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RESEARCH ARTICLE

Do Climate Policies Incentivize Firms to Commit to Setting a GHG Emissions Target?

Marco Hernandez-Vega[1,2,*] **and Eduardo Martínez González**[1]

[1] *Directorate General of Economic Research, Banco de Mexico, Mexico*

[2] *Anahuac Business School, Universidad Anahuac Mexico, Mexico*

Abstract: Since the 2016 Paris Agreement, firms have faced growing pressure to act on climate change, yet the influence of national climate policy frameworks on corporate target-setting remains underexplored. This paper examines whether advances in national climate policy are associated with firms' decisions to commit to setting greenhouse gas (GHG) reduction targets. To do so, we build a firm-level panel by matching public firms in the Science-Based Targets initiative to the national climate policy index, part of the Climate Change Performance Index, and green bond issuance from the Climate Bonds Initiative, covering 32 economies over 2017–2022. Moreover, the inclusion of firms from emerging economies contributes to the literature by recognizing the structural and institutional constraints that may hinder corporate commitments to set emissions targets. Using a correlated random effects probit model that accounts for unobserved firm heterogeneity, we find that stronger national climate policies are associated with a higher probability of commitment: a one-point increase in the policy index is associated with a rise of 8.3 and 8.9 percentage points for companies operating in advanced economies and emerging economies, respectively. Such results are concentrated in nonfinancial firms and low-emitting sectors. Green bond issuance is positively, though modestly, related to commitment. Taken together, the findings suggest that national climate policy advances are strongly associated with committing to set GHG emissions targets, but companies in high-emitting sectors may require additional, sector-specific incentives.

Keywords: binary response models, climate policy, GHG emissions targets, Science-Based Targets initiative (SBTi), corporate climate target-setting

1. Introduction

Since the 2016 Paris Agreement, countries and corporations have been pressured to implement effective measures to mitigate climate change. Understanding what drives firms to implement climate change mitigation actions is crucial in this context. The existing literature identifies a range of motivations, including exposure to physical climate risks, rising fossil fuel costs exacerbated by geopolitical events such as Russia's invasion of Ukraine, and reputational concerns among consumers and investors [1–6].

While physical and market-based factors are central to corporate climate actions, the role of public policy is equally essential. Recent survey data from the European Investment Bank [7] shows that half of European firms have experienced losses and supply disruptions due to extreme weather. In response, many are investing in resilience-enhancing technology and processes. In turn, governments play a pivotal role in setting the incentives to cut greenhouse gas (GHG) emissions [8–11].

Along with fiscal instruments, financial policies have emerged as key enablers of climate investment. The research by Vyshnevskyi and Sohn [11] and the article by Krogstrup and Oman [12] identify several tools to mobilize capital toward green projects, including the establishment of green bond contracts, the amendment of prudential regulations, shifts in the portfolio choices of central banks and institutional investors, and reallocation of financial resources to climate-friendly activities. Although Vyshnevskyi and Sohn [11] and Krogstrup and Oman [12] offer a rich conceptual overview, they do not present concrete estimations of the potential impact that such financial mechanisms may yield, leaving a gap between theoretical promise and measurable outcomes. Among these, facilitating green bond issuance has garnered particular attention, as it aligns well with both public and private sector incentives to promote cleaner energy solutions and foster long-term economic sustainability [13, 14].

Nevertheless, these instruments are often less effective in emerging market economies (EMEs), where elevated capital costs, exchange rate risks, and weak regulation and supervision hinder the scaling up of green finance. According to Perelli et al. [15], the cost of capital for solar projects in EMEs is two to three times higher than in advanced economies. They also mention that to meet Paris Agreement goals, annual climate mitigation investment in these economies must rise to USD 2 trillion by 2030—roughly 40% of global mitigation needs.

A key aspect of these investment practices is understanding the relationship between corporate economic, social, and governance (ESG) strategies and financial performance. While the relationship between ESG strategies and firm performance is well documented (e.g., the article by Friede et al. [16], the article by Shaikh [17], and the article by Engelhardt et al.

***Corresponding author:** Marco Hernandez-Vega, Directorate General of Economic Research, Banco de Mexico and Anahuac Business School, Universidad Anahuac Mexico, Mexico. Email: auhernandez@banxico.org.mx

[18]), the role of national climate policy frameworks in motivating corporate mitigation commitments remains unexplored, particularly in EMEs, where policy signals are often weaker, and firms face more significant barriers to green projects.

Hence, two main gaps remain in the literature. First, the role of climate policies in incentivizing firms to commit to setting GHG emissions targets. Second, the study of the case of EMEs, where companies face significant challenges.

This paper contributes to the literature by analyzing whether advances in national climate policies incentivize firms to commit to setting GHG emissions targets. Moreover, by incorporating firms domiciled in EMEs, the analysis contributes to filling a gap in the literature on climate policy effectiveness, since prior research has rarely considered the structural and institutional constraints that may hinder corporate commitments to set a GHG emissions target. For this purpose, we estimate a correlated random effects (CRE) panel probit model, which accounts for unobserved firm-level heterogeneity (fixed effects). Here, the dependent variable is a binary indicator for whether a firm committed to setting a GHG emissions target or not. The key explanatory variable is the National Climate Policy Index, a Climate Change Performance Index (CCPI) component that captures country-level progress in climate legislation and institutional capacity. In addition, we include country-level data on green bond issuance as a proxy for the financing of green projects. By distinguishing across firm types, sectors, and country groups, we provide empirical insights into the institutional and financial conditions that foster corporate climate action. We outline a simple conceptual framework linking policy incentives and signaling to firms' commitment decisions that motivate our empirical strategy. Our estimates should be interpreted as conditional associations rather than causal effects.

The results suggest that advances in national climate policies are associated with a higher probability of firms committing (an increase of 1 point in the index raises the probability by 8.4 percentage points). Such results remain when looking at firms domiciled in advanced economies (8.2 percentage points) and EMEs (8.85 percentage points). However, in this last case, such an effect is only statistically significant at the 10% level.

By distinguishing between firms in the financial services sector and the nonfinancial sector, the results show that national climate policies do not contribute to the chance of financial institutions committing to setting a GHG emissions target. One possible explanation for this result may be that these policies do not directly affect this type of firm. Still, such policies are essential for firms not in the financial services sector, raising the probability of these firms committing between 8 and 9 percentage points.

We also extend the analysis by focusing on nonfinancial firms and separating them into firms that belong to sectors known as the highest emitters of GHG and firms in the low emitters sectors. The results show that improving national climate policies increases the probability of low-emitting firms committing by 11.7 percentage points. At the same time, in the case of advanced economies, it raises such probability by 11.8 percentage points and for EMEs by 19 percentage points. Nevertheless, climate policy does not significantly affect the likelihood of higher-emitting firms committing. One possible explanation for these results may be that for firms in the highest emitters sectors, adapting their technology and practices to reduce their GHG emissions can be quite costly and take longer than for firms in other sectors. Also, in some countries, such industries may be an essential factor in their economies, making it more difficult to pressure them to cut GHG emissions. Lastly, a 1% increase in green bond issuance is modestly associated with a higher probability of committing. Taken together, our results suggest that national climate policy advances are strongly associated with firms committing to set a GHG emissions target, while high-emitting sectors may require additional sector-specific incentives.

The article is organized as follows: The second section describes the data and the sample selection process, and the third outlines the methodology. The fourth section presents the results, the fifth provides some robustness exercises, and the sixth concludes.

2. Conceptual Mechanism

We view a firm's decision to commit to set a GHG emissions reduction target as an investment under uncertainty. Committing to a Science-Based Targets initiative (SBTi) target is a serious commitment, as the company must meet strict requirements and work closely with SBTi experts to define a science-based target. This process is costly. For example, the company must invest in familiarizing personnel with decarbonization pathways, designing emissions reduction strategies, planning upgrades to production processes, and, in some cases, capital expenditures for new machinery and equipment. Nevertheless, it can also yield benefits, such as revealing operational inefficiencies, spurring process or production innovation, and lowering perceived risk among creditors. When these expected benefits outweigh the expected costs, the firm is more likely to commit.

This cost–benefit calculus is affected by the introduction of stricter national climate policies. On the one hand, tighter policies raise the expected costs of inaction by tightening current rules and signaling demanding future standards, which could be accompanied by severe penalties for non-compliance. On the other hand, new strict climate policies reduce uncertainty about the country's decarbonization path, encouraging firms to commit and avoid future frictions. Firms that commit may also be able to adapt more easily to an evolving regulatory environment because having an approved science-based target requires early planning, internal governance, and monitoring systems.

Moreover, when new national climate policies are announced, committing to set a science-based target that is subject to scrutiny and ongoing disclosure sends a strong signal that a company is willing to take emissions reduction seriously. According to research by Friede et al. [16], this signal helps to reduce information asymmetries with investors and customers and builds legitimacy by showing that committed firms will be ready to face a tighter regulatory environment.

3. Data and Methodology

3.1. SBTi firms data

The SBTi, launched in 2015, is a partnership between the Carbon Disclosure Project, the United Nations Global Compact, the World Resources Institute, and the World-Wide Fund for Nature. SBTi provides a framework and methodology for companies to set ambitious and credible GHG emissions targets. These targets are considered "science-based" when they reflect the latest climate science and aim to limit global warming to well below 2 °C.

GHG emissions targets are categorized into three scopes. Scope 1 includes direct emissions from sources owned or controlled by the company. Scope 2 covers indirect emissions from purchased energy. Lastly, scope 3 refers to other indirect emissions not owned or controlled by the reporting firm, such as emissions from the company's value chain. Science-based targets typically cover scopes 1 and 2, but if scope 3 exceeds 40% of the total sum of scopes 1, 2, and 3, the targets must be set to reduce emissions covered by the three scopes.

The target-setting process involves five steps: (1) submitting a letter of intent (Commitment), (2) defining targets consistent with SBTi's guidelines (Development), (3) submitting them for validation (Submission), (4) publicly announcing approved targets (Communicate Target), and (5) annually disclosing emissions and progress (Disclosure). Once committed, a company has 24 months to submit its targets to SBTi. During this period, SBTi assists companies in developing their emissions targets and the pathways to achieve them.

Firms in the SBTi are classified depending on their status in the process of setting a GHG emissions target: A status of *committed*, indicating that a firm has made public their willingness to work with the SBTi to set a target, and a status of *target-set* that suggests that a firm has gone over all steps required by the SBTi and now has an approved GHG emissions target. Also, the firms can be categorized as public (their stocks are available for trading to the public) or private (stocks are not publicly traded). Up to mid-2023, the year we accessed the data, 8,375 firms were partnering with the SBTi from around 86 countries, of which 4,690 (56%) of the total are private and 3,685 are public. In this work, we focus on public firms since it is not clear that green bond issuance by private firms can be publicly traded.

To align with the annually reported CCPI and CBI data, SBTi data is adapted to annual terms. We use the commitment date to reflect the initial climate actions' intent and exclude firms that failed to submit targets within the 24-month window and/or did not receive validation of their targets to avoid potential bias (around 18 companies). Out of the total sample of public companies, 48% or 1,775 firms are committed, and the rest, 1,910, have an approved target. Also, the number of committed firms in the sample covers almost 50% of the universe of committed firms in the SBTi database.

Figure 1 [19] shows the sample's evolution of firms committing annually since 2017. Most companies are located in advanced economies, whereas EMEs have the fewest number of companies. As can be seen in Figure 1, between 2017 and 2020, a few firms committed to GHG objectives, which reflects a low number of ones in the dependent variable. In 2021–2022, we observed a strong rebound in the number of firms committed. It is essential to clarify that firms committed in 2017 are included in 2018, and so on (firm-level commitment data was obtained from the SBTi [19] public registry).

The country with the highest number of firms committed is the United Kingdom (21% of the total). In second place is the United States (18%), followed by Germany (7%), France and Sweden (5% each), and Japan (4%). Regarding emerging economies, China and India have the most significant number of companies in the data (3% each) (see Figure 2) [19].

3.2. Climate policy data

To study the influence of climate change policies on firms' decision to commit, we used the CCPI. The CCPI enables transparent comparisons across countries on their advances toward climate protection. The last version of the index evaluates around 60 countries responsible for more than 92% of GHG emissions.

The CCPI is built from quantitative data on four major categories: "GHG Emissions," "Renewable Energy," "Energy Use," and "Climate Policy." The last category comprises two indicators: National and International Climate Policy. The first is the result of expert evaluations (nongovernmental institutions, universities, and think tanks) of a country's climate policy advances in reducing GHG emissions. The second qualifies the respective country's participation in international climate policy conferences. No single country has achieved a high enough score in these four components to achieve a score higher than 76.67 (the scale goes from 0 to 100). However, some countries have very low scores in all four categories (see Table 1).

Figure 1
Companies committed per year 2017–2022

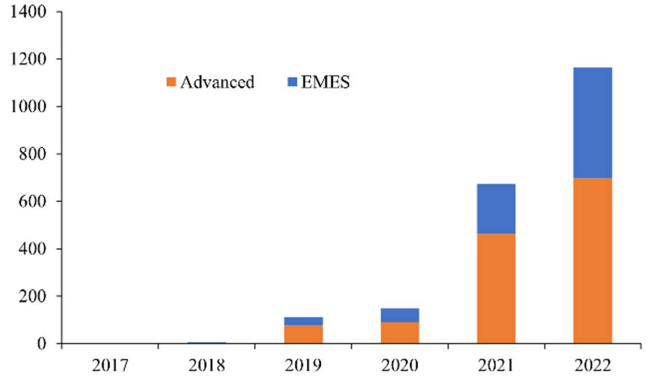


Figure 2
Companies committed per country 2017–2022

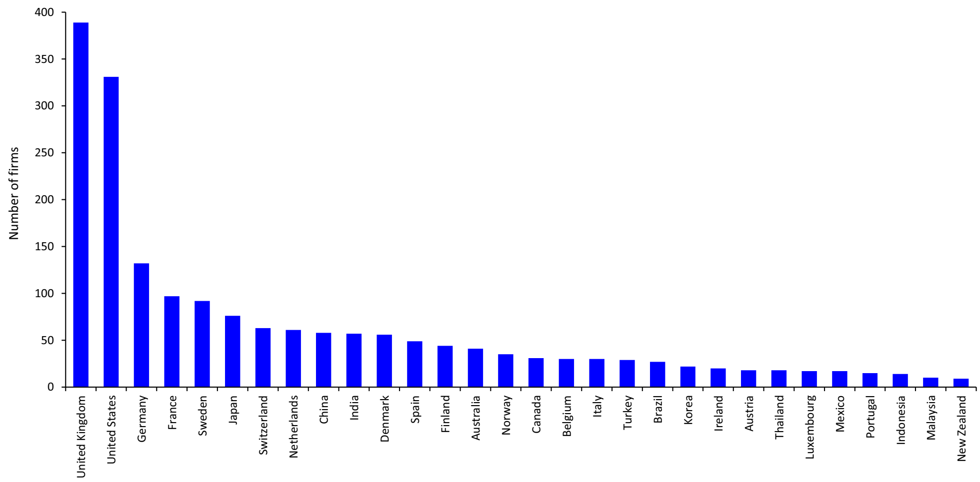


Table 1
Summary statistics

	Mean	Min	Max	Std. Dev.
Green Bond	20.60	0.02	91.30	23.50
Overall CCPI	53.11	18.60	76.67	16.45
GHG Emissions	24.91	5.40	44.44	8.83
Renewable Energy	6.99	1.13	19.21	3.28
Energy Use	10.21	2.87	16.34	3.32
Climate Policy	11.01	0.00	19.74	5.29
National	3.06	1.00	5.00	1.02
International	2.48	1.21	3.95	0.63

3.3. GHG emission

The GHG Emissions component of the CCPI assesses national performance across four dimensions: (a) the current level of GHG emissions per capita, (b) the trajectory of GHG emissions per capita over time, (c) the current level of GHG emissions per capita compared to a well-below 2 °C compatible pathway, and (d) GHG emissions reduction target for 2030 compared to a well-below 2 °C compatible pathway.

Regarding the (c) subcategory of the GHG Emissions component of CCPI, a "well-below 2 °C compatible" pathway, as defined by the Paris Agreement, requires GHG emissions to begin declining between 2020 and no later than 2025, with CO_2 emissions reaching net zero by around 2050. Lastly, subcategory (d) evaluates a country's 2030 mitigation target, that is, its emissions reduction plans for 2030.

Despite widespread efforts, progress remains limited. No country has scored above 44, with most ranking between 17 and 32. Note that there is also a significant difference between countries with the lowest and maximum scores (see Table 1).

3.4. Renewable energy

The Renewable Energy component within the CCPI assesses countries' performance and efforts in promoting and deploying renewable energy sources. It accounts for 20% of the overall CCPI and comprises four equally weighted sub-components: (a) current share of renewable energy sources per Total Primary Energy Supply (TPES), (b) past trend of energy supply from renewable energy sources per TPES, (c) current share of renewables per TPES compared to a well-below 2 °C compatible pathway, and (d) renewable energy 2030 target compared to a well-below 2 °C compatible pathway.

A "very high" rating is awarded when renewables account for at least 35% of TPES or when their share grows by 75% or more over five years. The benchmark for climate compatibility is 100% renewable energy by 2050, and countries are rated based on how closely their current performance and current targets align with this trajectory. Ratings range from "very high" to "very low" depending on the degree of deviation from these thresholds. Note that the average score in the Renewable Energy component is 6.99 (on a scale of 0–30), and the country with the best score nearly reached 20, while the lowest was 1.13 (see Table 1).

3.5. Energy use

The Energy Use component within the CCPI accounts for 20% of the overall index and evaluates countries' energy efficiency performance and efforts to reduce energy consumption. It comprises four equally weighted sub-components (5% each): current level, recent development, and the 2 °C compatibility of both the current level and the 2030 target. Lower energy consumption per capita and significant reductions over time are rewarded with higher ratings, reflecting a country's progress toward net-zero emissions.

Rates are determined by benchmarks. Less than 60 UnitTPES/-capita earns a "very high" score, while more than 150 is rated "very low". A decrease in energy use of over 15% in five years also earns top marks. The third sub-component compares current consumption to a modeled pathway from 1990 to 2050, rewarding countries that undercut it by more than 15%. Lastly, 2030 targets are assessed based on their proximity to the pathway, where targets that fall below it receive higher ratings. The average Energy Use score was 10.21 (on a scale from 0 to 20), but one country achieved a maximum score of 16.34, which is not high enough to attain the very high classification (see Table 1).

3.6. Climate policy

The last component of CCPI assesses the quality and ambition of countries' climate policy frameworks through an annual expert survey. According to the CCPI 2023, about 450 national climate specialists from NGOs, universities, and research institutes from around 84 countries rate their governments' performance on a scale from 1 ("weak") to 10 ("strong"), assessing policy design, implementation, and alignment with the targets of the Paris Agreement.

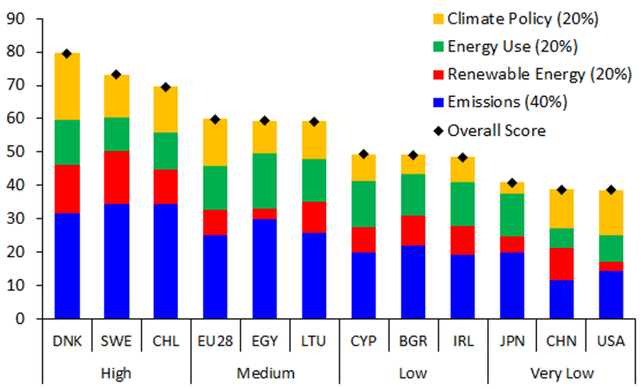
This category accounts for 20% of the overall index, equally divided between national and international dimensions. Its influence on short-term changes in the overall ranking often leads to notable upward movements. A Climate Policy score above 9 or 7 in the survey receives a "very high" or "high" rating (so far, only Denmark has achieved such a score). Anything above 5 still results in "medium" (In the CCPI 2023, the countries with a medium rating were Austria, Chile, China, Colombia, Finland, Germany, India, Latvia, Lithuania, Luxembourg, Morocco, Netherlands, Portugal, Sweden, and the United States). Anything below 3 is a "very low" performance (Argentina, Hungary, Korea, Russia, and Turkey). The simple average between national and international climate policy grades equals the Climate Policy category score.

National policy assessments include measures to promote renewable energies, improve energy efficiency, and reduce GHG emissions across key sectors and protect ecosystems. International policy evaluations focus on participation in UNFCCC conferences and other multilateral climate initiatives.

The CCPI index underwent a significant revision in 2017 to better reflect the road toward achieving the 2030 commitments established in the Paris Agreement. As a result, since 2018, the CCPI has not been compatible with its previous version. The only exception is the "Climate Policy" category, which remains compatible with all previous data.

A key result in the article by Caglar et al. [20] shows that no country was strong enough in all index categories to achieve an overall very high rating. In this way, the top three places remain empty, with Denmark in fourth place, as in several previous years, Sweden in fifth place, and Chile in sixth place. In that sense, Figure 3 shows the top three countries for high, medium, low, and very low scores in 2023. The United States has the third-lowest score among the "Very Low" category countries. According to the report by Burck et al. [21], the current national targets for reducing GHG emissions are not ambitious enough for a 1.5 °C world.

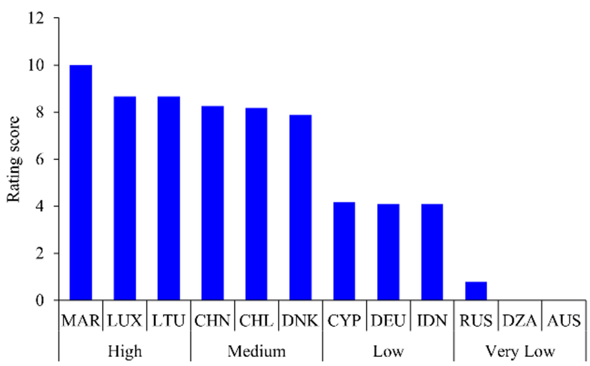
Figure 3
Top three countries for each category of the CCPI classification 2023



Note: DNK = Denmark, SWE = Sweden, CHL = Chile, EU28 = European Union 28 members, EGY = Egypt, LTU = Lithuania, CYP = Cyprus, BGR = , IRL= Ireland, JPN = Japan, CHN = China, and USA = United States. The number in parentheses is the weight of each CCPI component within the overall index.

Figure 4 presents an overview of the National subcategory within the Climate Policy component of the CCPI, which is also the independent variable used in further estimations. It shows the top three countries by the National rating score. Again, the very high position is empty because no country was strong enough to achieve this category.

Figure 4
Top three countries in the national climate policy category 2022



Note: MAR = Morocco, LUX = Luxembourg, LTU = Lithuania, CHN = China, CHL = Chile, DNK = Denmark, CYP = Cyprus, DEU = Germany, IDN = Indonesia, RUS = Russia, DZA = Algeria, and AUS = Australia.

3.7. Green bonds

In response to the escalating challenges of climate change and environmental degradation, financial markets are increasingly aligning with sustainability goals. Among the most prominent instruments are green loans and green bonds, which channel capital toward environmentally beneficial projects and reflect a shift in how public and private sectors integrate climate considerations into financial strategies.

Green loans, typically extended by financial institutions, are funds explicitly designated for projects with environmental benefits. Conversely, green bonds are debt instruments issued by governments, municipalities, and corporations, with proceeds explicitly assigned to finance sustainable and environmentally friendly projects.

Green bonds function similarly to conventional bonds, offering fixed returns and repayment at maturity, but differ in purpose: their proceeds are exclusively allocated to projects with positive environmental impact. Issued by governments, corporations, or financial institutions, these instruments are often verified by third-party organizations to ensure credibility and transparency. The Climate Bonds Initiative (CBI) plays a key role in this process by maintaining a directory of approved verifiers.

The CBI also provides free access to its green bond dataset. According to this institution, several types of green bonds exist, but the majority belong to two categories: "Use of Proceeds" bonds and "Use of Proceeds" revenue bonds. The difference between these types of bonds is that, in the first, the proceeds obtained can only be used to finance green projects, while in the second, the gains can also be directed to refinance green projects. Another characteristic of green bonds is that the issuer's balance sheet protects them.[1]

The most recent data show that developed economies have been the primary issuing market, accounting for 72% of the accumulated issuance since 2017. Regarding emerging markets, their issuance is less than 21%, and supranational markets represent 7.2% (Figure 5 [22]). The euro area is the biggest issuer of green bonds, with a contribution of 35% of the accumulated amount since 2014. Note that all regions reported a contraction in the issuance of green bonds during 2022 (Figure 6 [22]).

Green bond issuance varies drastically between advanced and EMEs (green bond issuance is obtained from the Climate Bonds Initiative [22]. This helps explain the difference between the maximum amount issued, USD 91.3 billion, and the minimum of USD 0.02 billion (see Table 1).

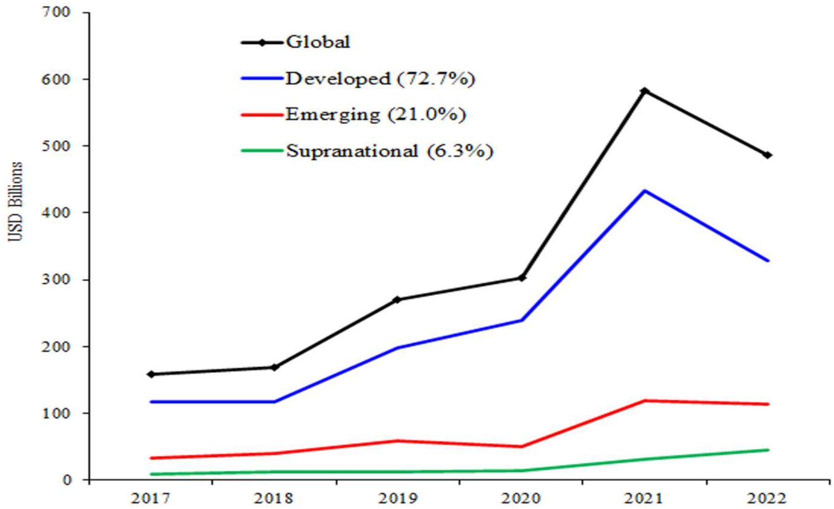
3.8. Sample selection

Since we are interested in the influence of climate policies on firms' decisions to take actions to mitigate climate change, this work focuses on firms committing to work with the SBTi to set a GHG emissions target. We omit *target-set* firms because while the commitment step is entirely up to the firm, once committed, there is a formal agreement with a stipulated deadline to complete all the steps needed to obtain an approved GHG emissions target from SBTi. Therefore, once a firm commits, gaining an approved GHG emissions target may depend more on the firm's willingness to fulfill the agreement with the SBTi than on the imposition of more robust climate policies.

We first match firms classified as committed per country in the SBTi data with the Climate Policy scores provided by Germanwatch and green bond issuance data per country supplied by the Climate Bond Initiative. Due to differences in country coverage across these datasets, in a first step, we identify firms domiciled in countries for which Climate Policy indices are not provided and countries for which Climate Policy indices are available but are not included in the SBTi dataset. In addition, there are some exceptional cases in the CCPI dataset. The first corresponds to Iceland and Singapore, which stopped being part of the index in 2017. The second is the case for

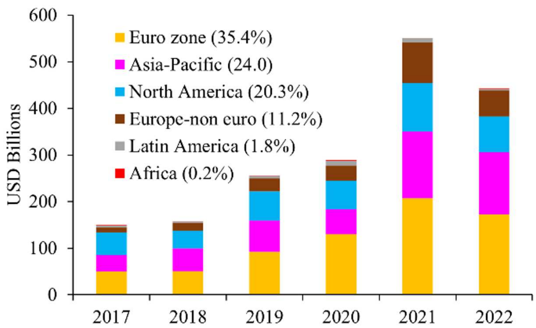
[1] CBI does not provide disaggregated information about which type of bond is issued more frequently or the issuance amount, Climate Bonds | Insights from Climate Bonds Data

Figure 5
Green bond issuance by market



Note: The supranational category refers to bonds' emission by international institutions such as the World Bank, the European Investment Bank, or by international financial institutions.

Figure 6
Green bond issuance by region



Colombia, the Philippines, and Vietnam, which first appeared in the CCPI index in 2022. The last case is Chile, which was included in 2020. Given the lack of data for these countries, we excluded them from the analysis. This process reduced the initial country sample from 80 in the SBTi data to 44 countries (see Tables A1–A3 in the supplementary material).

In the second step, we match the firms domiciled in those 44 countries with country data from the CBI. Of the 44 countries, we found that two (Cyprus and Malta) were not included in the CBI dataset. Of the 85 countries in the CBI dataset, 43 were not included in either the SBTi or the CCPI datasets, or in both. As a result, we ended up with data on firms in 42 countries. We also adjusted the database for countries that did not report, or reported only, green bond issuance data in one year between 2017 and 2022. There are two such cases: Egypt, which reported data only for 2020, and Estonia, which has no data for the entire period. In addition, we remove from the sample those countries with missing data from two consecutive years. This is because we will be using the growth rates of green bond issuance, and countries with consecutive missing data cannot be included (Czechia, Greece, Hungary, Morocco, Russia, Saudi Arabia, Thailand, and Turkey).

Due to data gaps, we began the analysis in 2017. Specifically, before this year, the number of firms committed was relatively small. At the same time, since then, there has been a significant increase in the number of companies involved that may not necessarily respond to stricter climate policies, but as a result of broader knowledge of what the SBTi does and its commitment to help firms set a science-based GHG emissions target. Also, during those same years, several countries were missing data, mainly developing economies and, on a relatively smaller scale, emerging economies. As a result, the final dataset consists of an unbalanced panel of 965 *committed* firms domiciled in 19 advanced economies and 13 EMEs, from the years 2017 and 2022 (see Tables A1–A4 in the supplementary material).

4. Methodology

This section describes the methodology used to assess whether climate policies influence firms' decisions to commit to setting GHG emissions targets. To achieve this goal, we rely on a nonlinear binary panel data model of the form:

$$P\left(y_{ijt} = 1 | x_{jt}, \alpha_i\right) = F(x_{jt}\beta + \alpha_i + u_{ijt}) \qquad (1)$$

where $P()$ denotes the probability of firm i in country j committing to set a target at time t for all $i = 1,\ldots,N$, $j = 1,\ldots,J$, and $t = 1,\ldots,T$, $F()$ is a cumulative distribution function, x_{jt} is a vector of observed conditioning continuous variables for country j is a vector of dummy variables, $\alpha_i = (\alpha_1,\ldots,a_N)$ is the vector of unobserved individual-specific effects, $\beta = (\beta_1,\ldots,\beta_k)$ is the vector of slope parameters to be estimated, and u_{it} is a vector of disturbances.

The variable y_{ijt} is our outcome binary indicator equal to 1 in the year a firm commits to set a GHG emissions reduction target. We focus on commitment because when a firm publicly announces its decision, it can plausibly be attributed to more stringent climate-protecting policies; that is, it is the ex ante choice we try to explain. In contrast, once a firm commits, obtaining an SBTi-approved target is the result of the firm's disposition to fulfill its commitment; that is, it is the ex post choice that mainly reflects the company's internal capabilities during the stages of execution, validation, and evaluation stages stipulated by SBTi, which are not part of our objective.

In addition, it is more likely that committing occurs close to the time new national policies are announced, while obtaining an approved target occurs with a lag of up to two years. Then, using firms with a target-set status could lead to post-treatment bias if the new policies influence the decision to commit and the time to approval through different channels. Lastly, while SBTi reports the commitment date for firms *committed*, it does not recover prior commitment dates for companies with a *target-set* status, limiting comparability. Lastly, since the national policy index varies across countries and time, our estimates should be interpreted as conditional associations.

The vector x_{jt} includes the following variables: First, the current change in the national component of the Climate Policy category of the CCPI (hereafter climate policy) as a measure of country j's advances in climate change mitigation policies. We do not use the general CCPI because its other components may generate an endogeneity problem. For example, a firm commitment can affect emissions and the use of renewable energy. Furthermore, we do not use the Climate Policy category but its national component because it directly measures advances in implementing climate-friendly policies.

Second, the lagged percentage change in the issuance of green bonds is included as a proxy of funding availability directed to climate-friendly projects in country j. Third, the difference in GDP per capita is introduced as a proxy for the possibility that individuals with higher income per capita can exert more pressure on firms to take action toward reducing GHG emissions [23]. Fourth is a dummy variable to account for firms that belong to sectors known to produce the highest amount of GHG emissions (according to Environment and Climate Change Canada [24], these sectors are chemicals, construction and building, food, beverages and tobacco, oil, gas and mining, transportation, and utilities). Fifth, a dummy variable to control for firms in the financial services sector. This last dummy is introduced to control for, albeit imperfectly, the search-for-yield behavior from issuing and trading green bonds that could incentivize firms in the financial services sector to declare themselves as green-friendly beyond concerns about climate change risks.

Several forms are proposed for the function $F(\cdot)$, the most common being the logistic and the standard normal distributions, yielding the logit and probit models, respectively. Choosing between these two models depends on whether individual-specific errors are present and if these are correlated with the regressor, which may be challenging for the probit model, particularly since in this model, the vector α_i must be estimated along with β. Additionally, given the nonlinearity of the mentioned distribution functions, it is impossible to use a within transformation to avoid estimating α_i as done in the linear case. Moreover, in a small T and large N panel, as it occurs here, the individual-specific effects (α_i) and the slope parameters (β) cannot be estimated consistently. In other words, the logit and probit models suffer from the incidental parameter problem [25].

In the case of the logit model, one suggested solution to obtain consistent estimates of β is to estimate the conditional maximum likelihood (CMLE), resulting in what is known as the fixed effects logit estimator. It is essential to highlight that the CMLE does not estimate the vector of individual-specific impacts, but what it does is find a joint distribution of the independent variable conditional on x_{jt}, $_i$, and $\bar{y}_{ij} = \sum_{t=1}^{T} y_{it}$. Such a distribution does not depend on α_i. Alas, the fixed effects logit model has the disadvantage that for small T and large N panels, consistent estimates of β require the strong independence assumption that y_{it} has to be independent of x_{jt} and α_i for all $i = 1,\ldots,N$, and $j = 1,\ldots,J$; see the book by Baltagi [25].

In the case of the probit model, it has been proposed to estimate the model assuming that the unobserved individual effects are random, yielding the random effects probit estimator. Unfortunately, the random effects probit model will not become equivalent to a fixed effects probit if the covariates are correlated with the individual-specific effects. Hence, another solution suggested by Wooldridge [26] and Lin and Wooldridge [27] based on the research by Mundlak [28] and Chamberlain [29] is to estimate a CRE probit model.

The CRE probit model for panel data assumes that introducing the cluster mean of the continuous explanatory variables allows the model to account for fixed effects. Specifically, let $\bar{x}_{jt}$ be the cluster mean of the continuous variables, and Φ denote the standard normal distribution, then:

$$P\left(y_{ijt} = 1 | x_{jt}, \bar{x}_j, \alpha_i\right) = \Phi(x_{jt}\hat{\beta} + \psi_\alpha + \bar{x}_j\hat{\eta}) \tag{2}$$

If the above assumption holds, we can use maximum likelihood (MLE). The research by Wooldridge [26] shows that introducing the mentioned cluster means the additional assumptions of strict exogeneity conditional on x_j and conditional independence on x_j and α_i also hold. Hence, the CRE probit estimator $\hat{\beta}$ is consistent. In addition, these assumptions allow for consistently estimating α_i 's unconditional distribution.

Now, remember that the estimated vector of parameters $\hat{\beta}$ only tells an incomplete history of the effect of the variables in x_j for the case of nonlinear models. In fact, $\hat{\beta}$ can only inform us about the sign of the effect and, at most, whether an element of x_j has a relatively bigger impact than others. In this scenario, the research by Wooldridge [26] proves that the assumptions required for estimating the CRE probit model are enough conditions to estimate average partial effects (APE) while averaging out α_i; that is, let $\widehat{ASF}$ denote the estimated average function given by:

$$\widehat{ASF}(x_t) = \frac{1}{N}\sum_{i=1}^{N}\Phi(x_{jt}\hat{\beta} + \psi_\alpha + \bar{x}_j\hat{\eta}) \tag{3}$$

where $\hat{\psi}_\alpha$ and $\hat{\eta}$ are estimated parameters. Then the estimated $\widehat{APE}$ of variable k on y_{it} is:

$$\widehat{APE}_{kt}(x_t) = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial\Phi(x_{jt}\hat{\beta} + \psi_\alpha + \bar{x}_j\hat{\eta})}{\partial x_{kt}} \tag{4}$$

4.1. Fixed or random effects

As mentioned above, it is essential to identify how individual-specific effects take place in the data. In other words, do they capture specific characteristics that remain constant across observations (fixed effects) or account for heterogeneity across firms in our sample (random effects)? To address the issue of choosing between fixed or random effects models, the standard tool in the literature is the Hausman test, in which the null hypothesis states that individual-specific effects are uncorrelated with the explanatory variables. However, such a test has the downside in that it cannot be performed after estimation using cluster robust standard errors.

Also, in some cases, the test fails to find a positive definite asymptotic variance-covariance matrix. As an alternative, Baltagi [25] proposes using Mundlak's approach [28], which allows for errors to be heteroskedastic or correlated between groups. This approach can be performed by estimating the CRE probit model. After estimation, we test whether the coefficients of the averaged variables ($\hat{\eta}$) are jointly statistically significantly different from zero. The results reject the null hypothesis that such coefficients are equal to zero, implying that fixed effects are present, so the CRE probit model is the most adequate.[2]

5. Results

This section presents the effect of a one-unit increase in the index and the growth rate of green bond issuance on firms' decision to commit, estimating separate models for advanced and emerging market economies (complete regressions output is shown in Tables A5–A7 in the supplementary material).

APEs from the panel CRE probit model are reported in Table 2. These suggest that, for all economies in our sample, a one-unit increase in the national climate policy index is associated with an 8.41 percentage points (pp) increase in the probability of firms committing. In turn, a 1% rise in the issuance of green bonds has a minimal contribution. This small association is expected given the amounts of green bonds issued, which range from USD 100 million to USD 90 billion. Focusing on the APEs of firms in advanced economies, a one-unit climb in the national climate policy index raises the probability of committing by 8.3 pp. At the same time, for EMEs, the effect size is 8.9 pp (Table 2 columns (2) and (3), respectively).

5.1. Financial and nonfinancial firms

Since there is a possibility that the incentives for firms in the financial services sector to commit to setting a GHG emissions target may be due to reasons beyond the implementation of climate policies (e.g., profiting from the issuance or trading in financial markets of green bonds), we believe extending the analysis to contrast financial and nonfinancial firms is relevant.

Table 3 shows the APEs obtained for financial and nonfinancial firms. Regarding financial firms, we find that a one-unit increase in the national climate policies component for the whole sample negatively impacts the probability of committing (a fall of 10.6 pp) but is barely statistically significant at the 10% level (*p*-value of 0.076). This significance disappears when looking only at advanced economies, which account for 89% of the sample size. A possible explanation for this negative sign is that this type of firm may be more globally dependent and less affected by national climate policies, particularly in emerging economies. In addition, these firms are known for having very low scope-1 and scope-2 emissions, making it easy to set low GHG emissions targets independently of how strict the regulations are in their countries. Lastly, we believe that sample size is another factor contributing to the significance of the negative parameter of the national climate policy variable for the whole sample.

For firms not in the financial sector, a one-unit increase in the national climate policy index is associated with a higher probability of committing, around 9 pp. In contrast, for firms in advanced economies, the contribution is 8.9 pp (Table 3 columns (2) and (4)). At this point, it is essential to clarify that when trying to repeat the differentiation between firms domiciled in advanced and EMEs, we found that only a few (five) firms in the financial services sector are located in EMEs. It resulted in insufficient group variation to estimate the model for this type of firm. Hence, the results in Table 3 columns (3) and (4) refer only to advanced economies.

Table 2
Average partial effects (APEs) for all firms

Variables	(1) Full Sample	(2) Advanced Economies	(3) EMEs
Δ_t National Climate Policy	0.084***	0.083***	0.089***
	(0.000)	(0.000)	(0.052)
Δ_{t-1} Green Bonds	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * p < 0.10, ** p < 0.05, *** p < 0.01.

5.2. Firms in highest emitters sectors

The information in our data allows for additional analysis of firms in the nonfinancial sector by separating them between firms in sectors known to be the highest GHG emitters (highest emitters hereafter) and firms in sectors that, by comparison, produce fewer GHG emissions (lowest emitters).

The APEs are shown in Tables 4, 5, and 6. We see that an improvement in national climate policies increases the probability of lowest emitters by 11.7 pp. At the same time, in the case of advanced and emerging economies, such probability is 11.8 and 19 pp, respectively. In turn, the issuance of green bonds positively contributes to a higher likelihood of committing to all specifications. Still, as in the previous cases, its contributions to the probability of committing are small. These patterns align with differences in abatement costs/capabilities, green-finance depth, and enforcement credibility across sectors and country contexts.

6. Robustness Test

This section shows the robustness of our results by contrasting the APEs from the CRE model against the estimated coefficients from a linear probability model with fixed effects (LPM) and the average marginal effects (AMEs) estimated from a logit fixed-effects model. Table 7 shows that climate policy has a statistically significant and positive impact on the probability of firms committing to set a GHG emissions target for all three models, but with some differences in their magnitude. The LPM model says that a one-unit increase in climate policies raises the probability of committing by 11.8 percentage points. In contrast, the CRE and logit models suggest a rise of 8.41 and 7.54 pp, respectively (Our results remain robust when contrasting APEs against AMEs for the case of financial and nonfinancial firms, as well as for the case of highest and lowest emitters, see our supplementary material).

So far, our estimations do not control for time-fixed effects because, when doing so, the maximum likelihood estimation fails to find a solution. A possible explanation for this is that since the number of positive answers increases each year (in our case, the number of firms committing), it raises the possibility of time-fixed effects becoming near-perfect predictors.[3]

[2] The results from the joint test of the averaged variables show a statistic of 143.86 with a *p*-value of 0.000

[3] We try to solve this problem by introducing country and region-specific time trends, but the results show that neither of such variables is statistically different from zero.

Table 3
Average partial effects (APEs) financial vs. nonfinancial firms

	Full sample		Advanced economies	
	(1)	(2)	(3)	(4)
variables	Financial	Nonfinancial	Financial	Nonfinancial
Δ_t National Climate Policy	-0.106*	0.090***	-0.085	0.089***
	(0.076)	(0.000)	(0.221)	(0.000)
Δ_{t-1} Green Bonds	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Average partial effects (APEs) full sample

Variable	Firm group	APE	*p*-value	Obvs.
Δ_t National Climate Policy	Highest emitters	0.037	0.110	1268
Δ_{t-1} Green Bonds	Highest emitters	0.001	0.000	
Δ_t National Climate Policy	Lowest emitters	0.117	0.000***	2336
Δ_{t-1} Green Bonds	Lowest emitters	0.001	0.000***	

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Average partial effects (APEs) advanced economies

Variable	Firm group	APE	p-value	Obvs.
Δt National Climate Policy	Highest emitters	0.025	0.324	1064
Δt-1 Green Bonds	Highest emitters	0.001	0.000***	
Δt National Climate Policy	Lowest emitters	0.118	0.000***	2132
Δt-1 Green Bonds	Lowest emitters	0.001	0.000***	

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Average partial effects (APEs) emerging economies

Variable	Firm group	APE	*p*-value	Obvs.
Δ_t National Climate Policy	Highest emitters	0.055	0.430	204
Δ_{t-1} Green Bonds	Highest emitters	0.001	0.000***	
Δ_t National Climate Policy	Lowest emitters	0.190	0.000***	204
Δ_{t-1} Green Bonds	Lowest emitters	0.001	0.000***	

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Average partial effects vs. average marginal effects

Variable	CRE[a]	LPM	Logit[b]
Δ_t National Climate Policy	0.084***	0.118***	0.075***
	(0.000)	(0.000)	(0.000)
Δ_{t-1} Green Bonds	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)

Note: Firm-based cluster robust standard errors included.
p-values in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7. Conclusions

We examine how country-level policy signals and financial depth relate to corporate target-setting. To do so, we build a firm-level panel by matching public firms in the SBTi to the national climate policy index and to green bond issuance covering 32 economies over 2017–2022. The inclusion of firms from emerging economies contributes to filling a gap in the literature by recognizing the structural and institutional constraints that may hinder corporate commitments to set emissions targets.

The results suggest that advances in national climate policies are associated with a higher probability of firms committing. Such results remain when looking at firms domiciled in advanced and emerging economies. However, the association is lower for EMEs. By distinguishing between firms in the financial services sector and the nonfinancial sector, the results show that national climate policies do not contribute to the likelihood of financial institutions committing. Still, such policies are essential for firms not in the financial services sector, raising the probability of these firms committing.

Focusing on nonfinancial firms and categorizing them into sectors known as the highest and lowest emitters of GHG, we find that national climate policies increase the probability of committing for firms operating in low-emitting sectors, but not for the highest emitters. A possible explanation for this result is given by Nagaj et al. [30] who state that the production processes of higher emitters make decarbonization difficult. For example, in the steel industry, production requires exceptionally high temperatures that can only be achieved using coal. The same authors also mention that the costs of substituting existing capital and the potential distortions such changes could imply are prohibitively high for other industries. Lastly, as happens with the oil industry, sometimes this type of industry represents one of the main drivers of economic activity in some countries, making it difficult to motivate these firms to reduce GHG emissions.

The results are robust to other binary response models, such as linear probability and logit models. Taken together, our results suggest that national climate policy advances are strongly associated with firms committing to set a GHG emissions target, while high-emitting sectors may require additional sector-specific incentives.

This study has some limitations that should be mentioned. First, it does not include firms' specific data, such as balance sheet information and whether the firm issues green bonds or has access to green loans. This is because these data can only be obtained from private datasets and are not freely available. Second, we lack data on enforcement measures implemented in each country to assess the underlying mechanism to explain differences across industries and countries. Third, some firms in the SBTi dataset may commit to setting a GHG emissions target as a form of greenwashing (a strategy used to claim that their products or services are climate-friendly) since there is no penalty for committing and then not completing the required steps to set such a target. However, it is difficult to account for it, given that only direct supervision from the appropriate authorities can identify which firms are using such strategies.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Firm-level information on corporate commitments and target validation is publicly available from the Science Based Targets initiative (SBTi) at https://sciencebasedtargets.org/target-dashboard. Aggregate green -bond issuance is obtained from the Climate Bonds Initiative (CBI) at https://www.climatebonds.net/data-insights/market-data/certified-climate-bonds-database. Due to confidentiality agreements, the raw CCPI data are not publicly available.

Author Contribution Statement

Marco Hernandez-Vega: Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Eduardo Martínez González:** Software, Validation, Formal analysis, Resources, Data curation, Writing – original draft, Visualization.

References

[1] Mahajan, R., Lim, W. M., Sareen, M., Kumar, S., & Panwar, R. (2023). Stakeholder theory. *Journal of Business Research*, *166*, 114104. https://doi.org/10.1016/j.jbusres.2023.114104

[2] Yuan, B., & Cao, X. (2022). Do corporate social responsibility practices contribute to green innovation? The mediating role of green dynamic capability. *Technology in Society*, *68*, 101868. https://doi.org/10.1016/j.techsoc.2022.101868

[3] Coelho, R., Jayantilal, S., & Ferreira, J. J. (2023). The impact of social responsibility on corporate financial performance: A systematic literature review. *Corporate Social Responsibility and Environmental Management*, *30*(4), 1535–1560. https://doi.org/10.1002/csr.2446

[4] Ekins, P., & Zenghelis, D. (2021). The costs and benefits of environmental sustainability. *Sustainability Science*, *16*(3), 949–965. https://doi.org/10.1007/s11625-021-00910-5

[5] Bjørn, A., Tilsted, J. P., Addas, A., & Lloyd, S. M. (2022). Can science-based targets make the private sector Paris-aligned? A review of the emerging evidence. *Current Climate Change Reports*, *8*(2), 53–69. https://doi.org/10.1007/s40641-022-00182-w

[6] Zhang, Z., Jiang, C., Gao, C., & Tang, B. (2025). The impact of the Russia–Ukraine conflict on renewable energy trade in countries along the belt and road: A cascading failure model. *Journal of Renewable and Sustainable Energy*, *17*(1), 015908. https://doi.org/10.1063/5.0233853

[7] European Investment Bank. (2023). *What drives firms' investment in climate action? Evidence from the 2022-2023 EIB Investment Survey*. Publications Office. https://data.europa.eu/doi/10.2867/048422

[8] de Mooij, R. A., Keen, M., & Parry, I. W. H. (2012). *Fiscal policy to mitigate climate change: A guide for*

policymakers. USA: International Monetary Fund. https://doi.org/10.5089/9781616353933.071

[9] Parry, I., Morris, A., & Williams III, R. C. (Eds.). (2015). *Implementing a US carbon tax: Challenges and debates*. UK: Routledge. https://doi.org/10.4324/9781315747682

[10] Tryndina, N., An, J., Varyash, I., Litvishko, O., Khomyakova, L., Barykin, S., & Kalinina, O. (2022). Renewable energy incentives on the road to sustainable development during climate change: A review. *Frontiers in Environmental Science*, *10*, 1016803. https://doi.org/10.3389/fenvs.2022.1016803

[11] Vyshnevskyi, I., & Sohn, W. (2026). Central banks' support for climate action: A literature review and key issues. *Journal of Economic Surveys*, *40*(1), 182–198. https://doi.org/10.1111/joes.12709

[12] Krogstrup, S., & Oman, W. (2019). Macroeconomic and financial policies for climate change mitigation: A review of the literature. *IMF Working Paper*, *2019*(185), 1–58. https://doi.org/10.5089/9781513511955.001

[13] Sharma, M., & Choubey, A. (2022). Green banking initiatives: A qualitative study on Indian banking sector. *Environment, Development and Sustainability*, *24*(1), 293–319. https://doi.org/10.1007/s10668-021-01426-9

[14] Grauwe, P. D. (2019). Green money without inflation. *Vierteljahrshefte zur Wirtschaftsforschung*, *88*(2), 51–54. https://doi.org/10.3790/vjh.88.2.51%0A

[15] Perelli, A., Sodré, E., Silva, V., & Santos, A. (2023). Maximizing returns and minimizing risks in hybrid renewable energy systems: A stochastic discounted cash flow analysis of wind and photovoltaic systems in Brazil. *Energies*, *16*(19), 6833. https://doi.org/10.3390/en16196833

[16] Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210–233. https://doi.org/10.1080/20430795.2015.1118917

[17] Shaikh, I. (2022). Environmental, social, and governance (ESG) practice and firm performance: An international evidence. *Journal of Business Economics and Management*, *23*(1), 218–237. https://doi.org/10.3846/jbem.2022.16202

[18] Engelhardt, N., Ekkenga, J., & Posch, P. (2021). ESG ratings and stock performance during the COVID-19 crisis. *Sustainability*, *13*(13), 7133. https://doi.org/10.3390/su13137133

[19] Science Based Targets initiative. (2023). *Companies taking action: Public registry*. https://sciencebasedtargets.org/target-dashboard

[20] Caglar, A. E., Avci, S. B., Ahmed, Z., & Gökce, N. (2024). Assessing the role of green investments and green innovation in ecological sustainability: From a climate action perspective on European countries. *Science of the Total Environment*, *928*, 172527. https://doi.org/10.1016/j.scitotenv.2024.172527

[21] Burck, J., Uhlich, T., Bals, C., Höhne, N., Nascimento, L., Tavares, M., & Strietzel, E. (2022). *Monitoring climate mitigation efforts of 60 countries plus the EU–covering 92% of the global greenhouse gas emissions*. Germany: CCPI.

[22] Climate Bonds Initiative. (2024). *Green bond database/market intelligence*. https://www.climatebonds.net/data-insights/market-data/certified-climate-bonds-database

[23] Liu, X., Wang, C., Shishime, T., & Fujitsuka, T. (2012). Sustainable consumption: Green purchasing behaviors of urban residents in China. *Sustainable Development*, *20*(4), 293–308. https://doi.org/10.1002/sd.484

[24] Environment and Climate Change Canada. (2023). *Facility greenhouse gas reporting: Overview of 2023 reported emissions*. Government of Canada. https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/facility-reporting/overview-2023.html

[25] Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Switzerland: Springer International Publishing. https://doi.org/10.1007/978-3-030-53953-5

[26] Wooldridge, J. M. (2019). Correlated random effects models with unbalanced panels. *Journal of Econometrics*, *211*(1), 137–150. https://doi.org/10.1016/j.jeconom.2018.12.010

[27] Lin, W., & Wooldridge, J. M. (2015). On different approaches to obtaining partial effects in binary response models with endogenous regressors. *Economics Letters*, *134*, 58–61. https://doi.org/10.1016/j.econlet.2015.05.019

[28] Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, *46*(1), 69–85. https://doi.org/10.2307/1913646

[29] Chamberlain, G. (1982). Multivariate regression models for panel data. *Journal of Econometrics*, *18*(1), 5–46. https://doi.org/10.1016/0304-4076(82)90094-X

[30] Nagaj, R., Gajdzik, B., Wolniak, R., & Grebski, W. W. (2024). The impact of deep decarbonization policy on the level of greenhouse gas emissions in the European Union. *Energies*, *17*(5), 1245. https://doi.org/10.3390/en17051245

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