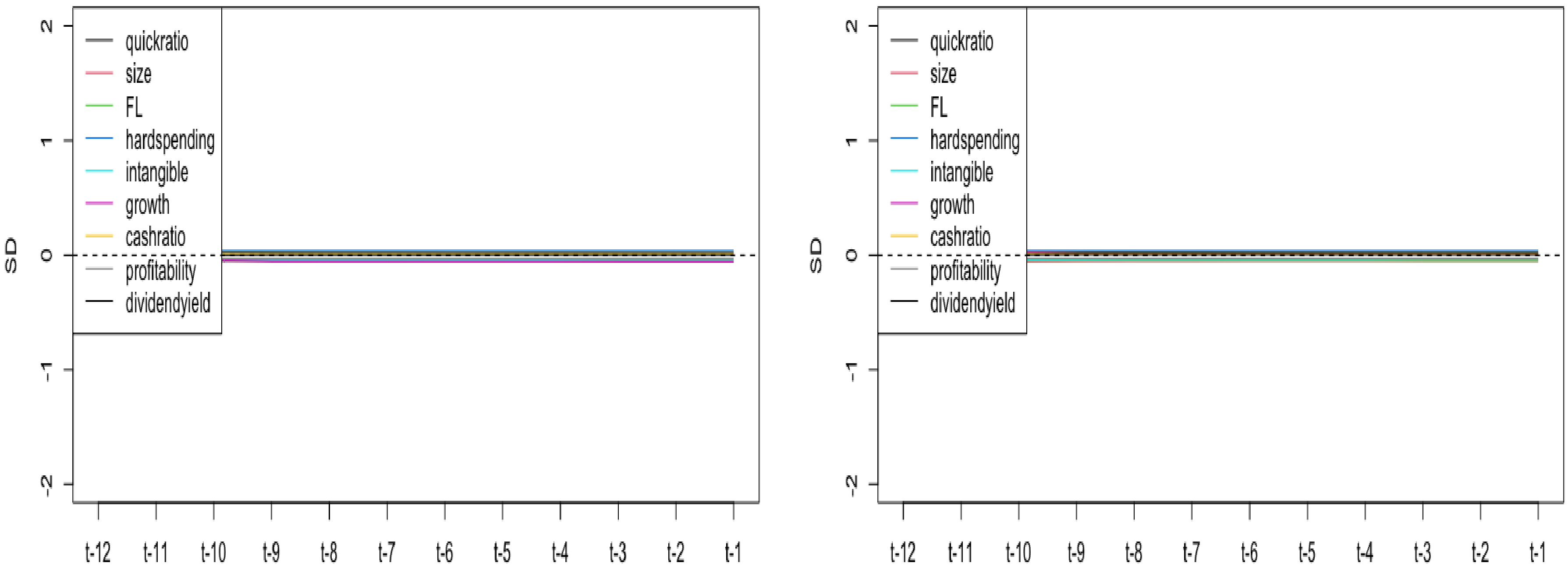

(a) CBPS Weighting

(b) PS Weighting

Figure A3: Covariates Balance

The figure plots the standardized mean difference between treated and matched firms' covariates over the 12-month pre-treatment period for two different weighting methods. The covariates we consider are firms' quick ratio, size, financial leverage, hardspending, intangibles, growth, cash ratio, profitability and dividend yield. Panel (a) plots the covariates balance based on the covariates balance propensity score (CBPS) weighting method. Panel (b) plots the covariates balance based on propensity score (PS) weighting.

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Appendix B

Appendix to Chapter 4

B.1 Theoretical Framework

I build on the theoretical framework of Gupta et al. (2022) to motivate the empirical questions on potential reason(s) why sustainable private investors may have or purchase higher asset-level emission compared to non sustainable private investors simply by observing the differential transaction price (DTP). One potential reason could be that sustainable private investors embark on ambitious projects i.e buy high carbon intensive assets with the aim to transform to low carbon intensive assets as this transformation likely produce the biggest gain from trade. But another reason could be greenwashing.

B.1.1 The model

Consider two types of market: public market and private market. In the public market, investors face environmental pressure ($\lambda > 0$) such as pressure from environmental activists such as Climate Action 100+ [1], pressure from compliance with environmental regulations and disclosure requirements translating into high cost of

[1] Climate Action 100+ is an an investor-led initiative to ensure the world's largest corporate greenhouse gas emitters take necessary action on climate change. https://www.climateaction100.org/about/

compliance. For instance, Duchin et al. (2022) show that firms in the public market (and large emitters) are more exposed to environmental pressure. In the private market, investors face lesser to no environmental pressure, that is, I set λ to 0 in this framework. This implies that investors in the public market faces environmental pressure while those in the private market face no such environmental pressure.

In this model, there are also two types of investors [2]. The first type of investors are financial investors **(FI)**. Financial Investors only care about the financial returns and nothing more. The second type of investors are Socially Responsible Investors **(SRI)** with broad mandate or Consequentialist SRI Investors; they care not only about financial return but also about the social cost of the firm whether they invest in it or not.

Dirty Asset or Plant

There is a dirty asset or plant that generates a profit (π) and also high social cost (C_H). The discounted social surplus for a plant that remains dirty forever is defined as:

$$\sum_{t=0}^{\infty} \beta^t (\pi - c_H) = \frac{\pi - c_H}{1 - \beta} \tag{A1}$$

where β is the discounting factor.

An investor can decide to transform this dirty asset to clean asset. By transforming the dirty asset to clean asset, the investor incur a transformation sunk cost (κ) that generates low social cost (C_L) for the clean asset.

The discounted social surplus of a transformed plant that remains clean forever is now defined as:

[2] The third type of investors as in the framework of Oehmke and Opp (2024) which Socially Responsible Investors **(SRI)** with narrow mandate; they care only about the social cost of the firm they invest in it. This type of investors generates the same result as financial investors in this model.

$$(\sum_{t=0}^{\infty}\beta^t\pi - c_L) - \kappa = \frac{\pi - c_L}{1-\beta} - \kappa \quad \text{(A2)}$$

where κ is the transformation sunk cost and the $C_H = 0$.

Investor per-period utility

Investor per-period utility depends on the type of investors and the market in which they operate or invest in. Investors that operate in the public markets are exposed to environmental pressure whether they are financial investors **(FI)** or SRI Investors **(SRI)**. SRI investors with broad mandate **(SRI)** - whether in the public or private market - suffer disutility from the social cost of the dirty asset irrespective of who owns the dirty asset.

Private Market Table B.1 present the investor per-period utility of the investor that operate in the private market conditional on whether she own a dirty plant or not. If a financial investor **(FI)**$_{private}$ in this market owns a dirty plant, her per-period utility is equal to π which is the per-period profit of the dirty plant. If a financial investor does not own a dirty plant, her per-period utility is equal to 0 as she doesn't care about the social cost of the plant. This is different for SRI investors with broad mandate **(SRI)**$_{private}$. **(SRI)**$_{private}$ care about social cost of the plant whether she owns it or not. If **(SRI)**$_{private}$ owns the dirty plant, her per period utility is $\pi - \gamma C_H$ where γ is the pro-social preference of the **(SRI)**$_{private}$ and $\gamma > 0$. If the **(SRI)**$_{private}$ does not own the dirty plant, she still suffer disutility from the social cost of the dirty plant and therefore, her per-period utility is equal to $-\gamma C_H$.

Dirty plant	Financial Investor	SRI with broad mandate (SRI)
Own	π	$\pi - \gamma C_H$
Not own	0	$-\gamma C_H$

Table B.1: Private Market: Investor per-period utility for the dirty plant.

Public Market Table B.2 present the investor per-period utility of the investor that operate in the public market conditional on whether own a dirty plant or not. What makes investor that operate in the public market different from the one in the private market is that the former is exposed to environmental pressure (λ) while the latter is not. If a financial investor **(FI)**$_{public}$ in public market own a dirty plant, her per-period utility is equal to π - λC_H. If a financial investor does not own a dirty plant, her per-period utility is equal to 0 as she doesn't care about the social cost of the plant. If **(SRI)**$_{public}$ owns the dirty plant, the period utility is $\pi - \gamma C_H$ - λC_H. If the **(SRI)**$_{public}$ does not own the dirty plant, her per-period utility is equal to $-\gamma C_H$.

Dirty plant	**Financial Investor**	**SRI with broad mandate (SRI)**
Own	π - λC_H	$\pi - \gamma C_H$ - λC_H
Not own	0	$-\gamma C_H$

Table B.2: Public Market: Investor per period utility for the dirty plant.

In this framework, what is influencing the investors' decision to hold, sell or transform the dirty plant is the investor's exposure to environmental pressure (λ). The investor's exposure to environmental pressure (λ) affects only those investors that own dirty assets in the public market. Financial investor in the public market will be willing to sell to any type of investors in the private market to get rid of her exposure to environmental pressure (λ).

B.1.2 Benchmark: Only financial investors

Consider two financial investors: one operates in the public market (FI_{public}) and the other financial investor operates in the private market ($FI_{private}$). The FI_{public} owns the dirty asset and her discounted utility is as follows:

$$\frac{\pi - \lambda C_H}{1-\beta} \tag{A3}$$

where λ is the exposure to environmental pressure.

Figure A1 presents the decision tree (and the discounted utility) for the FI_{public} options: to hold the dirty asset, to transform the dirty asset into a clean asset, or to sell the asset to the $FI_{private}$.

The FI_{public} will transform the asset if and only if the discounted utility from transforming the asset is greater than the discounted utility from holding the assets. i.e.

$$\frac{\pi - \lambda C_L}{1-\beta} - \kappa > \frac{\pi - \lambda C_H}{1-\beta} \iff \lambda > \frac{\kappa(1-\beta)}{C_H - C_L} \tag{A4}$$

However, FI_{public} will neither transform the asset or hold the asset if there is a presence of $FI_{private}$ even if $\lambda > \frac{\kappa(1-\beta)}{C_H - C_L}$. What is the maximum price that $FI_{private}$ is willing to pay? The maximum price that the $FI_{private}$ is willing to pay is equal to the changes in the discounted utility of when she owns the asset and when she does not own the asset, i.e.

$$\begin{aligned} P_{FI_{private}} &= FI_{private,own} - FI_{private,notown} \\ &= \frac{\pi}{1-\beta} - 0 \\ &= \frac{\pi}{1-\beta} \end{aligned} \tag{A5}$$

FI_{public} will sell the asset to $FI_{private}$ rather than hold or transform the asset as the maximum price that the $FI_{private}$ is willing to pay $\frac{\pi}{1-\beta}$ is greater than either the discounted utility of holding the asset $\frac{\pi-\lambda C_H}{1-\beta}$ or transforming the asset $\frac{\pi-\lambda C_L}{1-\beta} - \kappa$.

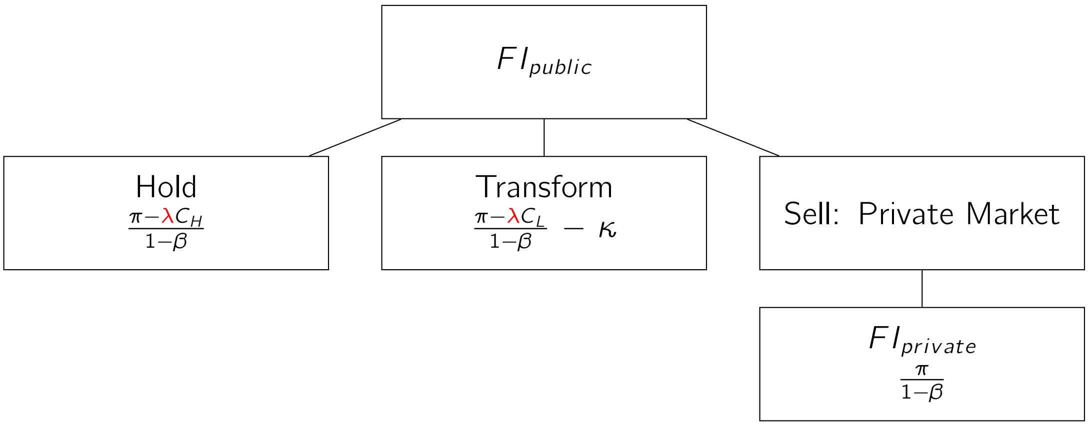

Figure A1: Decision Tree for Public Financial Investor Options

B.1.3 When there is a presence of SRI investor in the private market

Building on the benchmark where we have one FI_{public} and one FI_{public}. Suppose now that there is another type of investor in the private market, the SRI investor ($SRI_{private}$). As stated above, $SRI_{private}$ cares about the social cost of the plant whether she invests in it or not. Consider the decision of $SRI_{private}$ to transform the dirty asset, she will transform the asset if the discounted utility from transforming the asset is greater than the discounted utility from holding the assets. i.e.

$$\frac{\pi - \gamma C_L}{1-\beta} - \kappa > \frac{\pi - \gamma C_H}{1-\beta} \iff \gamma > \frac{\kappa(1-\beta)}{C_H - C_L} \tag{A6}$$

where γ is the pro-social preference parameter of the $SRI_{private}$.

The presence of the $SRI_{private}$ changes the dynamic of the private market, where she might be willing to offer a higher price to buy a dirty asset compared to $FI_{private}$, as $SRI_{private}$ derives disutility from the social cost of plant that she does not own. Assuming that $\gamma > \frac{\kappa(1-\beta)}{C_H-C_L}$, the maximum price that the $SRI_{private}$ will be willing to offer is:

$$
\begin{aligned}
P_{SRI_{private}} &= SRI_{private,own} - SRI_{private,notown} \\
&= \frac{\pi - \gamma C_L}{1-\beta} - \kappa - -\frac{\gamma C_H}{1-\beta} \\
&= \frac{\pi + \gamma(C_H - C_L)}{1-\beta} - \kappa
\end{aligned}
\tag{A7}
$$

Based on the $\gamma > \frac{\kappa(1-\beta)}{C_H - C_L}$ assumption, the maximum price that the $SRI_{private}$ is greater than that of the $FI_{private}$. Figure A2 presents the decision tree of the public financial investor option when there is a presence of the SRI investor in the private market. As shown earlier, FI_{public} will prefer to sell than to either hold or transform the asset. When there is a presence of SRI investor and her pro-social preference is high enough, the FI_{public} will prefer to sell to the $SRI_{private}$ rather than the $FI_{private}$.

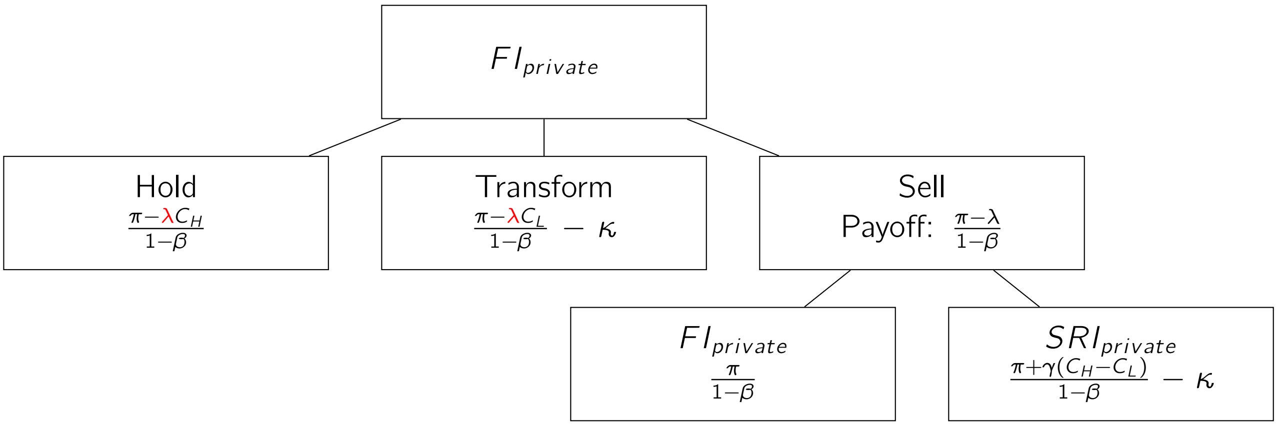

Figure A2: Decision Tree for Public Financial Investor Options when there is a presence of SRI investor.

B.1.4 Informational content of the differential transaction price (DTP)

The purpose of the exercise above or the theoretical framework is to show that the differential transactional price between the $SRI_{private}$ and $FI_{private}$ might contain important information about the expectation of the SRI investors in the private. It might capture the expectation of the SRI investor about future benefit and cost of transforming dirty asset to clean asset.

$$
\begin{aligned}
PD_{SRIprivate-FIprivate} = P_{SRI_{private}} - P_{FI_{private}} \\
&= \frac{\pi + \gamma(C_H - C_L)}{1-\beta} - \kappa - \frac{\pi}{1-\beta} \\
&= \frac{\gamma(C_H - C_L)}{1-\beta} - \kappa \\
&= \underbrace{\frac{\gamma(C_H - C_L)}{1-\beta}}_{\text{Benefit}} - \underbrace{\kappa}_{\text{Cost}}
\end{aligned}
\tag{A8}
$$

This helps to provide some indication whether SRI are embarking on ambitious projects which is expected to reflect in the price difference between $SRI_{private}$ and $FI_{private}$ or they are greewashing.

B.1.5 Transaction Price

First, I examine the transaction price of assets sold in the energy and utilities sector by public players to private players or other public players. Table B.3 shows that, on average, public buyers pay higher transaction price to acquire dirty assets compared to private buyers.

Table B.3: Transactions from public sellers to either public or private buyers

Both Buyers	n	mean	sd	median	min	max
Transaction value (TV)	222	397	913	106	0	7,889
Nameplate capacity (NPC)*1m	220	705,286	1,599,313	216,506	1,050	15,433,858
TV TO NPC	220	824	956	542	39	6,750
Private Buyers						
Transaction value (TV)	182	298	566	96	0	4,101
Nameplate capacity (NPC)*1m	182	697,200	1,630,805	189,400	1,050	15,433,858
TV TO NPC	182	741	804	488	39	4,813
Public Buyers						
Transaction value (TV)	40	848	1,729	214	1	7,889
Nameplate capacity (NPC)*1m	38	744,012	1,458,579	349,249	7,380	8,823,735
TV TO NPC	38	1,223	1,431	797	46	6,750

Figure A3 shows the distribution of the assets sold in the energy and utilities sector by public players to private players or other public players over the period 1998-2023. I use the nearest-neigbour matching method to match each transaction sold to public players with similar transaction sold to private players based on the on the nameplate capacity of the assets. Figure A4 shows the standardized mean difference and the variance ratio between the matched and control sets; and the standardized mean difference is close to zero, while the variance ratio is close to 1. This indicates that there are approximately no differences between the matched and the control sets based on the nameplate capacity.

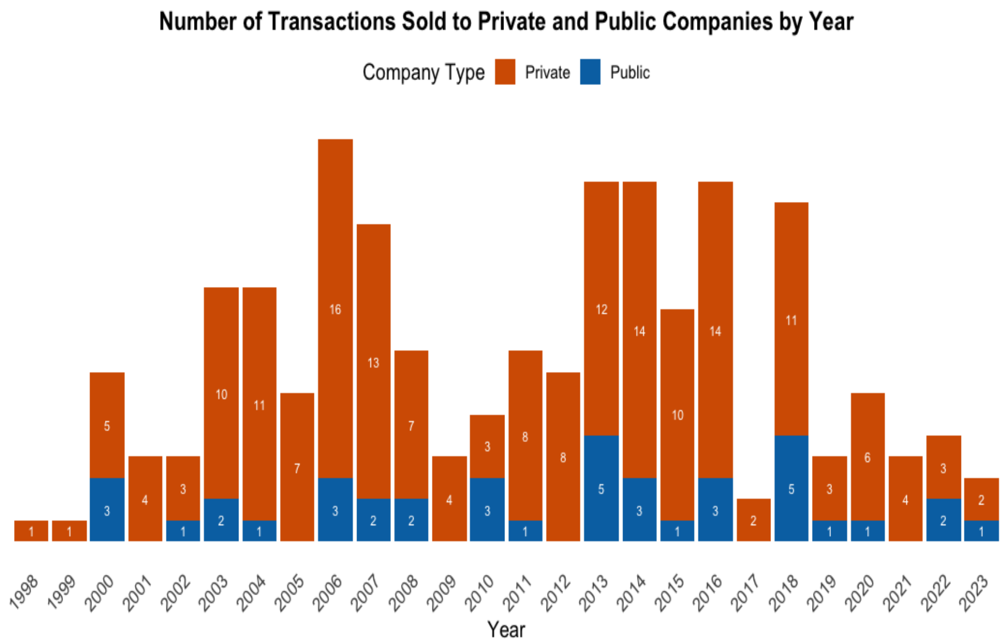

Figure A3: Distribution of the transactions from public sellers

Table B.4 shows the regression result of the transaction price differential between public and private players after applying the nearest-neighbor matching technique to match each transaction sold to the public player with a similar transaction sold to the private player based on the nameplate capacity of the assets. The result shows that the public players pay higher transaction value than private players to acquire a assets of similar nameplate capacity.

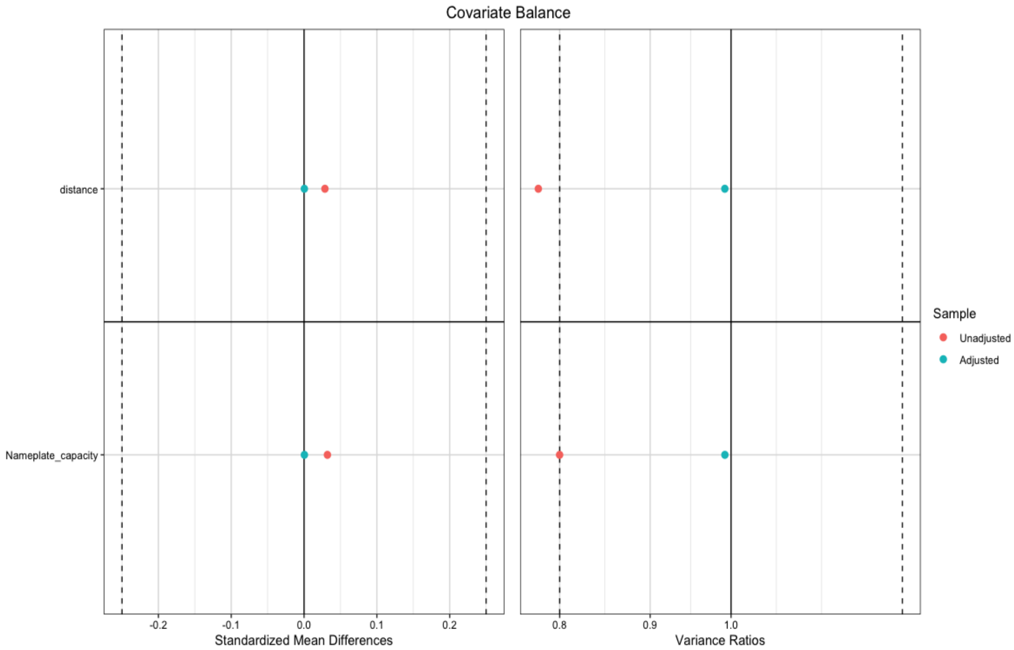

Figure A4: Covariates matching: Nearest-neighbour matching

Table B.4: Transaction price different between public and private buyer

This table examines whether there is a transaction price difference between public and private buyers. This regression result is performed after matching the transaction of public buyers to private players based on the nameplate capacity. The matching method used is nearest-neighbour matching method. The unit of observation is the transaction year level, and the independent variable is the transaction value. "Treat" is an indicator variable equal to one if the assets is sold to public players, and zero otherwise. Standard errors are reported in brackets. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Dependent variable:
	Transaction value
Nameplate capacity	0.001***
	(0.00004)
Treat (public buyer = 1)	325.847***
	(118.322)
Constant	−96.994
	(89.050)
Observations	76
R^2	0.759
Adjusted R^2	0.753
Residual Std. Error	515.754 (df = 73)
F Statistic	115.135*** (df = 2; 73)
Note:	*p<0.1; **p<0.05; ***p<0.01