Working Paper

# Corporate Strategy for the Green Transition: Are Executive Incentives Effective?

Cécile Cezanne[1], Francesco Quatraro[2] Sandra Rigot[3], and Eleonora Rubichi4

**Contacts**

cecile.cezanne@univ-cotedazur.fr

sandra.rigot@univ-paris13.fr

francesco.quatraro@unito.it

eleonora.rubichi@unito.it

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[1] Université Côte d'Azur – Groupe de Recherche en Droit, Economie, Gestion (GREDEG) –, France ; Chaire Energie & Prospérité

[2] Department of Economics and Statistics 'Cognetti De Martiis', University of Turin, Italy ; BRICK, Collegio Carlo Alberto, Turin, Italy

[3] Université Sorbonne Paris Nord – UFR SEG –, France ; Chaire Energie & Prospérité

[4] Université Côte d'Azur – Groupe de Recherche en Droit, Economie, Gestion (GREDEG) –, France

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# Corporate Strategy for the Green Transition: Are Executive Incentives Effective?

Cécile Cezanne[4], Francesco Quatraro[1,2], Sandra Rigot[3], and Eleonora Rubichi[1]

[1]Department of Economics and Statistics 'Cognetti De Martiis', University of Turin, Italy
[2]BRICK, Collegio Carlo Alberto, Turin, Italy
[3]Université Sorbonne Paris Nord – UFR SEG –, France
[4]Université Côte d'Azur – Groupe de Recherche en Droit, Economie, Gestion (GREDEG) –, France

cecile.cezanne@univ-cotedazur.fr,sandra.rigot@univ-paris13.fr
francesco.quatraro@unito.it,eleonora.rubichi@unito.it

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**Abstract**

This paper examines whether green incentives embedded in executive compensation schemes are associated with a reorientation of firms' innovative activities toward environmentally sustainable technologies. Drawing on agency theory and the attention-based view of the firm, we conceptualize green incentives as governance and management-control devices that can mitigate managerial short-termism and channel executive attention toward long-horizon environmental objectives, thereby redirecting firms' technological search. Using a panel of publicly listed U.S. and European firms that participate in the Carbon Disclosure Project over the period 2010–2020, we analyze green innovation as a multi-stage process comprising the reorientation of technological search (the distance of firms' patent portfolios from green domains), knowledge recombination (the citation of green prior art in non-green patents), and realized green innovation output (green patent counts and shares). Firms adopting green incentives exhibit higher green innovation output, a significant repositioning of their knowledge portfolios toward green technological domains, and a greater integration of green knowledge into non-green technologies. These associations are weaker among firms experiencing a recent deterioration in carbon performance, and are strongest among continental European firms. Overall, the findings suggest that executive green incentives are associated with the direction, and not merely the volume, of firms' innovative activities, highlighting the role of internal governance mechanisms in sustainability transitions while recognising the limits of causal inference in observational data.

Keywords: Green innovation; Executive incentives; Direction of technological change; Sustainability transitions

JEL Classification codes: O33, Q55; G34

# 1 Introduction

Climate change and the accelerating degradation of global ecosystems have become defining challenges of our time. Scientific assessments of planetary boundaries (Rockström et al., 2009; Steffen et al., 2015) show that anthropogenic pressures—ranging from greenhouse gas emissions to biodiversity loss—are pushing socio-ecological systems toward irreversible tipping points. In this context, the low-carbon transition is not only an environmental imperative but also a profound economic and institutional transformation. The 2015 Paris Agreement crystallized this urgency by committing signatory countries to hold global warming well below 2°C, requiring decisive changes in production systems, technological trajectories and corporate strategies. Understanding how firms adapt to these constraints is therefore essential for achieving both ecological sustainability and long-term economic resilience.

A large body of research emphasizes the pivotal role of innovation in enabling the decoupling of economic activity from environmental degradation. Eco-innovation, defined as the introduction of new or improved products, processes, or organizational practices that reduce environmental harm, has long been viewed as a cornerstone of the transition toward sustainable development (Kemp, 2010). Historically, technological and organizational systems have been locked into carbon-intensive trajectories (Unruh, 2000), and substantial path dependency prevents rapid reorientation toward greener technological domains. Eco-innovation can help overcome these lock-ins by enabling firms to reduce emissions, improve resource efficiency, and create new markets for sustainable goods and services (Porter & van der Linde, 1995). At the same time, from an ecological-economics perspective, the redirection of innovation is necessary not simply for competitiveness, but to keep economic activity within biophysical limits.

The determinants of eco-innovation have been extensively studied, particularly the role of environmental regulation and carbon pricing in inducing technological change (Johnstone et al., 2012; Ghisetti & Quatraro, 2013; Aghion et al., 2016). These policies help address the "double externality" inherent in eco-innovation (Rennings, 2000): knowledge spillovers that discourage private R&D investment, and environmental externalities that result in social benefits exceeding private returns. Yet, despite the clear influence of public policy, environmental transitions also depend on firms' internal capabilities and strategic orientations. Existing literature has emphasized that governance institutions, incentive structures and power relations shape the direction of technological change and the capacity of economic actors to respond to ecological constraints (Freeman & Louçã, 2001; Köhler, 2019). However, the internal drivers of eco-innovation, particularly those related to corporate governance, have received comparatively less attention.

Firms differ widely, however, in how they respond to these pressures. Innovation pathways are shaped by capabilities, routines, and institutional contexts, and transitions require actors to overcome technological lock-in and redirect search processes toward greener domains (Geels, 2002; Zeppini & van den Bergh, 2011). Because eco-innovation is costly, risky, and characterized by long time horizons, managerial decision-making plays a critical role in determining whether firms invest in sustainability-oriented technologies. Understanding the direction of corporate innovation, therefore, requires opening the black box of executive decision-making: which issues capture managerial attention, and how governance arrangements structure that attention. The attention-based view of the firm (Ocasio, 1997) holds that organizational behavior depends on which issues and answers decision-makers attend to, and that formal structures—including rules, procedures, and reward systems—channel this attention. From this perspective, the design of executive compensation is not only an instrument for aligning pecuniary interests, but also a device that regulates the salience of competing strategic issues on executives' decision agendas.

Agency theory offers a valuable perspective on why firms may underinvest in environmentally oriented innovation. Because eco-innovation is typically characterised by high uncertainty, long time horizons, and payoffs that are only partially appropriable, managers may prioritise short-term financial performance over long-term environmental objectives, even when the latter are value-enhancing from a societal perspective. This misalignment between managerial incentives and sustainability goals can result in persistent underinvestment in clean technologies. Executive compensation schemes that explicitly incorporate environmental and social performance criteria, hereafter "green incentives", have been proposed as a mechanism to mitigate these agency problems by aligning managerial rewards with broader ESG objectives and long-term risk exposure. Recent theoretical and empirical studies provide growing support for this view. From a contract-theoretic perspective, multi-dimensional compensation contracts that include environmental and social targets can be optimal when firms face long-term sustainability risks and stakeholder pressures (Chaigneau & Sahuguet, 2025).

Empirically, several studies have documented positive associations between ESG-linked compensation and corporate sustainability outcomes, including higher ESG performance and improved environmental practices (Berrone & Gomez-Mejia, 2009; Usman & Yahaya, 2024). However, this literature remains largely focused on aggregate ESG scores or compensation levels, is often country-specific, and pays limited attention to innovation processes and technological change (Veltri et al., 2025). As a result, it remains unclear whether green incentives merely improve firms' reported sustainability performance or whether they meaningfully influence the direction of technological search and the reorientation of innovation toward environmentally sustainable domains.

The present study addresses this gap by examining whether green incentives in executive compensation are associated with firms' green innovation performance. Going beyond patent counts, we assess whether such incentives are related to firms' technological trajectories by analyzing: (i) their output of green patents; (ii) the proximity of their innovation portfolios to green technological domains (green distance); and (iii) the integration of green knowledge into brown technologies through citations. Importantly, we investigate whether these associations vary with firms' recent carbon-performance trajectory, distinguishing firms whose emission intensity has recently deteriorated from firms whose trajectory has not worsened. This heterogeneity analysis characterizes the conditions under which incentive-based governance and green innovation co-vary; as we discuss below, several mechanisms—ranging from the absorption of managerial attention by short-term compliance pressures to differences in firms' pre-existing green technological capacity—may underlie it, and our research design does not allow us to fully adjudicate among them.

This paper adds to the literature by connecting the executive compensation literature with the ecological economics and innovation literatures on directed technological change. Recent evidence shows that ESG pay can reflect efficient contracting, stakeholder alignment, and credible commitment to sustainability pledges (Cohen et al., 2023), while work on green incentives emphasizes that such practices are embedded in broader environmental management-control systems and often follow prior monitoring experience (Derchi et al., 2023). Existing studies also link top-management compensation to eco-innovation strategies (Phung et al., 2023) and show that compensation structures can redirect executive attention toward green innovation (Zhang et al., 2026). We extend this literature by asking not only whether firms produce more green patents, but whether incentives are associated with a redirection of technological search and knowledge recombination, which are central mechanisms in sustainability transitions.

This distinction allows us to organize the empirical analysis around three stages of the innovation process: (i) search reorientation, captured by the distance of the firm's technological portfolio from green domains; (ii) knowledge recombination, captured by brown patents citing green prior art; and (iii) realized green innovation output, captured by green patents and their share in the firm's patent portfolio.

By linking detailed disclosure data from the Carbon Disclosure Project (CDP) with financial, governance, and patent data for U.S. and European companies from 2010 to 2020, we provide novel international evidence on how incentive structures are associated with private innovation in the context of sustainability transitions. Our findings contribute to the ecological economics field by showing that corporate governance mechanisms, specifically, incentive design, are related not only to the intensity of innovation but also to its *direction* and underlying knowledge structure. This sheds light on the institutional underpinnings of the low-carbon transition and highlights how internal firm dynamics interact with broader public policy, environmental constraints, and socio-technical transitions.

The rest of the paper is organized as follows. Section 2 discusses the background literature and develops the working hypotheses. Section 3 presents the empirical methodology, while Section 4 describes the datasets and the variables used for the analysis. In Section 5 we present the results of the baseline empirical analysis, of the heterogeneity analyses, and, in Section 6, the results of the robustness checks. Section 7 discusses the findings, draws the implications for research and policy, and concludes.

# 2 Background and Hypotheses

Our theoretical framework combines two complementary perspectives into a single argument about the direction of corporate innovation. Agency theory explains why, absent corrective governance, executives systematically underinvest in green innovation: its costs are immediate and its returns are distant, uncertain, and only partially appropriable. The attention-based view (ABV) of the firm explains how green incentives can correct this bias: by attaching rewards to climate-related objectives, they raise the salience of environmental issues on executives' decision agendas and thereby redirect the firm's technological search. The two perspectives are not alternative lenses applied to separate parts of the argument; rather, agency theory supplies the motivational premise—why attention is misallocated in the first place—and the ABV supplies the mechanism through which incentives operate. This integrated logic generates predictions not only about innovation output (Section 2.2), but also, and distinctively, about the earlier stages of the innovation process in which redirected attention should first become visible: the positioning of firms' knowledge portfolios relative to green domains and the recombination of green knowledge within existing technological activities (Section 2.3). Finally, because attention is a scarce resource whose allocation depends on the situation in which decision-makers are embedded, the same logic implies that the association between incentives and green innovation should vary with firms' recent carbon-performance trajectory (Section 2.4). Section 2.5 discusses alternative interpretations of this heterogeneity and the boundaries of our framework.

## 2.1 The agency problem in green innovation

The starting point of our argument is the observation that green innovation is a paradigmatic case of the agency problems that arise when ownership and control are separated (Jensen & Meckling, 1976; Shleifer & Vishny, 1997). Holmström (1979) shows that, under moral hazard, agents whose actions are imperfectly observable will underprovide effort on dimensions that are costly to them and weakly reflected in their compensation. Innovation activities are particularly exposed to this problem: they are risky, long-term, and their outcomes are noisy signals of managerial effort, so that managers evaluated on short-horizon financial results have weak incentives to pursue them (Holmström, 1989). Eco-innovation sharpens each of these features. Relative to conventional innovation, it is characterized by higher technological complexity, longer development cycles, and returns that are only partially appropriable because of the double externality that combines knowledge spillovers with environmental external benefits (Rennings, 2000; Barbieri et al., 2020). Executives facing short-term performance pressures may therefore rationally divert resources away from environmentally oriented technological search, even when such investments would be value-enhancing over longer horizons.

The multitask formulation of the agency problem (Holmström & Milgrom, 1991) makes the implication for compensation design explicit. When agents allocate effort across several tasks and compensation rewards only a subset of measurable dimensions, effort is drawn toward what is measured and away from what is not. If executive pay is tied exclusively to financial metrics, environmental objectives belong to the unmeasured dimensions and will be systematically neglected. Incorporating environmental criteria into compensation contracts—hereafter, green incentives—rebalances this allocation. Contract-theoretic work shows that multi-dimensional compensation contracts including environmental and social targets can be optimal when firms face long-term sustainability risks and stakeholder pressures (Chaigneau & Sahuguet, 2025), and empirical studies document positive associations between ESG-linked compensation and sustainability outcomes (Berrone & Gomez-Mejia, 2009; Flammer et al., 2019; Cohen et al., 2023; Usman & Yahaya, 2024).

Agency theory, however, explains the motivation for green incentives better than it explains their operation. Formally, it predicts that rewarding an outcome increases effort devoted to it; it is largely silent on how that effort is redirected inside the firm—on which projects are proposed, which technological alternatives are searched, and which knowledge is mobilized. Understanding whether green incentives are associated with the direction of technological change, and not merely with the volume of rewarded outputs, requires a theory of how governance structures shape managerial cognition and search. It is here that the attention-based view enters our framework.

## 2.2 Green incentives as attention-directing governance devices

The attention-based view of the firm (Ocasio, 1997) rests on three principles. First, decision-makers' behavior depends on which issues and answers they focus their limited attention on. Second, attention is situated: what decision-makers attend to depends on the particular context and procedures in which they are embedded. Third, and crucially for our purposes, the firm's formal structures—its rules, resource allocation procedures, communication channels, and reward systems—regulate the distribution of issues across decision-makers and thereby structure organizational attention. From this perspective, executive compensation is one of the attention structures of the firm: by specifying which objectives are measured and rewarded, it determines which issues recurrently reach the executive decision agenda.

Green incentives, in this reading, are more than a transfer of risk-adjusted rewards; they are managerial control devices that institutionalize the salience of climate-related objectives in top-management decision-making (Derchi et al., 2023). Once climate metrics enter the compensation contract, environmental performance is reviewed in board and executive meetings, targets are cascaded into planning and budgeting routines, and climate-related project proposals gain legitimacy in internal resource-allocation contests. Consistent with this view, recent evidence explicitly grounded in the attention-based perspective shows that the structure of executive compensation is related to firms' green innovation performance through the reallocation of executive attention (Zhang et al., 2026). Studies of managerial incentives more generally document associations between performance-based rewards and innovative activity (Aschenbrücker & Kretschmer, 2022), between equity-based and long-horizon incentives and green patenting (Hu & Hong, 2023), between reputational incentives and green innovation (Sun et al., 2024), and between executive compensation incentives and green innovation in heavily polluting industries (Zhao et al., 2025).

Two qualifications discipline the prediction that follows. First, the expected relationship is not mechanical: environmental and social metrics can be gamed when targets are vague, biased, or weakly verifiable, and poorly specified measures may induce symbolic compliance rather than substantive reallocation of attention and resources (Chaigneau & Sahuguet, 2025; Ritz, 2022). ESG-linked pay may also serve rationales—stakeholder signaling, greenwashing insurance—that need not entail any change in innovative behavior (Cohen et al., 2023). Second, our data capture the existence of executive-level green incentives, not their contractual weight or design quality, so estimates reflect average associations across heterogeneous incentive schemes. With these caveats in place, if green incentives do operate as attention-directing devices for a sufficient share of adopters, firms adopting them should display superior green innovation performance. We therefore restate our first hypothesis:

**HP1. The inclusion of green incentives in executive compensation is positively associated with firms' green innovation performance.**

## 2.3 From attention to search: technological distance and knowledge recombination

The distinctive contribution of the attention-based mechanism is that it locates the action upstream of innovation output. If green incentives operate by changing what executives attend to, their correlates should appear first in the direction of technological search—in the problems firms work on and the knowledge they mobilize—and only subsequently, and noisily, in realized green patents. Patent output is a delayed and truncated signal of search: green technologies are complex, development cycles are long, and many exploratory efforts never mature into patentable green inventions (Popp & Newell, 2012; Barbieri et al., 2020). An empirical design restricted to green patent counts would therefore miss precisely the early-stage reorientation that the attention mechanism predicts. For this reason, we examine two additional outcomes that capture successive stages of the search process: the proximity of firms' knowledge portfolios to green technological domains, and the incorporation of green knowledge into non-green inventions.

Consider first technological proximity. Innovation is a cumulative, path-dependent process in which firms search in the neighborhood of their existing competences (Fleming, 2001;

Colombelli et al., 2014). The green transition, from this perspective, is a gradual repositioning of the firm's knowledge base rather than a discrete jump: before producing green patents at scale, firms accumulate competences in technological classes that are increasingly related to green domains (Colombelli & Quatraro, 2019; Orsatti et al., 2020). Because exploratory movement across the technology space is costly, uncertain, and long-term, it is exactly the type of activity that executives neglect under short-horizon incentives and that redirected attention should encourage. If green incentives make green technological opportunities salient in resource-allocation decisions, adopting firms should exhibit a measurable movement of their patent portfolios toward green domains, whether or not this movement has yet translated into green patents. We therefore expect:

**HP2. The inclusion of green incentives in executive compensation is associated with a reduction in firms' technological distance from green domains.**

Consider next knowledge recombination. A substantial literature shows that new technologies emerge from the recombination of existing knowledge components, and that recombinant innovation is a central mechanism through which economies escape technological lock-in (Fleming, 2001; Zeppini & van den Bergh, 2011). Green technologies are especially recombination-intensive: they draw on broader, more heterogeneous, and more distant knowledge sources than conventional technologies (Barbieri et al., 2020; Orsatti et al., 2020). Backward patent citations offer a window into this process. Citation-based indicators have long been used to trace knowledge flows and map technological trajectories (Carpenter et al., 1980; Narin et al., 1987; Trajtenberg, 1990; Hall et al., 2005; Sternitzke, 2009; Arts et al., 2013), and exploratory or radical inventions characteristically draw on wider and less familiar prior art (Dahlin & Behrens, 2005; Schoenmakers & Duysters, 2010). When a firm's non-green (brown) patents begin to cite green prior art, green knowledge is being integrated into the firm's established technological activities—a hybridization of knowledge bases that precedes, and may prepare, formally green invention.

Attention matters for this stage for the same reason it matters for search proximity: recombining unfamiliar knowledge is costly and uncertain, and proposals to do so survive internal selection only when the issues they address are salient to decision-makers. If green incentives raise that salience, firms adopting them should draw more intensively on green prior art even within technological activities that remain formally brown. Accordingly:

**HP3. Firms adopting green incentives are more likely to integrate green technological knowledge into their existing innovation activities, as reflected in backward patent citations from brown patents to green prior art.**

Together, HP1, HP2 and HP3 organize the empirical analysis around three stages of one attention-driven process: search reorientation, captured by the distance of the firm's technological portfolio from green domains; knowledge recombination, captured by brown patents citing green prior art; and realized green innovation, captured by green patent counts and shares. Observing consistent associations across all three stages would indicate that green incentives co-vary with the direction of technological change, and not merely with the volume of patenting.

## 2.4 Heterogeneity: recent deterioration in carbon performance

The attention-based mechanism also implies that the association between green incentives and green innovation should not be uniform across firms. In the ABV, attention is a scarce resource and its allocation is situated: the issues that occupy decision-makers depend on the pressures and demands of the specific situation in which the firm finds itself (Ocasio, 1997). A salient dimension of that situation, in our context, is the firm's recent carbon-performance trajectory.

Firms whose emission intensity has recently deteriorated operate under a distinctive configuration of pressures. Worsening carbon metrics attract scrutiny from investors, regulators, customers, and disclosure initiatives, and they typically trigger demands for rapid, demonstrable correction. For executives, the issues made salient by such a situation are predominantly short-term and operational: strengthening measurement and reporting, deploying readily available abatement measures, managing the reputational and compliance consequences of the deterioration. Even when climate objectives are rewarded through compensation, the attention and resources that the incentive mobilizes are likely to be channeled toward these immediate corrective actions rather than toward long-horizon technological search, whose payoffs are too distant to relieve the current pressure. In multitask terms, deterioration changes the relative returns to the different climate-related activities the incentive rewards: operational remediation dominates exploratory innovation. In addition, incentive schemes adopted amid deteriorating performance may be partly reactive or symbolic—introduced to reassure stakeholders rather than to redirect strategy—which would further weaken their association with innovative outcomes (Cohen et al., 2023; Chaigneau & Sahuguet, 2025). For both reasons, we expect the association between green incentives and green innovation to be weaker among firms whose carbon performance has recently worsened.

Before stating the hypothesis, we are explicit about the construct involved. Our moderator, Deteriorating Carbon Performance (DCP), is a dummy variable indicating that the firm's emission intensity has increased relative to the recent past. It captures the direction of recent change in carbon performance, not the level of environmental performance, the firm's environmental strategy, or its accumulated environmental capabilities: a firm with comparatively strong environmental performance but a temporary increase in carbon intensity is coded as deteriorating, whereas a persistently carbon-intensive firm with a marginal improvement is not. The hypothesis is accordingly a claim about recent carbon-performance trajectories, and the empirical results should be read in the same terms:

**HP4. The positive association between green incentives and green innovation is weaker among firms experiencing a recent deterioration in carbon performance.**

We emphasize that HP4 predicts a conditional association, not a mechanism. The attentional account developed above—compliance pressures absorbing the attention and resources that incentives mobilize—is our preferred interpretation, but it is not the only candidate. We return to the alternatives, and to how we probe them empirically, in the next subsection and in Section 5.

## 2.5 Scope conditions and alternative interpretations

Our framework deliberately abstains from strong claims about environmental capabilities. Capability-based perspectives, and in particular the natural-resource-based view of the firm (Hart, 1995; Hart & Dowell, 2011), would generate a prediction observationally similar to HP4 through a different channel: firms with deteriorating carbon performance may possess weaker environmental routines, monitoring systems, and accumulated green competences, and may therefore be less able—rather than less attentive—to convert executive incentives into green innovation. Relatedly, firms with favorable carbon trajectories may already command stronger green technological foundations, so that the heterogeneity we document could reflect differences in pre-existing green innovation capacity rather than any consequence of the deterioration itself. Because our data do not directly measure environmental routines or management systems, we do not build hypotheses on the capability construct. We do, however, probe the most tractable version of this alternative in Section 5, where we control for firms' accumulated stock of green patents and its interaction with green incentives, and we examine whether the adoption of green incentives is itself predicted by prior carbon-performance deterioration, as a reactive-adoption account would suggest. These analyses narrow, but cannot eliminate, the set of admissible interpretations; throughout, we therefore present the heterogeneity results as conditional associations and treat the attentional and capability-based readings as complementary hypotheses for future research designs with direct measures of organizational attention and environmental capabilities.

In sum, our hypotheses describe how incentive design and managerial attention jointly relate to the direction of firms' technological search, and how this relationship varies with the situation in which firms are embedded. They imply that the footprint of green incentives should be visible not only in green patenting, but also—and earlier—in the structure of firms' knowledge portfolios and citation behavior.

# 3 Methodology

To estimate the association between green incentives and innovation performance, we implement a linear OLS model with firm fixed effects and year-industry fixed effects:ì

$$Y_{i,t} = a_i + a_t * a_s + bIncentives_{i,t-1} + c'X_{i,t-1} + \epsilon_{i,t}$$

Where $Y_{it}$ represents the dependent variable of firm i at time t, alternatively: the number of total patents (log) and green patents (log), the technology distance from green, and the total number of brown patents that cite green patents (log) to capture the greenness process of the companies and, finally the number of brown patents (log) to make a comparison with green ones; $a_i$ and $a_t*a_s$ denote, respectively, firm and year-industry fixed effects. $Incentives_{i,t-1}$ is our variable of interest, taking the value 1 if the firm provides incentives to executives and 0 otherwise. We interact this term with the *Deteriorating Carbon Performance (DCP)* dummy variable to capture the effectiveness of incentives with respect to the carbon performance in a given year. The dummy is equal to 1 if the company has increased emissions compared to the previous year and 0 otherwise. The vector $c'X_{i,t-1}$ represents time-varying firm-level control variables suggested by pertinent literature (Flammer, 2019; Krafft, 2013): total assets, return on asset ratio, cash holdings, Gearing, sales growth, productivity ratio (total sales scaled by the number of employees) and the net profit margin. We additionally include a set of corporate governance controls obtained from LSEG Refinitiv: board size, the share of independent board members, the percentage of female board members, and an overall ESG score. Finally, $\varepsilon_{i,t}$ represents the error term, clustered at the firm level. Moreover, we lag all right-hand variables by one year to mitigate bias from simultaneity[1].

# 4 Data and Variables

## 4.1 Sample

We consider companies that join the Carbon Disclosure Project (CDP) which is a not-for-profit organization that helps firms, cities, states, and regions from all over the world in measuring, managing, and reporting their environmental impact. The CDP database is one of the most comprehensive international sources of environmental information available. The organization conducts annual surveys to gather data from thousands of companies around the world on their greenhouse gas emissions, climate change risks and opportunities, and water management practices. Companies are then scored based on the completeness and quality of their disclosures, and the scores are made publicly available through the CDP's website. Our database is the result of a survey subjected for ten years (2010-2020) to the enterprises that decided to join the project. Here the firms answer questions related to how they manage sustainability and give information on their activity to measure and manage their risks and opportunities to climate change. Indeed, since the alignment with the TCFD recommendation (TCFD, 2017), firms are asked to answer questions which are contained within four domains: Governance, Strategy, Risk Management and Metrics & Targets. By linking governance reporting data with the Orbis global database (by Bureau van Dijk, a Moody's Analytics company) we are able to use information on the economic-financial achievements and corporate governance characteristics. Specifically, we matched CDP with Orbis using the International Securities Identification Number (ISIN) when present or the names of companies in CDP. Furthermore, we used Orbis IP which contains bibliographical and legal event patent data with which we construct a measure of innovation performance. In this case, the matching was possible using the Bureau van Dijk identification number for each company.

[1] Because the analysis relies on observational panel data, the coefficients should be interpreted as conditional associations rather than definitive causal effects. Firm fixed effects absorb time-invariant unobserved heterogeneity, year-industry fixed effects account for common shocks within industries, lagged covariates reduce simultaneity concerns, and additional robustness checks address observable selection. However, unobservable time-varying factors such as environmental culture, stakeholder pressure, or strategic sustainability orientation may still influence both incentive adoption and green innovation.

Table 1 shows the geographical breakdown of our sample. Our sample includes only Western companies, specifically from the United States and European countries. This allows us to focus our research on firms within similar socio-economic contexts, where environmental attention and legislation are different but comparable. As a result, we have a longitudinal panel that includes environmental information, firms' strategy information about the tools the companies are using to deal with the green transition, and patent data for a total of 309 innovator companies across the US and EU[2].

>>> INSERT TABLE 1 ABOUT HERE <<<

## 4.2 Variables

**Variables of interest**

Our explanatory variable is a dummy variable that captures if firms link the executive compensation to environmental goals achievement. We extrapolated this information from the CDP survey, from 2010 to 2020, in the Governance section. Precisely, we consider the answers to two specific questions about incentives, formulated as follows:

1- "Do you provide incentives for the management of climate-related issues, including the attainment of targets?"

2- "Provide further details on the incentives provided for the management of climate-related issues. - Who is entitled to benefit from these incentives?"

The answers to these questions are simply 'Yes' or 'No' for the first, and the possibility to choose between different options in the second. Those options slightly differ across years; for instance, in 2018 they included 27 options as shown in the note. [3]

Therefore, in order to harmonize those answers, we select responses that mention the following words: board, executives, executive officer, corporate executive team, ceo. We construct a

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[2] To avoid ambiguity across empirical exercises, we distinguish three samples. The descriptive CDP sample is used to document the diffusion of executive green incentives across countries, sectors, and years. The baseline estimation sample is the patent-estimation panel, which retains firms with patent information and non-missing financial and governance controls. The CEM robustness sample is a further restricted matched sample comparing firms that switch into executive green incentives with never-treated firms. Accordingly, the N reported in the baseline regressions and in the CEM appendix tables refers to firm-year observations, whereas Table A5 reports the units entering the matching procedure. This distinction explains why sample sizes differ across descriptive, baseline, and matched-sample analyses.

[3] Options in the 2018 questionnaire: Board Chair, Board/Executive board, Director on board, Corporate executive team, Chief Executive Officer (CEO), Chief Financial Officer (CFO), Chief Operating Officer (COO), Chief Procurement Officer (CPO), Chief Risk Officer (CRO), Chief Sustainability Officer (CSO), Other C-Suite

dummy variable equal to 1 if a company provides incentives to top executives or board members, and 0 otherwise. This approach allows us to capture companies that choose to incentivize environmental goal achievement at the highest organizational levels.

Importantly, this coding does not rely on arbitrary keywords in open-text narratives. The CDP questionnaire provides structured response categories indicating who benefits from climate-related incentives, although the exact menu of categories varies across years. Our harmonization therefore identifies top-management categories in a consistent way across survey waves. We nonetheless acknowledge that the resulting dummy captures the existence of executive-level green incentives, not their contractual weight, time horizon, enforceability, or the specificity of the underlying environmental target. The empirical estimates should therefore be interpreted as average associations across heterogeneous incentive designs.

>>> INSERT TABLE 2 ABOUT HERE <<<

>>> INSERT FIGURE 1 ABOUT HERE <<<

In our original sample, the number of companies offering incentives between 2010 and 2020 is 588 for a total of 2654 companies, i.e. 22%, while the share of innovator companies which stays in the sample for at least two years is higher, specifically around 50%. The table and graphs below show a steady increase in the use of incentives over the years. Figure 1 shows in the first graph (a) the trend in the share of incentives by region and the trend in the share of incentives by sector in the second graph (b), derived by dividing the total number of companies using this tool each year by the total number of companies. In our analysis, we also interact this dummy variable with a proxy for carbon performance. Specifically, we build another dummy variable to capture whether companies increased or decreased $CO_2$ emissions in a given year compared to the previous year. This allows us to examine whether the association between incentives and innovation differs between companies that are good carbon performers at time t and those that are not.

**Dependent variables**

*Innovation activity*

To measure firms' innovative performance, we use patent data from Orbis IP (BvD) database that we match to our data through the Bureau van Dijk identification number. This unique identifier links companies to their respective patent applications. In our analysis, we use the number of granted patents each year, differentiating between green patents and overall patents. We perform this distinction using the tagging system provided by the Cooperative Patent

Classification (CPC). Indeed, each patent is assigned a set of classification codes by the patent office prior to publication. These codes are then organized into over 260,000 categories by the CPC. The "Y02" tag within this classification system denotes patents that protect technologies designed for mitigation or adaptation against Climate Change. In addition to the simple patent count, we use as a dependent variable the share of green patents over the overall patents. This is to observe the change in the proportion of green patents with respect to the total patents the company produces.

*Green distance*

As a measure of the transition towards green innovation, we include in our analyses the green distance indicator. This indicator is measured using the co-occurrences of brown patent classes with green patent classes. Each patent has a certain number of identification classes that occur together and that serve to label all the characteristics of specific technology.

Prior research has conceptualized technological distance using patent-based measures that exploit technological relatedness across patent classes. In particular, Orsatti (2024), building on Akcigit et al. (2016), propose a symmetric measure of technological distance based on citation co-occurrences across IPC classes, which captures how closely different technologies are positioned in the innovation space. Applied at the level of a firm’s patent portfolio, this notion of technological distance reflects the overall proximity of the firm’s knowledge base to the green technological domain, even when the firm has not yet patented green technologies. By accounting for both patents that directly belong to the green domain and non-green patents that are technologically adjacent through related IPC classes, a portfolio-level distance measure captures firms’ potential to transition toward green innovation rather than only realized green outcomes.

Following these approaches, we measure the distance between these classes. First, as mentioned before, we distinguish between green classes and the non-green classes using the CPC classification; then we measure the number of co-occurrences of each brown class i with green classes j. In other words, we measure the number of patents in which the i brown class occurs with the j class. We perform the average distance of each class from green classes using the following equation:

$$d(i,j) = 1 - \frac{\#(i \cap j)}{\#(i \cup j)}$$

Where $d(i, j)$ is the green distance of the i brown class from the j green class. $\#(i \cap j)$represents the number of patents that have both the classes, while #(i ∪ j) represent the number of patent that have the i brown class plus the number of patent that have the green j class. If all patents that have the i class also have the j class the distance measure will be equal to 0. This green distance between classes serves to measure how close a patent portfolio of a firm is to the green domain each year. To do so, we take the average distance for each class to the all green classes with which it occurs, then we calculate the minimum distance of each patent from green - accounting just for the classes that are more closed to green - and, finally, we compute the distance of the entire portfolio of each firm each year. This final measure is given by the minimum distance to green of the patents that compose the portfolio of the firm. In this way, we know how close the firm is from doing green innovation each year.

The minimum-distance aggregation is intended to capture the closest technological bridge between a firm's existing knowledge base and the green domain. This is consistent with our interpretation of green distance as an early-stage indicator of potential technological reorientation. At the same time, the measure may be sensitive to a small number of patents close to the green domain. For this reason, we report a robustness check in Table A4 that controls for whether the firm has at least one green patent in the relevant year, verifying that the distance result is not mechanically driven by the presence of a single green patent.

We interpret the innovation variables as complementary indicators of different stages of technological reorientation. Green patent counts and green patent shares capture realized outputs. Green distance captures the positioning of the firm's broader knowledge portfolio relative to green technological domains. Brown-to-green backward citations capture the incorporation of green knowledge into non-green technological activities. This distinction helps address the concern that incentive adopters may simply be more innovative overall: compositional, distance-based, and citation-based outcomes allow us to assess whether innovation becomes greener in direction, not only larger in volume.

**Control variables**

In our regression analysis we include different firm characteristics that we know from the literature to be correlated with our main variables. We first control for the *size* of the companies using the natural logarithm of the book value of total asset (using the GDP deflator from the

World Bank database to correct for changes in prices in US and European countries). We use *Return on Asset* (ROA) which is the operating income over the book value of total assets and measures how efficient a company is in generating profit from its total assets. We control for *Gearing*, which represents the proportion of a company's assets financed by debt versus equity, and for *Cash holdings* as the sum of cash and short-term investments over total assets, measuring the firm's ability to pay its obligations on time. Given the distinctive investment profile of innovative ventures, which tend to favor equity over debt financing, accounting for cash holdings becomes pivotal in our analysis the association between incentives and innovation. To address labor productivity and profitability we consider the total sales (in natural logarithm form and deflated) over the number of employees (*Productivity*), the *Net Profit Margin* which calculates the percentage of profit a company produces from its total revenue, and the change over time of the total firm's revenue (*Growth*). We also take into account the overall firm's *Intangible* assets. Moreover, since in our model we interact our variable of interest with a dummy variable which is equal to 1 if the company has increased its emissions compared to the previous year, and 0 otherwise, as explained before, we also control for companies' emission intensity given by the total amount of scope 1 emissions scaled by total assets. Table 3 presents descriptive statistics of our sample regarding the variables of interest over the period 2010-2020.

In addition, we include a set of corporate governance controls. We control for board size, measured as the total number of board members, which captures differences in monitoring capacity and decision-making structures across firms. We include the share of independent board members (Board independence), which reflects the degree of oversight over managerial decisions and has been shown to influence both executive compensation design and corporate sustainability outcomes. We further control for board gender diversity, measured as the percentage of female board members (Board gender), given evidence that gender-diverse boards tend to be more attentive to long-term and ESG-related objectives. Finally, we include an overall ESG score to account for differences in firms' broader sustainability orientation that may independently influence both the adoption of green incentives and innovation outcomes. All governance variables are obtained from LSEG Refinitiv.

>>> INSERT TABLE 3 ABOUT HERE <<<

# 5 Results

## 5.1 Green incentives and green innovation output

Table 4 presents the baseline regressions estimating the association between executive green incentives and firms' green innovation performance. Columns differ with respect to the dependent variable. In Columns 1 to 3, the dependent variable is the logarithm of the total number of green patents, classified using the CPC Y02 classification provided by the European Patent Office and the United States Patent and Trademark Office. The coefficient on green incentives is positive and statistically significant, suggesting that incentives are associated with higher green innovative output. This finding is reinforced in Columns 4 to 6, where the dependent variable is the share of green patents over total patents, and the coefficient remains positive and significant.

>>> INSERT TABLE 4 ABOUT HERE <<<

Overall, Table 4 provides evidence consistent with HP1. Columns (3) and (6) show that firms adopting green incentives exhibit a statistically significant increase in both the number and the share of green patents. The result for green patent share is especially important because it suggests a compositional shift toward environmentally oriented technologies rather than a mere increase in overall patenting intensity.

## 5.2 Green incentives and early-stage technological reorientation

Table 5 shows that green incentives are associated with a statistically significant reduction in firms' technological distance from green domains. This measure does not rely solely on the direct production of green patents; rather, it captures how closely firms' broader patent portfolios are related to green technologies. The result therefore provides evidence consistent with a reorientation of technological search, not only with realized green innovation output. This finding supports HP2.

The results related to HP2 provide particularly important insights into the early dynamics of sustainability transitions. The reduction in technological distance from green domains associated with executive green incentives suggests that firms begin to reposition their technological search before such changes necessarily materialize in observable green patent outputs. From an evolutionary and attention-based perspective, this finding is consistent with green incentives covarying with the cognitive and organizational direction of search by making green technological opportunities more salient to decision-makers.

>>> INSERT TABLE 5 ABOUT HERE <<<

This is especially relevant in the context of green innovation, where uncertainty, long development cycles, and high coordination costs often delay the translation of exploratory efforts into patented outcomes. By lowering firms' technological distance from green domains, green incentives appear to be associated with experimentation, learning, and capability accumulation that precede formal green patenting. In this sense, green distance captures a transitional phase of innovation, consistent with views of sustainability transitions as gradual and path-dependent processes rather than abrupt technological shifts.

## 5.3 Green incentives and green knowledge recombination

Table 6 shows that green incentives are positively and significantly associated with the number of brown patents citing green prior art. This indicates that firms adopting executive green incentives are more likely to draw on green knowledge even within non-green technological domains. Such citation patterns provide evidence consistent with exploratory recombination and hybridization of knowledge bases, which are widely recognized as precursors of more substantive green innovation. HP3 is therefore supported.

>>> INSERT TABLE 6 ABOUT HERE <<<

The findings related to HP3 further deepen our understanding of how firms transition toward greener technological trajectories. The positive association between green incentives and backward citations from brown patents to green prior art suggests that firms integrate environmental knowledge into existing technological activities rather than immediately abandoning established domains. This pattern reflects technological hybridization, whereby green and brown knowledge bases coexist and interact during early stages of the transition.

Such hybridization is a critical mechanism for overcoming technological lock-in. Rather than requiring abrupt substitution of carbon-intensive technologies, transitions may unfold through incremental recombination processes that embed green functionalities within existing production systems. Green incentives appear to support this process by encouraging managers to engage in exploratory recombination and tolerate the uncertainty associated with drawing on unfamiliar knowledge domains. Backward citations thus reveal a subtle but meaningful reorientation of innovation activities that is invisible when focusing exclusively on green patent counts. This result reinforces the view that sustainability transitions are cumulative, recombinative, and deeply embedded in existing technological structures.

## 5.4 The role of recent carbon-performance trajectory

Table 7 examines whether the association between executive green incentives and green innovation varies with firms' recent carbon-performance trajectory. The Deteriorating Carbon Performance (DCP) dummy equals 1 when a firm's emission intensity worsens relative to the previous year and 0 otherwise. As discussed in Section 4, this variable captures the direction of recent change in carbon performance; it does not measure the level of environmental performance, the firm's environmental strategy, or its accumulated environmental capabilities. The coefficient on Green Incentives therefore captures the association for firms whose emission intensity did not recently worsen, while the interaction term Green Incentives × DCP captures whether this association differs among firms with recently deteriorating carbon performance.

Across both outcomes, the coefficient on Green Incentives is positive and statistically significant, while the interaction term is negative and significant. The positive association between executive green incentives and green patent output, as well as green patent share, is thus concentrated among firms whose carbon performance has not recently deteriorated, and is markedly weaker among deteriorating firms. Table 7 reports green patent output and green patent share; green distance and citation-based recombination are analyzed separately in Tables 5 and 6.

>>> INSERT TABLE 7 ABOUT HERE <<<

In sum, Table 7 provides evidence consistent with HP4: green incentives are more weakly associated with green innovation among firms experiencing a recent deterioration in carbon performance. We interpret this result as a conditional association rather than as evidence for a specific mechanism. The pattern is consistent with the attentional account developed in Section 2.4, in which the compliance and remediation pressures triggered by worsening carbon metrics absorb the managerial attention and resources that incentives mobilize, redirecting them toward short-term corrective action rather than long-horizon technological search. It is equally consistent, however, with at least three alternative accounts: deteriorating firms may divert financial and organizational resources toward immediate operational abatement; they may have adopted incentive schemes reactively, in response to the deterioration itself, with weaker strategic content; or they may differ systematically from non-deteriorating firms in their pre-existing green innovation capacity. Our design does not allow us to separate these mechanisms conclusively. The next subsection reports three diagnostic analyses that narrow, without eliminating, the set of admissible interpretations.

## 5.5 Probing alternative interpretations

The results documented in Table 7 admit several readings. In this subsection we report three diagnostic analyses designed to discriminate, as far as the data permit, among them: a decomposition of the moderator into level and trajectory components; a test of whether the interaction reflects pre-existing green technological capacity; and an analysis of whether incentive adoption is itself predicted by prior deterioration.

A first concern is that the DCP dummy may partly proxy for the level of firms' carbon intensity rather than for its recent trajectory: persistently carbon-intensive firms could differ from cleaner firms in many respects relevant to innovation. To separate the two margins, we construct an indicator equal to 1 when the firm's emission intensity exceeds the median of its industry-year cell, capturing high carbon-intensity levels, and re-estimate the interaction models including both Green Incentives × DCP and Green Incentives × High Level, together with the corresponding main effects. As reported in Table 8, the interaction with DCP remains negative and statistically significant, with a magnitude close to the baseline estimate, while the coefficient of the interaction with the level indicator is not statistically significant. This pattern indicates that the heterogeneity in Table 7 is associated with the direction of recent change in carbon performance rather than with persistent differences in emission-intensity levels, consistent with the situational reading proposed in Section 2.4.

>>> INSERT TABLE 8 ABOUT HERE <<<

A second concern, anticipated in Section 2.5, is that firms with favorable carbon trajectories may already possess stronger green technological foundations — more accumulated green patents and more mature green competences — so that the negative interaction could reflect differences in prior innovation capacity rather than anything associated with the deterioration itself. To address this possibility, we compute each firm's accumulated stock of green patents up to year $t-1$, using a perpetual-inventory method with a 15% annual depreciation rate, and re-estimate the models of Table 7 adding the (log) green patent stock and its interaction with Green Incentives. As reported in Table 9, the Green Incentives × DCP interaction remains negative and statistically significant and its magnitude is essentially unchanged, while the interaction with the green patent stock is positive and significant only in columns (4) and (6). The weaker association among deteriorating firms therefore does not appear to be an artifact of differences in accumulated green innovation capacity.

>>> INSERT TABLE 9 ABOUT HERE <<<

Finally, we examine whether the adoption of green incentives is itself predicted by prior carbon-performance deterioration, as a reactive-adoption account would imply. We estimate linear probability models in which first-time adoption of executive green incentives is regressed on the lagged DCP indicator, conditional on the full set of financial and governance controls and fixed effects. As reported in Table 10, lagged deterioration does not predict subsequent adoption but the opposite: firms that recently deteriorated are somewhat less likely to adopt one. This finding weighs against the view that the incentive schemes in our sample are predominantly reactive responses to worsening carbon metrics, although it cannot exclude reactive adoption in individual cases. If anything, the negative sign is consistent with an attention-based account: firms absorbed in remediating a recent deterioration plausibly have less organizational attention available to design and negotiate a new incentive scheme, rather than responding to deterioration by introducing one.

>>> INSERT TABLE 10 ABOUT HERE <<<

Taken together, these diagnostics indicate that the conditional association documented in Table 7 is robust to controlling for emission-intensity levels and for accumulated green innovation capacity, and is unlikely to be driven primarily by reactive adoption. They narrow, but do not eliminate, the set of admissible mechanisms; in particular, they cannot distinguish the attentional account from other channels operating through short-term compliance pressure. We therefore maintain an association-based interpretation of the heterogeneity results throughout the paper.

## 5.6 Heterogeneity across sectors and regions

Table 11 reports the third set of estimates, where firms are classified according to the well-established Pavitt taxonomy, as revisited in Bogliacino and Pianta, 2016. This classification captures systematic differences in the sources and patterns of innovation across sectors. Column 1 presents the baseline regression for the full sample, while Columns 2 to 5 provide results disaggregated by Pavitt groups[4].

[4,3] To address concerns about the comparability of coefficients across subsamples, we also estimate interaction-based specifications in which green incentives are interacted with each sectoral (Pavitt) and regional dummy, without imposing a baseline category. The results are reported in Tables A2 and A3 of the Appendix and are qualitatively consistent with the subsample evidence discussed in the main text.

Science-Based (SB) industries include sectors in which innovation is primarily driven by advances in scientific knowledge and formal R&D activities, such as the pharmaceutical and electronics industries. These firms typically operate their own research laboratories and show a high propensity to generate patents, especially through product innovation.

Scale-Intensive (SI) industries, on the other hand, are characterized by the importance of scale economies and the relative rigidity of production processes. In these sectors, such as automotive and basic metals, innovation is often incremental and focused on process improvements rather than radical breakthroughs.

Specialised Suppliers (SS) industries comprise mainly small and medium-sized enterprises producing machinery and equipment. Here, innovation relies less on formal R&D and more on design capabilities, engineering know-how, and the tacit knowledge embedded in the workforce.

Finally, Supplier-Dominated (SD) industries include more traditional sectors —such as food, textiles, and wood products— where firms typically do not conduct substantial in-house R&D. Technological change in these industries largely depends on the adoption of innovations developed by suppliers of equipment and intermediate goods.

This sectoral breakdown allows us to explore whether the association between executive green incentives and innovation varies across different innovation regimes. To avoid relying only on comparisons of statistical significance across subsamples, we also estimate formal interaction-based specifications in which green incentives are interacted with Pavitt sectoral categories (Appendix Table A2). These estimates show that the positive association is concentrated in Science-Based and Scale-Intensive industries, while the coefficient is negative for Specialized Suppliers. This pattern suggests that incentives are more effective where internal R&D capabilities and formal innovation processes are already in place, whereas their role may be weaker or more complex in sectors relying primarily on customer interaction, tacit engineering capabilities, or externally supplied technologies.

In Table 12, we report regional subsample estimates, and in Appendix Table A3 we provide the corresponding interaction-based tests estimated on the full sample. The interaction estimates show that the association between green incentives and green patenting is strongest and statistically significant for European firms, while the UK and US coefficients are positive but imprecisely estimated. We therefore interpret the regional evidence cautiously: it is consistent with the view that supportive institutional and regulatory contexts amplify internal governance mechanisms, but it should not be read as definitive evidence of statistically different effects across all regions.

>>> INSERT TABLES 11 AND 12 ABOUT HERE <<<

Table 13 summarizes the hypotheses and empirical results. Taken together, the results provide consistent evidence that executive green incentives are associated not only with the quantity of green innovation, but also with the direction and structure of firms' technological search, with associations that vary according to prior carbon performance and institutional context.

>>> INSERT TABLE 13 ABOUT HERE <<<

# 6 Robustness checks

To assess the robustness of our baseline results, we conduct three additional analyses.

First, we address a potential concern regarding the operationalization of the carbon-performance moderator. In the baseline analysis, the DCP dummy equals 1 if the firm's emission intensity increased relative to the previous year. This measure may be sensitive to short-term fluctuations driven by cyclical factors or temporary capacity expansions. As a robustness check, we construct an alternative DCP dummy equal to 1 if the firm's emission intensity exceeds the average of the three preceding years, which reduces the dependence of the classification on a single annual comparison. As reported in Table A1, the results are qualitatively and quantitatively consistent with the baseline findings: green incentives remain positively and significantly associated with green patent output and the share of green patents, and the interaction term remains negative and significant. We note that this alternative indicator, like the baseline one, remains a measure of recent change in carbon performance rather than of a medium-term performance trajectory in levels, and its classification may still be affected by production expansion, product-mix changes, or other operational shocks; the level-based analysis in Section 5.5 addresses the complementary margin, and the interpretation of both indicators remains confined to recent carbon-performance deterioration.

Second, we address a potential concern regarding the construction of the green distance measure. Since the minimum distance equals zero whenever a firm holds at least one green patent, regardless of the overall structure of its portfolio, the baseline estimates could be mechanically driven by this property of the measure. To verify that this is not the case, we replicate the green distance regressions controlling for a dummy variable equal to 1 if the firm produced at least one green patent in a given year. As reported in columns (4) to (6) of Table A4, the coefficient on green incentives remains stable in sign, magnitude, and statistical significance, and the green patent dummy itself is not statistically significant. These findings suggest that our results on technological distance reflect a genuine reorientation of firms' technological search rather than an artifact of the minimum distance aggregation.

Third, to address concerns about self-selection on observable characteristics, we implement Coarsened Exact Matching (CEM) following Iacus et al. (2012) and Lamperti et al. (2017), among others. We define treated firms as switchers--firms that adopt green executive incentives at least once over the period 2010-2020--and control firms as never-treated firms. Always-treated firms are excluded from the matching procedure because they do not provide a pre-treatment observation window. Table A5 reports the units entering the matching procedure, while Table A6 reports the post-matching panel regressions using firm-year observations. Matching is performed on firm characteristics observed in 2010, the first year of our sample, to ensure that covariates are measured before most adoption events and to avoid potential endogeneity in time-varying characteristics. We impose exact matching on country of origin, one-digit NAICS sector, and firm size tercile, achieving balance by construction on the matching dimensions. The matched sample is then used as the estimation sample for panel regressions identical to those reported in the baseline analysis. The results in Table A6 are qualitatively consistent with the baseline estimates: green executive incentives remain positively and significantly associated with green patent output, green patent share, and green knowledge recombination, and negatively associated with technological distance from green domains. CEM should be interpreted as a robustness check for selection on observable pre-treatment characteristics, not as a complete solution to endogeneity or unobserved selection.

# 7 Discussion and Conclusion

This study examines whether and how green incentives embedded in executive compensation are associated with firms' innovation behavior in the context of the low-carbon transition. By linking governance disclosures from the Carbon Disclosure Project (CDP) with financial, governance, and patent data for U.S. and European firms over the period 2010–2020, we provide evidence on the relationship between internal governance mechanisms and both the intensity and the direction of technological change.

Our results show that firms adopting green incentives exhibit significantly higher levels of green innovation output, as measured by both the number and the share of green patents. The result for the green patent share is particularly informative, because it indicates a compositional shift toward environmentally oriented technologies rather than a mere increase in overall patenting intensity. Beyond output, a central contribution of this paper lies in documenting associations at earlier stages of the innovation process. Firms adopting green incentives display a significant reduction in their technological distance from green domains, indicating a repositioning of technological search that precedes, or accompanies, realized green patenting. They are also more likely to cite green prior art in their non-green patents, revealing an incremental and recombinative process in which green knowledge is progressively integrated into existing technological activities. Taken together, these patterns are consistent with the attention-based mechanism developed in Section 2: green incentives co-vary with what firms search for and which knowledge they mobilize, and not only with the volume of green outputs they produce.

The recombination result deserves emphasis from an ecological-economics standpoint. The hybridization of green and brown knowledge bases — green functionalities embedded within existing technological activities — reflects a gradual weakening of carbon-intensive lock-in, consistent with evolutionary perspectives in which transitions unfold through recombination, learning, and experimentation rather than through the abrupt substitution of technological regimes (Zeppini & van den Bergh, 2011). Backward citations reveal a subtle but meaningful reorientation of innovation activities that remains invisible when the analysis focuses exclusively on green patent counts.

These associations are not uniform across firms. They are significantly weaker among firms experiencing a recent deterioration in carbon performance. We interpret this heterogeneity strictly as a conditional association. It is consistent with the situated-attention argument advanced in this paper — worsening carbon metrics trigger compliance and remediation pressures that absorb the very attention and resources that incentives mobilize — but it is also compatible with resource diversion toward short-term abatement, with the reactive adoption of incentive schemes, and with differences in firms' pre-existing green technological capacity. The diagnostic analyses in Section 5 narrow this set of interpretations: the heterogeneity is associated with the trajectory rather than the level of carbon intensity (Table 8), is robust to controlling for firms' accumulated green patent stocks and their interaction with incentives (Table 9), and does not appear to be driven primarily by reactive adoption (Table 10). Nevertheless, we do not claim to have identified the underlying mechanism. In particular, while capability-based perspectives such as the natural-resource-based view (Hart, 1995; Hart & Dowell, 2011) offer a plausible reading of the moderation — deteriorating performance signaling weaker environmental routines and monitoring systems — our data do not measure such capabilities directly, and we deliberately refrain from capability-based claims. Adjudicating between attentional and capability-based accounts requires research designs with direct measures of organizational attention and environmental management capabilities, a point to which we return below.

The heterogeneity analyses across sectors and regions add further nuance. The association between green incentives and green innovation is concentrated in Science-Based and Scale-Intensive industries, where formal R&D processes and internal innovation capabilities are most developed, and is strongest — and statistically significant — among continental European firms, while the corresponding coefficients for the United Kingdom and the United States are positive but imprecisely estimated. This regional pattern is consistent with the view that supportive institutional and regulatory contexts amplify the salience of climate objectives inside the firm, but it should not be read as definitive evidence of statistically different associations across all regions.

From a policy perspective, our findings suggest that incentive-based corporate governance mechanisms may complement, but are unlikely to substitute for, environmental policy. The associations we document are concentrated among firms whose carbon performance has not recently deteriorated and which operate in R&D-intensive sectors and supportive institutional contexts. For firms under acute carbon pressure — arguably those whose reorientation matters most for the transition — executive incentives alone do not appear to be associated with a comparable redirection of innovative activity. In such contexts, green incentives are best viewed as complementary tools to be combined with environmental regulation, carbon pricing, mission-oriented innovation policies, and strategic public investment, in line with the broader ecological-economics emphasis on the institutional embedding of sustainability transitions.

For corporate boards and governance bodies, the results underscore the importance of incentive design. Generic ESG-linked compensation is unlikely to be sufficient, and poorly specified metrics can invite symbolic compliance (Chaigneau & Sahuguet, 2025; Ritz, 2022). To the extent that green incentives operate by directing executive attention, their design should make long-horizon technological objectives — not only short-term operational metrics — salient and rewarded: clearly defined, verifiable, innovation-oriented environmental targets, embedded in multi-year compensation structures that reflect the temporal profile of sustainability challenges. Aligning incentive metrics with firms' technological strategies and sectoral transition pathways may enhance their credibility and their capacity to reach the search and recombination stages of the innovation process, rather than its reporting layer alone.

Despite its contributions, this study has limitations. First, although we mitigate endogeneity concerns through firm and industry-year fixed effects, lagged covariates, governance controls, and CEM matching on observable pre-treatment characteristics, we cannot rule out selection on unobservables: firms adopting green incentives may already possess stronger sustainability orientations or face greater stakeholder pressure. All results should therefore be interpreted as robust conditional associations rather than causal estimates. Second, our incentive measure captures the existence of executive-level green incentives, not their contractual weight, time horizon, or the specificity of the underlying targets; the estimates are average associations across heterogeneous incentive designs. Third, the carbon-performance moderator captures the direction of recent change in emission intensity; it is not a measure of environmental strategy or capability, and our conclusions about heterogeneity are correspondingly confined to recent carbon-performance deterioration. Fourth, our sample is limited to CDP participants, which are typically larger and more transparent than the broader corporate population, so the findings may not generalize to smaller firms or less disclosure-intensive contexts. Finally, patents do not capture the full spectrum of green innovation, including organizational, process, and business-model innovation.

These limitations map directly into avenues for future research. Research designs incorporating direct measures of organizational attention — for instance, the climate content of board agendas, earnings calls, or managerial communications — could test the attentional mechanism that our results are consistent with but cannot isolate. Direct measures of environmental capabilities, such as environmental management systems, certification, or monitoring infrastructure, would allow the capability-based account to be confronted with the attentional one within a single design. Studying how executive green incentives interact with external policy instruments such as carbon pricing, green subsidies, or industrial policy would clarify complementarities across governance levels, and extending the analysis to emerging economies and non-patent-intensive sectors would illuminate institutional and technological diversity in transition dynamics. Finally, linking incentive design to environmental outcomes, such as emissions trajectories or resource use, would connect corporate governance research more tightly to ecological performance.

Overall, this study suggests that executive compensation design is not merely a matter of aligning incentives with short-term financial performance, but a governance instrument associated with the direction of technological change. By making environmental objectives salient in executive decision-making, green incentives co-vary with how firms search, recombine knowledge, and gradually reorient their innovation trajectories toward sustainability. The strength of these associations, however, depends on firms' carbon-performance situation, their sectoral innovation regime, and the institutional context in which they operate — reinforcing the need for integrated approaches that align corporate governance, public policy, and ecological constraints in the pursuit of a low-carbon transition.

## Use of Generative AI

Generative AI, including the web service of ChatGPT, was used for language editing. All text was reviewed and edited by the authors.

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**Table 1: Country Frequencies and Percentages**

| Country | Freq. | Percent | Cum. |
|---|---|---|---|
| **United States** | 7,667 | 46.07 | 46.07 |
| **United Kingdom** | 2,420 | 14.54 | 60.61 |
| **Germany** | 1,089 | 6.54 | 67.15 |
| **Italy** | 891 | 5.35 | 72.5 |
| **France** | 858 | 5.16 | 77.66 |
| **Spain** | 671 | 4.03 | 81.69 |
| **Sweden** | 605 | 3.64 | 85.33 |
| **Finland** | 484 | 2.91 | 88.24 |
| **Denmark** | 374 | 2.25 | 90.48 |
| **Netherlands** | 374 | 2.25 | 92.73 |
| **Belgium** | 286 | 1.72 | 94.45 |
| **Ireland** | 209 | 1.26 | 95.7 |
| **Poland** | 198 | 1.19 | 96.89 |
| **Portugal** | 176 | 1.06 | 97.95 |
| **Austria** | 165 | 0.99 | 98.94 |
| **Greece** | 55 | 0.33 | 99.27 |
| **Luxembourg** | 55 | 0.33 | 99.6 |
| **Romania** | 44 | 0.26 | 99.87 |
| **Czechia** | 11 | 0.07 | 99.93 |
| **Slovakia** | 11 | 0.07 | 100 |
| **Total** | 16,643 | 100 | |

**Table 2: Distribution of Incentives by year**

| year | Incentives | | Total |
|---|---|---|---|
| | 0 | 1 | |
| 2010 | 408 | 96 | 504 |
| 2011 | 420 | 140 | 560 |
| 2012 | 433 | 166 | 599 |
| 2013 | 406 | 221 | 627 |
| 2014 | 392 | 250 | 642 |
| 2015 | 387 | 269 | 656 |
| 2016 | 371 | 276 | 647 |
| 2017 | 371 | 306 | 677 |
| 2018 | 351 | 284 | 635 |
| 2019 | 548 | 316 | 864 |
| 2020 | 635 | 383 | 1,018 |
| Total | 4,722 | 2,707 | 7,429 |

**Table 3: Summary statistics of variables**

| | Description | mean | sd | min | max |
|---|---|---|---|---|---|
| Variable of interest | | | | | |
| Incentives | Dummy for incentives to executives | 0.36 | 0.48 | 0.00 | 1.00 |
| Innovation variables | | | | | |
| N° of green patents | N° of green patents each year (log) | 0.55 | 1.01 | 0.00 | 6.13 |
| Green share | N° of patents over total patents | 0.07 | 0.19 | 0.00 | 1.00 |
| Green distance | Min distance of firm's patents portfolio from green classes | 0.46 | 0.32 | 0.00 | 0.69 |
| N° of green citations | N° of brown patents citing green patents (log) | 1.19 | 1.46 | 0.00 | 6.60 |
| Cross-sectional return variables | | | | | |
| Size | Total assets (log) | 15.30 | 1.58 | 10.86 | 18.22 |
| Leverage | Total debt over shareholders' equity | 0.25 | 0.13 | 0.00 | 0.55 |
| ROA | Return on Assets (profitability) | 4.83 | 4.28 | -5.98 | 16.20 |
| Productivity | Total sales scaled by the n° of employees | 5.94 | 0.73 | 2.41 | 10.81 |
| Growth | Revenue growth over time | 0.03 | 0.32 | -0.96 | 14.07 |
| Cash holdings | Cash and short-term investments scaled by total assets | 0.10 | 0.08 | 0.01 | 0.35 |
| NPM | Net profit margin | 7.31 | 9.90 | -166.95 | 196.08 |
| Intangible | Intangible assets scaled by total assets (log) | 13.71 | 1.72 | 9.66 | 17.07 |
| Emissions intensity | Scope 1 emissions scaled by total assets | 0.23 | 1.68 | 0.00 | 114.02 |
| ESG | Refinitiv ESG Score | 57.82 | 17.78 | 0.77 | 95.16 |
| Independent board (%) | Percentage of independent board members | 69.72 | 22.18 | 0.00 | 100.00 |
| members (%) | Percentage of female on the board | 22.19 | 11.97 | 0.00 | 75.00 |
| Board gender diversity (%) Board size | The total number of board members | 10.96 | 3.30 | 1.00 | 30.00 |

**Table 4 – Executive incentives and green innovation output**

| | Green pat | Green pat | Green pat | share | share | share |
|---|---|---|---|---|---|---|
| Green Incentives | 0.599** | 0.495** | 0.399*** | 0.077*** | 0.067*** | 0.052*** |
| | (0.253) | (0.210) | (0.115) | (0.029) | (0.024) | (0.017) |
| Size | | 0.518** | 0.268 | | 0.056 | 0.034 |
| | | (0.259) | (0.310) | | (0.039) | (0.055) |
| Productivity | | 0.462 | 0.356 | | 0.033 | 0.027 |
| | | (0.334) | (0.414) | | (0.051) | (0.064) |
| Leverage | | | -0.848 | | | -0.261** |
| | | | (0.693) | | | (0.128) |
| ROA | | | 0.010 | | | -0.005 |
| | | | (0.026) | | | (0.004) |
| Growth | | | -0.799** | | | -0.093 |
| | | | (0.310) | | | (0.057) |
| Cash Holdings | | | 0.569 | | | -0.048 |
| | | | (0.928) | | | (0.152) |
| NPM | | | 0.016 | | | 0.005** |
| | | | (0.014) | | | (0.002) |
| Intangibles | | | 0.321** | | | 0.036 |
| | | | (0.163) | | | (0.030) |
| ESG score | | | 0.005 | | | 0.001 |
| | | | (0.008) | | | (0.001) |
| Board ind. | | | -0.001 | | | 0.000 |
| | | | (0.006) | | | (0.001) |
| Fem % | | | 0.005 | | | 0.001 |
| | | | (0.008) | | | (0.001) |
| Board size | | | -0.087*** | | | -0.005 |
| | | | (0.031) | | | (0.005) |
| *N* | 1848 | 1848 | 1536 | 1848 | 1848 | 1536 |
| $R^2$ | 0.896 | 0.899 | 0.916 | 0.837 | 0.839 | 0.852 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation output. Dependent variables are the log number of green patents in Columns 1-3 and the share of green patents over total patents in Columns 4-6. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table 5 – Incentives and technological reorientation**

| | Green dist | Green dist | Green dist |
|---|---|---|---|
| Green Incentives | -0.057** | -0.063*** | -0.048** |
| | (0.024) | (0.024) | (0.024) |
| Size | | 0.014 | 0.005 |
| | | (0.046) | (0.090) |
| Productivity | | 0.073 | 0.014 |
| | | (0.057) | (0.077) |
| Leverage | | | 0.329 |
| | | | (0.214) |
| ROA | | | -0.000 |
| | | | (0.008) |
| Growth | | | 0.142* |
| | | | (0.075) |
| Cash Holdings | | | 0.004 |
| | | | (0.219) |
| NPM | | | -0.000 |
| | | | (0.004) |
| Intangibles | | | -0.016 |
| | | | (0.049) |
| ESG score | | | -0.002 |
| | | | (0.001) |
| Board ind. | | | -0.001 |
| | | | (0.001) |
| Fem % | | | 0.001 |
| | | | (0.002) |
| Board size | | | -0.006 |
| | | | (0.008) |
| $N$ | 1848 | 1848 | 1536 |
| $R^2$ | 0.679 | 0.680 | 0.686 |

OLS fixed-effect estimates of the association between executives' green incentives and firms' technological distance from green domains. The dependent variable in all columns is green technological distance. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * $p < .1$, ** $p < .05$, *** $p < .01$

**Table 6 – Executive incentives and green knowledge recombination**

| | Green cit | Green cit | Green cit |
|---|---|---|---|
| Green Incentives | 0.499** | 0.421** | 0.318*** |
| | (0.242) | (0.202) | (0.101) |
| Size | | 0.403 | 0.612 |
| | | (0.261) | (0.382) |
| Productivity | | 0.310 | 0.285 |
| | | (0.268) | (0.306) |
| Leverage | | | -1.741** |
| | | | (0.847) |
| ROA | | | 0.056** |
| | | | (0.021) |
| Growth | | | -0.819** |
| | | | (0.374) |
| Cash Holdings | | | 1.445* |
| | | | (0.809) |
| NPM | | | -0.020* |
| | | | (0.011) |
| Intangibles | | | 0.082 |
| | | | (0.224) |
| ESG score | | | 0.007 |
| | | | (0.007) |
| Board ind. | | | 0.005 |
| | | | (0.006) |
| Fem % | | | 0.000 |
| | | | (0.009) |
| Board size | | | -0.068* |
| | | | (0.037) |
| *N* | 1848 | 1848 | 1536 |
| $R^2$ | 0.916 | 0.918 | 0.930 |

OLS fixed-effect estimates of the association between executives' green incentives and green knowledge recombination. The dependent variable in all columns is the log number of brown patents citing green patents. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table 7 – Executive incentives, green innovation and recent carbon-performance deterioration**

| | Green pat | Green share |
|---|---|---|
| Green Incentives | 0.526*** | 0.081*** |
| | (3.77) | (3.53) |
| DCP | 0.114 | 0.025 |
| | (1.35) | (1.46) |
| Green Inc. x DCP | -0.297** | -0.065** |
| | (-2.21) | (-2.52) |
| Size | 0.259 | 0.034 |
| | (0.84) | (0.64) |
| Leverage | -1.019 | -0.303** |
| | (-1.53) | (-2.49) |
| ROA | 0.000 | -0.006 |
| | (0.02) | (-1.48) |
| Productivity | 0.435 | 0.039 |
| | (1.07) | (0.60) |
| Growth | -0.813*** | -0.099* |
| | (-2.63) | (-1.71) |
| Cash Holdings | 0.679 | -0.022 |
| | (0.75) | (-0.15) |
| NPM | 0.019 | 0.006** |
| | (1.42) | (2.56) |
| Intangibles | 0.337** | 0.038 |
| | (2.01) | (1.25) |
| CO2 emissions/size | 0.804 | 0.017 |
| | (0.80) | (0.10) |
| ESG score | 0.006 | 0.001 |
| | (0.73) | (0.97) |
| Board ind. | 0.001 | 0.001 |
| | (0.18) | (0.85) |
| Fem % | 0.004 | 0.001 |
| | (0.60) | (0.41) |
| Board size | -0.085*** | -0.005 |
| | (-2.80) | (-0.89) |
| *N* | 1536 | 1536 |
| $R^2$ | 0.918 | 0.854 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation output, conditional on prior carbon performance. The dummy variable DCP equals 1 if the firm increased its carbon intensity, measured as CO2 emissions over assets, relative to the previous year. Dependent variables are the log number of green patents in Column 1 and the share of green patents over total patents in Column 2. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table 8 – Executive incentives and green innovation: recent deterioration versus level of carbon intensity**

| | (1)<br>Green pat | (2)<br>Share |
|---|---|---|
| Green Incentives | 0.583*** | 0.109*** |
| | (0.178) | (0.029) |
| DCP | 0.208 | 0.029 |

| | | |
|---|---|---|
| | (0.141) | (0.024) |
| Green Inc. x DCP | -0.241* | -0.067*** |
| | (0.144) | (0.025) |
| High Level | 0.015 | -0.007 |
| | (0.153) | (0.035) |
| Green Inc. x High Level | -0.099 | -0.027 |
| | (0.205) | (0.041) |
| Financial controls | Yes | Yes |
| Governance controls | Yes | Yes |
| Firm FE | Yes | Yes |
| Industry x Year FE | Yes | Yes |
| *N* | 1536 | 1536 |
| $R^2$ | 0.918 | 0.855 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation output, decomposing the carbon-performance moderator into a trajectory component and a level component. DCP (Deteriorating Carbon Performance) equals 1 if the firm's emission intensity increased relative to the previous year; High Level equals 1 if the firm's emission intensity exceeds the median of its industry-year cell. Both interactions with green incentives are included simultaneously. Dependent variables are the log number of green patents in Column 1 and the share of green patents over total patents in Column 2. Financial and governance controls (identical set as Table 7), firm fixed effects, and industry×year fixed effects are included in all columns. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles.

Financial and governance control coefficients omitted from the table for brevity (identical set as Table 7). Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

**Table 9 – Executive incentives, recent carbon-performance deterioration and accumulated green patent stocks**

| | (1) Green pat | (2) Share | (3) Green pat (2000) | (4) Share (2000) | (5) Green pat (2005) | (6) Share (2005) |
|---|---|---|---|---|---|---|
| Green Incentives | 0.550*** | 0.100*** | 0.222 | 0.023 | 0.240 | 0.027 |
| | (0.158) | (0.027) | (0.232) | (0.039) | (0.227) | (0.038) |
| DCP | 0.213 | 0.029 | 0.221 | 0.031 | 0.224 | 0.032 |
| | (0.139) | (0.023) | (0.143) | (0.023) | (0.144) | (0.024) |
| Green Inc. x DCP | -0.249* | -0.070*** | -0.247* | -0.070*** | -0.256* | -0.072*** |
| | (0.143) | (0.025) | (0.147) | (0.025) | (0.148) | (0.026) |
| ln(1+GreenStock t-1) | | | -0.411** | -0.087*** | -0.406** | -0.087*** |
| | | | (0.169) | (0.023) | (0.160) | (0.023) |
| Green Inc. x ln(GreenStock) | | | 0.083 | 0.020** | 0.082 | 0.019** |
| | | | (0.066) | (0.008) | (0.064) | (0.008) |
| Financial controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Governance controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry x Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 1536 | 1536 | 1536 | 1536 | 1536 | 1536 |
| $R^2$ | 0.918 | 0.854 | 0.920 | 0.857 | 0.920 | 0.857 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation output, controlling for firms' accumulated stock of green patents and its interaction with green incentives. The green patent stock is computed with a perpetual-inventory method (15% annual depreciation); Columns 3–4 and 5–6 use alternative pre-sample base years, as indicated in the column headers. DCP (Deteriorating Carbon Performance) equals 1 if the firm's emission intensity increased relative to the previous year. Dependent variables are the log number of green patents and the share of green patents over total patents, as indicated in the column headers. Financial and governance controls, firm fixed effects, and industry×year fixed effects are included in all columns. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles.

Financial and governance control coefficients omitted from the table for brevity. Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01

**Table 10 – Adoption of green incentives and prior carbon-performance deterioration**

| | (1)<br>LPM, natural sample | (2)<br>LPM, sample2 | (3)<br>Logit 1-digit, natural sample | (4)<br>Logit 1-digit, sample2 |
|---|---|---|---|---|
| DCP (t-1) | -0.039** | -0.027 | -0.432** | -0.215 |
| | (0.017) | (0.025) | (0.195) | (0.287) |
| Financial controls (t-1) | Yes | Yes | Yes | Yes |
| Governance controls (t-1) | Yes | Yes | Yes | Yes |
| Firm FE | No | No | No | No |
| Industry x Year FE | Yes (2-digit) | Yes (2-digit) | Yes (1-digit) | Yes (1-digit) |
| Country FE | Yes | Yes | Yes | Yes |
| *N* | 2668 | 959 | 2563 | 862 |

Estimates of the probability of adopting executive green incentives as a function of lagged carbon-performance deterioration, testing whether incentive adoption is a reactive response to worsening carbon metrics. The dependent variable is first-time adoption of executive green incentives. DCP (t−1) is the one-year-lagged Deteriorating Carbon Performance indicator. Columns 1–2 report linear probability models and Columns 3–4 report logit models; the "natural sample" comprises all firm-years at risk of adoption, while "sample 2" restricts to firm-years included in the common estimation sample used in Tables 5–6 (i.e., with non-missing values in the baseline green-distance specification) — a restriction adopted here only as a robustness check on sample composition, with no substantive link to the adoption decision itself. Financial and governance controls are entered at t−1. Industry×year and country fixed effects are included as indicated; firm fixed effects are not applicable given the first-time-adoption design. Standard errors, reported in parentheses, are clustered at the firm level.

Financial and governance control coefficients omitted from the table for brevity (identical set as Table 5–6, entered at t-1). Standard errors in parentheses. * p<.1, ** p<.05, *** p<.01. Firm fixed effects are not applicable: see comment above.

**Table 11 – Sectoral heterogeneity**

| | Green pat | SB | SI | SS | SD |
|---|---|---|---|---|---|
| Green Incentives | 0.407** | 0.246* | 0.536*** | -0.422* | 0.352* |
| | (0.165) | (0.134) | (0.151) | (0.239) | (0.199) |
| Size | 0.147 | -0.522 | 0.629 | -1.455*** | 0.069 |
| | (0.303) | (0.340) | (0.415) | (0.354) | (0.596) |
| Leverage | -1.241* | 1.664* | -1.496** | -3.930** | -5.589*** |
| | (0.674) | (0.859) | (0.726) | (1.667) | (0.924) |
| ROA | 0.016 | -0.050 | 0.008 | 0.005 | 0.007 |
| | (0.028) | (0.058) | (0.035) | (0.063) | (0.047) |
| Productivity | 0.227 | 0.104 | 0.498 | 0.508 | -1.449* |
| | (0.307) | (0.306) | (0.312) | (0.712) | (0.761) |
| Growth | -0.611* | 0.339 | -0.726** | 2.038** | -0.524 |
| | (0.323) | (0.412) | (0.325) | (0.835) | (0.475) |
| Cash Holdings | 0.700 | 0.593 | -1.143 | 8.091*** | 1.375 |
| | (0.858) | (0.877) | (0.977) | (2.021) | (1.358) |
| NPM | 0.013 | 0.023 | 0.009 | 0.031 | 0.030 |
| | (0.014) | (0.036) | (0.018) | (0.036) | (0.023) |
| Intangibles | 0.368* | -0.079 | 0.473** | 0.635* | 0.478 |
| | (0.193) | (0.182) | (0.210) | (0.323) | (0.328) |
| *N* | 1721 | 524 | 444 | 147 | 166 |
| $R^2$ | 0.908 | 0.891 | 0.910 | 0.968 | 0.943 |

OLS fixed-effect estimates of the association between executives' green incentives and green patenting activity, distinguishing companies by Pavitt industry classifications. Column 1 reports the baseline regression for the full sample, while Columns 2-5 present estimates for each Pavitt class. Formal interaction-based tests of sectoral heterogeneity are reported in Appendix Table A2. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles.

* p < .1, ** p < .05, *** p < .01

**Table 12 – Geographical heterogeneity**

| | Green pat | Share |
|---|---|---|
| **EU Sample** | | |
| Green Incentives | 0.600*** | 0.075*** |
| | (0.147) | (0.027) |
| *N* | 664 | 664 |
| $R^2$ | 0.922 | 0.840 |

| | | |
|---|---|---|
| **US Sample** | | |
| Green Incentives | 0.127 | 0.029 |
| | (0.148) | (0.031) |
| *N* | 718 | 718 |
| $R^2$ | 0.908 | 0.855 |

| | | |
|---|---|---|
| **UK sample** | | |
| Green Incentives | 0.495*** | 0.059** |
| | (0.156) | (0.023) |
| *N* | 274 | 274 |
| $R^2$ | 0.988 | 0.963 |

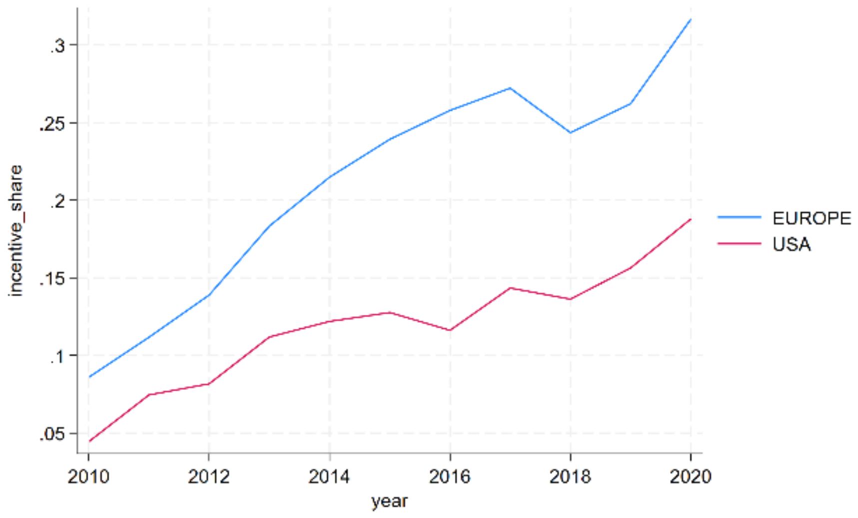
OLS fixed-effect estimates of the association between executives' green incentives and green patenting activity across geographical regions. Panel 1 focuses on European firms, Panel 2 on U.S. firms, and Panel 3 on firms based in the United Kingdom. Formal interaction-based tests of regional heterogeneity are reported in Appendix Table A3. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles.

* p < .1, ** p < .05, *** p < .01

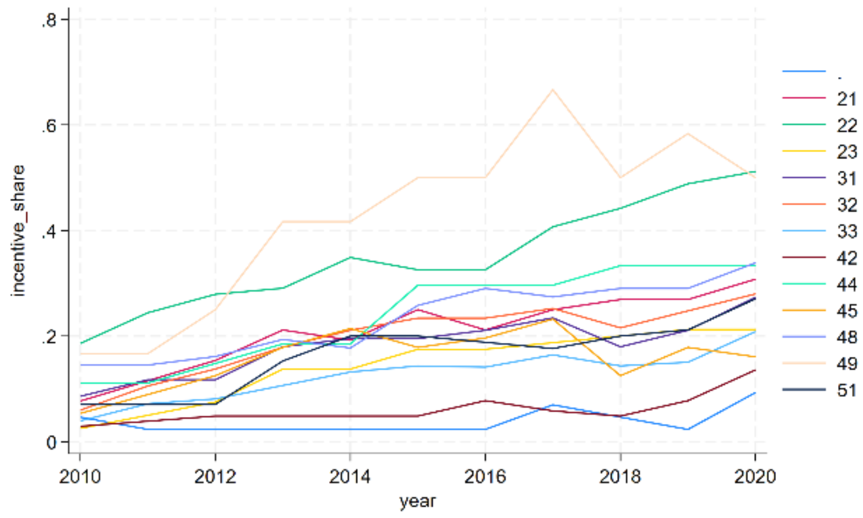
**Table 13. Summary of Hypotheses and Empirical Results**

| Hypothesis | Theoretical mechanism | Empirical test / dependent variable | Expected sign | Main result |
|---|---|---|---|---|
| HP1. Green incentives are positively associated with green innovation performance. | Agency theory (multitask) and the attention-based view: green incentives realign rewarded dimensions and raise the salience of climate objectives on the executive decision agenda. | Green patents (log) and share of green patents over total patents (Table 4). | Positive | Supported. Green incentives are positive and significant for both the number and the share of green patents (Table 4). |
| HP2. Green incentives are associated with a reduction in firms' technological distance from green domains. | Attention-directed, path-dependent search: redirected managerial attention repositions the firm's knowledge portfolio toward green domains before green output materializes. | Green technological distance (Table 5). | Negative | Supported. Green incentives are associated with significantly lower technological distance from green domains (Table 5); robust to controlling for holding at least one green patent (Table A4). |
| HP3. Green incentives are associated with the integration of green knowledge into non-green (brown) technologies. | Recombinant innovation under redirected attention: green knowledge is hybridized into existing brown activities, a precursor of substantive green invention. | Brown patents citing green prior art (Table 6). | Positive | Supported. Green incentives are positive and significant for backward citations from brown to green prior art (Table 6). |
| HP4. The positive association between green incentives and green innovation is weaker among firms experiencing a recent deterioration in carbon performance. | Situated attention: compliance and remediation pressures from worsening carbon metrics absorb the attention and resources that incentives mobilize, shifting them from exploratory search to short-term correction. Presented as a conditional association, not a mechanism. | Interaction Green Incentives × Deteriorating Carbon Performance (DCP) on green patents and green patent share (Table 7). | Negative interaction | Supported. The interaction is negative and significant for both outcomes; the association is concentrated among non-deteriorating firms (Table 7). Diagnostics: driven by the trajectory, not the level, of carbon intensity (Table 8); robust to accumulated green patent stocks (Table 9); not explained by reactive adoption (Table 10). |

**Figure 1**




(a) Share of green incentives by region




(b) Share of green incentives by sector

Notes: The figure plots, over time by Region, the share of companies adopting green incentives for the executive.

Notes: The figure plots the share of companies adopting green incentives for the executive overtime by sector (NAICS two digits) in USA and in EUROPE. 21 - Mining, Quarrying, and Oil and Gas Extraction; 22 - Utilities; 23 - Construction; 31, 32, 33 - Manufacturing; 42 - Wholesale Trade; 44, 45 - Retail Trade; 48, 49 - Transportation and Warehousing; 51 - Information.

# 8 Appendix

**Table A1 – Executive incentives, innovation and carbon-performance deterioration**

| | Green pat | share |
|---|---|---|
| Green Incentives | 0.550*** | 0.100*** |
| | (3.48) | (3.71) |
| DCP (L3) | 0.213 | 0.029 |
| | (1.54) | (1.26) |
| Green inc. x DCP (L3) | -0.249* | -0.070*** |
| | (-1.73) | (-2.81) |
| Size | 0.362 | 0.057 |
| | (1.09) | (0.96) |
| Leverage | -0.937 | -0.285** |
| | (-1.37) | (-2.36) |
| ROA | 0.007 | -0.005 |
| | (0.27) | (-1.20) |
| Productivity | 0.415 | 0.031 |
| | (1.01) | (0.49) |
| Growth | -0.743** | -0.093* |
| | (-2.57) | (-1.71) |
| Cash Holdings | 0.404 | -0.061 |
| | (0.44) | (-0.41) |
| NPM | 0.017 | 0.005** |
| | (1.29) | (2.41) |
| Intangibles | 0.244 | 0.022 |
| | (1.54) | (0.71) |
| CO2 emissions/size | 0.457 | -0.028 |
| | (0.52) | (-0.18) |
| ESG score | 0.005 | 0.001 |
| | (0.64) | (1.02) |
| Board ind. | -0.002 | 0.000 |
| | (-0.36) | (0.20) |
| Fem % | 0.005 | 0.000 |
| | (0.66) | (0.35) |
| Board size | -0.089*** | -0.005 |
| | (-2.92) | (-1.07) |
| *N* | 1536 | 1536 |
| $R^2$ | 0.918 | 0.854 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation output, with a focus on how this association varies depending on medium-term carbon performance. The dummy variable DCP equals 1 if the firm's emission intensity exceeds the average of the three preceding years, capturing medium-term emission trends. Dependent variables are the log number of green patents in Column 1 and the share of green patents over total patents in Column 2. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table A2 – Sectoral heterogeneity**

| | Green patents | Green share |
|---|---|---|
| Green Inc. × SB | 0.270* | 0.016 |
| | (0.163) | (0.029) |
| Green Inc. × SD | 0.432** | 0.071** |
| | (0.191) | (0.031) |
| Green Inc. × SI | 0.498*** | 0.050 |
| | (0.152) | (0.031) |
| Green Inc. × SS | -0.416** | 0.044 |
| | (0.203) | (0.035) |
| Size | 0.672** | 0.093 |
| | (0.301) | (0.057) |
| Leverage | -1.501** | -0.334** |
| | (0.696) | (0.130) |
| ROA | 0.007 | -0.004 |
| | (0.023) | (0.004) |
| Productivity | 0.513 | 0.040 |
| | (0.396) | (0.063) |
| Growth | -0.706** | -0.080 |
| | (0.302) | (0.059) |
| Cash Holdings | 0.618 | -0.018 |
| | (0.911) | (0.151) |
| NPM | 0.008 | 0.004** |
| | (0.011) | (0.002) |
| Intangibles | 0.176 | 0.017 |
| | (0.184) | (0.032) |
| ESG score | 0.003 | 0.001 |
| | (0.007) | (0.001) |
| Board ind. | -0.002 | -0.000 |
| | (0.006) | (0.001) |
| Fem % | 0.006 | 0.001 |
| | (0.007) | (0.001) |
| Board size | -0.056* | -0.001 |
| | (0.030) | (0.006) |
| *N* | 1323 | 1323 |
| $R^2$ | 0.913 | 0.847 |

OLS fixed-effect estimates of the association between executives' green incentives and green patenting activity, incorporating interaction terms between green incentives and Pavitt industry classifications. Rather than splitting the sample, all specifications are estimated on the full sample, with sector-specific associations identified through interactions between the green incentives dummy and each Pavitt category. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table A3 – Geographical heterogeneity**

| | Green patents | Green share |
|---|---|---|
| Green Inc. × EU | 0.386** | 0.053** |
| | (0.183) | (0.022) |
| Green Inc. × UK | 0.274 | 0.002 |
| | (0.293) | (0.074) |
| Green Inc. × US | 0.228 | 0.037 |
| | (0.140) | (0.025) |
| Size | 0.481 | 0.086 |
| | (0.330) | (0.056) |
| Leverage | -1.348* | -0.331*** |
| | (0.695) | (0.126) |
| ROA | 0.007 | -0.004 |
| | (0.023) | (0.004) |
| Productivity | 0.603 | 0.046 |
| | (0.420) | (0.066) |
| Growth | -0.779** | -0.082 |
| | (0.323) | (0.060) |
| Cash Holdings | 0.667 | -0.026 |
| | (0.929) | (0.153) |
| NPM | 0.010 | 0.004** |
| | (0.011) | (0.002) |
| Intangibles | 0.244 | 0.018 |
| | (0.187) | (0.032) |
| ESG score | 0.005 | 0.001 |
| | (0.007) | (0.001) |
| Board ind. | -0.003 | -0.000 |
| | (0.006) | (0.001) |
| Fem % | 0.006 | 0.001 |
| | (0.008) | (0.001) |
| Board size | -0.072** | -0.002 |
| | (0.033) | (0.006) |
| *N* | 1323 | 1323 |
| $R^2$ | 0.911 | 0.847 |

OLS fixed-effect estimates of the association between executives' green incentives and green patenting activity, incorporating interaction terms between green incentives and regional dummies. Rather than splitting the sample, all specifications are estimated on the full sample, with region-specific associations identified through interactions between the green incentives dummy and each geographical area. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table A4** - Executive incentives and technological distance: robustness check

| | Green dist | Green dist | Green dist | Green dist | Green dist | Green dist |
|---|---|---|---|---|---|---|
| Green Incentives | -0.057** | -0.063*** | -0.048** | -0.058** | -0.063*** | -0.048** |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| Green pat. (0/1) | | | | -0.029 | -0.027 | -0.004 |
| | | | | (0.048) | (0.048) | (0.053) |
| Size | | 0.014 | 0.005 | | 0.010 | 0.005 |
| | | (0.046) | (0.090) | | (0.046) | (0.091) |
| Productivity | | 0.073 | 0.014 | | 0.071 | 0.014 |
| | | (0.057) | (0.077) | | (0.056) | (0.077) |
| Leverage | | | 0.329 | | | 0.328 |
| | | | (0.214) | | | (0.210) |
| ROA | | | -0.000 | | | -0.000 |
| | | | (0.008) | | | (0.008) |
| Growth | | | 0.142* | | | 0.141* |
| | | | (0.075) | | | (0.075) |
| Cash Holdings | | | 0.004 | | | 0.004 |
| | | | (0.219) | | | (0.219) |
| NPM | | | -0.000 | | | -0.000 |
| | | | (0.004) | | | (0.004) |
| Intangibles | | | -0.016 | | | -0.016 |
| | | | (0.049) | | | (0.050) |
| ESG score | | | -0.002 | | | -0.002 |
| | | | (0.001) | | | (0.001) |
| Board ind. | | | -0.001 | | | -0.001 |
| | | | (0.001) | | | (0.001) |
| Fem % | | | 0.001 | | | 0.001 |
| | | | (0.002) | | | (0.002) |
| Board size | | | -0.006 | | | -0.006 |
| | | | (0.008) | | | (0.008) |
| *N* | 1848 | 1848 | 1536 | 1848 | 1848 | 1536 |
| $R^2$ | 0.679 | 0.680 | 0.686 | 0.679 | 0.680 | 0.686 |

This table estimates the association between executives' green incentives and technological distance from the green domain. Columns (1) to (3) report the baseline specifications. Columns (4) to (6) replicate the baseline adding a dummy variable equal to 1 if the firm produced at least one green patent in a given year, to verify that results are not driven by the mechanical properties of the minimum-distance measure. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01

**Table A5** - Composition of the CEM matched sample

| Variable name | Count | Matched |
|---|---|---|
| always_treated | 145 | |
| never_treated | 709 | 313 |
| switcher_valid | 418 | 313 |
| excluded_2010_adopter | 12 | |
| Notes: Counts refer to units entering the CEM matching procedure. always_treated firms lack a pre-treatment observation window and are excluded from the matching pool. Twelve switchers whose first adoption is observed in 2010 are additionally excluded, as 2010 is not a pre-treatment year for them; the remaining 418 switchers all have first adoption in 2011-2020. | | |

**Table A6 -** CEM matched sample

| | (1)<br>Green pat | (2)<br>Green share | (3)<br>Green distance | (4)<br>Green cit |
|---|---|---|---|---|
| Green Incentives | 0.485*** | 0.061*** | -0.045* | 0.337*** |
| | (0.100) | (0.017) | (0.023) | (0.089) |
| Size | 0.084 | 0.012 | 0.121 | 0.039 |
| | (0.360) | (0.072) | (0.107) | (0.364) |
| Leverage | -0.956 | -0.244 | 0.011 | -0.725 |
| | (0.891) | (0.153) | (0.252) | (0.751) |
| ROA | 0.003 | -0.005 | -0.004 | 0.056*** |
| | (0.030) | (0.004) | (0.009) | (0.021) |
| Productivity | 0.918*** | 0.073 | 0.061 | 0.616* |
| | (0.351) | (0.068) | (0.119) | (0.342) |
| Growth | -0.984*** | -0.133** | 0.212*** | -1.158*** |
| | (0.326) | (0.060) | (0.073) | (0.368) |
| Cash Holdings | 0.140 | 0.031 | -0.227 | 1.617** |
| | (0.874) | (0.168) | (0.238) | (0.818) |
| NPM | 0.017 | 0.005** | -0.002 | -0.010 |
| | (0.016) | (0.002) | (0.004) | (0.009) |
| Intangibles | 0.487*** | 0.057 | -0.065 | 0.460** |
| | (0.172) | (0.039) | (0.059) | (0.196) |
| ESG score | 0.001 | 0.001 | -0.000 | -0.009 |
| | (0.010) | (0.002) | (0.002) | (0.008) |
| Board ind. | 0.006 | 0.001 | -0.003* | 0.021*** |
| | (0.007) | (0.001) | (0.002) | (0.007) |
| Fem % | 0.006 | 0.001 | -0.001 | 0.010 |
| | (0.009) | (0.002) | (0.002) | (0.009) |
| Board size | -0.021 | 0.001 | -0.013* | 0.024 |
| | (0.033) | (0.006) | (0.007) | (0.027) |
| *N* | 979 | 979 | 979 | 979 |
| $R^2$ | 0.927 | 0.863 | 0.682 | 0.941 |

OLS fixed-effect estimates of the association between executives' green incentives and green innovation outcomes, estimated on the CEM-matched sample. The matching procedure retains 313 treated and 313 control units; the regression N reports the corresponding matched firm-year observations. The specification is identical to the baseline analysis and includes the full set of financial and governance controls. Heteroskedasticity-robust standard errors, reported in parentheses, are clustered at the firm level. All economic variables are trimmed at the 5th and 95th percentiles. * p < .1, ** p < .05, *** p < .01.

**Table A6.1 -** CEM balance on matching variable: size tercile

| | (1)<br>Treated (pre)<br>pct | (2)<br>Control (pre)<br>pct | (3)<br>Treated (post)<br>pct | (4)<br>Control (post)<br>pct |
|---|---|---|---|---|
| 1 | 15.1 | 25.4 | 19.2 | 19.2 |
| 2 | 24.6 | 19.7 | 27.2 | 27.2 |
| 3 | 38.5 | 11.6 | 24.6 | 24.6 |
| Missing | 21.8 | 43.3 | 29.1 | 29.1 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 |

**Table A6.2 -** CEM balance on matching variable: industry (NAICS 1-digit)

| | (1)<br>Treated (pre)<br>pct | (2)<br>Control (pre)<br>pct | (3)<br>Treated (post)<br>pct | (4)<br>Control (post)<br>pct |
|---|---|---|---|---|
| 1 | | 0.8 | | |
| 2 | 22.0 | 13.1 | 17.6 | 17.6 |
| 3 | 54.1 | 57.3 | 58.1 | 58.1 |
| 4 | 15.3 | 18.8 | 15.3 | 15.3 |
| 5 | 7.4 | 6.1 | 7.7 | 7.7 |
| 9 | 0.5 | 0.3 | 0.3 | 0.3 |
| Missing | 0.7 | 3.7 | 1.0 | 1.0 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 |

**Table A6.3 -** CEM balance on matching variable: country

| | (1)<br>Treated (pre)<br>pct | (2)<br>Control (pre)<br>pct | (3)<br>Treated (post)<br>pct | (4)<br>Control (post)<br>pct |
|---|---|---|---|---|
| 1 | 1.0 | 1.0 | 0.3 | 1.0 |
| 10 | 5.0 | 5.2 | 5.1 | 4.5 |
| 11 | 0.5 | 0.3 | 0.6 | 0.6 |
| 12 | 2.2 | 0.7 | 2.6 | 1.0 |
| 13 | 0.2 | 1.1 | 0.3 | 1.3 |
| 14 | 1.7 | 0.6 | 1.0 | 0.6 |
| 15 | | 0.3 | | |
| 17 | 4.1 | 4.5 | 3.5 | 5.1 |
| 18 | 6.0 | 2.5 | 6.4 | 3.2 |
| 19 | 17.0 | 12.6 | 17.3 | 16.6 |
| 2 | 1.4 | 1.3 | 1.3 | 1.6 |
| 20 | 39.2 | 54.3 | 45.0 | 45.0 |
| 3 | 0.2 | | | |
| 4 | 1.9 | 2.4 | 1.9 | 2.9 |
| 5 | 3.3 | 3.2 | 3.2 | 3.8 |
| 6 | 9.6 | 2.4 | 6.1 | 3.2 |
| 7 | 5.5 | 5.8 | 4.8 | 7.3 |

| | | | | |
|---|---|---|---|---|
| 8 | 0.2 | | | |
| 9 | 1.0 | 1.8 | 0.6 | 2.2 |
| Total | 100.0 | 100.0 | 100.0 | 100.0 |