Climate Disclosure: Theory and Evidence*

Florian Perusset†

December 14, 2025

Abstract

This paper investigates the real effects of climate disclosure requirements. In a model where investors are heterogeneous in their aversion to pollution, I demonstrate that more stringent climate disclosure requirements have an ambiguous impact on pollution and welfare in equilibrium. While reducing the funding allocated to the dirty firm, they also result in the dirty firm being financed by investors who are less concerned about pollution, thereby undermining its incentives to adopt green technology. Using data on the staggered adoption of mandatory climate disclosure requirements across countries, I provide supportive empirical evidence of these mechanisms.

Keywords: Socially responsible investing, disclosure, greenwashing, shareholder composition.

JEL Classification: G11, G14, G18, G32, G38.

---

*I am especially grateful to Erwan Morellec and Federica Zeni for their invaluable support and guidance. I also thank Madhushree Ayalasomayajula, Luise Eisfeld, Andreas Fuster, Thierry Foucault, Deeksha Gupta, John Kuong, Jan Schneemeier, Pascal St-Amour, Victoria Vanasco, Jinran Wang, Dong Yan, Anthony Lee Zhang, and seminar participants at the EPFL/UNIL PhD Workshop, the EPFL/HEC Lausanne Brown Bag, the SFI Research Days 2025 in Gerzensee, and the FTG Summer School 2025 in Seattle for helpful comments and feedback. All errors are my own.

†EPF Lausanne and Swiss Finance Institute. E-mail: florian.perusset@epfl.ch

1 Introduction

Climate disclosure requirements have become increasingly prominent over the last decade. For example, the Corporate Sustainability Reporting Directive (CSRD), a new EU regulation that entered into force on 5 January 2023, strengthens rules regarding the social and environmental information that firms must report. The Council of the EU emphasized that the CSRD could "attract additional investment and funding to facilitate the transition to a sustainable economy".[1] In California, two landmark climate-disclosure laws were adopted in October 2023. These laws require large firms to disclose their greenhouse gas emissions, climate-related financial risk, as well as measures they take to mitigate those risks.[2]

Conventional wisdom suggests that promoting more transparent information benefits sustainable investments, allowing more informed decisions from market participants, which could facilitate firms' adoption of more sustainable technologies. Recent empirical studies also view climate disclosure requirements as beneficial. Ilhan, Krueger, Sautner, and Starks (2023) document that institutional investors value and demand climate risk disclosures. Krueger, Sautner, Tang, and Zhong (2024) find a positive relation between firms' ESG disclosure requirements and stock liquidity and conclude that regulations promoting ESG disclosure benefit capital markets.

However, despite the growing adoption of climate disclosure requirements across the globe, there is a lack of direct evidence on their real effects. In this paper, I aim to study

[1]In the US, the SEC adopted comprehensive climate-related disclosure rules on March 6, 2024, which would require publicly listed firms to report qualitative and quantitative information on greenhouse gas emissions, climate-related risks, and transition strategies. However, shortly after adoption, the rules were challenged in multiple legal proceedings, and the SEC voluntarily stayed their implementation pending judicial review. Subsequently, the SEC announced that it would no longer defend the rules in court, effectively suspending their enforcement.

[2]SB 253 (the Climate Corporate Data Accountability Act) requires large companies doing business in California to publicly report their greenhouse gas emissions, including direct (Scope 1), indirect energy-related (Scope 2), and, eventually, value-chain emissions (Scope 3). SB 261 (the Climate-Related Financial Risk Act) requires large firms to disclose their climate-related financial risks and the measures they take to mitigate and adapt to those risks. Together, these laws significantly expand mandatory climate and sustainability reporting for both public and private companies operating in California.

this question both theoretically and empirically. First, I develop a model showing that, under endogenous shareholder base formation, improving climate disclosure requirements has ambiguous effects on pollution and welfare in equilibrium when accounting for heterogeneous shareholder preferences toward externalities.

On the one hand, more stringent climate disclosure requirements reduce the mass of investors investing in the dirty sector, thereby reducing pollution. On the other hand, it also reshapes firms' shareholder bases, resulting in dirty firms financed by investors who are, on average, less concerned about pollution. This latter effect undermines the adoption of green technology by dirty firms. Thus, more stringent climate disclosure requirements can backfire and result in lower welfare and/or a higher level pollution.

More specifically, I develop a model in which two firms (clean and dirty) are financed by a continuum of responsible investors. The dirty firm is more productive than the clean firm, but generates pollution. After receiving funding from investors, the dirty firm decides whether to operate its current production technology or to adopt a less polluting or green technology at a cost. Investors are heterogeneous in their aversion to holding polluting firms and decide which firm to invest in, anticipating firms' adoption decisions. In particular, while some investors are mainly concerned with financial returns, others suffer from a high disutility when investing in a polluting firm. More specifically, investors exhibit warm-glow disutility in investing in polluting firms, in line with empirical evidence on social preferences (see Riedl and Smeets (2017), Heeb, Kölbel, Paetzold, and Zeisberger (2023), or Bonnefon, Landier, Sastry, and Thesmar (2025)). Moreover, investors do not know which firm is polluting, but they receive an informative signal before investing about which firm is clean and which is dirty. The precision of the signal is exogenous and reflects the stringency of the climate disclosure requirements imposed by the regulator.

In this framework, I demonstrate that improving climate disclosure requirements decreases the mass of investors who choose to invest in the dirty firm, thereby reducing the size of the dirty sector. However, it also reshapes firms' shareholder base, resulting in the dirty firm being financed by investors who are, on average, less concerned about pollution. The latter effect undermines the incentive of the dirty firm to adopt green technology. Depending on which of these effects dominates, more stringent climate disclosure requirements could result in more pollution and lower welfare in equilibrium. This challenges the conventional view that improving climate disclosure is always beneficial and suggests that some level of greenwashing could be optimal.

I also provide empirical evidence supporting the novel predictions of my theory. Using data from Krueger et al. (2024) on the staggered implementation of mandatory ESG disclosure requirements across countries, I show that after the implementation of mandatory disclosure requirements, the share of institutional investors invested in polluting firms decreases. As institutional investors have been recognized to be an important driver of firms' sustainability (see Dyck, Lins, Roth, and Wagner (2019)), this suggests that polluting firms' shareholders are becoming less environmentally friendly after the implementation of more stringent disclosure requirements, in line with the theoretical prediction of the model.

Using green patents issuance as a proxy for firms' green investments, I also show that firms are issuing fewer green patents following the introduction of mandatory disclosure requirements and that this effect is more pronounced for more polluting firms. This is consistent with the model's prediction that, after the implementation of more stringent climate disclosure requirements, capital is reallocated away from dirty to clean firms, with dirty firms ending up being financed by investors who care less about pollution, in turn undermining incentives for these firms to adopt greener technologies. Furthermore, I show that firms spend less on R&D and tend to increase their emissions after the implementation of the laws, consistent with the fact that firms reduce their investment in green technologies. I also show that these effects are more pronounced for more polluting firms, as predicted by the theory.

Moreover, I show that, perhaps surprisingly, following the adoption of mandatory climate disclosure requirements and the divestment by institutional investors, firms' cost of capital does not increase. I also show that firms do not seem to become more financially distressed. Therefore, these findings reveal that firms do not reduce green investments in response to a higher cost of capital or due to financial distress.[3] Interestingly, the fact that firms' cost of

[3] Bellon and Boualam (2024) find that financially distressed firms increase their pollution.

capital is not affected by the divestment of institutional investors shows that my results are driven by a distinct channel than the cost of capital channel, which has been the subject of an extensive research in sustainable finance but whose real effects are still highly debated (Hartzmark and Shue (2022), Berk and Van Binsbergen (2025)). This reinforces the evidence in favor of the channel highlighted in the model, that firms reduce green investments because, following the adoption of more stringent climate disclosure requirements, polluting firms end up being held by shareholders who are less averse to pollution, and not because of an impact on their cost of capital.

Related Literature. This paper contributes to several strands of literature. First, it belongs to the growing theoretical literature on sustainable investing. Research has shown how divestment could incentivize firms to adopt environmentally friendly technologies (Heinkel, Kraus, and Zechner (2001), Davies and Van Wesep (2018), Chowdhry, Davies, and Waters (2019), Edmans, Levit, and Schneemeier (2022), Allen, Barbalau, and Zeni (2023), Oehmke and Opp (2024), Landier and Lovo (2024)). Other articles have investigated the impact of activism on environmental corporate policies (see Broccardo, Hart, and Zingales (2022) or Gryglewicz, Mayer, and Morellec (2024)). Although activism and divestment are often treated separately in the literature and seen as substitutes, they are interrelated in my model. Indeed, funding for clean and dirty sectors is endogenously determined alongside shareholder bases, and firms' adoption decisions in turn depend on the composition of their shareholder bases.

Second, I contribute to the growing literature on ESG or climate disclosure. Recent empirical studies suggest that better disclosure requirements are beneficial to sustainable investments (Ilhan et al. (2023), Emiris, Harris, and Koulischer (2024), Krueger et al. (2024)). Ilhan et al. (2023) provide evidence that institutional investors value and demand climate risk disclosure. Emiris et al. (2024) show that mutual funds tend to decrease their emissions' intensity following the implementation of ESG disclosure rules, while Krueger et al. (2024) document a positive effect of enhanced climate disclosure requirements on firm-level stock liquidity. In contrast to these papers, I focus on the real effect of climate disclosure requirements. I show that more stringent climate disclosure requirements negatively affect firms' green investments. I am also contributing to the theoretical literature on climate disclosure (Chen and Schneemeier (2022), Aghamolla and An (2023), Xue (2023), Gupta and Starmans (2024)). Chen and Schneemeier (2022) investigate the effect of disclosure in the presence of informed trading and stock market feedback. They demonstrate that managers' ability to manipulate (or greenwash) their disclosure reduces investors' incentives to acquire information but also encourages investors to trade on private information. Aghamolla and An (2023) study mandatory versus voluntary disclosure requirements in the presence of agency conflict between managers and shareholders. They show that when the manager can privately select projects that vary in sustainability and profitability, mandatory disclosure requirements can result in overinvestment in green technologies compared to shareholders' preferred level. Xue (2023) studies optimal ESG disclosure requirements in a noisy rational expectations model. He shows that more precise disclosure requirements are not necessarily desirable as they change how investors use information. I pin down a different economic mechanism, as in my model, an increase in precision of disclosure requirements reshapes firms' shareholder bases, resulting in the dirty firm being held by shareholders who are less averse to pollution, which undermines incentives for this type of firm to adopt green technology. My paper also differs from Gupta and Starmans (2024), who study dynamic climate disclosure requirements. They show that under certain conditions, disclosure requirements that become more stringent over time can be preferable to full transparency. In contrast, I study the precision of climate disclosure requirements in a static framework, and I show that more precise requirements are not necessarily beneficial due to shareholders' endogenous response. This is different, as my model remains agnostic about the optimal dynamics of climate disclosure requirements.

Third, my paper belongs to the literature that studies firms' decisions under endogenous shareholder base formation (Döttling, Levit, Malenko, and Rola-Janicka (2024), Levit, Malenko, and Maug (2024)). Levit et al. (2024) study secondary market trading and voting in a single-firm setting. They show that inefficiencies arise when post-trade voting outcomes are determined by the median rather than the average shareholders. In this paper, I focus on the primary market to study the impact of disclosure requirements on capital allocation in an economy, and I abstract from differences between the average and the median shareholder. In a recent paper, Bisceglia, Piccolo, and Schneemeier (2022) show that when socially responsible investors and profit-motivated investors interact, the former tend to concentrate on a subset of firms that crowd out green investments of excluded firms and create product market power. However, they only consider secondary market trading and abstract from disclosure. Huang and Kopytov (2023) study optimal taxation and subsidy under endogenous shareholder base formation and show that pollution can increase with regulation stringency. In contrast, I focus on the impact of climate disclosure requirements under endogenous shareholders' base formation. Moreover, while Huang and Kopytov (2023) is a purely theoretical study, I also provide extensive empirical support of my predictions.

2 The Model

The model is based on Huang and Kopytov (2023). It differs as I consider imperfect information about firms' externality to investigate the implications of climate disclosure under endogenous shareholders' base formation.

I consider an economy that consists of two sectors or firms $i \in \{c, d\}$, where c stands for clean (or non-polluting) firms, and d for dirty (or polluting) firms. The firms are financed by a continuum of mass one of risk-neutral investors who are heterogeneous in their preference for greenness. Investors do not observe firms' externalities but instead receive a signal that reveals which firm is clean before investing. The clean firm is not polluting, but is less profitable than the dirty firm. The dirty firm is endowed with brown technology and can adopt a less polluting technology (green technology) at a cost.

There are two periods, $t = 1, 2$, and no discounting. At time $t = 1$, after receiving an informative signal about which firm is polluting, investors choose the firm they invest in, trading off the financial return with its sustainability. At time $t = 2$, the dirty firm chooses whether to operate under brown production technology or adopt green technology at a cost. The firm manager is risk-neutral and makes decisions that maximize the utility of the average shareholder.

2.1 Production technology

Firms receive capital from investors and produce final goods using an AK production technology. The clean firm produces $y_c = \alpha_c k_c$, where α_c and k_c denote respectively the productivity and the capital allocated to the clean firm.

For simplicity, I assume that the clean firm does not pollute. The dirty firm receives capital and decides whether to operate under the brown production technology resulting in a level of pollution (or negative externality) e per unit of capital or to adopt a green production technology by facing a proportional cost $f > 0$ per unit of capital, and resulting in a level of externality κe per unit of capital with $\kappa \in (\underline{\kappa}, 1)$, where $\underline{\kappa} > 0$.[4] I assume that the manager makes the decision that maximizes average shareholders' valuation. The output of the dirty firm is $y_d = k_d(\alpha_d - f\mathbb{1}_{\{a=1\}})$, where $\mathbb{1}_{\{a=1\}}$ denotes the adoption decision of the dirty firm. Moreover, I assume that $\Delta \equiv \alpha_d - \alpha_c > 0$, which implies that the clean firm is less productive than the dirty firm but pollutes less.

2.2 Investor preferences

There is a unit mass of risk-neutral atomistic investors who are heterogeneous in their preferences for greenness. Each investor is endowed with one unit of capital and chooses which type of firm to invest in, considering the firm's decision to adopt a greener production technology. Investors value financial payoff and suffer from disutility for the (negative) externality generated by the firm in which they decide to invest. That is, investors suffer from a warm-glow disutility from investing in a polluting firm, in line with the empirical evidence on social preferences (see Riedl and Smeets (2017), Heeb et al. (2023) or Bonnefon et al. (2025)).[5] Specifically, investors of type λ suffer from non-pecuniary disutility λe_i when holding shares of the firm of type i, where e_c is normalized to 0 and $e_d = e$.[6] $\lambda \in [0, \overline{\lambda}]$ governs the aversion

[4] As shown in Section 3.1.2, $\underline{\kappa} > 0$ ensures that the dirty firm raises nonzero capital when it decides to adopt the green technology.

[5] I show in Appendix A.1 that the model's predictions continue to hold in the case where investors have preferences for impact, as in Gupta, Kopytov, and Starmans (2022) or Oehmke and Opp (2024), for instance.

[6] More precisely, the preferences of the investors can also be labeled as narrow-consequentialist. Their preferences can be considered as warm-glow in the sense that they derive disutility from their holding in the

to holding polluting firms and differs across investors with a cumulative distribution function $G(.)$.

The productivity α_i is observable for investors; however, investors do not observe which firm is clean and dirty. From the perspective of investors, there are two firms with productivity α_i and externality e_i, for $i = 1, 2$. Before choosing which type of firm to invest in, investors receive a signal $s \in \{F_1, F_2\}$ which is informative about which firm is clean and which firm is dirty. Namely, $s = F_1$ means that firm 1 is the clean firm and that firm 2 is the dirty one. Investors know that the clean firm has externality 0 and the dirty firm has externality e.

Before observing the signal, each firm is equally likely to be clean or dirty for investors, that is, $\mathbb{P}(e_i = 0) = \frac{1}{2}$ for $i = 1, 2$. More importantly, although investors observe firms' productivity, they do not know which firm (clean or dirty) is more or less productive. Hence, they know that the clean firm has externality $e_c = 0$ and the dirty firm has externality $e_d = e$, but they do not know whether $\alpha_c > \alpha_d$ or $\alpha_c < \alpha_d$. In other words, they cannot associate productivity with externalities.[7]

The precision of the signal is denoted by $\pi = \mathbb{P}(s = F_1 | e_1 = e_c) \in (\frac{1}{2}, 1]$ and reflects the quality of the climate disclosure requirements. A more precise signal (i.e., a higher π) means that investors have better information about firms' externalities and can be interpreted as a legal framework that prompts firms to report more information regarding their sustainability.

Investors form expectations about firms' adoption decisions. Investors' valuation of one

dirty firm. However, since the negative externalities they internalize are evaluated relative to a counterfactual scenario in which they invest in the clean firm, they can also be considered narrow-consequentialists as in Allen et al. (2023), for instance.

[7] I believe that this assumption is conservative given that there is a debate in the asset pricing literature on the existence of a *greenium*. Some papers find that green assets tend to underperform brown assets (e.g., Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023)), while others find the opposite (Pástor, Stambaugh, and Taylor (2022), Zhang (2025)).

dollar invested in each type of firm $i = 1, 2$ is given by

$$v_i = \alpha_i - (f + \kappa\lambda\mathbb{E}[e_i|s])\mathbb{1}_{\{a_i=1\}} - (1 - \mathbb{1}_{\{a_i=1\}})\lambda\mathbb{E}[e_i|s] \tag{1}$$

Using Bayes' Law we have that $\mathbb{P}(e_1 = 0|s = F_1) = \pi$ and $\mathbb{P}(s = F_1) = \mathbb{P}(s = F_2) = \frac{1}{2}$. We can compute the expected externality for the two firms as a function of the realization of the signal

$$\begin{aligned}
\mathbb{E}[e_1|s = F_1] &= e(1 - \pi), \\
\mathbb{E}[e_1|s = F_2] &= e\pi, \\
\mathbb{E}[e_2|s = F_1] &= e\pi, \\
\mathbb{E}[e_2|s = F_2] &= e(1 - \pi).
\end{aligned}$$

Moreover, from (1) we have that an investor with preference λ invests all her wealth in the firm with the highest valuation. As the valuation of investors v_i decreases in λ, there exists a cut-off $\hat{\lambda}$ such that investors with $\lambda > \hat{\lambda}$ invest in the clean firm and investors with $\lambda < \hat{\lambda}$ invest in the dirty firm. This leads to the following lemma.

Lemma 1. *There exists a cut-off $\hat{\lambda}$ so that investors with preference $\lambda < \hat{\lambda}$ invest in the dirty firm and investors with $\lambda > \hat{\lambda}$ invest in the clean firm.*

2.3 Green technology adoption

At $t = 2$, after investors have chosen the firm in which they invest and the shareholder bases have been formed, we have that the dirty firm adopts green technology if it maximizes the average utility of its shareholders. Hence, the dirty firm chooses to adopt green technology if

$$\int_0^{\hat{\lambda}} (\alpha_d - f - \lambda\kappa\mathbb{E}[e_i|s])dG(\lambda) > \int_0^{\hat{\lambda}} (\alpha_d - \lambda\mathbb{E}[e_i|s])dG(\lambda)$$

which is equivalent to

$$f < (1 - \kappa)\mathbb{E}[e_i|s])\psi(\hat{\lambda}) \tag{2}$$

with

$$\psi(\hat{\lambda}) = \frac{\int_0^{\hat{\lambda}} \lambda dG(\lambda)}{G(\hat{\lambda})} \tag{3}$$

where $\psi(.)$ is a continuous function, with $\lim_{\hat{\lambda}\to 0} \psi(\hat{\lambda}) = 0$, $\psi(\hat{\lambda}) < \hat{\lambda}$, and $\frac{\partial\psi(\hat{\lambda})}{\partial\hat{\lambda}} > 0$.

3 Equilibrium Characterization

There are two potential equilibria to be considered: one in which the dirty firm adopts the green technology (green equilibrium) and one in which the dirty firm does not adopt the green technology and chooses to operate under the current technology (brown equilibrium). Moreover, we can assume without loss of generality that firm 1 is the clean firm. In what follows, I characterize the different equilibria as a function of the realization of the signal $s = \{F_1, F_2\}$.

3.1 Signal is correct

First, consider the case where the signal is correct, that is, $s = F_1$. There are two different equilibria.

3.1.1 Brown equilibrium

In this case, the dirty firm does not adopt the green technology at time $t = 2$. From (1), we have that at $t = 1$, investors choose to invest in the clean firm if and only if

$$\alpha_2 - \lambda \mathbb{E}[e_2|s = F_1] < \alpha_1 - \lambda \mathbb{E}[e_1|s = F_1]$$

which yields

$$\lambda > \frac{\Delta}{(2\pi - 1)e} \equiv \hat{\lambda}_B \tag{4}$$

with $\frac{\partial \hat{\lambda}_B}{\pi} < 0$, which implies that the size of the dirty sector shrinks as disclosure requirements become more accurate.

Thus, in equilibrium, investors with $\lambda \in [0, \hat{\lambda}_B]$ invest in the dirty firm and investors with $\lambda \in [\hat{\lambda}_B, \overline{\lambda}]$ invest in the clean firm. For this to be an equilibrium, it must be that the dirty firm finds it optimal not to adopt the green technology at time $t = 2$, which is the case if and only if

$$f > (1 - \kappa)\mathbb{E}[e_2|s = F_1]\psi(\hat{\lambda}_B) = (1 - \kappa)\pi e \psi(\hat{\lambda}_B) \tag{5}$$

Looking at (5), we have that this equilibrium exists if $\hat{\lambda}_B$ is sufficiently small, which means that shareholders of the dirty firm are not too averse to holding polluting firms. By equation (4), this happens if Δ is sufficiently small. The intuition for this result is as follows. When Δ is small, the dirty firm has a small financial advantage over the clean firm, and only investors with very low λ, i.e., profit-oriented investors, are willing to hold the polluting firm. In turn, dirty firms owned by profit-oriented investors do not find it optimal to adopt green technology. In this equilibrium, output Y_B^1, pollution P_B^1 and welfare W_B^1 are given by

$$Y_B^1 = \alpha_d G(\hat{\lambda}_B) + \alpha_c(1 - G(\hat{\lambda}_B)) \tag{6}$$

$$P_B^1 = G(\hat{\lambda}_B)e \tag{7}$$

$$\begin{aligned} W_B^1 &= \alpha_d G(\hat{\lambda}_B) + \alpha_c(1 - G(\hat{\lambda}_B)) - e\int_0^{\hat{\lambda}_B} \lambda dG(\lambda)\mathbb{E}[e_2|s = F_1] \\ &= \alpha_c + \Delta G(\hat{\lambda}_B) - \pi e \int_0^{\hat{\lambda}_B} \lambda dG(\lambda) \end{aligned} \tag{8}$$

where welfare is defined as the aggregate utility of investors.

3.1.2 Green equilibrium

In this equilibrium, the dirty firm adopts green technology at time $t = 2$. In equilibrium, at time $t = 1$, investors with $\lambda \in [0, \hat{\lambda}_G)$ invest in dirty firm, and investors with $\lambda \in [\hat{\lambda}_G, \overline{\lambda}]$ invest in clean firm, where $\hat{\lambda}_G$ is given by

$$\hat{\lambda}_G = \frac{\Delta - f}{e[(1+\kappa)\pi - 1]} \tag{9}$$

and assuming that $\Delta > f$ and that $\kappa > \underline{\kappa} \equiv \frac{1-\pi}{\pi}$, we have that the dirty firm raises nonzero capital in this equilibrium. Moreover, we have that $\frac{\partial \hat{\lambda}_G}{\partial \pi} < 0$, which implies that when disclosure requirements become more accurate, the size of the dirty firm is shrinking.

For this to be an equilibrium, it must be that the dirty firm finds it optimal to adopt the green technology at time $t = 2$, which is the case whenever

$$f < (1-\kappa)\mathbb{E}[e_2|s = F_1]\psi(\hat{\lambda}_G) = (1-\kappa)e\pi\psi(\hat{\lambda}_G). \tag{10}$$

As $\frac{\partial \psi(\hat{\lambda})}{\partial \hat{\lambda}} > 0$, the green equilibrium exists if $\hat{\lambda}_G$ is sufficiently large which is the case if Δ is sufficiently large (see equation (9)). The intuition for this result is as follows. Δ sufficiently large means that the dirty firm has a large financial advantage over the clean firm, which implies that only investors with a strong aversion to holding polluting firms, i.e., a high λ, will decide to invest in the clean firm. Hence, in equilibrium, the dirty firm will also be held by investors with a relatively high aversion to pollution, and therefore, it will find it optimal to adopt green technology.

In this equilibrium, output Y_G^1, pollution P_G^1 and welfare W_G^1 are given by

$$Y_G^1 = (\alpha_d - f)G(\hat{\lambda}_G) + \alpha_c(1 - G(\hat{\lambda}_G)) \tag{11}$$

$$P_G^1 = G(\hat{\lambda}_G)\kappa e \tag{12}$$

$$W_G^1 = \alpha_c + (\Delta - f)G(\hat{\lambda}_G) - \kappa\pi e \int_0^{\hat{\lambda}_G} \lambda dG(\lambda) \tag{13}$$

The following proposition summarizes the conditions for the existence of the two equilibria.

Proposition 1. *When the signal is correct, if $f > (1-\kappa)e\pi\psi(\overline{\lambda})$, only the brown equilibrium exists. If $f \leq (1-\kappa)e\pi\psi(\overline{\lambda})$, there exists $\overline{\lambda}(2\pi - 1)e \geq \overline{\Delta} > \underline{\Delta} > \frac{(2\pi-1)f}{(1-\kappa)\pi}$ such that*
i) if $\Delta < \underline{\Delta}$, only the brown equilibrium exists;
ii) if $\Delta \geq \overline{\Delta}$, only the green equilibrium exists;
iii) if $\Delta \in [\underline{\Delta}, \overline{\Delta})$, both equilibria co-exist.
Moreover, if both equilibria coexist, then $\hat{\lambda}_G > \hat{\lambda}_B$, where $\hat{\lambda}_B$ and $\hat{\lambda}_G$ are given by equations (4) and (9) respectively.

First, Proposition 1 states that in case the signal is correct, the green equilibrium does not exist if the cost of adopting green technology is too high. From Lemma 1, we have that the dirty firm is held by low-λ investors. This means that if the adoption cost is so large that even an average investor in the population does not want the dirty firm to adopt the green technology, i.e., $f > (1-\kappa)e\pi\psi(\overline{\lambda})$, then the dirty firm does not adopt the green technology and the brown equilibrium prevails. Second, if the adoption cost f is not too large, then both equilibria can exist depending on how large the difference in productivity between the clean and dirty firm Δ is. As mentioned above, if Δ is sufficiently small, that is, $\Delta < \underline{\Delta}$ the dirty firm does not find optimal to adopt green technology and the green equilibrium does not exist while if Δ is sufficiently large, that is, $\Delta > \overline{\Delta}$, then the dirty firm finds optimal to adopt green technology and the brown equilibrium does not exist. Moreover, both equilibria can co-exist if Δ is intermediate. In this case, Proposition 1 states that the size of the dirty sector is always larger when the dirty firm chooses to adopt green technology, i.e., $\hat{\lambda}_G > \hat{\lambda}_B$. The intuition for this result is that more investors decide to invest in the dirty firm when it decides to adopt green technology.

3.1.3 Equilibrium comparison

In the brown equilibrium, the dirty firm does not adopt green technology. Therefore, it only attracts investors whose aversion to holding polluting firms is low, that is, investors with $\lambda < \hat{\lambda}_B$. In the green equilibrium where the dirty firm chooses to adopt the green technology to reduce its pollution, the size of the dirty firm becomes larger as more investors decide to hold the dirty firm, i.e. $G(\hat{\lambda}_G) > G(\hat{\lambda}_B)$ when both equilibria co-exist. Therefore, the pollution may be larger in the green equilibrium. As in Acemoglu and Rafey (2023) or Huang and Kopytov (2023), I assume that this is not the case.

Assumption 1. *Adoption of the green technology reduces aggregate pollution if* $G(\hat{\lambda}_G)\kappa < G(\hat{\lambda}_B)$*, where* $\hat{\lambda}_B$ *and* $\hat{\lambda}_G$ *are respectively given by equations (4) and (9).*

Under Assumption 1, the adoption of green technology always leads to a lower level of pollution. However, as adopting green technology is costly, it might not be socially desirable. The following lemma shows that under a mild assumption, provided that the cost of adopting the green technology is low enough, welfare is always higher under the green equilibrium, which implies that adopting the green technology is socially desirable.

Lemma 2. *There exists a threshold* $\overline{f}^1 > 0$ *so that the green equilibrium exists and is socially preferable, that is,* $W^1_G > W^1_B$ *for* $f < \overline{f}^1$*. A sufficient condition for the existence of* $\overline{f}^1$ *is that* W^1_G *is a decreasing function of* κ*.*

Furthermore, we make the following assumption to determine which equilibrium prevails when both coexist.

Assumption 2. *If the two equilibria coexist, the socially preferable one is played.*

This latter assumption is similar to Huang and Kopytov (2023) and ensures that my results are driven by economic forces rather than coordination failures.

3.2 Signal is incorrect

Now consider the case where the signal is incorrect, that is $s = F_2$. In this case, since $\alpha_2 = \alpha_d > \alpha_1 = \alpha_c$ and $\mathbb{E}[e_2|S = F_2] = e(1-\pi) < \mathbb{E}[e_1|S = F_2] = e\pi$ as $\pi \in (\frac{1}{2}, 1]$ we have from (1) that all investors invest in firm 2 that is the polluting firm. In this case, the green equilibrium in which the dirty firm chooses to adopt the green technology prevails if

$$f < (1-\kappa)(1-\pi)e\psi(\overline{\lambda}). \tag{14}$$

Otherwise, the brown equilibrium prevails.

Equation (14) reveals in case the signal is incorrect, the green equilibrium is less likely to prevail when disclosure requirements increase. Indeed, as π increases the left-hand side of (14) decreases. The intuition for this result is that when the signal is wrong, all investors invest in the dirty firm, and as π increases, the perceived externality generated by the dirty firm becomes less important for investors. Hence, investors are less willing dirty firm to adopt the green technology at time $t = 2$. This result suggests that increasing disclosure requirements can have adverse effects on firms' willingness to adopt green technologies.

In this brown equilibrium, we have that output Y_B^2, pollution P_B^2 and welfare W_B^2 are respectively given by

$$Y_B^2 = \alpha_d \tag{15}$$

$$P_B^2 = e \tag{16}$$

$$W_B^2 = \alpha_d - \mathbb{E}[e_2|s = F_2] \int_0^{\overline{\lambda}} \lambda dG(\lambda) = \alpha_d - e(1-\pi)\psi(\overline{\lambda}) \tag{17}$$

Similarly, in the green equilibrium, we have

$$Y_G^2 = \alpha_d - f \tag{18}$$

$$P_G^2 = \kappa e \tag{19}$$

$$W_G^2 = \alpha_d - f - \kappa e(1-\pi)\psi(\overline{\lambda}) \tag{20}$$

This leads to the following proposition.

Proposition 2. *When the signal is incorrect, then the green equilibrium prevails if* $f < (1-\kappa)(1-\pi)e\psi(\overline{\lambda})$*, and otherwise the brown equilibrium prevails.*

Proposition 2 states that when the signal is incorrect, the dirty firm decides to adopt green technology provided that the cost of adoption f is not too large. Otherwise, the dirty firm does not adopt green technology. In this case, the equilibrium is always unique and depends only on the cost of adoption, as when the signal is incorrect, all investors decide to invest in the dirty firm, and the clean firm receives zero funding.

4 Model Analysis

In this section, I investigate the impact of more precise disclosure requirements, i.e., an increase in π, on the model's outcomes. In my model, more precise disclosure requirements can be interpreted as regulations that force firms to disclose (more) information about ESG-related issues, as mandated by recent changes in the law.[8] To gain insight into the economic mechanisms at play, it is useful to analyze the impact of the signal in the different states of nature separately, that is, for $s = F_1$ (signal is correct) and $s = F_2$ (signal is incorrect).

4.1 Signal is correct

As shown by equation (10), when the signal is correct, the green equilibrium prevails if

$$\underbrace{f}_{\text{Adoption cost}} < \underbrace{(1-\kappa)e\pi}_{\text{Expected reduction in pollution}} \times \underbrace{\psi(\hat{\lambda}_G(\pi))}_{\text{Average shareholder disutility}} \tag{21}$$

The left-hand side gives the adoption cost. For the dirty firm to adopt green technology at $t = 2$, this cost must be less than the expected reduction in pollution multiplied by the average shareholder's disutility of holding the dirty firm when it adopts green technology. An increase in π has two opposite effects on the green equilibrium. First, as π increases, the expected reduction in pollution increases as shareholders have a better estimation of the quantity of pollution generated by the dirty firm. On the other hand, an increase in π results

[8]For example, in the EU, the Corporate Sustainability Reporting Directive (CSRD) prompts firms to disclose detailed information on their sustainability efforts. Moreover, the International Sustainability Standards Board (ISSB) launched its first set of proposals on ESG reporting standards in June 2023.

in a lower average shareholder disutility (shareholder base effect)

$$\frac{\partial \psi(\hat{\lambda}_G(\pi))}{\partial \pi} = \underbrace{\frac{\partial \psi}{\partial \hat{\lambda}_G}}_{>0} \times \underbrace{\frac{\partial \hat{\lambda}_G}{\partial \pi}}_{<0} < 0$$

An increase in π results in a lower $\hat{\lambda}_G$ and since shareholders investing in the dirty firm are shareholders with $\lambda \in [0, \hat{\lambda}_G]$, this in turn implies that the average shareholder investing in the dirty firm becomes less concerned about pollution as π increases. Hence, the dirty firm has less incentive to adopt green technology. This is the shareholder base effect. This implies that the green equilibrium is less likely to exist under better disclosure requirements. Using similar arguments, it is also possible to show that the same mechanism also makes the brown equilibrium more likely to prevail.

Moreover, equations (6) and (11) show that when the signal is correct, the output decreases in the precision of the signal in both green and brown equilibrium. In addition, equations (16) and (19) also show that the pollution decreases in the precision of the signal in both equilibria. The reason is that when the precision of the signal increases, the mass of shareholders invested in the dirty firm becomes smaller, which means that the dirty firm receives less funding (i.e., the size of the dirty firm shrinks) at the expense of the clean firm. As the dirty firm is more profitable and more polluting compared to the clean firm, output and pollution decrease as the size of the dirty firm shrinks.

Furthermore, looking at equations (8) and (13) reveals that in both green and brown equilibria, the impact of signal precision π on welfare is ambiguous. This leads to the following proposition.

Proposition 3. *When the signal is correct:*

1. *An increase in precision π leads to two opposite effects. First, a more precise signal increases the expected reduction in pollution perceived by shareholders. Second, a more precise signal makes the average shareholder of the dirty firm less averse to pollution (shareholder base effect). A more precise signal facilitates (hampers) the adoption of green technology if the former (latter) effect dominates the latter (former).*

2. *In any given equilibrium (green and brown), an increase in precision leads to lower output and pollution and has an ambiguous effect on welfare.*

4.2 Signal is incorrect

When the signal is incorrect, recall that all investors choose to invest their wealth in the dirty firm and that the clean firm receives zero funding. In this case, the dirty firm chooses to adopt the green technology at time $t = 2$ if

$$f < (1-\kappa)(1-\pi)e\psi(\overline{\lambda}).$$

It is immediate to see that an increase in precision π makes the green equilibrium harder to achieve. The increase in precision implies that the expected pollution is lower for shareholders; hence, as shareholders perceive pollution as less costly, they are less willing for the dirty firm to adopt the green technology. Moreover, in this case, the shareholder base effect is absent, as the precision of the signal does not affect the composition of the dirty firm's shareholder base.

Moreover, equations (15) and (18) show that the output is independent of the precision of the signal when the signal is incorrect. Furthermore, equations (16) and (19) also show that pollution is independent of the precision of the signal. The reason is that the shareholder base is not affected by the precision of the signal, since all investors decide to invest in the dirty firm when the signal is incorrect.

In addition, (17) and (20) reveal that in both green and brown equilibria, the welfare increases with the precision of the signal. This is because when the signal is incorrect, all investors invest in the dirty firm, and as previously mentioned, the perceived externality decreases as the precision of the signal increases, resulting in higher welfare. This leads to the following proposition.

Proposition 4. *When the signal is incorrect:*

1. *The green equilibrium is less likely to prevail as the signal becomes more precise.*

2. *In a given equilibrium (green and brown), output and pollution are independent of precision, while a more precise signal increases welfare.*

Hence, taking the equilibrium as given, better disclosure requirements improve welfare. However, it also makes the green equilibrium less likely to prevail, which could reduce welfare and increase pollution, as pollution is lower and welfare is higher under the green equilibrium than under the brown equilibrium.

4.3 Equilibrium

Finally, I assess the impact of more stringent disclosure requirements on the expected adoption of green technology. To that extent, consider the condition for green adoption at time $t = 2$ given by (2). The dirty firm is expected to adopt the green technology at time $t = 2$ if

$$f < (1-\kappa)\frac{e}{2}\left[\pi(\psi(\hat{\lambda}_G(\pi)) - \psi(\overline{\lambda})) + \psi(\overline{\lambda})\right] \equiv \hat{f} \tag{22}$$

with $\psi(\hat{\lambda}_G(\pi)) < \psi(\overline{\lambda})$, and we have that

$$\frac{\partial \hat{f}}{\partial \pi} = (1-\kappa)\frac{e}{2}(\psi(\hat{\lambda}_G(\pi)) - \psi(\overline{\lambda})) + (1-\kappa)\frac{e}{2}\pi\frac{\partial \psi}{\partial \pi} < 0 \tag{23}$$

This implies that increasing the stringency of disclosure requirements makes the dirty firm less likely to adopt green technology. Equation (23) shows the marginal effect of an increase in precision π on the constraint for the adoption of green technology.

The first term of equation (23) represents the marginal effect of increasing the precision π on the expected reduction in externality when the signal is correct, multiplied by the difference in shareholders' bases between the case where the signal is correct and incorrect. This effect is negative, given that the difference in shareholder bases is negative. Indeed, a smaller mass of shareholders are invested in the dirty firm when the signal is correct, and these shareholders are, on average, less concerned about pollution. This makes the adoption of green technology more difficult when the signal becomes more precise.

The second term of equation (23) represents the shareholder base effect. It shows the impact of increasing the signal precision on the dirty firm's shareholder base when the signal is correct. We have $\frac{\partial\psi}{\partial\pi} = \frac{\partial\psi}{\partial\hat{\lambda}_G}\frac{\partial\hat{\lambda}_G}{\partial\pi} < 0$, which means that increasing the precision of the signal makes the average shareholder invested in the dirty firm less averse to pollution when π increases. Hence, this implies that the dirty firm is less willing to adopt green technology following an increase in precision. Thus, we can see that both effects go in the same direction and make the constraint on the adoption of green technology tighter, making the dirty firm less likely to adopt green technology at the time $t = 2$. This leads to the following proposition.

Proposition 5. *An increase in signal precision π reduces the incentive of the dirty firm to adopt green technology.*

Moreover, recall from Section 3 that when the signal is correct, the size of the dirty sector shrinks, following an increase in precision π, while the size of the dirty sector is independent of the precision when the signal is incorrect. Hence, an increase in the precision of the signal reduces the expected size of the dirty sector. On this hand, increasing the precision of the signal is beneficial.

However, Proposition 5 shows that increasing the precision of the signal also reduces the incentive for the dirty firm to adopt green technology. This highlights a trade-off behind climate disclosure requirements. On the one hand, improving climate disclosure requirements reduces the size of the dirty sector, thereby reducing externalities. On the other hand, improving climate disclosure requirements also makes the dirty firm less likely to adopt green technology. If this second effect dominates, better climate disclosure requirements could increase pollution and/or result in lower welfare.

This result contradicts the conventional wisdom that better climate disclosure requirements promote the green transition and suggests that some level of greenwashing could be optimal. It also cautions against recent regulations that aim to strengthen climate disclosure requirements. My findings predict that such regulations undermine firms' adoption of green technologies and do not necessarily improve welfare or reduce pollution due to shareholders' endogenous response. This is a novel finding specific to my theory. Before turning to the empirical analysis, I summarize below the testable predictions generated by my theory.

Prediction 1. *Following the implementation of more stringent climate disclosure requirements, polluting firms are held by shareholders who are less averse to pollution.*

Prediction 2. *Green investment should decrease after the implementation of more stringent climate disclosure requirements, particularly for more polluting firms.*

Prediction 1 follows directly from the first part of Proposition 3 that states that if the signal is correct, a more precise signal makes the average shareholder invested in the dirty firm more averse to pollution, and from the result of Section 3.2 that in the case where the signal is incorrect all investors invest in the dirty firm. Taken together, this implies that more stringent climate disclosure requirement (i.e., a more precise signal) makes, on average, the shareholders of the dirty firm less averse to pollution.

Prediction 2 follows directly from the result of Proposition 5, which states that the incentive for the dirty firm to adopt green technology is decreasing in the precision of the signal. This implies that green investment is expected to be lower following the implementation of mandatory climate disclosure requirements. Recall that in my model, only the dirty firm can undertake green investments. Hence, if the dirty firm reduces green investments, green investments decrease in the economy. In practice, all firms can make green investments. Therefore, my model predicts that more stringent climate disclosure reduces green investments, in particular for more polluting firms.

5 Empirical Analysis

I test the model's predictions using data on the staggered adoption of mandatory ESG disclosure requirements across countries from Krueger et al. (2024). I use firms' emissions to distinguish clean and dirty firms. Based on the findings of Dyck et al. (2019), who document that institutional investors are an important driver of firms' sustainability, I use the share of institutional investors to gauge shareholders' aversion to pollution to test Prediction 1. The idea is that if a firm has a higher share of institutional investors, it means that its shareholder base is more averse to pollution or more environmentally friendly. Moreover, I use the number of green patents issued as a proxy for firms' green investments to test Prediction

2.

5.1 Data and Variables

I collect data on mandatory ESG disclosure requirements around the world from Krueger et al. (2024), financial data from Compustat Global and North America, and data on (green) innovations using patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017) for the sample period 2001-2024.[9] I also collect emissions data from Trucost and quarterly institutional investors' holding data from FactSet. Due to data limitation issues, I only have emissions data from 2010 to 2021. Patent data from Kogan et al. (2017) are available up to 2023. I define green patents using the OECD classification of green patents following Haščič and Migotto (2015). I exclude financial (SIC code between 6000 and 6999), utilities (SIC code between 4900 and 4999), and firms with negative book equity or missing data on one of the variables of interest. All continuous variables are winsorized at the 1st and 99th percentiles.

The empirical analysis is divided into two different parts. In the first part, I use institutional investors' holding data to investigate how the composition of shareholder bases varies following the implementation of mandatory ESG disclosure requirements. For this part, I use quarterly institutional investors' holdings from FactSet that I merge with data on the staggered implementation of ESG disclosure requirements around the world from Krueger et al. (2024), financial data from Compustat, and emissions data from Trucost. My final sample for this part comprises 3,028 firm-year observations and 884 unique firms from 41 countries, spanning the period from 2010 to 2020. In the second part of the analysis, I use data on green patents to investigate how green investments vary after the implementation of mandatory ESG disclosure requirements. I use patent data from Kogan et al. (2017) that I merge with the dataset that I get from the first part (i.e., the institutional ownership holding data). Hence, the sample for this part consists of a subsample of the first part and consists of 1,057 firm-year observations and 319 unique firms from 22 countries, spanning the period from 2010 to 2020. More details on the data and variable definitions are provided in Appendix

[9]The sample begins in 2001, as the data on mandatory disclosure requirements are from that year.

B.1. Table 1 provides descriptive statistics for all variables.

5.2 Institutional investors ownership

My model predicts that following the implementation of mandatory disclosure requirements, capital will be reallocated from dirty to clean firms, with dirty firms ending up being held by less responsible investors (Prediction 1), undermining their incentives to make green investments (Prediction 2). As mandatory disclosure requirements are adopted at different points in time for different countries, this corresponds to a staggered difference-in-difference (DiD) specification.

In what follows, I estimate how the share of institutional investors varies following the implementation of mandatory ESG disclosure requirements as a function of firms' emissions. In line with the findings of Dyck et al. (2019), who show that the firms' E&S performance tends to improve with institutional investor ownership, and that this relationship seems to be causal, I assume that institutional investors are, on average, more concerned about pollution than other investors. Hence, according to Prediction 1, the share of institutional investors should decline more for more polluting firms after the implementation of mandatory disclosure requirements. My baseline specification to test Prediction 1 is the following:

$$\begin{aligned}\text{Share inst. investors}_{i,c,t+1} = {} & \beta_1 \text{Mandatory disclosure}_{c,t} \times \text{Above Med Emissions}_{i,c,t} \\ & + \gamma' X_{i,c,t} + \delta_j + \delta_t + \epsilon_{i,c,t+1}, \end{aligned} \tag{24}$$

where Share inst. investors$_{i,c,t+1}$ is median share of institutional investors invested in firm i in country c and year $t+1$. Institutional investors' holding data are available at a quarterly frequency; hence, I take the median over the year as the regression is estimated at a yearly frequency. Mandatory disclosure$_{c,t}$ is a dummy variable equal to one if there is a mandatory ESG disclosure requirement in the country c at year t, Above Med Emissions$_{i,c,t}$ is an dummy variable equal to one in case firm i in country c has above median emissions in year t. $X_{i,c,t}$ is a vector of firm and country-level control variables. As control variables, I follow the literature (see Ferreira and Matos (2008), Dyck et al. (2019)) and include a set of variables that are determinants of institutional investors' ownership. The control variables are log(Market-cap), Dividend yield, log(Capex/Assets), Leverage, Cash/Assets,

Table 1: Descriptive statistics

	Panel A: Institutional investors					
	N	Mean	Std Dev	Q25	Median	Q75
Mandatory Disclosure	3028	0.16	0.36	0.00	0.00	0.00
Share inst. ownership	3028	71.65	27.69	54.88	81.37	93.85
log(Scope 1)	3028	10.44	2.86	8.54	10.21	12.22
log(Scope 1+2)	3028	11.43	2.64	9.67	11.30	13.11
Intensity Scope 1	3028	189.32	542.36	6.94	16.24	56.13
Intensity Scope 1+2	3028	251.76	623.27	19.20	40.98	109.58
Dividend yield	3028	0.01	0.02	0.00	0.00	0.02
Leverage	3028	0.27	0.20	0.11	0.26	0.41
Market-to-book	3028	1.85	1.64	0.87	1.29	2.15
log(Market-cap)	3028	7.91	1.81	6.66	7.98	9.12
log(Capex/Assets)	3028	-3.52	1.16	-4.10	-3.41	-2.75
Cash/Assets	3028	0.20	0.20	0.05	0.13	0.28
log(Market-cap/GDP)	3028	-20.99	3.27	-23.34	-21.62	-18.98
GDP Growth (in %)	3028	1.92	2.41	1.62	2.46	2.95
	Panel B: Green investment					
	N	Mean	Std Dev	Q25	Median	Q75
Mandatory Disclosure	1057	0.16	0.37	0.00	0.00	0.00
Nb Green Patents	1057	3.16	7.20	0.00	0.00	2.00
Nb Green Patents citations	1057	16.71	57.11	0.00	0.00	5.00
log(Scope 1)	1057	10.04	2.98	8.26	9.97	11.59
log(Scope 1+2)	1057	11.15	2.85	9.32	11.03	13.02
Intensity Scope 1	1057	60.03	223.58	6.16	12.92	23.18
Intensity Scope 1+2	1057	97.38	265.86	20.13	36.02	61.66
Size	1057	7.42	2.39	6.03	7.59	9.18
log(K/L)	1057	4.26	1.21	3.55	4.16	4.90
Leverage	1057	0.21	0.17	0.05	0.19	0.32
Cash/Assets	1057	0.28	0.23	0.10	0.22	0.40
Market-to-book	1057	2.36	2.20	1.02	1.70	2.89
Tangibility	1057	0.18	0.17	0.06	0.13	0.23
ROA	1057	-0.01	0.20	-0.03	0.04	0.08
R&D/Assets	1057	0.09	0.11	0.02	0.06	0.12
log(GDP)	1057	29.49	1.82	28.60	30.50	30.66
GDP Growth (in %)	1057	2.10	2.54	1.79	2.46	2.95

This table provides descriptive statistics for all variables defined in Appendix B.1. The sample period is 2010 to 2020. All continuous variables are winsorized at the 1st and 99th percentiles.

Market-to-Book and log(Market-cap/GDP). δ_j and δ_t represent, respectively, industry and year fixed-effects. Industries are defined based on two-digit SIC codes. Standard errors are clustered at the country-year level as laws are adopted at the country level in different years.[10] As the implementation of mandatory ESG disclosure is staggered over time, I use the estimator form Gardner, Thakral, Tô, and Yap (2024) to account for the potential bias resulting from standard OLS estimators in the context of staggered treatments.

The coefficient of interest in this specification is β_1 and shows how the relationship between institutional investors' share and the implementation of mandatory disclosure requirements varies with firms' pollution. According to Prediction 1, β_1 should be negative, as more polluting firms should be held by less responsible investors following the implementation of mandatory climate disclosure requirements.

The results are presented in Table 2. We can see that the coefficient of interest, that is, the coefficient on the interaction terms, is negative and statistically significant, in line with Prediction 1. This indicates that following the implementation of mandatory climate disclosure requirements, the share of institutional investors is becoming smaller for more polluting firms, measured by Scope 1 or Scope 1 and 2 emissions. Using the results from Table 1, we can also infer the economic significance of this result. For firms with above median Scope 1 emissions, the introduction of mandatory climate disclosure reduces their share of institutional investors by about 17%, which corresponds to around 26% of the average share of institutional investors in the sample.[11] Therefore, this result is not only statistically significant but also economically important.

This is consistent with the theoretical prediction that following the implementation of more stringent climate disclosure requirements, capital will be reallocated away from dirty to the clean firms, with dirty firms ending up being financed by investors who are less concerned about pollution, as measured by the decline in the share of institutional investors for more polluting firms.

In Appendix B.2, I perform several robustness checks for this result. First, I estimate a

[10]The results are robust to alternative clustering at the firm or country level.

[11]We have similar results if we use Scope 1 and 2 emissions instead of Scope 1 emissions.

similar specification as (24), but I consider emissions intensity instead of total emissions.[12] As we can see in Table B2, the results continue to hold in this case. In particular, the coefficient on the interaction term remains both statistically and economically significant. Second, I also re-estimate the specification (24), but I interact the dummy variable Mandatory disclosure$_{c,t}$ with another dummy that takes the value of one for firms with emissions above the third quartile emissions (instead of above median emissions). As shown in Table B3, this specification produces results similar to those presented in Table 3. Third, I also consider another specification where I interact the dummy variable Mandatory disclosure$_{c,t}$ with a continuous variable, the natural logarithm of firms' emissions. I show in Table B4 that my results remain robust to this specification as well.

A necessary assumption for identifying the treatment effect in a difference-in-difference specification is the parallel trends assumption. That is, in the absence of treatment, the average change in the outcome variable would have been the same for both treated and control firms. Although this assumption cannot be tested directly, I plot in Figure 1 the difference in the share of institutional investors over time between firms with above and below-median emissions. The figure shows that for the years before the treatment, the coefficients are not statistically different from zero. This implies that the trends in outcomes for the treatment and control groups are similar before the treatment, consistent with the parallel trends assumption. The coefficients only become negative and statistically significant from year $t = +1$ onward, due to the treatment.

[12] Emissions intensity is defined as emissions scaled by revenue, as shown in Table B1.

Table 2: Effect of mandatory disclosure on institutional investors

	(1)	(2)
Mandatory Disclosure x Above Med Scope 1	-16.97***	
	(2.733)	
Mandatory Disclosure x Above Med Scope 1 + 2		-17.23***
		(2.536)
Mean dep. var.	70.346	70.346
Std dep. var.	28.441	28.441
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	1631	1631

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead share of institutional ownership (median over the year computed from quarterly holding data) on an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Med Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

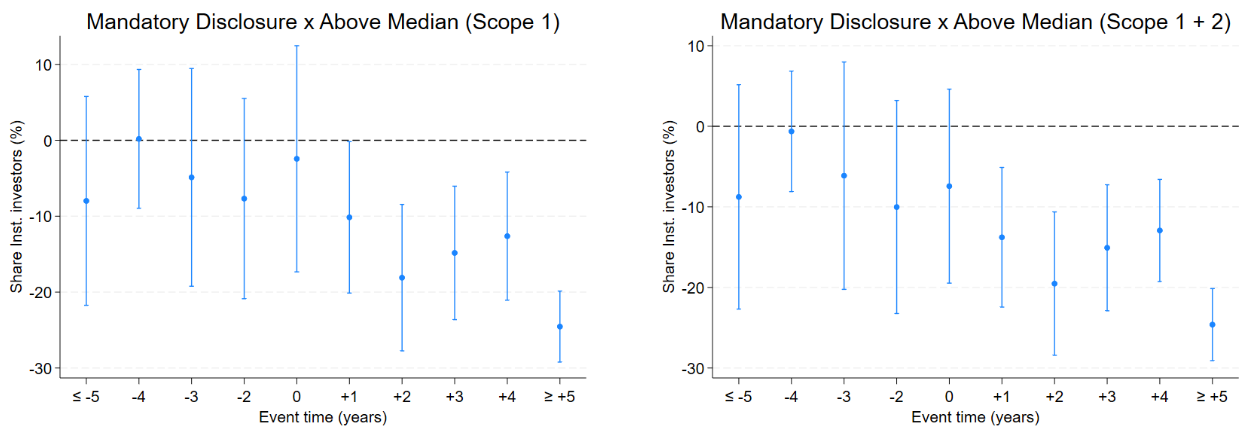

Figure 1: This figure shows the average difference in the share of institutional investors between above and below median emission firms, where emissions are measured by Scope 1 (left panel) and Scope 1+2 (right panel) emissions, conditioning on industry, year fixed-effect, and control variables. The point estimate refers to the coefficient β_2 in specification (24) for each event-time year, together with 95% confidence intervals, relative to year $t = -1$ (which is omitted).

5.3 Green investment

The second key prediction of the model is that, because less environmentally friendly investors ultimately finance dirty firms, they will have lower incentives to invest in green technology, resulting in lower green investment in the economy, as summarized by Prediction 2. I test this prediction by using green patent issuance as a proxy of green investments and the staggered implementation of mandatory ESG disclosure requirements across countries. More specifically, I investigate the effect of the implementation of mandatory disclosure requirements on firms' green patent issuance and how this effect varies with firms' emissions. I estimate the following specification:

$$\begin{aligned}\text{Nb green patents}_{i,c,t+1} = &\ \beta_1 \text{Mandatory disclosure}_{c,t} \\ &+ \beta_2 \text{Mandatory disclosure}_{c,t} \times \text{Above Med Emissions}_{i,c,t} \\ &+ \gamma' X_{i,c,t} + \delta_j + \delta_t + \epsilon_{i,c,t+1},\end{aligned} \tag{25}$$

where Nb green patents$_{i,c,t+1}$ is the number of green patents issued by firm i in country c at year $t+1$, Mandatory disclosure$_{c,t}$ is a dummy variable equal to one if there is a mandatory ESG disclosure requirement in the country c at year t (and equal to zero otherwise), Above Med Emissions$_{i,c,t}$ is a dummy variable equal to one if firm i in country c has above median emissions at year t (and equal to zero otherwise), $X_{i,c,t}$ is a vector of firm and country level control variables, and δ_j, δ_t represent industry and year fixed-effects. As control variables, I follow the empirical literature on innovation (see Schroth and Szalay (2010), Aghion, Van Reenen, and Zingales (2013)) and include the following variables: Size (measured by log(Sale)), log(K/L), Leverage, Market-to-book, Tangibility, ROA, Cash/Assets, R&D/Assets, log(GDP), GDP Growth. Standard errors are clustered at the country-year level. As before, I estimate regression (25) using the Gardner et al. (2024) estimator to account for potential bias resulting from the staggered DiD specification.

The coefficients of interest in equation (25) are β_1 and β_2. When omitting the interaction term, β_1 measures the impact of the implementation of mandatory climate disclosure requirements on the number of green patents issued. According to Prediction 2, β_1 should be negative. β_2 measures how the impact of the adoption of climate disclosure requirements on green innovation varies with firms' pollution. According to Prediction 2, β_2 should also be negative.

Table 3: Effect of mandatory disclosure on green innovation

	(1)	(2)	(3)
Mandatory Disclosure	-4.347***		
	(1.076)		
Mandatory Disclosure x Above Med Scope 1		-5.587***	
		(1.150)	
Mandatory Disclosure x Above Med Scope 1 + 2			-5.591***
			(1.168)
Mean dep. var.	4.015	4.015	4.015
Std dep. var.	8.098	8.098	8.098
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N. obs.	541	541	541

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead number of green patents issued on Mandatory disclosure$_{i,c,t}$ and an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Med Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

In column (1) of Table 3, we can see that the number of green patents issued is significantly lower after the adoption of mandatory ESG disclosure requirements. The effect is statistically and economically significant. We have that the number of patents issued falls by around 4.3 in the year following the adoption of mandatory disclosure requirements. This represents around 100% of the average number of green patents issued per year for all the firms in the sample.

In columns (2) and (3) of Table 3, we can see that β_2 is negative. The interpretation is that following the introduction of mandatory disclosure requirements, the number of green patents issued falls more for more polluting firms. The effect is both statistically and economically significant for both Scope 1 and Scope 1+2 emissions. The reduction in the number of green patents issued after the implementation of mandatory disclosure requirements for a firm with above median Scope 1 emissions decreases by around 5.6, which also represents more than 100% of the average number of green patents issued per year.[13] These results are in line with Prediction 2 that more stringent ESG disclosure requirements hinder the adoption of green technologies, and that the reduction in green investment is mainly driven by more polluting firms.

In Appendix B.2, I perform several robustness checks for this result. First, as shown in Table B2, the results continue to hold in this case where we consider emission intensity instead of total emissions as in specification (25). Second, as shown in Table B6, the results are robust if we consider a dummy that take the value of one for firms with emissions above third quartile emissions instead of above median emissions, or if we consider a specification where the dummy variable Mandatory disclosure$_{c,t}$ is interacted with the natural logarithm of firms' emissions, as shown in Table B7. Moreover, as the number of green patents is a count variable, I also estimate (25) using a Poisson specification. As shown in Table B8, the results continue to hold under this specification. I also report the results from a standard OLS regression, and as we can see, the results are close to those found in Table 3, alleviating concerns regarding potential bias due to heterogenous treatment effect coming from the staggered difference-in-difference specification. Finally, because the distribution of the number of green patents issued per year is highly skewed (as shown in Table 1), with a lot of firms issuing zero green patents during many years, I also consider a similar specification with the natural logarithm of the number of green patents as the dependent variable. As we can see in Table B9, the previous results continue to hold in this case. The number of green patents issued continues to decrease following the implementation of mandatory ESG

[13]These numbers are roughly equal if we take Scope 1+2 emissions instead.

disclosure requirements, and in particular for more polluting firms. Moreover, the decrease remains both statistically and economically significant.

Figure 2 plots the event-time dynamic of the treatment effect of the implementation of mandatory disclosure requirements. We can observe that before the treatment, the coefficients are not statistically different from zero, and become negative only a few years after. As done for the share of institutional investors, Figure 3 plots the year-by-year difference in the number of green patents issued between firms with above and below median emissions, for both Scope 1 and Scope 1+2 emissions. We can see that the difference in the number of green patents issued is not statistically different from zero for the years before the implementation of mandatory disclosure requirements (the treatment), and that it becomes negative only after the treatment.

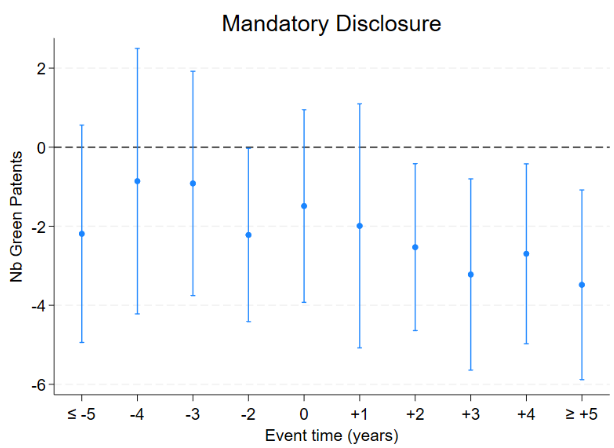

Figure 2: This figure shows the event-time dynamic of mandatory disclosure requirements on the number of green patents issued. The point estimate refers to the coefficient β_1 in specification (25) for each event-time year, together with 95% confidence intervals, relative to year $t = -1$ (which is omitted).

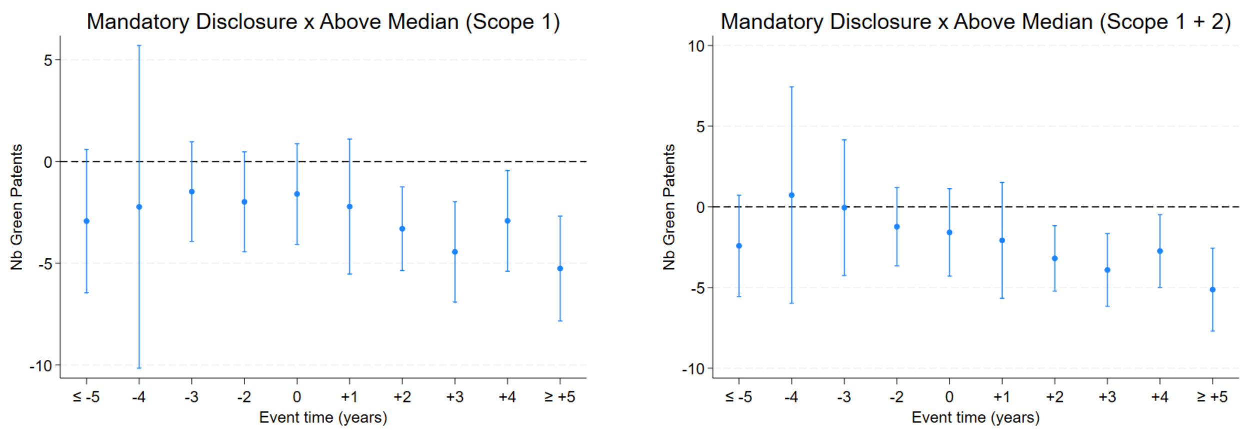

Figure 3: This figure shows the average difference in numbers of green patents issued between above and below median emission firms, where emissions are measured by Scope 1 (left panel) and Scope 1+2 (right panel) emissions, conditioning on industry, year fixed-effect, and control variables. The point estimate refers to the coefficient β_2 in specification (25) for each event-time year, together with 95% confidence intervals, relative to year $t = -1$ (which is omitted).

6 Additional Results and Robustness

6.1 Carbon emissions

My model predicts an ambiguous impact of more stringent climate disclosure requirements on aggregate pollution and welfare, but a negative impact on green investments, particularly for more polluting firms (see Prediction 2). The empirical analysis of Section 5.3 shows that green investments decrease following the implementation of mandatory disclosure requirements, consistent with the theory. In this section, I explore whether this reduction in green investments translates into lower firms' carbon emissions.

I estimate a similar specification as (25), where I use the natural logarithm of the one-year ahead CO_2 emissions as the dependent variable (measured either by Scope 1 or Scope 1+2 emissions).[14] Table B10 illustrates the impact of climate disclosure requirements on firms' emissions. The results show that firm emissions decrease after the implementation

[14]For this specification, I use as control variables: Size, Leverage, Market-to-book, Tangibility, and ROA as in Azar, Duro, Kadach, and Ormazabal (2021).

of mandatory climate disclosure requirements, and in particular for more polluting firms. Although the model does not predict a clear relation between the stringency of climate disclosure requirements and aggregate pollution, the fact that firms' emissions decline more for more polluting firms, as shown by the interaction terms, is consistent with the theoretical prediction that following the implementation of mandatory disclosure requirements, more polluting firms have lower incentives to adopt green technologies. Moreover, this is also consistent with the empirical evidence showing that firms, and in particular more polluting firms, engage less in green innovation.

This finding also relates Azar et al. (2021), who documents that following the investment of large shareholders, polluting firms tend to reduce their carbon emissions, consistent with the fact that those investors engage with firms. In my framework, as the share of institutional investors invested in polluting firms decreases following the adoption of mandatory climate disclosure requirements, one could expect those firms to become more polluting. This channel is indeed confirmed in the data, as after the adoption of mandatory disclosure requirements, the share of institutional investors in more polluting firms decreases, and (polluting) firms' emissions also increase.

6.2 Financing frictions

A potential concern is that the decrease in green investment following the implementation of mandatory climate disclosure requirements may be driven by an increase in firms' cost of capital rather than a change in their shareholder base composition.

Indeed, as shown in Section 5.2, the share of institutional investors invested in more polluting firms drops following the implementation of mandatory climate disclosure requirements. If institutional investors have price impacts, this could result in an increase in the cost of capital for more polluting firms, thereby leading to underinvestment in green technologies, as in Hartzmark and Shue (2022) for instance.[15] I test this hypothesis by regressing the

[15] A body of literature in asset pricing has demonstrated that investors can have price impact when rebalancing from brown to green stocks, thereby raising brown firms' cost of capital (see, for instance Pástor et al. (2022), Van der Beck (2021)).

one-year-ahead firms' equity return on the dummy variable for mandatory disclosure and the interaction of the dummy variable for mandatory disclosure and a dummy variable equal to one for above median emission firms. If, following the implementation of mandatory climate disclosure requirements, divestment from institutional investors generates price impact, then the one-year-ahead equity return should decrease, corresponding to an increase in the cost of capital for those firms. Hence, if this channel is effective, the coefficient from the regression of the one-year ahead cost of capital on the dummy for the mandatory disclosure implementation should be negative, and the same should be true for the coefficient of the interaction term between the mandatory disclosure dummy the the above median emission dummy, reflecting that the effect should be more pronounced for more polluting firms. The results are shown in Table B11. As we can see in the table, the implementation of the mandatory disclosure requirement does not affect equity return, as none of the coefficients are statistically different from zero. The coefficient on the interaction term is also not statistically different from zero, which implies that divestment from institutional investors in more polluting firms does not materially affect their cost of capital. Hence, these findings contradict the hypothesis that firms' green investments decrease due to an increase in their cost of capital resulting from institutional investors' divestment.

As an additional robustness check, I also investigate how the firms' cost of debt varies following the implementation of the mandatory disclosure requirements. Similarly, if, following the implementation of mandatory disclosure requirements, firms' cost of debt is becoming higher, this could also explain the reduction in green investment after the implementation of mandatory disclosure requirements. Therefore, I also test for this alternative channel by regressing the one-year-ahead cost of debt on the dummy variable for mandatory disclosure requirements implementation and the interaction between the dummy for mandatory disclosure and above median emissions. As shown in Table B11, the results show that the cost of debt is not increasing but is either remaining constant or decreasing following the implementation of mandatory disclosure requirements. Therefore, this eliminates the possibility that firms reduce green investment because they are facing a higher cost of debt and thereby increasing their cost of capital, or preventing them from borrowing to invest in green technologies, for instance.

Finally, another related channel could be that following the implementation of mandatory disclosure requirements, firms reduce green investments because they are becoming more financially distressed, due to an increase in reputational risk, for instance.[16] I test for this alternative channel using the Altman Z-Score as a measure of financial distress. Specifically, I use a dummy variable that takes the value one in case the firm has an Altman Z-Score in the bottom decile of the sample, and I regress the one-year-ahead value of this variable on the dummy variable for mandatory disclosure requirements implementation and the interaction between the dummy for mandatory disclosure and above median emissions. The results in Table B11 show that firms are not becoming more likely to become financially distressed following the implementation of mandatory disclosure requirements. Therefore, this rules out the potential explanation that firms would reduce green investments in response to enhanced climate disclosure requirements because mandatory climate disclosure requirements make them more financially distressed.

6.3 Measurement of innovation

Patents citations. In Section 5.3, I document a decrease in the number of green patents issued following the adoption of mandatory disclosure requirements, and particularly for more polluting firms. In Appendix B.2, I show that these results are robust when using the number of green patents weighted by citations, rather than simply the number of green patents issued, as is more common in the literature on innovation (see, for instance Schroth and Szalay (2010), Aghion et al. (2013)). In particular, I show that the results from my main specification given by equation (25) are robust when considering the number of green patents weighted by citations. In Table B12, I further show that the results continue to hold for patent citations. These findings establish that my results are not sensitive to the measurements of green innovation.

R&D expenditures. In the baseline analysis, I proxy green investment by green patents, as patents can be classified between green and non-green following the OECD classification method. However, the number of (green) patents is an output-based measure of innova-

[16] This relates to the findings of Bellon and Boualam (2024), who shows that firms tend to increase pollution intensity when becoming financially distressed.

tion, measuring successful innovations. Moreover, not all types of innovations are patented. For instance, firms could invest in R&D not only to develop new technologies but also to improve their ability to adopt externally developed technologies.[17] Hence, I also consider measuring green innovation using R&D expenditures, an input-based measure of innovation. Although I cannot differentiate between green and non-green R&D expenditures, I use total R&D expenditures as a proxy for green R&D expenditures, a proxy commonly used in the sustainable finance literature (see Brown, Martinsson, and Thomann (2022), Brown, Martinsson, Strömberg, and Thomann (2024)). Hence, I re-estimate specification (25) using the natural logarithm of R&D expenditures as a dependent variable, using the same control variables as in Section 5.3.[18] Table B13 shows that following the adoption of mandatory climate disclosure requirements, firms invest significantly less in R&D, and that this effect is more pronounced for more polluting firms. The results are both economically and statistically significant.

7 Conclusion

In this paper, I develop a model where two firms, clean and dirty, are financed by a mass of responsible investors who are heterogeneous in their aversion to holding polluting firms. The dirty firm is more productive than the clean firm but generates pollution. After receiving funding from investors, the dirty firm decides whether to operate its current production technology or to adopt a less polluting or green technology at a cost. Investors decide which firm to invest in, anticipating firms' adoption decisions. However, investors do not know which firm is polluting, but they receive an informative signal before investing about which firm is clean and which is dirty. The precision of the signal is exogenous and represents the stringency of climate disclosure requirements.

In this framework, I demonstrate that increasing the stringency of climate disclosure requirements decreases the mass of investors who choose to invest in the dirty firm, thereby

[17]See Cohen and Levinthal (1989) and Cohen, Levinthal, et al. (1990).

[18]Note that I do not include R&D expenditures in the control variables since it becomes the dependent variable.

reducing pollution. On the other hand, more stringent climate disclosure requirements also reshape firms' shareholder base, resulting in the dirty firm being financed by investors who, on average, are less concerned about pollution. The latter effect undermines the incentive of the dirty firm to adopt green technology. Therefore, the impact of more stringent climate disclosure requirements on pollution and welfare is ambiguous. This result challenges the conventional view that improving climate disclosure requirements is beneficial and suggests that some level of greenwashing could be optimal. It also constitutes caution against recent regulations that aim to strengthen climate disclosure requirements.

I also provide empirical evidence supporting the novel predictions of my theory. Using data on the staggered implementation of mandatory ESG disclosure requirements across countries, I show that after the implementation of mandatory disclosure requirements, the share of institutional investors, who have been recognized to be an important driver of firms' sustainability, invested in polluting firms decreases. I also show that green investment decreases and that this effect is more pronounced for more polluting firms. This is consistent with the theoretical prediction that, after the implementation of more stringent climate disclosure requirements, capital is reallocated away from dirty to clean firms, with dirty firms ending up being financed by investors who care less about pollution, in turn undermining incentives for these firms to adopt greener technologies.

References

Acemoglu, D., & Rafey, W. (2023). Mirage on the horizon: Geoengineering and carbon taxation without commitment. *Journal of Public Economics*, *219*, 104802.

Aghamolla, C., & An, B.-J. (2023). Mandatory vs. voluntary esg disclosure, efficiency, and real effects. *Nanyang Business School Research Paper*(22-41).

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. *American economic review*, *103*(1), 277–304.

Allen, F., Barbalau, A., & Zeni, F. (2023). Reducing carbon using regulatory and financial market tools. *Available at SSRN*, *4357160*.

Azar, J., Duro, M., Kadach, I., & Ormazabal, G. (2021). The big three and corporate carbon emissions around the world. *Journal of Financial Economics*, *142*(2), 674–696.

Bellon, A., & Boualam, Y. (2024). Pollution-shifting vs. downscaling: How financial distress affects the green transition. *Kenan Institute of Private Enterprise Research Paper*(4761314).

Berk, J. B., & Van Binsbergen, J. H. (2025). The impact of impact investing. *Journal of Financial Economics*, *164*, 103972.

Bisceglia, M., Piccolo, A., & Schneemeier, J. (2022). Externalities of responsible investments. *Available at SSRN 4183855*.

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

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

Bonnefon, J.-F., Landier, A., Sastry, P., & Thesmar, D. (2025). The moral preferences of investors: Experimental evidence. *Journal of Financial Economics*, *163*, 103955.

Broccardo, E., Hart, O., & Zingales, L. (2022). Exit versus voice. *Journal of Political Economy*, *130*(12), 3101–3145.

Brown, J. R., Martinsson, G., Strömberg, P., & Thomann, C. (2024). *Carbon pricing and investment* (Tech. Rep.). Working Paper.

Brown, J. R., Martinsson, G., & Thomann, C. (2022). Can environmental policy encourage technical change? emissions taxes and r&d investment in polluting firms. *The Review* *of financial studies*, *35*(10), 4518–4560.

Chen, H., & Schneemeier, J. (2022). Responsible investors and stock market feedback. *Available at SSRN 4296418*.

Chowdhry, B., Davies, S. W., & Waters, B. (2019). Investing for impact. *The Review of Financial Studies*, *32*(3), 864–904.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: the two faces of r & d. *The economic journal*, *99*(397), 569–596.

Cohen, W. M., Levinthal, D. A., et al. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly*, *35*(1), 128–152.

Davies, S. W., & Van Wesep, E. D. (2018). The unintended consequences of divestment. *Journal of Financial Economics*, *128*(3), 558–575.

Döttling, R. J., Levit, D. Y., Malenko, N., & Rola-Janicka, M. A. (2024). *Voting on public goods: Citizens vs. shareholders* (Tech. Rep.). National Bureau of Economic Research.

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? international evidence. *Journal of financial economics*, *131*(3), 693–714.

Edmans, A., Levit, D., & Schneemeier, J. (2022). Socially responsible divestment. *European Corporate Governance Institute–Finance Working Paper*(823).

Emiris, M., Harris, J., & Koulischer, F. (2024). The effect of environmental preferences on investor responses to esg disclosure. *Available at SSRN 4457989*.

Ferreira, M. A., & Matos, P. (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of financial economics*, *88*(3), 499–533.

Gardner, J., Thakral, N., Tô, L. T., & Yap, L. (2024). Two-stage differences in differences.

Gryglewicz, S., Mayer, S., & Morellec, E. (2024). Investor activism and the green transition.

Gupta, D., Kopytov, A., & Starmans, J. (2022). The pace of change: Socially responsible investing in private markets. *Available at SSRN*.

Gupta, D., & Starmans, J. (2024). Dynamic green disclosure requirements. *Available at SSRN 4557187*.

Hartzmark, S. M., & Shue, K. (2022). Counterproductive sustainable investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

Haščič, I., & Migotto, M. (2015). Measuring environmental innovation using patent data.

Heeb, F., Kölbel, J. F., Paetzold, F., & Zeisberger, S. (2023). Do investors care about impact? *The Review of Financial Studies*, *36*(5), 1737–1787.

Heinkel, R., Kraus, A., & Zechner, J. (2001). The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis*, *36*(4), 431–449.

Huang, S., & Kopytov, A. (2023). Sustainable finance under regulation.

Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies*, *36*(7), 2617–2650.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The quarterly journal of economics*, *132*(2), 665–712.

Krueger, P., Sautner, Z., Tang, D. Y., & Zhong, R. (2024). The effects of mandatory esg disclosure around the world. *Journal of Accounting Research*, *62*(5), 1795–1847.

Landier, A., & Lovo, S. (2024). Socially responsible finance: How to optimize impact. *The Review of Financial Studies*, hhae055.

Levit, D., Malenko, N., & Maug, E. (2024). Trading and shareholder democracy. *The Journal of Finance*, *79*(1), 257–304.

Oehmke, M., & Opp, M. M. (2024). A theory of socially responsible investment. *Review of Economic Studies*, rdae048.

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

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

Schroth, E., & Szalay, D. (2010). Cash breeds success: The role of financing constraints in patent races. *Review of Finance*, *14*(1), 73–118.

Van der Beck, P. (2021). *Flow-driven esg returns* (Tech. Rep.). Swiss Finance Institute.

Xue, H. (2023). Esg disclosure, market forces, and firm investment.

Zhang, S. (2025). Carbon returns across the globe. *The Journal of Finance*, *80*(1), 615–645.

Appendix

A Theory

A.1 Preferences for Impact

In this section, I extend the baseline model of Section 2 by considering the case where investors have preferences for impact, as in e.g., Gupta, Kopytov, and Starmans (2022), Oehmke and Opp (2024). For brevity, I only focus on changes relative to the baseline model of Section 2. Investors derived a positive utility $\lambda \in [0, \overline{\lambda}] \sim G(\lambda)$ per unit of perceived externality reduction. That is, they derive a positive utility of $+\lambda e$ if they expect the firm to reduce its externality by e units.

At time $t = 1$, investors' valuation of one dollar invested in firm $i = 1, 2$ is now given by

$$v_i = \alpha_i - f\mathbb{1}_{\{a_i=1\}} + \lambda(\mathbb{E}[e_i|s, a_i = 0] - \mathbb{E}[e_i|s, a_i = 1]),$$

where $\mathbb{E}[e_i|s, a_i = 1]$ is the expected externality of firm i, after having observed the signal $s = \{F_1, F_2\}$, when investors expect firm i to adopt the green technology, and $\mathbb{E}[e_i|s, a_i = 0]$ is the expected externality of firm i when investors expect firm i not to adopt the green technology. Hence, investors derived a positive utility from the expected externality reduction of the firm. At time $t = 2$, the dirty firm decides to adopt the green technology if and only if

$$\int_0^{\hat{\lambda}} (\alpha_d - f + \lambda(1 - \kappa)\mathbb{E}[e_i|s])dG(\lambda) > \int_0^{\hat{\lambda}} \alpha_d dG(\lambda),$$

which is equivalent to

$$f < (1 - \kappa)\mathbb{E}[e_i|s])\psi(\hat{\lambda}). \tag{A.1}$$

As for the baseline model, we can characterize the solution as a function of the realization of the signal s, by assuming, without loss of generality, that firm 1 is the clean firm.

A.1.1 Signal is correct

When $s = F_1$ (signal is correct), then all investors invest in the dirty firm since $\alpha_2 + \lambda(1 - \kappa)e\pi > \alpha_1$, as $\alpha_1 = \alpha_c$ and $\alpha_2 = \alpha_d$. At $t = 2$, the dirty firm decides to adopt green technology if

$$f < (1-\kappa)\pi e\psi(\overline{\lambda})$$

and does not adopt otherwise.

A.1.2 Signal is incorrect

When $s = F_2$ (signal is incorrect), there are two equilibria, a brown equilibrium in which the dirty firm does not adopt, and a green equilibrium in which it adopts the green technology.

In the brown equilibrium, the dirty firm does not adopt the green technology, and all investors invest in the dirty firm as $\alpha_d = \alpha_2 > \alpha_1 = \alpha_c$, and they anticipate the dirty firm not to adopt. At time $t = 2$, the dirty firm decides not to adopt the green technology if

$$f > (1-\kappa)e(1-\pi)\psi(\overline{\lambda}).$$

In the green equilibrium, the dirty firm adopts green technology at time $t = 2$. At time $t = 1$, investors invest in the clean firm if

$$\lambda > \frac{\Delta + f}{(1-\kappa)e\pi} \equiv \lambda_G,$$

and in the dirty firm if $\lambda < \hat{\lambda}_G$, where $\frac{\partial \hat{\lambda}_G}{\partial \pi} < 0$. At time $t = 2$, the dirty firm adopts the green technology if

$$f < (1-\kappa)(1-\pi)e\psi(\hat{\lambda}_G(\pi)),$$

with $\frac{\partial \psi(\hat{\lambda})}{\partial \pi} < 0$.

A.1.3 Expected adoption decision

Taking into account both realizations of the signal, the dirty firm is expected to adopt the green technology at time $t = 2$ if

$$f < (1-\kappa)\frac{e}{2}\left[\pi(\psi(\overline{\lambda}) - \psi(\hat{\lambda}_G)) + \psi(\hat{\lambda}_G))\right] \equiv \hat{f}$$

with

$$\frac{\partial \hat{f}}{\partial \pi} = (1-\kappa)\frac{e}{2}\left[\psi(\overline{\lambda}) - \psi(\hat{\lambda}_G) + (1-\pi)\frac{\partial \psi(\hat{\lambda}_G)}{\partial \pi}\right] < 0.$$

Hence, Predictions 1 and 2 continue to hold.

A.2 Proof of Lemma 2

The green equilibrium exists if $f < (1-\kappa)e\pi\psi(\hat{\lambda}_G(f))$. Let f^1 be the solution of the equation $f = (1-\kappa)e\pi\psi(\hat{\lambda}_G(f))$. Since the right-hand side of this equation increases in f and is positive when $f = 0$, this implies that this equation has a unique solution $f^1 > 0$. Hence, the green equilibrium exists whenever $f \in [0, f^1]$. Moreover, we have

$$W_G^1 = \alpha_c + (\Delta - f)G(\hat{\lambda}_G) - \kappa\pi e \int_0^{\hat{\lambda}_G} \lambda dG(\lambda) = W_G^1(f, \kappa)$$
$$W_B^1 = \alpha_c + \Delta G(\hat{\lambda}_B) - \pi e \int_0^{\hat{\lambda}_B} \lambda dG(\lambda)$$

Assuming that W_G^1 is decreasing in κ,[19] we have that $W_G^1(0,\kappa) > W_G^1(0,1)$ as and by assumption $\kappa < 1$. Moreover, inspection of equations (4), (9) and W_G^1 above reveal that $W_G^1(0,1) = W_B^1$ thus $W_G^1(0,\kappa) > W_B^1$. Now, consider $f \in [0, f^1]$ so that the green equilibrium exists. Define $\overline{f}^1 = f^1$ if $W_G^1(f) > W_B^1 \; \forall f \in [0, f^1]$. If $\exists \tilde{f} \in [0, f^1]$ such that $W_G^1(f) < W_B^1$ then $\overline{f}^1 = \inf\{f \in [0, f^1] : W_G^1(f) < W_B^1\}$.

A.3 Proof of Proposition 1

Case 1: If $f > (1-\kappa)e\pi\psi(\overline{\lambda})$ then we have that $\psi(\hat{\lambda}) < \psi(\overline{\lambda}) < \frac{f}{(1-\kappa)e\pi}$ for $\hat{\lambda} \in [0, \overline{\lambda}]$, therefore the green equilibrium does not exists.

Case 2: If $f \leq (1-\kappa)e\pi\psi(\overline{\lambda}) \iff \psi(\overline{\lambda}) \geq \frac{f}{(1-\kappa)e\pi}$, then there exists a unique $\underline{\Delta}$ such that $\psi(\hat{\lambda}_G(\underline{\Delta})) = \frac{f}{(1-\kappa)e\pi}$. Similarly, there exists a unique $\overline{\Delta} \leq \overline{\lambda}(2\pi - 1)e$ such that $\psi(\hat{\lambda}_B(\overline{\Delta})) = \frac{f}{(1-\kappa)e\pi}$. This implies that the green equilibrium exists for $\Delta \geq \underline{\Delta}$ and the brown equilibrium exists for $\Delta < \overline{\Delta}$. Next, we can show that $\overline{\Delta} > \underline{\Delta}$. Assume that $\Delta = \overline{\Delta}$, then $\psi(\hat{\lambda}_B(\overline{\Delta})) = \frac{f}{(1-\kappa)e\pi}$ which implies that $\overline{\Delta} > \frac{(2\pi-1)f}{(1-\kappa)\pi}$, by using (4) and the fact that $\psi(\hat{\lambda}) < \hat{\lambda}$. Moreover, using (9), after tedious computations we can show that $\hat{\lambda}_G(\overline{\Delta}) > \hat{\lambda}_B(\overline{\Delta})$ and therefore $\psi(\hat{\lambda}_G(\overline{\Delta})) > \psi(\hat{\lambda}_B(\overline{\Delta})) = \frac{f}{(1-\kappa)e\pi}$ which implies that the green equilibrium exists if $\Delta = \overline{\Delta}$ and that $\overline{\Delta} > \underline{\Delta}$ as $\psi(\hat{\lambda}_G(\overline{\Delta})) > \psi(\hat{\lambda}_G(\underline{\Delta})) = \frac{f}{(1-\kappa)e\pi}$.

Finally, we can show that when both equilibria exist then $\hat{\lambda}_G > \hat{\lambda}_B$. First, we have that $\hat{\lambda}_G\big(\Delta = \frac{(2\pi-1)f}{(1-\kappa)\pi}\big) = \frac{f}{(1-\kappa)e\pi}$. Moreover, we have $\psi\big(\hat{\lambda}_G\big(\Delta = \frac{(2\pi-1)f}{(1-\kappa)\pi}\big)\big) = \psi\big(\frac{f}{(1-\kappa)e\pi}\big) < \frac{f}{(1-\kappa)e\pi}$

[19]This assumption is sufficient but not necessary.

which implies that the green equilibrium does not exist if $\Delta = \frac{(2\pi-1)f}{(1-\kappa)\pi}$. Hence, $\underline{\Delta} > \frac{(2\pi-1)f}{(1-\kappa)\pi}$ as the green equilibrium exists for $\Delta \geq \underline{\Delta}$. If the green equilibrium exists then $\Delta \geq \underline{\Delta} > \frac{(2\pi-1)f}{(1-\kappa)\pi}$ and $\hat{\lambda}_G - \hat{\lambda}_B > 0 \iff \Delta > \frac{(2\pi-1)f}{(1-\kappa)\pi}$. Therefore, if both green and brown coexist then $\hat{\lambda}_G > \hat{\lambda}_B$. When both equilibria coexist, we have that $\hat{\lambda}_G > \hat{\lambda}_B$, which implies that polluting firms receive more capital in the green equilibrium but also pollute less. Hence, it could be that pollution is higher in the green than in the brown equilibrium, as shown by Huang and Kopytov (2023).

A.4 Proof of Proposition 3

The first part of the proposition follows directly from the interpretation of equation (21) in the text. The second part of the proposition can be demonstrated by taking the derivative of equations (6)-(8) and (11)-(13) with respect to π.

A.5 Proof of Proposition 4

The first part of the proof follows directly from the text. The proof for the second part follows directly from equations (15)-(17) and (18)-(20).

B Empirics

B.1 Variables Definitions

Table B1: Variable Descriptions and Sources

Variable	Description	Source
Mandatory Disclosure	Dummy variable equals one starting from the first year in which a country introduced mandatory ESG disclosure, and zero otherwise.	Krueger et al. (2024)

Variable	Description	Source
Share inst. ownership	Share of institutional investors in a given firm (median over the year).	FactSet
Nb Green Patents	Number of green patents issued during a given year. Green patents are patents with CPC code Y02, based on the OECD classification.	Kogan et al. (2017)
Nb Green Patents citations	Number of green patents issued weighted by the number of citations. Green patents are patents with CPC code Y02, based on the OECD classification.	Kogan et al. (2017)
log(Scope 1)	Natural logarithm of firms' scope 1 emissions.	Trucost
log(Scope 1 + 2)	Natural logarithm of firms' scope 1 and 2 emissions.	Trucost
Intensity Scope 1	Scope 1 emissions scaled by revenue	Trucost
Intensity Scope 1 + 2	Scope 1 and 2 emissions scaled by revenue	Trucost
Size	Natural logarithm of sales, i.e, log(*sale*).	Compustat
Dividend yield	Ratio of dividend per share Ex-Date (dvpsx_f) to closing share price prccm.	Compustat
log(K/L)	Natural logarithm of the physical capital (ppent) to labor (emp).	Compustat
Leverage	Ratio of total debt (dlc + dltt) to total assets (at).	Compustat
Market-to-Book	Ratio of the market value of equity (abs(prcc_f) * csho) and total debt (dlc + dltt) to total assets (at).	Compustat

Variable	Description	Source
Tangibility	Ratio of property, plant, and equipment (ppent) to total assets (at).	Compustat
ROA	Return on assets, calculated as net income (ni) divided by total assets (at).	Compustat
Cash/Assets	Ratio of cash (che) to total assets (at).	Compustat
R&D/Assets	R&D expenditure (xrd) divided by total assets (at).	Compustat
log(Market-cap)	Natural logarithm of market value of equity (abs(prcc_f) * csho).	Compustat
log(Capex/Assets)	Capital expenditure divided (capx) by total assets (at).	Compustat
log(Market-cap/GDP)	Natural logarithm of market value of equity (abs(prcc_f) * csho) divided by total GDP.	Compustat/World Bank
log(GDP per capita)	Natural logarithm of GDP per capita.	World Bank
log(GDP)	Natural logarithm of total GDP.	World Bank
GDP Growth	Growth rate of total GDP (in %).	World Bank
Annual return	Annual equity return	Compustat
Cost of debt	Ratio between interest expenses (xint) over total debt (dltt + dlc).	Compustat
Low Z-score	Dummy variable that takes the value one if the firm's Altman Z-Score is in the bottom decile of the sample.	Compustat

B.2 Additional Results

Table B2: Institutional investors - Above median Emissions intensity

	(1)	(2)
Mandatory Disclosure x Above Med Int Scope 1	-14.23***	
	(3.265)	
Mandatory Disclosure x Above Med Int Scope 1 + 2		-13.70***
		(3.103)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	1631	1631

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead share of institutional ownership (median over the year computed from quarterly holding data) on an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Med Int Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B3: Institutional investors - Above Q3 Emission dummy

	(1)	(2)
Mandatory Disclosure x Above Q3 Scope 1	-17.13***	
	(2.831)	
Mandatory Disclosure x Above Q3 Scope 1 + 2		-16.41***
		(2.882)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	1631	1631

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead share of institutional ownership (median over the year computed from quarterly holding data) on an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Q3 Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B4: Institutional investors - log(Emissions)

	(1)	(2)
Mandatory Disclosure x log(Scope 1)	-1.308***	
	(0.172)	
Mandatory Disclosure x log(Scope 1 + 2)		-1.178***
		(0.163)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	1631	1631

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead share of institutional ownership (median over the year computed from quarterly holding data) on an interaction term Mandatory disclosure$_{c,t}$ $\times$ log(Emissions)$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B5: Green innovation - Above median Emissions intensity

	(1)	(2)
Mandatory Disclosure x Above Med Int Scope 1	-4.779***	
	(1.197)	
Mandatory Disclosure x Above Med Int Scope 1 + 2		-4.404***
		(1.420)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	541	541

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead number of green patents issued on an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Int Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B6: Green innovation - Above Q3 Emission dummy

	(1)	(2)
Mandatory Disclosure x Above Q3 Scope 1	-5.902***	
	(1.232)	
Mandatory Disclosure x Above Q3 Scope 1 + 2		-5.573***
		(1.230)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	541	541

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead number of green patents issued on an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Q3 Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B7: Green innovation - log(Emissions)

	(1)	(2)
Mandatory Disclosure x log(Scope 1)	-0.401***	
	(0.0797)	
Mandatory Disclosure x log(Scope 1 + 2)		-0.372***
		(0.0763)
Controls	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
N. obs.	541	541

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead number of green patents issued on an interaction term Mandatory disclosure$_{c,t}$ $\times$ log(Emissions)$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B8: Green innovation - Poisson specification

	OLS			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Scope 1	Scope 1+2	Total	Scope 1	Scope 1+2
Mandatory Disclosure	-1.998***			-0.398***		
	(0.763)			(0.116)		
Mandatory Disclosure x Above Med Scope 1		-3.101***			-0.376***	
		(0.827)			(0.116)	
Mandatory Disclosure x Above Med Scope 1 + 2			-3.073***			-0.370***
			(0.846)			(0.116)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	537	537	537	530	530	530

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the OLS and Poisson regressions of the one-year-ahead number of green patents issued on Mandatory disclosure$_{i,c,t}$ and an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Med Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B9: Green innovation - log(Nb green patents)

	(1)	(2)	(3)
Mandatory Disclosure	-0.811***		
	(0.217)		
Mandatory Disclosure x Above Med Scope 1		-0.819***	
		(0.220)	
Mandatory Disclosure x Above Med Scope 1 + 2			-0.819***
			(0.220)
Mean dep. var.	1.377	1.377	1.377
Std dep. var.	1.145	1.145	1.145
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N. obs.	281	281	281

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the natural logarithm of the one-year-ahead number of green patents issued on Mandatory disclosure$_{i,c,t}$ and an interaction term Mandatory disclosure$_{c,t} \times$Above Med Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B10: CO_2 emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mandatory Disclosure	0.503***	0.221**						
	(0.131)	(0.092)						
Mandatory Disclosure × Above Med Scope 1			0.770***					
			(0.129)					
Mandatory Disclosure × Above Med Scope 1+2				0.300***				
				(0.096)				
Mandatory Disclosure × Above Med Int Scope 1					1.077***			
					(0.162)			
Mandatory Disclosure × Above Med Int Scope 1+2						0.694***		
						(0.132)		
Mandatory Disclosure × Above Q3 Scope 1							0.964***	
							(0.145)	
Mandatory Disclosure × Above Q3 Scope 1+2								0.375***
								(0.110)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	640	640	640	640	640	640	640	640

This table shows the estimates of the regression of the one-year-ahead natural logarithm of emissions measured by Scope 1 (columns (1), (3), (5) and (7)) or Scope 1+2 emissions (columns (2), (4), (6) and (8)) on Mandatory disclosure$_{i,c,t}$ and an interaction term, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B11: Financing channel

	Annual return			Cost of debt			Low Z-score		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mandatory Disclosure	0.011			0.013			0.016		
	(0.053)			(0.008)			(0.023)		
Mandatory Disclosure × Above Med Scope 1		-0.076			-0.027***			-0.053**	
		(0.056)			(0.008)			(0.024)	
Mandatory Disclosure × Above Med Scope 1+2			-0.010			0.002			-0.032
			(0.056)			(0.008)			(0.027)
Controls	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	1631	1631	1631	1135	1135	1135	1188	1188	1188

This table shows the estimates of the regression of the one-year-ahead Annual return, cost of debt and Low Z-score dummy on Mandatory disclosure$_{i,c,t}$ and an interaction term Mandatory disclosure$_{c,t}$ $\times$ Above Med Emissions$_{i,c,t}$ where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B12: Green patents citations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mandatory Disclosure	-42.03***						
	(12.78)						
Mandatory Disclosure x Above Med Scope 1		-54.68***					
		(13.82)					
Mandatory Disclosure x Above Med Scope 1 + 2			-54.05***				
			(13.97)				
Mandatory Disclosure x Above Med Int Scope 1				-62.52***			
				(17.19)			
Mandatory Disclosure x Above Med Int Scope 1 + 2					-64.86***		
					(18.37)		
Mandatory Disclosure x Above Q3 Scope 1						-61.30***	
						(14.93)	
Mandatory Disclosure x Above Q3 Scope 1 + 2							-58.40***
							(14.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	541	541	541	541	541	541	541

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead number of green patents issued weighted by citations on Mandatory disclosure$_{i,c,t}$ and an interaction term where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables. The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B13: R&D expenditures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mandatory Disclosure	-0.636***						
	(0.105)						
Mandatory Disclosure × Above Med Scope 1		-0.560***					
		(0.114)					
Mandatory Disclosure × Above Med Scope 1+2			-0.564***				
			(0.115)				
Mandatory Disclosure × Above Med Int Scope 1				-0.592***			
				(0.150)			
Mandatory Disclosure × Above Med Int Scope 1+2					-0.647***		
					(0.164)		
Mandatory Disclosure × Above Q3 Scope 1						-0.420***	
						(0.134)	
Mandatory Disclosure × Above Q3 Scope 1+2							-0.544***
							(0.122)
Mean dep. var.	-3.290	-3.290	-3.290	-3.290	-3.290	-3.290	-3.290
Std dep. var.	1.342	1.342	1.342	1.342	1.342	1.342	1.342
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. obs.	534	534	534	534	534	534	534

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the estimates of the regression of the one-year-ahead natural logarithm of RD expenditure (scaled by total assets) on Mandatory disclosure$_{i,c,t}$ and an interaction term where emissions are measured by either Scope 1 emissions or Scope 1 and 2 emissions, and a set of control variables (the same as in Table 3). The regressions include industry and year fixed effects. Standard errors (in parentheses) are clustered at the country-year level.

Table B14: Descriptive statistics - Financing

	N	Mean	Std Dev	Q25	Median	Q75
Annual return	2806	0.16	0.79	-0.21	0.03	0.34
Altman Z- Score	1976	3.57	5.06	1.37	2.45	4.28
Cost of debt	1826	0.07	0.16	0.03	0.05	0.07

This table presents descriptive statistics for the financing variables defined in Appendix B.1. The sample period is 2010 to 2020. All variables are winsorized at the 1st and 99th percentiles.