

The Impact of Carbon Reduction Talents on Corporate Carbon Emissions

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Abstract

This study examines the role of carbon reduction talent in shaping corporate carbon emissions using U.S. firm-level data from 2010 to 2020. We find that firms with a higher share of carbon reduction talent emit significantly less carbon. This effect becomes stronger following the Paris Agreement. Firms employing more carbon reduction talent also exhibit better carbon management practices and more efficient green innovation, and they receive favorable capital market responses, including lower carbon risk premium, narrower bond yield spreads, more accurate analyst forecasts, and greater ownership by green-oriented institutional investors. Overall, the results highlight firm-internal human capital as an important driver of corporate decarbonization and value creation.

Keywords: Carbon reduction talents, carbon emissions, green skills, Paris Agreement

1. Introduction

Climate change has become a first-order economic risk for firms and investors, fundamentally reshaping corporate behavior and capital markets. A growing body of research in finance and economics documents that corporate carbon emissions are priced by investors, affect firms' cost of capital, and influence asset valuations in the presence of climate regulation and transition risk (Bolton and Kacperczyk, 2021; Ilhan et al., 2021). In response to these pressures and the commitments embedded in the Paris Agreement, firms have increasingly adopted decarbonization strategies ranging from technological investments and operational adjustments to enhanced disclosure and regulatory compliance (Krueger, Sautner, and Starks, 2020).

Despite this extensive focus on external forces and technological responses, much less is known about the role of internal organizational capabilities in driving effective

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decarbonization. In particular, firms have increasingly invested in specialized human capital, such as professionals in carbon management, energy transition, and climate strategy, to address climate-related challenges. However, systematic evidence on whether and how carbon reduction talent translates into meaningful emission reductions remains scarce. This study addresses this gap by examining the role of carbon reduction talent in shaping firms' emission outcomes and by analyzing how climate policy, through the Paris Agreement, amplifies the effectiveness of such human capital investments.

A distinctive feature of this study is the construction of a novel, employee-based measure of carbon reduction talent at the firm level. Rather than relying on corporate job postings or aggregate ESG indicators, we identify carbon reduction talent directly from realized job titles and job descriptions, capturing employees whose roles are explicitly related to decarbonization activities such as carbon management, energy transition, and climate strategy. This approach allows us to observe firms' internal decarbonization capacity embedded in their workforce. Our measurement framework builds on authoritative external sources on green skills and occupations, including LinkedIn's Global Green Skills Reports, and combines these sources with a systematically developed and validated keyword classification scheme. We integrate machine-assisted text analysis with manual verification to ensure both coverage and accuracy. By exploiting detailed job-level employment records, we capture meaningful within-firm and across-firm variation in carbon reduction talent over time. This employee-level measure enables us to examine how firms internalize climate objectives through workforce composition.

We analyze a sample of 1,603 U.S. firms from 2010 to 2020, comprising 9,820 firm-year observations, to examine whether firms' employment of carbon reduction talent translates into meaningful reductions in corporate carbon emissions. We find a robust negative relation between firms' exposure to carbon reduction talent and their carbon emissions: a one-standard-deviation increase in carbon reduction talent is associated with a 6.75% reduction in absolute emissions and a 6.78% reduction in emission intensity. This pattern highlights the importance of firm-internal capabilities in driving decarbonization outcomes. Moreover, the emission-reducing effect of carbon reduction talent intensifies following the Paris Agreement, suggesting that climate policy amplifies the effectiveness of investments in specialized human capital. These findings reveal the critical importance of carbon reduction talent as a core determinant of firms' carbon emission reductions.

A key challenge in estimating the effect of carbon reduction talent on firms' carbon

emissions is endogeneity, as firms with stronger environmental preferences or superior management may be more likely to invest in such talent. To address this concern, we exploit exogenous variation in firms' access to carbon-related human capital stemming from their early exposure to graduates of universities with strong programs in energy, climate, and environmental sciences. Because carbon-related expertise is highly specialized and costly to acquire or replace, firms with greater early access to such graduates are more likely to develop and sustain carbon reduction capabilities over time, satisfying the relevance condition. At the same time, this early educational exposure predates major climate policy shocks and firms' subsequent emission outcomes, making it unlikely to be directly related to later emission trajectories. Using this instrumental variable strategy, we show that the emission-reducing effect of carbon reduction talent remains economically meaningful and statistically significant, supporting a causal interpretation of our results.

We further investigate the mechanisms through which carbon reduction talent contributes to firms' emission reductions by examining its role in carbon management and green innovation. We find that firms with greater exposure to carbon reduction talent adopt more effective carbon management practices, including improved emissions reporting, stronger renewable energy initiatives, lower carbon-related risks embedded in products and services, and greater engagement in environmentally friendly products. In addition, these firms generate more climate-related innovations, as reflected in higher levels of green patenting and citations. These findings indicate that carbon reduction talent improves firms' carbon performance by strengthening internal management capabilities, enhancing innovation, and improving the transparency of climate-related information.

We also examine how capital markets respond to firms' investments in carbon reduction talent. A growing literature shows that climate-related risks are priced in equity and debt markets and affect analysts' information processing and institutional investors' portfolio allocations (Bolton and Kacperczyk, 2021; Ilhan et al., 2021; Seltzer et al., 2022). Consistent with prior literature, we find that firms with greater exposure to carbon reduction talent experience more favorable capital market outcomes, including lower carbon risk premia, narrower bond yield spreads, more accurate analyst earnings forecasts, and higher ownership by green-oriented institutional investors. These findings suggest that carbon reduction talent improves firms' information environments and mitigates investors' perceived exposure to climate-related risks.

Our study is closely related to Darendeli, Law, and Shen (2022), who examine firms' green hiring using job postings data. We differ in three key respects. First, while their measure captures firms' hiring intentions, we focus on realized employment and construct an employee-based measure of carbon reduction talent using actual job titles and job descriptions, allowing us to capture firms' internal decarbonization capacity. Second, our identification strategy relies on an instrumental variable that is directly linked to the supply of carbon reduction talent, firms' pre-existing exposure to graduates from carbon-focused academic programs, providing a more direct source of variation in specialized decarbonization expertise. Third, we extend the analysis beyond firm-level real outcomes by examining capital market responses, showing that carbon reduction talent is associated with lower carbon risk premia, narrower bond yield spreads, more accurate analyst forecasts, and greater ownership by green-oriented institutional investors.

This study contributes to the finance literature in several important ways. First, we extend the growing literature on climate risk and corporate behavior by identifying carbon reduction talent as a previously underexplored yet economically meaningful determinant through which firms reduce carbon emissions. While prior studies primarily emphasize external pressures, such as climate regulation, investor preferences, or disclosure mandates (e.g., Bolton and Kacperczyk, 2021; Ilhan et al., 2021; Krueger, Sautner, and Starks, 2020), we highlight firm-level human capital as a central internal capability that enables effective decarbonization.

Second, our findings contribute to the human capital and corporate finance literature by showing that specialized labor shapes firms' real outcomes, innovation activities, and risk profiles. Existing research documents that workforce composition and specialized skills affect firm productivity, innovation, and strategic outcomes (e.g., Bosetti, Cattaneo, Verdolini, 2015; Bena, Ortiz-Molina, and Simintzi, 2022; Babina et al., 2024). Building on this literature, we demonstrate that carbon reduction talent not only improves firms' operational emission performance but also strengthens carbon management practices, fosters green innovation, and enhances firms' information environments. These results underscore the role of human capital investments in translating environmental objectives into tangible corporate outcomes.

Third, this study adds to the asset pricing and capital markets literature by documenting that carbon reduction talent attenuates the pricing of carbon risk across multiple markets. Prior work shows that carbon exposure affects expected stock returns,

credit spreads, analyst behavior, and institutional ownership (Bolton and Kacperczyk, 2021; Ilhan et al., 2021; Seltzer et al., 2022). We extend this line of research by showing that firms with greater exposure to carbon reduction talent face lower carbon risk premia, narrower bond yield spreads, more accurate analyst forecasts, and higher ownership by green-oriented institutional investors. Together, these findings provide novel evidence that labor composition influences how climate risks are perceived and priced by investors and financial intermediaries.

Finally, by exploiting the Paris Agreement as a quasi-natural experiment and employing instrumental variable strategies, we provide causal evidence that investments in carbon reduction talent lead to economically meaningful reductions in corporate carbon emissions. In doing so, our study bridges the climate finance, human capital, and corporate policy literatures, offering a unified framework for understanding how firms internalize climate objectives through workforce composition rather than relying solely on external regulation or market pressure.

This study proceeds as follows. Section 2 reviews literature and develops our hypotheses. Section 3 describes data and variable definitions. Section 4 provides empirical results. Section 5 illustrates channels. Section 6 discusses capital market responses, and Section 7 concludes.

2. Literature review and hypotheses development

2.1 Literature review

Research on corporate carbon emissions has primarily focused on institutional investors (Dyck et al., 2019; Ilhan et al., 2023; Fan et al., 2024), environmental regulations, and market-based incentives like carbon pricing (Martinsson et al., 2024). While these studies emphasize external pressures, internal workforce composition has received comparatively less attention. Existing research highlights green finance and investment transparency as key drivers of decarbonization (De Angelis et al., 2023; Feldhütter et al., 2024), yet how firms internally manage carbon reduction remains insufficiently examined. Additionally, firms' ability to measure and respond to climate risks is increasingly critical (Li et al., 2024), suggesting that internal expertise plays a crucial role in corporate decarbonization efforts.

The Paris Agreement (2015) accelerated corporate decarbonization efforts (Bolton and Kacperczyk, 2023). LinkedIn's Global Green Skills Report (2024) highlights rising demand for sustainability professionals, yet green talent supply has lagged, constraining

firms' emission reduction efforts (LinkedIn, 2022, 2023). Workforce shifts in energy and transportation are particularly crucial, with demand for renewable energy and EV-related skills outpacing supply (Kaura, 2023, 2024). The shift toward sustainability-linked finance (Feldhütter et al., 2024) and increased regulatory scrutiny on emissions disclosure (Tomar, 2023) further necessitate internal expertise. However, integrating sustainability talent into corporate structures presents challenges. Gatignon (2022) finds that CSR initiatives can enhance sustainability outcomes but also create coordination inefficiencies, a challenge that may extend to carbon reduction talent integration.

Specialized talent has been shown to enhance firm performance, as seen in AI-driven innovation (Babina et al., 2024). By analogy, carbon reduction talents may help firms assess climate risks, optimize supply chains, and develop low-emission technologies, thereby strengthening their ability to adapt to regulations and market pressures.

Firms with strong climate risk adaptation strategies better manage supply chain emissions and regulatory compliance (LaCour-Little et al., 2024; Pankratz and Schiller, 2024). Moreover, firms respond to environmental policies like emissions taxes by increasing green R&D investments (Brown et al., 2022). These efforts require specialized expertise, as carbon reduction talents help firms assess climate risks, optimize supply chains, and develop low-emission technologies, enhancing their ability to adapt to regulations and market pressures.

Carbon emissions are categorized into Scope 1 (direct emissions from fuel combustion and manufacturing) and Scope 2 (indirect emissions from purchased electricity) (Shive and Forster, 2020; Azar et al., 2021). Since carbon reduction talents enhance operational efficiency and energy management, their impact is expected to be stronger on Scope 1 than Scope 2, where firms have less direct control.

In summary, while prior research has extensively examined regulatory and financial factors affecting corporate emissions, the influence of internal talent capabilities remains unexplored. Given the increasing importance of green skills in corporate decision-making and emissions management, this study investigates how carbon reduction talents influence corporate emissions.

2.2 Hypothesis development

Firms benefit from hiring specialized talents to enhance performance and innovation (Babina et al., 2024). In the context of decarbonization, carbon reduction talents contribute to effective emissions management, helping lower overall corporate emissions. Recent

studies document a growing demand for sustainability professionals, particularly in carbon-intensive sectors, as firms seek to strengthen internal capabilities for climate risk mitigation (Kaura, 2023). Accordingly, this study proposes:

Hypothesis 1: A higher share of carbon reduction talents is associated with lower corporate carbon emissions.

The effectiveness of carbon reduction talents depends on firms' control over emissions. Scope 1 emissions arise from internal production activities, while Scope 2 emissions depend on external energy providers. Since carbon reduction talents primarily enhance internal processes, their impact should be stronger on Scope 1:

Hypothesis 2: A higher share of carbon reduction talents has a stronger negative effect on Scope 1 than Scope 2 emissions, as firms have greater control over direct emissions.

The Paris Agreement (2015) intensified regulatory and market pressures, prompting firms to strengthen emission reduction commitments (Bolton and Kacperczyk, 2023). Given these trends, the impact of carbon reduction efforts on emissions is anticipated to increase following the Paris Agreement:

Hypothesis 3: The impact of carbon reduction talents intensified post-Paris Agreement (2015) due to regulatory and market pressures.

3. Data and Methodology

3.1 Sample construction and definition of carbon reduction talents

This study integrates three major databases covering 1,603 firms from 2010 to 2020 with 9,820 firm-year observations. Carbon emissions data from Trucost include Scope 1 (direct emissions) and Scope 2 (indirect emissions from purchased energy). Carbon reduction talents data from Revelio aggregate information from LinkedIn. Due to the lack of a standardized definition, this study employs a classification process based on LinkedIn's Global Green Skills Report and paper (Sautner et al., 2023). The dataset development followed a structured approach to accurately identify corporate carbon reduction talents.

3.2 Keyword collection

To identify carbon reduction talents, this study first developed a comprehensive keyword dictionary. First, we referred to LinkedIn Global Green Skills Reports (2022, 2023) and extracted job titles and skill-related keywords associated with green and sustainability-related functions. Specifically, we compiled all the terms potentially related to carbon transition mentioned in the two reports, including 76 unique green job titles (e.g.,

sustainability manager, solar consultant, risk advisor) and 94 decarbonization-relevant skill terms (e.g., carbon capture, remediation). These terms formed the basis of the initial keyword set for subsequent filtering.

Second, we utilized ChatGPT to assist with the initial screening and expansion of keywords. On the one hand, overly broad or ambiguous terms (e.g., business strategy, negotiation) that often resulted in misclassification were removed. On the other hand, we employed ChatGPT to suggest semantically precise expansions of valid terms. For example, the solar industry was extended to include solar energy, solar panel, and solar installer to improve contextual accuracy and classification granularity. Through this process, we constructed an initial list of approximately 80 keywords (version 1).

Third, based on the preliminary keyword set, a testing and validation phase was conducted using a randomly selected sample file containing approximately 16,000 job-level observations. Each observation in the dataset corresponds to a unique employment record, including the employee identifier, affiliated company, job title, job description, and employment start and end dates. These records reflect actual employment, rather than prospective roles listed in job postings. For the classification of carbon reduction talents, only the employee identifier, job title, and job description were used to determine whether the role was related to carbon reduction. While not used in the classification stage, the affiliated company and employment period were later used to construct the firm-year panel dataset and to ensure accurate aggregation of carbon reduction talent across companies and over time.

Repeated records for the same individual within the same firm and year were excluded to avoid double-counting. However, individuals appearing in different firms or across distinct employment periods within the same year were retained to ensure accurate calculation of each firm's annual share of carbon reduction talents.

Version 1 of the keyword list was then applied to this dataset. Observations with at least one keyword match in either the Job title or description were provisionally classified as carbon reduction talents, yielding approximately 100 initial candidates. To enhance classification accuracy, the entire file was submitted to ChatGPT, which was instructed to classify each employee as either carbon reduction relevant or irrelevant based on their job title and description. These classifications were then manually reviewed. For example, one employee was identified as carbon reduction relevant because the job description referenced active involvement in carbon sequestration and low-carbon fuel technologies,

both directly associated with emission reduction. Upon verification, this observation and its corresponding keyword (carbon sequestration) were retained.

Throughout this process, the keyword set was both expanded and refined. Ambiguous or misleading terms were removed, while more precise expressions were added. For instance, the term climate generated many false positives (e.g., acclimate) and was therefore replaced with more targeted phrases such as climate finance and climate strategy. These iterative adjustments led to the development of version 2, which included a broader and more accurate set of keywords for identifying carbon reduction talents.

We repeated the keyword adjustment, testing, and manual validation process (Steps 2 and 3) across 4 additional sample files and then applied the procedure to a broader test set of 10 randomly selected samples. Given the large data volume, line-by-line manual verification was infeasible. As an alternative, the final set of 1,184 observations, provisionally identified as carbon reduction talents, was submitted to ChatGPT for batch evaluation. This review confirmed that all entries were strongly related to decarbonization work. The finalized keyword list contained 375 terms, including 23 job title keywords and 352 job description keywords, as detailed in Appendix B.

Finally, applying the validated keyword set yielded a dataset of 1,246,013 job-level observations spanning the period 2010 to 2020. These records represent all positions matched through keyword identification. We then merged this dataset with firm-level carbon emissions data from Trucost and financial data from Compustat, using firm identifiers and year as keys. After filtering for valid matches, we obtained a final sample of 9,820 firm-year observations for empirical analysis.

Financial variables are obtained from Compustat. We exclude firms in the financial services (SIC 6000–6999) and utilities (SIC 4900–4999) industries.

3.3 Corporate carbon emission variables

Following prior studies, we measure firm i 's carbon emissions in year t using $\log Emi_{i,t}$, which is defined as the natural logarithm of total carbon emissions. We separately construct emissions for Scope 1 and Scope 2. Specifically, $\log EmiScope1_{i,t}$ captures direct emissions from firm i 's internal operations, while $\log EmiScope2_{i,t}$ captures indirect emissions from purchased electricity, heat, or steam. We also construct $\log EmiScope12_{i,t}$ to measure total emissions as the sum of Scope 1 and Scope 2 emissions. We apply a natural logarithmic transformation to all emission measures to mitigate skewness and improve comparability across firms (Shive and Forster, 2020; Azar et al., 2021). In addition to emission levels, we

construct intensity-based measures by scaling emissions by total assets. Specifically, $\log IntATScope1_{i,t}$, $\log IntATScope2_{i,t}$, and $\log IntATScope12_{i,t}$ are defined as the natural logarithm of Scope 1, Scope 2, and total emissions, respectively, divided by total assets (Ilhan et al., 2021; Hsu et al., 2023).

3.4 Carbon reduction talents variable

The detailed procedure used to identify carbon reduction talent is described in Section 3.2. We measure a firm's exposure to carbon reduction talent using $ShareDecarbTalent_{i,t}$, which is defined as the proportion of carbon reduction talent employed by firm i in year t .

3.4 Control variables

Control variables are selected based on methodologies established in prior research on climate finance and corporate outcomes (e.g., Bolton and Kacperczyk, 2021; Sautner et al., 2023). These firm-level variables include $Size_{i,t}$ (log of total assets), $BM_{i,t}$ (book-to-market ratio), $ROA_{i,t}$ (return on assets), $Leverage_{i,t}$ (total debt divided by total assets), $PPE_{i,t}$ (capital intensity, measured as net property, plant, and equipment over total assets), $Cash_{i,t}$ (cash holdings relative to total assets), $Capex_{i,t}$ (capital expenditures scaled by total assets), $EBIT_{i,t}$ (earnings before interest and taxes over total assets), and $RevGrowth_{i,t}$ (year-over-year revenue growth). All firm level continuous variables, except $ShareDecarbTalent$ and log-transformed variables, are winsorized at the 1% level to reduce outlier influence.

3.5 Descriptive statistics

Table 1 summarizes the definitions, measurement approaches, and data sources for all variables used in the empirical analysis. Panel A of Table 1 reports that the average total carbon emissions (Scopes 1 and 2) amount to $2,457.65 \times 10^3$ tons CO₂e, with Scope 1 emissions accounting for $2,071.81 \times 10^3$ tons and Scope 2 emissions at 385.84×10^3 tons CO₂e. The distribution is highly right skewed, indicating that a small number of firms are responsible for disproportionately high emissions. To enhance comparability across firms, emissions data are log-transformed and normalized by total assets. Panel A also reports an average $ShareDecarbTalent$ of 0.010, with the 25th percentile (P25) at 0.001 and the 75th percentile (P75) at 0.010, indicating substantial variation across industries. Further, Panel B shows that the top three sectors with the highest concentration of carbon reduction talents include electric, gas, and sanitary services (SIC 49), pipelines, except natural gas (SIC 46), and metal mining (SIC 10), representing the industries with the greatest investment in energy transition, carbon management, and policy advisory roles. Conversely, Panel C reveals that the top three sectors with the least integration of carbon reduction-related

positions are building materials, hardware, and garden supplies (SIC 52), home furniture and equipment stores (SIC 57), and apparel and accessory stores (SIC 56), which reflects minimal emphasis on decarbonization within these industries.

[Table 1]

Table A.1 of Internet Appendix provides insights into the background of carbon reduction talents. Panel A shows a 66.67% male and 33.37% female composition, indicating a male-dominated workforce. Panel B highlights educational attainment, with the majority holding a bachelor's degree (47.62%), followed by master's (23.68%) and MBA (16.78%), suggesting that carbon professionals typically have higher education but limited representation at the doctoral level (6.58%). Panel C presents predicted ethnicity, where White employees (75.06%) comprise the largest group, followed by Asian/Pacific Islanders (9.47%) and Black employees (7.90%). These figures suggest that the carbon workforce is predominantly male, highly educated, and disproportionately White.

4. Empirical results

4.1 Regression results

We employ ordinary least squares (OLS) regressions as our primary empirical approach to examine the relation between carbon reduction talent and corporate carbon emissions. The baseline specification is as follows:

$$\log Emi_{i,t+1} = \alpha + \beta ShareDecarbTalent_{i,t} + \sum \delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \quad (1)$$

where $\log Emi_{i,t+1}$ denotes firm i 's carbon emissions in year $t+1$. We measure emissions separately for Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased electricity, heat, or steam), and the sum of Scope 1 and Scope 2 emissions, with all measures expressed in natural logarithms. $ShareDecarbTalent_{i,t}$ captures the share of carbon reduction talent employed by firm i in year t . $Controls_{i,t}$ include standard firm-level financial characteristics. γ_{FE} denotes fixed-effects, including firm fixed effects and year fixed effects, and state-by-year fixed effects. $\varepsilon_{i,t}$ is the error term.

Table 2 reports the baseline results using the full sample from 2010 to 2020. Columns (1)-(3) present regressions using emission levels, measured in tons of CO₂e, while Columns(4)-(6) report results based on carbon intensity measures. All specifications control for firm and year fixed effects. The estimated effects are economically meaningful and robust across alternative emission measures and fixed-effect structures. In Column (1), a one-standard-deviation increase in $ShareDecarbTalent_{i,t}$ (SD = 0.023; see Table 1) is associated with a 6.75% reduction in total emissions. Column (4) yields a comparable

estimate, with a one-standard-deviation increase in $ShareDecarbTalent_{i,t}$ corresponding to a 6.78% reduction in emission intensity. Taken together, the baseline results consistently point to a negative association between carbon reduction talent and corporate carbon emissions, providing economically meaningful evidence that firms with greater decarbonization-related human capital tend to exhibit lower carbon emissions.

[Table 2]

We also employ long-differences regression (Babina et al., 2024) to analyze the long-term impact of changes in carbon transition talents on firm performance. We further apply long-differences to control variables to account for dynamic firm characteristics. The model estimates changes in $logEmi_{i,t}$ over two intervals, 2010–2015 and 2016–2020, capturing the effect of changes in carbon transition talents. The long-differences regression is specified as:

$$\Delta logEmi_i = \alpha + \beta \Delta ShareDecarbTalent_i + \sum \delta \Delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \quad (2)$$

Where $\Delta logEmi_i$ represents the change in firm i 's carbon emissions over the periods 2010–2015 or 2016–2020, calculated as the difference between $log(emissions)$ in years. Emissions are evaluated separately for Scope 1, Scope 2, and the combined total of Scopes 1 and 2. The key independent variable, $\Delta ShareDecarbTalent_i$, captures the change in the share of carbon transition talents within the firm over the same periods. Control variables, $\Delta Controls_{i,t}$, consist of financial characteristics also measured in long differences. γ_{FE} includes state by year fixed effects, while $\varepsilon_{i,t}$ denotes the error term.

Following Babina et al. (2024), we test alternative specifications using lagged control variables instead of differencing. Table A.2 of Internet Appendix presents results. Specifically, we use 2010 values in Panel A and 2016 values in Panel B to ensure that control variables are predetermined and not affected by contemporaneous emission outcomes. In Panel A of Table A.2, which focuses on the pre-Paris period (2010 to 2015), column (4) shows that a one standard deviation increases in $\Delta ShareDecarbTalent_i$ ($SD = 0.023$) is associated with a 9.34% reduction in the summation of Scope 1 and 2 emissions. Column (5) shows a stronger effect on Scope 1 emissions, while column (6) reports a non-significant reduction in Scope 2 emissions. In Panel B, corresponding to the post-Paris period (2016 to 2020), column (4) shows that the same increase in $\Delta ShareDecarbTalent_i$ is associated with a 7.46% reduction in the summation of Scope 1 and 2 emissions. Column (5) again shows a stronger effect on Scope 1 emissions, and column (6) indicates a significant reduction in Scope 2 emissions. These findings suggest that carbon reduction

talents became more effective in the post-Paris period. Results remain robust under these variations, further validating the long-term relationship between changes in carbon reduction talent and emissions. Together, these results show that firms with greater increases in carbon reduction talents achieved larger emissions reductions after the Paris Agreement.

4.3 The difference-in-differences regressions

To further assess whether firms adjusted their employment of carbon reduction talent following the Paris Agreement, we employ a difference-in-differences (DiD) design that exploits cross-sectional variation in firms' carbon emission intensity prior to the Agreement. Specifically, we compare changes in $ShareDecarbTalent_{i,t}$, the proportion of employees engaged in carbon reduction-related activities, between high-emission and low-emission firms before and after the Paris Agreement. The DiD specification is given by:

$$ShareDecarbTalent_{i,t} = \alpha + \beta Treatment_i \times Post_t + \sum \delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \quad (3)$$

Where $ShareDecarbTalent_{i,t}$ represents firm i 's proportion of employees engaged in carbon reduction-related activities in year t . $Treatment_i$ is an indicator that equals one if firm i is classified as high emission in 2014 and zero otherwise. $Post_t$ is an indicator that equals one for years after 2016 and zero otherwise. $Treatment_i \times Post_t$ captures the differential change in $ShareDecarbTalent_{i,t}$ for high-emission firms post-Paris Agreement. $Controls_{i,t}$ include the firm-level financial variables used in Equation (1), along with their corresponding interaction terms. γ_{FE} represents firm fixed effects and year fixed effects, while $\varepsilon_{i,t}$ is the error term.

Table 3 reports the DiD results. The coefficient on $Treatment_i \times Post_t$ is negative and statistically significant when emissions are measured using the combined Scope 1 and Scope 2 emissions as well as Scope 1 emissions. Economically, the increase in carbon reduction talent following the Paris Agreement is associated with a 6.97% reduction in total emissions (Column (1)) and a 7.25% reduction in Scope 1 emissions (Column (2)). These magnitudes are larger than those observed in the baseline specifications, highlighting the role of the Paris Agreement in strengthening firms' incentives to invest in decarbonization-related human capital. In contrast, while $ShareDecarbTalent_{i,t}$ is negatively and significantly associated with Scope 2 emissions, the interaction term $Treatment_i \times Post_t$ is not statistically significant for Scope 2 emissions. This pattern suggests that carbon reduction talent already played an important role in managing Scope 2 emissions prior to the Paris Agreement, whereas the policy shock primarily intensified firms' efforts to reduce

Scope 1 emissions, which are more closely tied to internal production processes. Overall, these results provide DiD evidence that the Paris Agreement heightened firms' awareness of the importance of carbon reduction talent and amplified its effectiveness in reducing carbon emissions, particularly those arising from firms' own operations.

[Table 3]

Figure A.1 of Internet Appendix also illustrates the overall share of carbon reduction talents from 2010 to 2020. Although decarbonization efforts intensified following the Paris Agreement in 2015, there is no clear upward trend in talent share. This suggests that firms primarily reallocated existing employees rather than expanding their sustainability workforce.

Figure A.2 of Internet Appendix provide supplementary descriptive evidence, showing changes in talent composition across six decarbonization domains from 2010 to 2020, classified using EPA's GHG Reduction Programs. This figure breaks down carbon reduction talent measures into six functional categories: (i) carbon offsetting and trading, (ii) industrial decarbonization, (iii) green mobility, (iv) supply chain carbon reduction, (v) energy transition, and (vi) circular economy. While a few areas such as offsetting and trading, mobility, and industrial decarbonization showed modest growth after 2015, the overall share remained stable. These trends suggest that firms focused on selected decarbonization domains rather than expanding their sustainability workforce more broadly. Talent increased in carbon offsetting and trading, green mobility, and industrial decarbonization, while roles in energy transition, supply chain carbon reduction, and circular economy declined. This suggests that growth is concentrated in newer, scalable domains, while limited changes in energy transition and circular economy may reflect earlier adoption or lower labor intensity.

4.4 Endogeneity

A potential concern in estimating the effect of carbon reduction talent on firms' carbon emissions is endogeneity. Firms with stronger environmental commitments or superior unobserved management quality may be more likely to self-select into hiring carbon reduction professionals. To address this concern, we adopt an instrumental variable (IV) approach following Babina et al., 2024.

Our instrument exploits cross-sectional variation in firms' pre-existing exposure to carbon-related human capital. Specifically, we construct *CarbonEdu*₂₀₁₀, defined as the share of a firm's employees in 2010 who graduated from universities specializing in carbon

reduction-related fields, identified based on the Academic Ranking of World Universities (ARWU) in Energy Science & Engineering. Because historical rankings are unavailable, we assume stability in the relative ranking of top universities over time and use the 2024 ARWU ranking as a proxy for long-standing academic excellence in carbon-related disciplines.

$CarbonEdu_{i,2010}$ satisfies the relevance condition for two reasons. First, graduates from top programs in climate, energy, and environmental sustainability are more likely to possess skills directly applicable to carbon reduction, such as carbon management, renewable energy systems, and environmental accounting. Firms employing a higher share of such graduates in 2010 were therefore better positioned to build long-term recruitment pipelines through alumni networks and institutional ties. Second, carbon-related positions require highly specialized expertise and are costly to train or replace, making firms' early exposure to carbon-educated workers a strong predictor of their subsequent stock of carbon reduction talent. As a predetermined measure that predates firms' post-2010 carbon strategies, $CarbonEdu_{i,2010}$ is unlikely to be influenced by later emission outcomes, supporting its exogeneity.

We implement the IV strategy using the following first-stage regressions:

$$ShareDecarbTalent_{i,t} = \alpha + \beta CarbonEdu_{i,2010} + \sum \delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \quad (4)$$

$$ShareDecarbTalent_{i,t} \times Post_t = \alpha + \beta CarbonEdu_{i,2010} \times Post_t + \sum \delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \quad (5)$$

The second-stage regression is specified as:

$$\begin{aligned} \log Emi_{i,t+1} = & \alpha + \beta_1 ShareDecarbTalent_{i,t} + \beta_2 ShareDecarbTalent_{i,t} \times Post_t \\ & + \sum \delta \Delta Controls_{i,t} + \gamma_{FE} + \varepsilon_{i,t} \end{aligned} \quad (6)$$

where $Post_t$ is an indicator for the post-Paris Agreement period. $ShareDecarbTalent_{i,t}$ denotes firm i 's share of carbon reduction talent in year t , instrumented using $CarbonEdu_{2010}$. $\log Emi_{i,t+1}$ denotes firm i 's carbon emissions in year $t+1$, measured separately for Scope 1 emissions, Scope 2 emissions, and their sum, with all measures expressed in natural logarithms. $Controls_{i,t}$ include the firm-level financial variables used in Equation (1), along with their corresponding interaction terms. We include firm and year fixed effects, and state-by-year and industry-by-year fixed effects.

Table 4 reports the IV results. Columns (1)–(2) and (5)–(6) present the first-stage regressions under alternative fixed-effect structures. In both cases, $CarbonEdu_{i,2010}$ is positively and significantly associated with $ShareDecarbTalent_{i,t}$, indicating that firms with greater exposure to carbon-educated workers in 2010 subsequently developed larger stocks

of carbon reduction talent.

The second-stage results provide strong evidence that carbon reduction talent causally reduces firms' carbon emissions. A one-standard-deviation increase in predicted $ShareDecarbTalent_{i,t}$ is associated with a 33.29% reduction in total emissions (Scope 1 + Scope 2). More importantly, a one-standard-deviation increase in the interaction term $ShareDecarbTalent_{i,t} \times Post_t$ is associated with a 62.99% reduction in total emissions following the Paris Agreement (Column (3)). The magnitude of this effect increases further when controlling for state-by-year and industry-by-year fixed effects: in Column (7), a one-standard-deviation increase in predicted $ShareDecarbTalent_{i,t} \times Post_t$ corresponds to a 78.86% reduction in total emissions.

[Table 4]

Table A.3 in the Internet Appendix reports additional instrumental variable specifications that alternatively control for industry-by-year fixed effects and state-by-year fixed effects, respectively. The results remain qualitatively unchanged across these alternative fixed-effect structures, confirming the robustness of our findings. Taken together, the IV evidence alleviates endogeneity concerns and provides causal support for the conclusion that investments in carbon reduction talent substantially reduce firms' carbon emissions, with effects that are markedly stronger in the post-Paris Agreement period.

5. Channels

In this section, we examine two sets of potential mechanisms through which firms with a higher share of decarbonization-related talent reduce their carbon emissions. First, we investigate whether decarbonization talent enhances firms' carbon management strategies, including emission monitoring, disclosure, and mitigation efforts. Second, we examine the role of decarbonization talent in promoting firms' green innovation activities. To mitigate endogeneity concerns, all channel variables are measured one year ahead, and the regressions include standard control variables.

5.1 Carbon management strategies

To explore the mechanisms through which carbon reduction talent affects firms' carbon performance, we first examine several dimensions of firms' carbon management. Specifically, we consider four measures capturing the strength of firms' emission management and disclosure practices: (1) GHG emissions reporting, (2) renewable energy programs, (3) product and service carbon risks, and (4) environmental products. Measures

of GHG emissions reporting, renewable energy programs, and product and service carbon risks are obtained from Morningstar Sustainalytics, while the environmental products measure is sourced from Refinitiv. These databases provide score-based assessments of firms' carbon management strategies. Higher scores indicate stronger performance for GHG emissions reporting, renewable energy programs, and environmental products, whereas lower scores for product and service carbon risks reflect lower exposure to carbon-related risks.

Panel A of Table 5 reports summary statistics for the channel variables. Panel B presents regression results for the carbon management channels. Across all specifications, the coefficient on $ShareDecarbTalent_{i,t}$ is statistically significant and economically meaningful. Firms that employ a higher share of carbon reduction talent exhibit more transparent GHG emissions reporting, greater engagement in renewable energy programs, lower carbon-related risks embedded in their products and services, and higher involvement in environmental products. These findings suggest that carbon reduction talent enhances firms' internal carbon management capabilities and improves the quality of their climate-related disclosures.

5.2 Green innovation activities

To examine the green innovation channel, we regress firm-level measures of green-related innovation outcomes on $ShareDecarbTalent_{i,t}$, controlling for the control variables used in Table 2, as well as firm and year fixed effects². Following prior research (Chemmanur et al., 2019), we obtain firm-level patent and citation data from the dataset constructed by Kogan, Papanikolaou, Seru, and Stoffman (KPSS, 2017). The KPSS dataset contains detailed information on all patents granted by the USPTO over the period 1926–2023 and links each patent to the assignee's PERMNO. We use this to merge the patent data with Compustat. We identify green-related innovation patents using the Y02 and Y04S classifications of the Cooperative Patent Classification (CPC) system. The Y02 category covers technologies related to climate change mitigation, including renewable energy and energy efficiency, while Y04S focuses on smart grid technologies that enhance the efficiency of electricity distribution. Following Chen, Chen, and Peng (2025), we further classify each green patent as either product- or process-related. The sample is restricted to firms with at least one green patent during the sample period. The final merged Revelio–

² Our channel regressions are robust when controlling state-by-year fixed effects.

Trucost–KPSS–Compustat dataset yields 2,635 firm-year observations.

Panel C of Table 5 reports the regression results. In column (1), the dependent variable is the number of green patents scaled by R&D expenditures, and in column (2), it is the number of green citations scaled by R&D expenditures. The coefficients on *ShareDecarbTalent* are positive and statistically significant at the 5% level or better in both specifications, indicating that firms with a higher proportion of decarbonization talent exhibit superior green innovation outcomes.

We further examine the effects of decarbonization talent on different dimensions of green innovation by distinguishing between product- and process-related patents. Following Ganglmair, Robinson, and Seeligson (2022), we classify patents as product-related (process-related) when more than 50 percent of their claims are related to product (process) innovations. Columns (3) and (4) report results for product-related green patents and product-related green patent citations, scaled by R&D expenditures. The coefficients on *ShareDecarbTalent_{i,t}* are positive and statistically significant, indicating that decarbonization talent is associated with greater product-oriented green innovation. Columns (5) and (6) present the corresponding results for process-related green patents and process-related green patent citations. Taken together, the results in Table 6 suggest that decarbonization talent enhances green innovation through both product development and process improvement channels.

6. Capital market responses after hiring carbon reduction talents

6.1 Carbon premium

Prior research documents a positive relation between firms' carbon emissions and expected stock returns, reflecting compensation for investors' exposure to carbon pricing and regulatory risks. Building on this insight, we examine whether carbon reduction talent attenuates the carbon premium by mitigating firms' carbon risk (Bolton and Kacperczyk, 2021).

Our analysis is based on 97,554 firm-month observations for firms that hire carbon reduction talent between 2010 and 2020 and satisfy the data requirements for return regressions. The sample spans a six-year window from three years before to three years after the hiring year. We estimate the following specification:

$$\begin{aligned} Return_{i,\tau,t+1} = & \alpha + \beta_1 \log Emi_{i,t+1} \times ShareDecarbTalent_{i,t} + \beta_2 \log Emi_{i,t+1} \\ & + \beta_3 ShareDecarbTalent_{i,t} + \sum \delta Controls_{it} + \gamma_{FE} + \varepsilon_{i,t} \end{aligned} \quad (7)$$

Where i indexes firm, τ indicates month, and t indexes year. $Return_{i,\tau,t+1}$ is firm i 's monthly

stock return in month τ in year $t+1$. $\log Emi_{it}$ captures firm-level carbon emissions or emission intensity, while $ShareDecarbTalent_{it}$ measures the share of carbon reduction talent employed. $Controls_{it}$ include standard firm-level characteristics. γ_{FE} denotes alternative fixed-effect structures, including year or month fixed effects, industry fixed effects, and DGTW benchmark fixed effects following Daniel et al. (1997).

Panel A of Table 6 reports summary statistics for the return measures, while Panel B presents the regression results. Consistent with prior evidence, the coefficients on $\log Emi_{i,t+1}$ are positive and statistically significant across specifications, indicating the presence of a carbon premium associated with higher emissions. Importantly, the interaction term $\log Emi \times ShareDecarbTalent$ is negative and statistically significant when emissions are measured using Scope 2 emissions and the combined Scope 1 and Scope 2 measure. This pattern suggests that the positive relation between emissions and expected returns is attenuated for firms with greater exposure to carbon reduction talent. Overall, results in Table 6 indicate that while carbon-intensive firms command higher expected returns, the hiring of carbon reduction talent mitigates investors' required compensation for carbon risk, consistent with a reduction in the carbon premium following firms' investments in decarbonization-related human capital.

[Table 6]

6.2 Bond yield spread

Prior research shows that carbon-intensive firms face higher borrowing costs because credit markets price carbon-related risks (Seltzer et al., 2022). If carbon reduction talent improves firms' ability to manage such risks, the adverse effect of emissions on credit spreads should be attenuated. To test this conjecture, we estimate specifications analogous to Equation (7), replacing the dependent variable with the corporate bond yield spread in basis points for firm i in year $t+1$, $YS_{i,t+1}$. The yield spread, obtained from Datastream, is defined as the difference between the yield on a corporate bond and the yield on a matched Treasury bond with comparable maturity. Table 7 reports the estimation results. Consistent with prior evidence, the coefficients on carbon emissions are positive and statistically significant across all specifications, indicating that firms with higher emissions face higher bond yield spreads. Importantly, the interaction terms between carbon emissions and $ShareDecarbTalent_{i,t}$ are negative and statistically significant. This pattern suggests that the positive association between emissions and borrowing costs is weaker for firms employing a greater share of carbon reduction talent.

[Table 7]

6.3 Analyst forecast error

We next examine whether the hiring of carbon reduction talent improves analyst forecast accuracy among high-emission firms. Prior studies document that firms exposed to greater climate risk tend to exhibit lower analyst forecast accuracy, reflecting more volatile earnings and cash flows as well as analysts' limited ability to assess climate-related risks (e.g., Zhang and Kanagaretnam, 2025). In contrast, firms with more transparent environmental and climate risk disclosures are associated with higher forecast accuracy (e.g., Dhaliwal et al., 2012). Therefore, we hypothesize that although high-emission firms generally face lower analyst forecast accuracy, this adverse effect is mitigated when firms employ a greater share of carbon reduction talent.

To examine analysts' responses to firms' hiring of carbon reduction talent, we define *Forecast accuracy*_{*i,t+1*} as the negative absolute difference between actual earnings per share and the consensus analyst forecast scaled by the firm's year-end stock price for firm *i* in year *t+1*. We regress *Forecast accuracy*_{*i,t+1*} on the interaction term *ShareDecarbTalent*_{*i,t*} × *logEmi*_{*i,t*} and a set of control variables, including Size, BM, ROA, Leverage, PPE, Cash, Capex, EBIT, RevGrowth, and analyst coverage. All specifications include firm and year fixed effects, consistent with prior studies (e.g., Baginski and Hassell, 1997; Mattei and Platikanova, 2017).

Table 8 reports the results. The coefficient on the interaction term *ShareDecarbTalent*_{*i,t*} × *logEmi*_{*i,t*} is positive and statistically significant across all specifications, indicating that the negative association between carbon emissions and analyst forecast accuracy is attenuated for firms with greater exposure to carbon reduction talent. Consistent with prior evidence, the coefficient on *logEmi*_{*i,t*} is negative and statistically significant when emissions are measured using Scope 2 emissions or the combined Scope 1 and Scope 2 measure, suggesting that firms with higher emissions tend to exhibit lower forecast accuracy. Overall, results in Table 8 suggest that carbon reduction talent improves the information environment of high-emission firms by reducing uncertainty related to climate risks, thereby enhancing analysts' ability to form more accurate earnings expectations.

[Table 8]

6.4 Green institutional ownership

Institutional investors, particularly those with sustainability-oriented preferences, have increasingly incorporated climate considerations into their capital allocation decisions. Prior studies show that firms with weaker climate risk management and disclosure tend to attract less investment from climate-conscious institutions (e.g., Ilhan et al., 2023). Survey evidence further suggests that divestment is an important tool through which investors manage climate-related risks (Krueger, Sautner, and Starks, 2020), and empirical work documents those institutional investors significantly reduce their holdings in firms with high carbon intensity (Bolton and Kacperczyk, 2021). While high-emission firms generally face lower ownership by climate-conscious institutional investors, we expect this negative relation to be mitigated among firms with greater exposure to carbon reduction talent. By enhancing firms' carbon management capabilities and improving the credibility of their climate-related disclosures, carbon reduction talent may alleviate investors' concerns about future carbon risks, thereby making such firms more attractive to green-oriented institutional investors.

To examine this conjecture, we follow Dyck et al. (2019) and Ilhan et al. (2023) and classify institutional investors as green-oriented if the Environmental Performance Index (EPI) score of their home country, obtained from the Yale Center for Environmental Law and Policy, is above the cross-country median. This classification captures cross-country variation in environmental preferences that shapes investors' sensitivity to firms' carbon strategies. We define *Green institutional ownership* $_{i,t+1}$ as the ratio of shares held by green-oriented institutional investors to total common shares outstanding for firm i in year $t+1$. We then regress *Green institutional ownership* $_{i,t+1}$ on the interaction term *ShareDecarbTalent* $_{i,t} \times \log Emi_{i,t+1}$ and control variables.

Table 9 presents the results. Consistent with prior evidence, the coefficients on *logEmi* $_{i,t+1}$ are negative and statistically significant across all specifications, indicating that firms with higher carbon emissions attract lower ownership by green-oriented institutional investors. Importantly, the interaction term *ShareDecarbTalent* $_{i,t} \times \log Emi_{i,t+1}$ is positive and statistically significant at the 5% level or better, suggesting that the negative association between carbon emissions and green institutional ownership is attenuated for firms employing a greater share of carbon reduction talent. Overall, these findings indicate that while carbon-intensive firms generally face divestment pressure from climate-conscious institutions, investments in carbon reduction talent mitigate this effect by

strengthening firms' carbon management and disclosure practices, thereby improving their attractiveness to green-oriented institutional investors.

[Table 9]

7. Conclusion

Carbon reduction talent has become an increasingly critical form of human capital for firms navigating the transition to a low-carbon economy. Using a comprehensive sample of U.S. firms from 2010 to 2020, we show that firms employing a greater share of carbon reduction talent achieve substantially lower carbon emissions. A one-standard-deviation increase in carbon reduction talent is associated with a 6.75% reduction in total emissions. Importantly, this effect intensifies following the Paris Agreement, reflecting heightened regulatory scrutiny and market discipline. In the post-Paris Agreement period, increases in carbon reduction talent are associated with a 6.97% reduction in total emissions and a 7.25% reduction in Scope 1 emissions, highlighting the central role of firm-internal capabilities in driving decarbonization. Instrumental variable analyses further establish a causal relationship between carbon reduction talent and emission reductions, and these results remain robust to alternative fixed-effect structures and different measures of carbon emissions.

We further identify the mechanisms through which carbon reduction talent translates into lower emissions. Firms with greater carbon reduction talent exhibit stronger carbon management practices, including more transparent GHG emissions reporting, greater engagement in renewable energy programs, lower carbon-related risks embedded in products and services, and higher involvement in environmental products. In addition, carbon reduction talent fosters green innovation, as reflected in higher green innovation outputs. Beyond operational outcomes, we document meaningful capital market responses. Firms with higher levels of carbon reduction talent face lower carbon risk premia, narrower bond yield spreads, more accurate analyst forecasts, and greater ownership by green-oriented institutional investors, indicating improved information environments and reduced perceived climate risk. Overall, our findings highlight the central role of workforce composition in shaping firms' climate performance and capital market outcomes.

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Table 1
Summary statistics

The sample includes 9,820 U.S. firm-year observations from 2010 to 2020. Panel A presents summary statistics for key variables. Carbon emissions (*EmiScope12*, *EmiScope1*, and *EmiScope2*) are the dependent variables, while *ShareDecarbTalent* is the explanatory variable: (i) the study focuses on Scope 1 and Scope 2 emissions, as they are directly influenced by firms and have less measurement ambiguity than Scope 3; (ii) carbon emissions are log-transformed to mitigate extreme values and scaled by total assets to account for firm size; (iii) *ShareDecarbTalent* measures the proportion of employees specializing in carbon reduction, renewable energy, and sustainability. Other variable definitions are in the Appendix A. Panels B and C present the top 10 industries with the highest and lowest *ShareDecarbTalent*, along with their carbon emissions. All firm level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1% level to reduce outlier influence.

Panel A. Summary statistics						
	N	P25	P50	Mean	P75	SD
<i>Emission variables</i>						
EmiScope12 (tons CO ₂ e) × 10 ⁻³	9,820	34.342	139.448	2457.653	709.454	10083.077
EmiScope1 (tons CO ₂ e) × 10 ⁻³	9,820	10.732	48.703	2071.811	301.677	9621.652
EmiScope2 (tons CO ₂ e) × 10 ⁻³	9,820	15.286	55.746	385.842	247.174	1176.643
IntATScope12 (tons CO ₂ e /millions USD)	9,820	13.192	40.127	135.760	102.965	300.339
IntATScope1 (tons CO ₂ e /millions USD)	9,820	4.242	15.696	103.120	48.805	279.982
IntATScope2 (tons CO ₂ e /millions USD)	9,820	5.861	15.106	30.852	37.249	41.960
<i>Independent variables</i>						
ShareDecarbTalent	9,820	0.001	0.003	0.010	0.010	0.023
<i>Other firm-level variables</i>						
Size	9,820	7.281	8.380	8.414	9.575	1.716
BM	9,820	0.188	0.358	0.437	0.603	0.416
ROA	9,820	0.009	0.042	0.028	0.081	0.117
Leverage	9,820	0.134	0.277	0.292	0.411	0.205
PPE	9,820	0.083	0.187	0.276	0.409	0.247
Cash	9,820	0.032	0.088	0.147	0.200	0.164
Capex	9,820	0.015	0.030	0.043	0.056	0.044
EBIT	9,820	0.036	0.075	0.069	0.122	0.117
RevGrowth	9,820	-0.022	0.049	0.073	0.133	0.224

Table 1
(Continued)

Panel B. Top 10 industries with the highest ratio of carbon reduction talents					
Rank	Industry name	SIC	N	Emission (Scopes 1 and 2) (tons CO ₂ e) × 10 ⁻⁶	
				Mean	Median
1	Electric, Gas, and Sanitary Services	49	578	16.7344	7.2982
2	Pipelines, Except Natural Gas	46	6	4.8550	4.8028
3	Metal Mining	10	49	3.1809	0.2768
4	Heavy Construction Other Than Building	16	62	0.1037	0.0641
5	Engineering, Accounting, Research, and Management	87	184	0.0484	0.0254
6	Agricultural Production — Crops	1	10	0.2973	0.1808
7	Bituminous Coal and Lignite Mining	12	29	6.7309	6.9286
8	Textile Mill Products	22	32	0.9250	0.0872
9	Electronic and other Electrical Equipment and Components, except Computer Equipment	36	699	0.3539	0.0807
10	Construction Special Trade Contractors	17	59	0.6279	0.2259
Panel C. Top 10 industries with the lowest ratio of carbon reduction talents					
Rank	Industry name	SIC	N	Emission (Scopes 1 and 2) (tons CO ₂ e) × 10 ⁻⁶	
				Mean	Median
1	Building Materials, Hardware, Garden Supplies	52	35	1.7919	2.3446
2	Home Furniture, Furnishings, and Equipment Stores	57	47	0.4784	0.5139
3	Apparel and Accessory Stores	56	149	0.2664	0.1669
4	Personal Services	72	30	0.1832	0.1931
5	Motion Pictures	78	15	0.0700	0.0594
6	General Merchandise Stores	53	94	3.8058	1.3404
7	Local and Suburban Transit	41	3	0.0625	0.0469
8	Food Stores	54	40	2.2470	0.3574
9	Non-Depository Credit Institutions	61	54	0.0505	0.0266
10	Miscellaneous Retail	59	134	1.0289	0.2163

Table 2
Main regression results

This table reports the main regression results examining the association between firms' carbon emission measures and the share of decarbonization-related talent (*ShareDecarbTalent*). The dependent variable in Columns (1)-(3) use Log(Emission), and Columns (4)-(6) use Log(Emission/Total Assets), both measured for Scope 1, Scope 2, and the summation of Scope 1 and 2. All specifications control for firm and year fixed effects. Control variables include firm characteristics (*Size*, *BM*, *ROA*, *Leverage*, *PPE*, *Cash*, *Capex*, *EBIT*, *RevGrowth*). All firm level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. Standard errors are clustered at the firm level, and *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Log (Emission)			Log (Emission/total assets)		
	Scopes 1 and 2	Scope 1	Scope 2	Scopes 1 and 2	Scope 1	Scope 2
	(1)	(2)	(3)	(4)	(5)	(6)
ShareDecarbTalent	-2.9329* (-1.700)	-3.9338** (-2.447)	-4.5989** (-2.497)	-2.9473* (-1.848)	-3.9481*** (-2.682)	-4.6132*** (-2.680)
Size	0.6359*** (17.721)	0.5878*** (14.357)	0.6771*** (18.125)	-0.3634*** (-10.137)	-0.4115*** (-10.070)	-0.3221*** (-8.612)
BM	0.0161 (0.542)	0.0106 (0.305)	-0.0261 (-0.837)	0.0105 (0.353)	0.0051 (0.145)	-0.0317 (-1.006)
ROA	-0.5877*** (-3.775)	-0.5579*** (-2.907)	-0.7729*** (-4.713)	-0.6153*** (-3.982)	-0.5855*** (-3.076)	-0.8004*** (-4.911)
Leverage	-0.1714* (-1.815)	-0.1263 (-1.015)	-0.2036** (-2.209)	-0.1934** (-2.072)	-0.1483 (-1.198)	-0.2255** (-2.471)
PPE	0.3138 (1.482)	0.1820 (0.758)	0.4178* (1.769)	0.3259 (1.539)	0.1941 (0.809)	0.4299* (1.818)
Cash	-0.3345*** (-3.095)	-0.3125** (-1.991)	-0.2595** (-2.302)	-0.3314*** (-3.085)	-0.3094** (-1.977)	-0.2564** (-2.291)
Capex	-0.6433 (-1.216)	-0.9698* (-1.665)	0.3864 (0.850)	-0.6019 (-1.136)	-0.9284 (-1.592)	0.4278 (0.940)
EBIT	1.3472*** (6.513)	1.4583*** (5.908)	1.5496*** (6.986)	1.2590*** (6.214)	1.3701*** (5.625)	1.4614*** (6.685)
RevGrowth	0.1572*** (3.193)	0.1672*** (3.126)	0.1797*** (3.583)	0.1534*** (3.126)	0.1634*** (3.064)	0.1758*** (3.518)
Constant	6.7047*** (22.434)	6.3103*** (18.248)	5.1864*** (17.152)	6.7068*** (22.476)	6.3124*** (18.306)	5.1885*** (17.135)
<i>N</i>	9,820	9,820	9,820	9,820	9,820	9,820
adj. <i>R</i> ²	0.214	0.123	0.186	0.167	0.150	0.108
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 3**Paris Agreement and the Emissions Impact of Carbon Reduction Talents**

This table reports the main regression results examining the association between firms' carbon emission measures and the share of decarbonization-related talent (*ShareDecarbTalent*). The dependent variable in Columns (1)-(3) use Log(Emission), and Columns (4)-(6) use Log(Emission/Total Assets), both measured for Scope 1, Scope 2, and the summation of Scope 1 and 2. *Post* is an indicator variable equal to one for the post-Paris Agreement period (2016–2020) and zero otherwise. All specifications control for firm and year fixed effects. Control variables include firm characteristics (*Size*, *BM*, *ROA*, *Leverage*, *PPE*, *Cash*, *Capex*, *EBIT*, *RevGrowth*). All firm level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. Standard errors are clustered at the firm level, and *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Log (Emission)			Log (Emission/total assets)		
	Scopes 1 and 2	Scope 1	Scope 2	Scopes 1 and 2	Scope 1	Scope 2
	(1)	(2)	(3)	(4)	(5)	(6)
ShareDecarbTalent×Post	−3.0311*** (−2.891)	−3.1523*** (−3.098)	0.8372 (0.478)	−1.6634* (−1.901)	−1.7846* (−1.816)	2.2049 (1.470)
ShareDecarbTalent	−0.9951 (−0.705)	−1.7794 (−1.297)	−3.9938** (−2.108)	−1.2675 (−0.908)	−2.0518 (−1.541)	−4.2662** (−2.166)
Post	−0.0715 (−0.452)	−0.5264*** (−2.711)	−0.2684 (−1.273)	0.0237 (0.154)	−0.4312** (−2.253)	−0.1733 (−0.839)
Size×Post	−0.0420*** (−3.009)	−0.0112 (−0.679)	−0.0165 (−0.839)	−0.0528*** (−3.924)	−0.0220 (−1.367)	−0.0273 (−1.418)
BM×Post	0.1019** (1.974)	0.1060* (1.662)	0.0724 (1.238)	0.0933* (1.788)	0.0973 (1.522)	0.0638 (1.072)
ROA×Post	0.4650* (1.740)	0.4147 (1.217)	0.5829** (2.059)	0.4551* (1.708)	0.4048 (1.192)	0.5730** (2.027)
Leverage×Post	0.2673** (2.026)	0.1849 (1.074)	0.2545** (2.056)	0.2688** (2.036)	0.1864 (1.082)	0.2560** (2.065)
PPE×Post	−0.0443 (−0.416)	0.1889 (1.383)	0.3963** (2.089)	−0.0540 (−0.513)	0.1792 (1.317)	0.3866** (2.044)
Cash×Post	0.0370 (0.227)	−0.1675 (−0.799)	0.0920 (0.554)	0.0867 (0.580)	−0.1178 (−0.586)	0.1416 (0.930)
Capex×Post	2.7088*** (4.393)	2.4846*** (3.451)	0.0982 (0.132)	2.6374*** (4.309)	2.4132*** (3.359)	0.0268 (0.036)
EBIT×Post	−0.6284** (−2.000)	−0.7216* (−1.720)	−0.3336 (−1.038)	−0.7365** (−2.497)	−0.8297** (−2.031)	−0.4417 (−1.466)
RevGrowth×Post	0.4378*** (5.386)	0.3784*** (4.289)	0.4946*** (5.723)	0.4300*** (5.313)	0.3706*** (4.216)	0.4868*** (5.647)
Size	0.6715*** (19.435)	0.6248*** (16.441)	0.6956*** (18.416)	−0.3185*** (−9.291)	−0.3652*** (−9.687)	−0.2944*** (−7.852)
BM	−0.0850** (−1.965)	−0.0908* (−1.685)	−0.0946* (−1.888)	−0.0842* (−1.904)	−0.0899* (−1.650)	−0.0937* (−1.814)
ROA	−0.9260*** (−4.928)	−0.8676*** (−3.460)	−1.2278*** (−5.740)	−0.9499*** (−4.940)	−0.8915*** (−3.506)	−1.2517*** (−5.770)
Leverage	−0.3473** (−2.545)	−0.2291 (−1.249)	−0.3791*** (−3.014)	−0.3577*** (−2.616)	−0.2396 (−1.303)	−0.3896*** (−3.088)
PPE	0.2349 (1.067)	−0.0967 (−0.379)	−0.0050 (−0.020)	0.2409 (1.096)	−0.0907 (−0.356)	0.0009 (0.004)
Cash	−0.3407** (−2.128)	−0.1956 (−0.850)	−0.3496** (−2.150)	−0.3802** (−2.396)	−0.2351 (−1.025)	−0.3890** (−2.416)
Capex	−1.8425*** (−2.618)	−1.7576** (−2.270)	0.7568 (1.044)	−1.7634** (−2.511)	−1.6785** (−2.169)	0.8359 (1.154)
EBIT	1.7513*** (6.050)	1.9462*** (4.919)	1.7883*** (6.213)	1.7482*** (6.237)	1.9431*** (4.964)	1.7852*** (6.444)
RevGrowth	−0.1572*** (−2.808)	−0.1151* (−1.733)	−0.1737*** (−2.780)	−0.1536*** (−2.668)	−0.1114* (−1.647)	−0.1700*** (−2.657)
Constant	6.5400*** (22.444)	6.1527*** (18.852)	5.2549*** (16.525)	6.4499*** (22.376)	6.0626*** (18.756)	5.1649*** (16.370)
Observations	9,820	9,820	9,820	9,820	9,820	9,820
Adjusted R ²	0.237	0.141	0.200	0.192	0.167	0.126
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 4**Instrumental variable regression results**

This table reports instrumental variable regression results examining the relationship between carbon emissions and the share of decarbonization-related talent (*ShareDecarbTalent*), using *CarbonEdu*₂₀₁₀ as an instrument. *CarbonEdu*₂₀₁₀ is defined as the share of a firm's employees in 2010 who graduated from universities specializing in carbon reduction-related fields, identified based on university rankings in Energy Science & Engineering from the Academic Ranking of World Universities (ARWU). Columns (1)-(2) and (5)-(6) present the first-stage regression results, where the dependent variables are *ShareDecarbTalent* and *ShareDecarbTalent* × *Post*, respectively. Columns (3)-(4) and (7)-(8) report the corresponding second-stage regression results. The dependent variable in Columns (3) and (7) is *Log(Emission)*, while Columns (4) and (8) use *Log(Emission/Total Assets)*. Emissions are measured using Scope 1 emissions, Scope 2 emissions, and the summation of Scope 1 and 2. All specifications include the firm-level control variables used in Table 2. All firm-level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1 percent level to mitigate the influence of outliers. Columns (1)-(4) include firm and year fixed effects, while Columns (5)-(8) incorporate state-by-year and industry-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ShareDecarbTalent	ShareDecarbTalen × Post	Log (Emission)	Log (Emission/total assets)	ShareDecarbTalent	ShareDecarbTalent×Post	Log (Emission)	Log (Emission/total assets)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CarbonEdu ₂₀₁₀	0.3308*** (3.917)	-0.0093 (-0.636)			0.3373*** (3.737)	-0.0343** (-2.399)		
CarbonEdu ₂₀₁₀ ×Post	-0.2730*** (-3.183)	0.0692*** (2.990)			-0.2908*** (-3.229)	0.0875*** (3.848)		
ShareDecarbTalent			-14.4725*** (-3.154)	-14.1009*** (-3.041)			0.4339 (0.091)	1.5385 (0.320)
ShareDecarbTalent× Post			-27.3866* (-1.959)	-29.6625** (-2.106)			-34.2885** (-2.193)	-36.5647** (-2.345)
Controls	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2
Constant	0.0258*** (4.130)	0.0132*** (4.165)	5.5905*** (20.080)	5.8024*** (20.517)	0.0283*** (5.716)	0.0093*** (3.269)	4.8974*** (17.937)	5.0580*** (18.399)
Observations	9,758	9,758	9,758	9,758	9,758	9,758	9,758	9,758
Adjusted R ²	0.136	0.143	0.570	0.254	0.155	0.159	0.710	0.505
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	N	N	N	N
Industry×Year FE	N	N	N	N	Y	Y	Y	Y
State×Year FE	N	N	N	N	Y	Y	Y	Y

Table 5. Channels

This table examines the potential mechanisms through which decarbonization-related talent improves firms' carbon performance. Panel A reports summary statistics for the channel variables. Panels B to D present regression results for the carbon management and green innovation efficiency, green innovation output channels, respectively. The carbon management channels include the extent of a firm's disclosure of GHG emissions ($EmiReport_{i,t+1}$); the strength of a firm's initiatives and targets to increase the use of renewable energy ($RenewEnergy_{i,t+1}$); the level of unmanaged risk a firm faces related to carbon issues in its products and services ($CarbonUnmanageRisk_{i,t+1}$); and the firms' reporting on at least one product line or service that is designed to have positive effects on the environment or which is environmentally labeled and marketed ($EnvironProduct_{i,t+1}$). The green innovation efficiency channel variables are the total number of green patents scaled by R&D expenses ($Product\ green\ patents_{i,t+1}$); the total number of green citations scaled by R&D expenses ($Green\ citations_{i,t+1}$); the total number of product green patents scaled by R&D expenses ($Product\ green\ patents_{i,t+1}$); the total number of product green citations scaled by R&D expenses ($Product\ green\ citations_{i,t+1}$); the total number of process-related green patents scaled by R&D expenses ($Process\ green\ patents_{i,t+1}$); and the total number of process-related green citations scaled by R&D expenses ($Process\ green\ citations_{i,t+1}$). All firm level continuous variables, except $ShareDecarbTalent$ and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. T -statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary statistics						
Variables	N	p25	Median	Mean	p75	SD
<i>EmiReport</i> _{<i>i,t</i>+1}	3,781	0	0.250	0.256	0.500	0.285
<i>RenewEnergy</i> _{<i>i,t</i>+1}	3,781	0	0	0.110	0.135	0.196
<i>CarbonUnmanageRisk</i> _{<i>i,t</i>+1}	3,887	0	0	4.275	0	8.558
<i>EnvironProduct</i> _{<i>i,t</i>+1}	8,313	0	0	0.334	0.678	0.363
<i>Green patents</i> _{<i>i,t</i>+1}	2,635	0	0	0.002	0	0.009
<i>Green citations</i> _{<i>i,t</i>+1}	2,635	0	0	0.005	0	0.019
<i>Product green patents</i> _{<i>i,t</i>+1}	2,635	0	0	0.002	0	0.006
<i>Product green citations</i> _{<i>i,t</i>+1}	2,635	0	0	0.003	0	0.015
<i>Process green patents</i> _{<i>i,t</i>+1}	2,635	0	0	0.001	0	0.004
<i>Process green citations</i> _{<i>i,t</i>+1}	2,635	0	0	0.001	0	0.008
Panel B. Regression results of carbon management strategies						
	<i>EmiReport</i> _{<i>i,t</i>+1}	<i>RenewEnergy</i> _{<i>i,t</i>+1}	<i>CarbonUnmanageRisk</i> _{<i>i,t</i>+1}	<i>EnvironProduct</i> _{<i>i,t</i>+1}		
	(1)	(2)	(3)	(4)		
<i>ShareDecarbTalent</i> _{<i>i,t</i>}	3.7617*	6.9804**	−31.2659**	1.9397**		
	(1.685)	(2.578)	(−2.013)	(2.109)		
Control variables (as in Table 2)	Y	Y	Y	Y		
Firm FE	Y	Y	Y	Y		
Year FE	Y	Y	Y	Y		
N	3,781	3,781	3,887	7,977		
adj. <i>R</i> ²	0.148	0.058	0.053	0.071		
Panel C. Regression results of green innovation efficiency						
	<i>Green patents</i> _{<i>i,t</i>+1}	<i>Green citations</i> _{<i>i,t</i>+1}	<i>Product green patents</i> _{<i>i,t</i>+1}	<i>Product green patents</i> _{<i>i,t</i>+1}	<i>Process green patents</i> _{<i>i,t</i>+1}	<i>Process green citations</i> _{<i>i,t</i>+1}
	(1)	(2)	(3)	(4)	(5)	(6)
<i>ShareDecarbTalent</i> _{<i>i,t</i>}	0.3165**	0.7253**	0.1613*	0.4716**	0.0672	0.1277
	(2.553)	(2.439)	(1.940)	(2.215)	(1.311)	(1.566)
Control variables (as in Table 2)	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
N	2,635	2,635	2,635	2,635	2,635	2,635
adj. <i>R</i> ²	0.083	0.115	0.058	0.097	0.014	0.038

Table 6. Carbon premium

This table presents the ordinary least squares (OLS) regression analyzing estimated carbon premium following firms' hiring of decarbonization-related talent. The sample includes 97,554 firm-month observations covering the period from 2010 to 2020. Panel A reports the summary statistics for the dependent variables in Panel B, which is monthly stock return (Column (1)-(3)) and DGTW adjusted return (Column (4)-(6)), respectively. DGTW adjusted return is monthly return minus the value-weighted return of firms in the same size, book-to-market ratio, and momentum quintiles (Daniel et al. 1997). *logEmi* denotes the natural logarithm of the firm's carbon emissions, measured alternatively as Scope 1 emissions (Columns (1) and (4)), Scope 2 emissions (Columns (2) and (5)), and the sum of Scope 1 and Scope 2 emissions (Columns (3) and (6)), respectively. *ShareDecarbTalent* denotes the share of decarbonization-related talent. DGTW fixed effects are based on the $5 \times 5 \times 5$ portfolios on size, book-to-market ratios, and momentum (Guernsey et al., 2022). The definitions of other variables are in the Appendix. Industry fixed effects are based on three-digit SIC industries. All firm level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. *T*-statistics based on robust standard errors clustered at the firm are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary statistics						
	N	P25	P50	Mean	P75	SD
Return (%)	97,554	-4.187	1.354	1.618	6.744	12.851
DGTW adj. return (%)	97,554	-4.313	0.107	0.490	4.553	10.833
Panel B. Regression						
	Raw Return			DGTW adj. return		
	Scope1 (1)	Scope2 (2)	Scope1 and 2 (3)	Scope1 (4)	Scope2 (5)	Scope1 and 2 (6)
<i>logEmi</i>	0.061* (1.663)	0.114** (2.203)	0.091* (1.816)	0.088** (2.495)	0.132** (2.551)	0.124** (2.502)
<i>logEmi</i> × <i>ShareDecarbTalent</i>	-2.467 (-1.437)	-4.957** (-1.987)	-3.309* (-1.647)	-3.321** (-2.031)	-5.619** (-2.453)	-4.271** (-2.250)
<i>ShareDecarbTalent</i>	35.248* (1.699)	57.867** (2.122)	46.587* (1.833)	47.199** (2.423)	67.544*** (2.700)	60.483** (2.547)
<i>Leverage</i>	0.067 (0.305)	0.049 (0.216)	0.063 (0.287)	0.127 (0.623)	0.102 (0.485)	0.122 (0.595)
<i>Invest/A</i>	-0.016 (-0.526)	-0.013 (-0.432)	-0.014 (-0.457)	-0.016 (-0.465)	-0.014 (-0.426)	-0.013 (-0.400)
<i>Log(PPE)</i>	0.055 (1.109)	0.034 (0.617)	0.037 (0.651)	-0.044 (-1.332)	-0.065 (-1.561)	-0.069 (-1.617)
<i>Salesgr</i>	-0.000 (-0.923)	-0.000 (-1.140)	-0.000 (-0.992)	-0.000** (-2.362)	-0.000*** (-2.623)	-0.000** (-2.452)
<i>EPSgr</i>	-1.074*** (-3.799)	-1.086*** (-3.882)	-1.078*** (-3.834)	-1.055*** (-4.143)	-1.068*** (-4.214)	-1.060*** (-4.178)
<i>Beta</i>	-0.048 (-1.512)	-0.047 (-1.479)	-0.047 (-1.502)	-0.015 (-0.518)	-0.013 (-0.463)	-0.014 (-0.495)
<i>Volatility</i>	12.598*** (8.574)	12.583*** (8.550)	12.585*** (8.566)	9.874*** (8.072)	9.946*** (8.072)	9.893*** (8.075)
N	97,554	97,554	97,554	97,554	97,554	97,554
adj. R^2	0.239	0.239	0.239	0.030	0.030	0.030
Year/Mon FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
DGTW FE	Yes	Yes	Yes	No	No	No

Table 7. Bond yield spread

This table presents the relationship between hiring decarbonization-related talent and firms' credit ratings and bond yield spreads. The dependent variable is the YS (bond yield spread in basis points), defined as the difference between the yield on a corporate bond and the yield on a matched Treasury bond of comparable maturity. Control variables include MarketLeverage (book value of debt divided by the sum of book debt and market equity), Volatility (annualized stock return volatility), ROA (net income divided by total assets), ROAVol (standard deviation of ROA over the prior five years), Size (log of total assets), FirmAge (years since first appearance in Compustat), and RD (R&D expenses scaled by total assets). Bond-level controls include Coupon (bond coupon rate), BondAge (years since bond issuance), LnAmt (natural logarithm of bond issuance amount), LFFL (yield to maturity), and Rating (bond credit rating). All firm-level continuous variables are winsorized at the 2% level. *T*-statistics, reported in parentheses, are based on robust standard errors clustered at the bond level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) YS	(2) YS	(3) YS	(4) YS	(5) YS	(6) YS
Log(Emission1)	4.3301** (2.08)			7.0150*** (2.81)		
Log(Emission2)		6.1600*** (3.19)			16.0910*** (5.73)	
Log(Emission12)			6.9666*** (2.63)			11.4850*** (3.48)
Log(Emission1)×ShareDecarbTalent				-403.1308* (-1.75)		
Log(Emission2)×ShareDecarbTalent					-504.1113*** (-4.21)	
Log(Emission12)×ShareDecarbTalent						-562.6961** (-2.19)
ShareDecarbTalent				6007.2333* (1.85)	6414.0091*** (3.75)	8424.0444** (2.26)
MarketLeverage	416.1176*** (12.49)	413.7499*** (12.45)	415.6615*** (12.49)	418.6869*** (12.49)	418.1988*** (12.56)	419.8153*** (12.47)
Volatility	130.1502*** (8.60)	128.5471*** (8.49)	130.0739*** (8.60)	129.9879*** (8.57)	128.1902*** (8.46)	129.5158*** (8.53)
ROA	-186.9334*** (-3.86)	-186.8073*** (-3.86)	-186.6114*** (-3.85)	-185.8817*** (-3.83)	-185.2529*** (-3.83)	-185.4402*** (-3.82)
ROAVol	158.8620* (1.84)	159.9502* (1.85)	157.2652* (1.82)	156.8393* (1.79)	149.4192* (1.70)	152.8797* (1.74)
Size	-54.1467*** (-6.93)	-55.1161*** (-7.08)	-55.7806*** (-7.03)	-54.6437*** (-6.98)	-59.8970*** (-7.60)	-57.3260*** (-7.15)
FirmAge	38.1838** (2.55)	39.7458** (2.60)	35.0726** (2.34)	40.5598** (2.71)	34.3486** (2.27)	35.4289** (2.37)
RD	-7.6037 (-0.08)	0.6616 (0.01)	-10.8380 (-0.12)	-2.9440 (-0.03)	-4.1668 (-0.05)	-4.7032 (-0.05)
Coupon	43.3815 (0.94)	43.4650 (0.95)	44.0962 (0.97)	44.1899 (0.97)	47.0666 (1.04)	45.5264 (1.00)
BondAge	-37.3060 (-1.53)	-37.7005 (-1.55)	-37.8623 (-1.55)	-37.0280 (-1.51)	-38.5057 (-1.58)	-37.7013 (-1.54)
Lnamt	-13.1359** (-2.24)	-13.2598** (-2.28)	-13.1151** (-2.24)	-13.1141** (-2.22)	-12.5188** (-2.12)	-13.0002** (-2.19)
LFFL	0.0292 (0.39)	0.0176 (0.24)	0.0281 (0.38)	0.0336 (0.45)	0.0140 (0.20)	0.0341 (0.46)
Rating	23.6545*** (8.13)	23.7388*** (8.16)	23.6765*** (8.14)	23.5891*** (8.02)	23.6763*** (8.11)	23.5908*** (8.01)
Constant	-1225.5153 (-1.55)	-1307.9305 (-1.63)	-1101.4168 (-1.39)	-1378.3723* (-1.75)	-1155.7553 (-1.46)	-1178.7559 (-1.50)
Year×Industry FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y	Y	Y
N	20,945	20,945	20,945	20,945	20,945	20,945
Adjusted R ²	0.8541	0.8543	0.8542	0.8542	0.8546	0.8543

Table 8. Analyst forecast accuracy

This table reports ordinary least squares (OLS) regression results examining the relationship between firms' decarbonization-related talent and the carbon awareness of analyst forecast accuracy. The sample includes 8,513 firm-year observations covering the period from 2010 to 2020. The dependent variable, Analyst Forecast Accuracy, is defined as the negative of the absolute difference between actual earnings per share (EPS) for fiscal year t and the median analyst forecast, scaled by the year-end stock price. $\log Emi$ in Columns (1)–(3) represents the natural logarithm of Scope 1, Scope 2, and the sum of Scope 1 and Scope 2 carbon emissions (in metric tons of CO₂), respectively. $ShareDecarbTalent$ denotes the proportion of a firm's employees engaged in carbon-reduction-related roles. Control variables include Size, BM, ROA, Leverage, PPE, Cash, Capex, EBIT, RevGrowth, and numest (number of analyst estimates). The definitions of other variables are in the Appendix. All firm level continuous variables, except $ShareDecarbTalent$ and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. T -statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: <i>Forecast Accuracy</i>		
	Scope1	Scope2	Scope1 and 2
	(1)	(2)	(3)
<i>logEmi</i>	–0.000 (–1.291)	–0.001** (–2.220)	–0.001** (–1.982)
<i>logEmi</i> × <i>ShareDecarbTalent</i>	0.040** (2.015)	0.033* (1.875)	0.045** (2.007)
<i>ShareDecarbTalent</i>	–0.610** (–2.323)	–0.459** (–2.412)	–0.697** (–2.251)
N	8,513	8,513	8,513
adj. R ²	0.521	0.521	0.521
Control variables	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y

Table 9. Green institutional ownership

This table reports ordinary least squares (OLS) regression results examining the relationship between firms' decarbonization-related talent and the carbon sensitivity of green institutional ownership. The dependent variable, *Green Institutional Ownership*, is defined as the ratio of the number of shares held by institutional investors with green-oriented preferences to the total number of common shares outstanding. Institutional investors are classified as green-oriented if the Environmental Performance Index (EPI) score of their home country, sourced from the Yale Center for Environmental Law and Policy, exceeds the cross-country median. The sample includes 6,659 firm-year observations covering the period from 2010 to 2020. $\text{Log}(\text{Emission})$ in Columns (1)–(3) represents the natural logarithm of Scope 1, Scope 2, and the sum of Scope 1 and Scope 2 carbon emissions (in metric tons of CO₂), respectively. *ShareDecarbTalent* denotes the proportion of a firm's employees engaged in carbon-reduction-related roles. The definitions of other variables are in the Appendix. All firm level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. *T*-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: Green Institutional Ownership		
	Scope1	Scope2	Scope1 and 2
	(1)	(2)	(3)
<i>logEmi</i>	–0.007* (–1.859)	–0.015*** (–3.313)	–0.011** (–2.387)
<i>logEmi</i> × <i>ShareDecarbTalent</i>	0.400*** (4.573)	0.333** (2.021)	0.391*** (3.395)
<i>ShareDecarbTalent</i>	–4.840*** (–5.384)	–4.035*** (–3.003)	–4.993*** (–4.298)
N	6,659	6,659	6,659
adj. R2	0.219	0.214	0.217
Control variables	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y

Appendix A

Variable definitions

This table provides definitions for all variables used in the analysis.

Variable	Definition	Source
Dependent Variables		
$\log Emi_{i,t+1}$	Logarithm of firm i 's carbon emissions in year $t+1$, measured separately for Scope 1 emissions, Scope 2 emissions, and the combined Scope 1 and Scope 2 emissions.	Trucost
$\log IntAT_{i,t+1}$	Logarithm of firm i 's carbon emission intensity in year $t+1$, defined as carbon emissions scaled by total assets (Compustat data item AT). Emission intensity is measured separately for Scope 1 emissions, Scope 2 emissions, and the combined Scope 1 and Scope 2 emissions.	Trucost; Compustat
$\Delta \log Emi_i$	change in firm i 's carbon emissions over the periods 2010–2015 or 2016–2020, calculated as the difference between carbon emissions in years. Emissions are evaluated separately for Scope 1, Scope 2, and the combined total of Scopes 1 and 2.	Trucost
Independent Variables		
$ShareDecarbTalent_{i,t}$	The proportion of firm i 's employees engaged in carbon reduction-related roles in year t , such as renewable energy, carbon accounting, and sustainability initiatives, measured annually at the firm level.	Revelio
$\Delta ShareDecarbTalent_{i,t}$	Change in the share of carbon transition talents within the firm over the periods 2010–2015 or 2016–2020.	Revelio
Other firm-level variables		
$Size_{i,t}$	Logarithm of the total assets (Compustat data item AT) for firm i in year t .	Compustat
$BM_{i,t}$	Difference between common equity (Compustat data item CEQ) and preferred stock capital (PSTK) at the end of the year divided by the equity market value (MKVALT) for firm i in year t .	Compustat
$ROA_{i,t}$	Net income (Compustat data item NI) scaled by total assets (Compustat data item AT) for firm i in year t .	Compustat
$BookLeverage_{i,t}$	Sum of the book value of long-term debt (Compustat data item DLTT) and the book value of current liabilities (DLC) at the end of the year divided by total assets at the end of the year (Compustat data item AT) for firm i in year t .	Compustat
$PPE_{i,t}$	Net Property, plant, and equipment (Compustat data item PPENT) divided by total assets (Compustat data item AT) for firm i in year t .	Compustat
$Cash_{i,t}$	Cash and short-term investments (Compustat data item CHE) divided by total assets (Compustat data item AT) for firm i in year t .	Compustat
$Capex_{i,t}$	Capital expenditures at the end of the year (Compustat data item CAPX) divided by total assets at the end of the year (Compustat data item AT) for firm i in year t .	Compustat
$EBIT_{i,t}$	Earnings before interest and taxes (Compustat data item EBIT) at the end of the year divided by total assets at the end of the year (Compustat data item AT) for firm i in year t .	Compustat
$RevGrowth_{i,t}$	Revenue growth rate, calculated as the difference in total revenue from the previous year, divided by total revenue of the previous year (Compustat data item REVT) for firm i in year t .	Compustat

Appendix A
(Continued)

Variable	Definition	Source
DiD variables		
$Treatment_i$	An indicator that equals one if firm i is classified as high emission in 2014 and zero otherwise.	Trucost; Compustat
$Post_t$	An indicator that equals one for years after 2016 and zero otherwise.	Compustat
Instrumental Variables		
$CarbonEdu_{i,2010}$	The share of a firm's workers in 2010 who graduated from universities specializing in carbon reduction-related fields, as identified by their rankings in Energy Science & Engineering in the Academic Ranking of World Universities (ARWU) for firm i .	Revelio
Channel variables		
$EmiReport_{i,t+1}$	The extent of firm i 's disclosure of GHG emissions in year $t+1$.	Sustainalytics
$RenewEnergy_{i,t+1}$	The strength of firm i 's initiatives and targets to increase the use of renewable energy programs in year $t+1$.	Sustainalytics
$CarbonUnmanageRisk_{i,t+1}$	The level of unmanaged risk firm i faces related to carbon issues in its products and services in year $t+1$.	Sustainalytics
$EnvironProduct_{i,t+1}$	Firm i 's reporting that at least one product line or service that is designed to have positive effects on the environment in year $t+1$.	Refinitiv
$Green\ patents_{i,t+1}$	The total number of green patents scaled by R&D expenses for firm i in year $t+1$.	KPSS
$Green\ citations_{i,t+1}$	The total number of green citations scaled by R&D expenses for firm i in year $t+1$.	KPSS
$Product\ green\ patents_{i,t+1}$	The total number of product green patents scaled by R&D expenses for firm i in year $t+1$.	KPSS; CPC
$Product\ citations_{i,t+1}$	The total number of product green citations scaled by R&D expenses for firm i in year $t+1$.	KPSS; CPC
$Process\ green\ patents_{i,t+1}$	The total number of process-related green patents scaled by R&D expenses for firm i in year $t+1$.	KPSS; CPC
$Process\ green\ citations_{i,t+1}$	The total number of process-related green citations scaled by R&D expenses for firm i in year $t+1$.	KPSS; CPC
Capital market response variables		
$Return_{i,\tau,t+1}$	Firm i 's monthly stock return in month τ in year $t+1$.	CRSP
$YS_{i,t+1}$	Corporate bond yield spread in basis points for firm i in year $t+1$.	Datastream
$Forecast\ accuracy_{i,t+1}$	The negative absolute difference between actual earnings per share and the consensus analyst forecast scaled by the firm's year-end stock price for firm i in year $t+1$.	I/B/E/S
$Green\ institutional\ ownership_{i,t+1}$	The ratio of shares held by green-oriented institutional investors to total common shares outstanding for firm i in year $t+1$.	ThomsonReuters

Appendix B

Keyword list for identifying carbon reduction talents

This table lists all 375 keywords used to identify carbon reduction talents, comprising 23 job title keywords and 352 job description keywords. The keyword set was developed through an iterative screening process informed by the LinkedIn Global Green Skills Report, with classification accuracy enhanced using ChatGPT–assisted evaluation. These keywords serve as the basis for constructing the *ShareDecarbTalent* variable used in the empirical analysis.

Field Used	Keyword	Field Used	Keyword
Job title	carbon accountant	Job description	environmental service
Job title	carbon auditor	Job description	environmental solution
Job title	carbon footprint	Job description	environmental standard
Job title	carbon inventory	Job description	environmental technologies
Job title	carbon management	Job description	environmental technology
Job title	carbon reduce	Job description	ethical sourcing
Job title	carbon reduction	Job description	ev batteries
Job title	carbon trade	Job description	ev battery
Job title	carbon trading	Job description	ev charge
Job title	climate	Job description	ev charging
Job title	emission	Job description	ev design
Job title	energy	Job description	ev engineer
Job title	environmental	Job description	ev manufacture
Job title	green technology	Job description	ev manufacturing
Job title	hydrogen	Job description	ev supply chain
Job title	pollution	Job description	ev100
Job title	renewable	Job description	extreme weather
Job title	solar	Job description	fabric recycling
Job title	sustainability	Job description	fuel cell
Job title	sustainable product	Job description	future energy
Job title	waste management	Job description	gas emission
Job title	wind energy	Job description	geothermal energy
Job title	wind turbine	Job description	ghg emission account
Job description	air pollution	Job description	ghg protocol
Job description	alternative fuel	Job description	global warm
Job description	battery electric	Job description	green building
Job description	battery management system	Job description	green committee
Job description	battery power	Job description	green engineer
Job description	battery technology	Job description	green finance
Job description	bioenergy	Job description	green financing
Job description	biofuel	Job description	green footprint
Job description	biogas	Job description	green infrastructure
Job description	biomass energy	Job description	green initiative
Job description	biomass power	Job description	green innovation

Appendix B
(Continued)

Field Used	Keyword	Field Used	Keyword
Job description	bioremediation	Job description	green it
Job description	cap and trade system	Job description	green kpi
Job description	carbon absorption	Job description	green mission program
Job description	carbon account	Job description	green model
Job description	carbon asset management	Job description	green office initiative
Job description	carbon aware design	Job description	green operation
Job description	carbon budget	Job description	green power
Job description	carbon capture	Job description	green practice
Job description	carbon concentration	Job description	green product
Job description	carbon credit	Job description	green retail
Job description	carbon cycle	Job description	green service
Job description	carbon depot	Job description	green supply chain
Job description	carbon digitalization	Job description	green talent
Job description	carbon dioxide	Job description	green tech
Job description	carbon disclosure project	Job description	green technologies
Job description	carbon emission	Job description	green technology
Job description	carbon fee	Job description	greener future
Job description	carbon footprint	Job description	greenhouse gas
Job description	carbon free	Job description	heat power
Job description	carbon impact	Job description	hvac load management
Job description	carbon inject	Job description	hybrid solar
Job description	carbon intensity	Job description	hydrogen
Job description	carbon liability	Job description	invest energy
Job description	carbon literacy	Job description	iso 14001
Job description	carbon market	Job description	iso 14064–1
Job description	carbon neutral	Job description	iso 14064–2
Job description	carbon offset	Job description	iso 14064–3
Job description	carbon price	Job description	iso 14067
Job description	carbon pricing	Job description	iso 14068–1
Job description	carbon recycle	Job description	iso 50001
Job description	carbon recycling	Job description	landfill gas
Job description	carbon reduce	Job description	led lighting retrofitting
Job description	carbon reduction	Job description	leed building expertise
Job description	carbon risk	Job description	leed certificate
Job description	carbon sequester	Job description	leed certification
Job description	carbon sequestration	Job description	leed certified
Job description	carbon sink	Job description	leed gold

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(Continued)

Field Used	Keyword	Field Used	Keyword
Job description	carbon storage	Job description	leed platinum
Job description	carbon tax	Job description	leed silver
Job description	carbon transparency	Job description	li-ion batteries
Job description	carbon-neutral	Job description	li-ion battery
Job description	carbon-to-liquid	Job description	lithium batteries
Job description	central air-conditioning monitoring systems	Job description	lithium battery
Job description	circular economy	Job description	lithium-ion batteries
Job description	clean energy	Job description	lithium-ion battery
Job description	clean power	Job description	low carbon
Job description	climate action	Job description	low-carbon
Job description	climate adaptation	Job description	lowloss power distribution
Job description	climate change	Job description	manage energy
Job description	climate crisis	Job description	material recovery
Job description	climate finance	Job description	materials recovery
Job description	climate goal	Job description	methane emission
Job description	climate impact	Job description	microgrid
Job description	climate policy	Job description	nature based solution
Job description	climate product	Job description	negative emission
Job description	climate resilience	Job description	net zero
Job description	climate risk	Job description	new energy
Job description	climate smart agriculture	Job description	nuclear power
Job description	climate solution	Job description	onshore wind
Job description	climate strategies	Job description	on-site generation
Job description	climate strategy	Job description	optimize energy usage
Job description	climate system	Job description	pas 2060
Job description	climate week	Job description	permaculture
Job description	closed loop recycling	Job description	plastic free package
Job description	closed-loop recycling	Job description	plastic free packaging
Job description	co2 concentrate	Job description	plastic-free package
Job description	co2 concentration	Job description	plastic-free packaging
Job description	co2 depot	Job description	pollution prevention
Job description	co2 impact	Job description	pre combustion ccs
Job description	co2 inject	Job description	pre-combustion ccs
Job description	co2 recycle	Job description	re concentrate carbon
Job description	conservation easement	Job description	re concentrate co2
Job description	conservation management	Job description	re100
Job description	critical energy infrastructure protection	Job description	recycled raw material

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(Continued)

Field Used	Keyword	Field Used	Keyword
Job description	decarbonization vision	Job description	recycling and reuse
Job description	decarbonized energy	Job description	recycling initiative
Job description	decarbonized fuel	Job description	recycling policy
Job description	decarbonized power	Job description	recycling practice
Job description	deliver energy	Job description	recycling program
Job description	direct air capture	Job description	recycling technology
Job description	distribute power	Job description	reduce energy usage
Job description	distributed energy generation	Job description	reduce energy waste
Job description	distributed energy resource	Job description	reduce methane emission
Job description	eco friendly	Job description	reducing energy usage
Job description	eco-friendly	Job description	reduction in energy usage
Job description	effort energy	Job description	reductions in energy usage
Job description	electric bus	Job description	renewable energy
Job description	electric car	Job description	renewable natural
Job description	electric energy	Job description	renewable technologies
Job description	electric hybrid	Job description	renewable technology
Job description	electric vehicle	Job description	resource reuse
Job description	electrical energy	Job description	reuse and recycling
Job description	electrical vehicle	Job description	sbti
Job description	electrification	Job description	scale solar
Job description	elevator peak-off-peak control	Job description	science based target
Job description	emission calculation	Job description	science-based target
Job description	emission control	Job description	smart energy project
Job description	emission reduction	Job description	smart grid
Job description	emission trade	Job description	smart meter
Job description	emission trading	Job description	smart recycling machine
Job description	emissions control	Job description	socially responsible
Job description	emissions trade	Job description	solar distributed generation
Job description	emissions trading	Job description	solar distribution
Job description	energy advice	Job description	solar energy
Job description	energy adviser	Job description	solar epc
Job description	energy application	Job description	solar farm
Job description	energy audit	Job description	solar industries
Job description	energy blockchain	Job description	solar industry
Job description	energy calculation	Job description	solar installation
Job description	energy conservation	Job description	solar panel
Job description	energy consult	Job description	solar power

Appendix B
(Continued)

Field Used	Keyword	Field Used	Keyword
Job description	energy consumption	Job description	solar program
Job description	energy distribution	Job description	solar pv
Job description	energy efficiency	Job description	solar system
Job description	energy efficient	Job description	solar track
Job description	energy engineer	Job description	solid oxide fuel
Job description	energy intelligence software	Job description	source power
Job description	energy management	Job description	source reduction
Job description	energy monitor	Job description	supply energy
Job description	energy optimization	Job description	sustainability
Job description	energy performance	Job description	sustainable alternative to electricity
Job description	energy policy	Job description	sustainable business strategies
Job description	energy productivity	Job description	sustainable business strategy
Job description	energy recovery	Job description	sustainable construction
Job description	energy reduce	Job description	sustainable design
Job description	energy reduction	Job description	sustainable development
Job description	energy reform	Job description	sustainable energy
Job description	energy saving	Job description	sustainable engineer
Job description	energy solution	Job description	sustainable extraction
Job description	energy star	Job description	sustainable fashion
Job description	energy storage	Job description	sustainable infrastructure
Job description	energy system	Job description	sustainable invest
Job description	energy transmission	Job description	sustainable land
Job description	energy transport	Job description	sustainable material
Job description	energy-efficient	Job description	sustainable package
Job description	environmental affair	Job description	sustainable packaging
Job description	environmental awareness	Job description	sustainable plans and solutions
Job description	environmental benefit	Job description	sustainable procurement
Job description	environmental concern	Job description	sustainable product
Job description	environmental conservation	Job description	sustainable supply chain
Job description	environmental data management	Job description	sustainable transport
Job description	environmental footprint	Job description	syngas power plant
Job description	environmental impact analysis	Job description	synthetic fuel
Job description	environmental impact assessment	Job description	tree preservation
Job description	environmental impact report	Job description	virtual power plant
Job description	environmental investigate	Job description	waste disposal
Job description	environmental investigation	Job description	waste management
Job description	environmental management	Job description	waste recycling

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(Continued)

Field Used	Keyword	Field Used	Keyword
Job description	environmental policy	Job description	waste to energy
Job description	environmental project	Job description	wind energy
Job description	environmental protection	Job description	wind farm
Job description	environmental remediation	Job description	wind power
Job description	environmental responsibility	Job description	wind resource
Job description	environmental science		

Internet Appendix for
“The Impact of Carbon Reduction Talents on Corporate Carbon Emissions”

This appendix provides supplementary information and presents the results of robustness tests as shown below:

Figure A.1: Changes in ShareDecarbTalent after the Paris Agreement

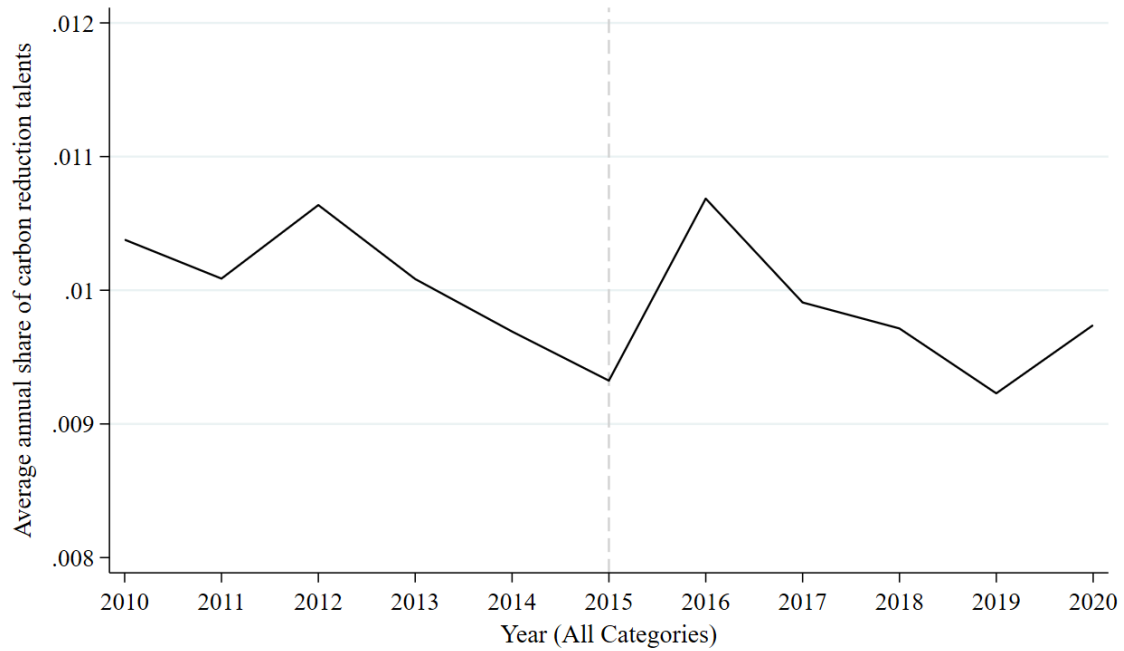
Figure A.2: Changes in ShareDecarbTalent across six sectors after the Paris Agreement

Table A.1: Summary Statistics: Background of carbon reduction talents

Table A.2: Long-differences regression results

Table A.3: Instrument variable regressions (Controlling for industry by year fixed effects and state fixed effects, respectively)

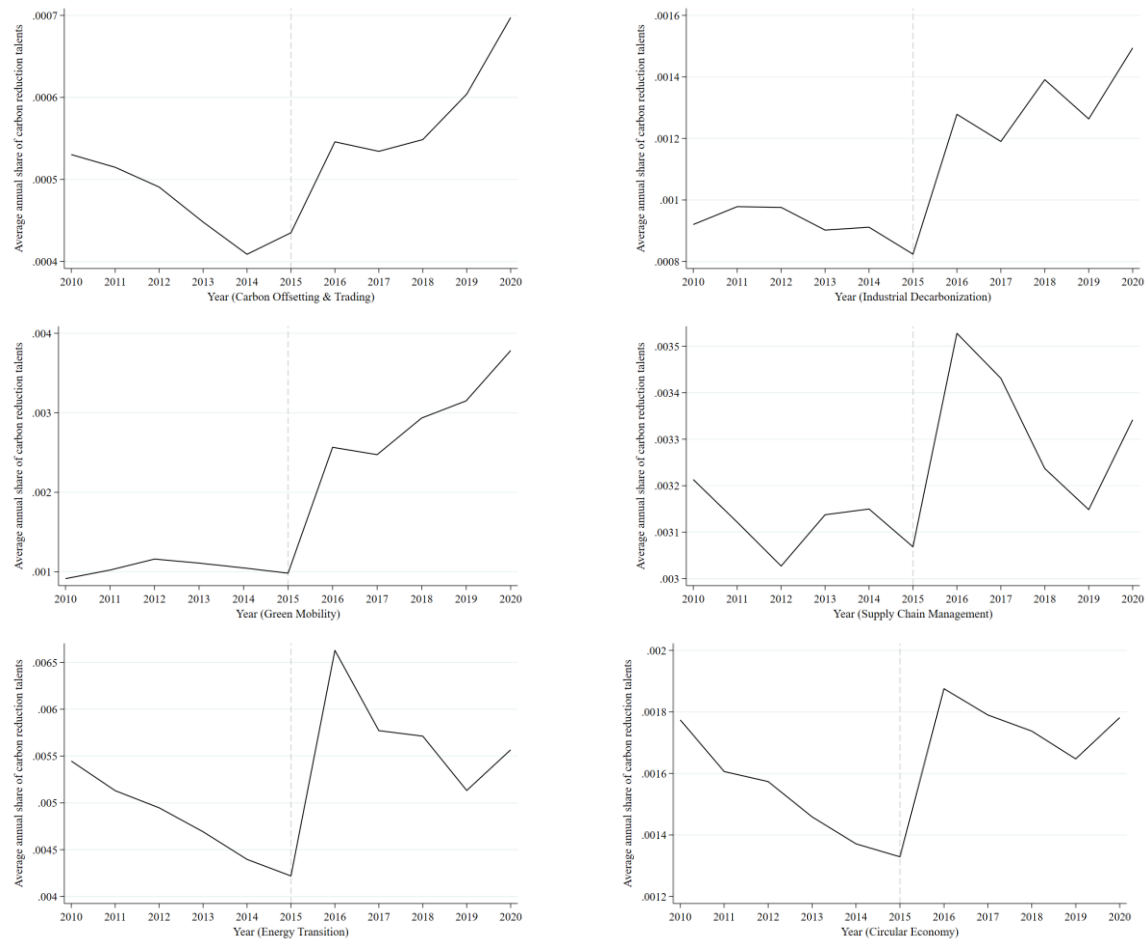
Figure A.1



Changes in ShareDecarbTalent after the Paris Agreement

This figure illustrates changes in *ShareDecarbTalent* following the Paris Agreement. *ShareDecarbTalent* measures the annual proportion of a firm's employees engaged in carbon reduction roles, including renewable energy, carbon accounting, and sustainability initiatives. The metric is constructed using Revelio data and covers firm-level observations from 2010 to 2020.

Figure A.2



Changes in ShareDecarbTalent across six sectors after the Paris Agreement

This figure illustrates the changes in *ShareDecarbTalent* across six key sectors following the Paris Agreement. The classification of carbon reduction–related roles is based on EPA’s GHG Reduction Programs & Strategies and LinkedIn’s Global Green Skills Report, which highlight emerging trends in sustainability–focused employment. The six sectors are defined as follows: (i) Carbon Offsetting & Trading—Jobs associated with corporate participation in carbon markets and carbon trading mechanisms; (ii) Industrial Decarbonization—Positions focused on reducing industrial emissions through carbon capture technologies and low–carbon materials; (iii) Green Mobility—Employment in low–carbon transportation, including electric vehicle (EV) technology and sustainable mobility solutions; (iv) Supply Chain Carbon Reduction—Professionals involved in carbon–conscious supply chain management and carbon disclosure initiatives; (v) Energy Transition—Roles related to promoting renewable energy development and improving energy efficiency; (vi) Circular Economy—Roles centered on carbon recycling, waste reduction, and resource circularity. This classification provides insight into the evolving landscape of carbon reduction talents in response to global climate policies.

Table A.1**Background of carbon reduction talents**

This table presents descriptive statistics on the background characteristics of carbon reduction talents based on all available observations from the Revelio database. Panel A reports predicted gender. Panel B reports highest level of education. Panel C reports predicted ethnicity: (i) Api represents the probability of being Asian/Pacific Islander; (ii) Hispanic represents the probability of being Hispanic or Latino; (iii) Native represents the probability of being American Indian or Alaskan Native. To ensure data completeness, observations with missing values in any variable are excluded from the analysis.

Panel A. Predicted sex		
	N	%
Female	118,972	33.332
Male	237,960	66.668
Total	356,932	100.000
Panel B. Highest degree		
	N	%
Associate	12,805	3.588
Bachelor	169,973	47.621
Doctor	23,488	6.581
High School	6,236	1.747
MBA	59,903	16.783
Master	84,527	23.682
Total	356,932	100.000
Panel C. Predicted ethnicity		
	N	%
Asian/Pacific Islanders	33,790	9.469
Black	28,194	7.901
Hispanic	25,541	7.158
Multiple	1,230	0.345
Native	257	0.072
White	267,823	75.055
Total	356,835	100.000

Table A.2**Long-differences regression results**

This table presents the long differences regression results, examining the relationship between $\Delta \text{Log}(\text{Emission})$ and $\Delta \text{ShareDecarbTalent}$ over two distinct six-year periods: 2010–2015 and 2016–2020. Panel A reports results for 2010–2015, while Panel B reports results for 2016–2020. Columns (4)–(6) incorporate two-digit SIC industry fixed effects. All firm level continuous variables, except $\Delta \text{ShareDecarbTalent}$ and log-transformed variables, are winsorized at the 1% level to reduce outlier influence. Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Regression results with long differences from 2010 to 2015

	$\Delta \text{Log}(\text{Emission})$			$\Delta \text{Log}(\text{Emission})$		
	Scopes 1 and 2	Scope 1	Scope 2	Scopes 1 and 2	Scope 1	Scope 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{ShareDecarbTalent}$	0.6344 (0.182)	-2.5085 (-0.699)	-0.2288 (-0.058)	0.1489 (0.038)	-3.4484 (-0.865)	0.2588 (0.062)
ΔSize	0.6480*** (7.939)	0.5614*** (5.955)	0.7288*** (8.429)	0.6472*** (7.920)	0.5426*** (5.387)	0.7678*** (8.606)
ΔBM	-0.0295 (-0.327)	-0.0474 (-0.486)	-0.0789 (-0.798)	-0.0432 (-0.466)	-0.0543 (-0.534)	-0.0799 (-0.801)
ΔROA	-0.8169* (-1.827)	-1.1295** (-2.186)	-1.1612** (-2.337)	-1.1090** (-2.383)	-1.4563*** (-2.659)	-1.4713*** (-2.712)
$\Delta \text{Leverage}$	-0.0071 (-0.038)	-0.1034 (-0.418)	-0.3140 (-1.285)	-0.0720 (-0.356)	-0.1309 (-0.497)	-0.4849* (-1.754)
ΔPPE	0.2093 (0.384)	0.5240 (0.845)	0.2048 (0.319)	0.6078 (1.022)	1.1125* (1.661)	0.4358 (0.650)
ΔCash	-0.1828 (-0.452)	-0.0785 (-0.158)	-0.2121 (-0.475)	-0.0885 (-0.205)	0.1397 (0.267)	-0.2482 (-0.517)
ΔCapex	-0.4223 (-0.312)	0.2605 (0.173)	-1.8978 (-1.547)	-0.4046 (-0.288)	0.4734 (0.294)	-2.1252 (-1.639)
ΔEBIT	0.9019* (1.894)	0.9944* (1.818)	1.1345** (2.204)	1.1668** (2.356)	1.3353** (2.331)	1.2231** (2.039)
$\Delta \text{RevGrowth}$	-0.0472 (-0.435)	0.1050 (0.847)	-0.1287 (-0.942)	0.0074 (0.065)	0.1760 (1.368)	-0.0985 (-0.681)
Constant	-0.1120*** (-3.032)	-0.1929*** (-4.068)	0.0011 (0.020)	-0.3368*** (-5.882)	-0.7899*** (-12.725)	0.3502*** (4.424)
N	479	479	479	479	479	479
adj. R^2	0.143	0.072	0.082	0.129	0.070	0.044
State×Year FE	N	N	N	Y	Y	Y

Panel B. Regression results with long differences from 2016 to 2020

	$\Delta \text{Log}(\text{Emission})$			$\Delta \text{Log}(\text{Emission})$		
	Scopes 1 and 2	Scope 1	Scope 2	Scopes 1 and 2	Scope 1	Scope 2
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{ShareDecarbTalent}$	-5.5904*** (-3.297)	-5.9891*** (-3.290)	-6.1305*** (-3.154)	-4.8665** (-2.426)	-5.4965** (-2.460)	-5.7977*** (-2.792)
ΔSize	0.6766*** (12.829)	0.6329*** (9.734)	0.7316*** (13.348)	0.6889*** (12.733)	0.6559*** (9.885)	0.7270*** (12.106)
ΔBM	0.1247* (1.931)	0.1335* (1.722)	0.0743 (1.071)	0.1198* (1.889)	0.1362* (1.766)	0.0830 (1.182)
ΔROA	-0.8026** (-2.088)	-0.5572 (-1.255)	-0.9213** (-2.504)	-0.6483* (-1.717)	-0.4165 (-0.935)	-0.7971** (-2.142)
$\Delta \text{Leverage}$	-0.0780 (-0.442)	0.0183 (0.079)	-0.0324 (-0.198)	-0.0323 (-0.186)	0.0811 (0.351)	-0.0008 (-0.005)
ΔPPE	0.0273 (0.093)	-0.3358 (-0.903)	-0.0976 (-0.336)	0.0634 (0.216)	-0.2844 (-0.759)	-0.1751 (-0.589)
ΔCash	-0.9822*** (-4.503)	-1.3123*** (-4.174)	-0.8284*** (-3.630)	-0.9977*** (-4.548)	-1.3288*** (-4.018)	-0.8504*** (-3.697)
ΔCapex	0.3378 (0.305)	-0.1180 (-0.095)	2.5341** (2.296)	0.6508 (0.574)	0.5017 (0.391)	2.6525** (2.324)
ΔEBIT	2.2428*** (4.554)	2.1995*** (4.018)	2.3292*** (4.312)	2.1093*** (4.256)	2.1316*** (3.800)	2.1946*** (3.871)
$\Delta \text{RevGrowth}$	-0.0175 (-0.103)	-0.1030 (-0.602)	0.0276 (0.157)	-0.0043 (-0.025)	-0.1221 (-0.687)	0.0492 (0.268)
Constant	-0.1437*** (-4.491)	-0.1824*** (-4.584)	-0.1416*** (-3.983)	-0.0115 (-0.343)	0.2029 (1.558)	-0.2457* (-1.821)
N	1,059	1,059	1,059	1,059	1,059	1,059
adj. R^2	0.212	0.123	0.185	0.226	0.130	0.178
State×Year FE	N	N	N	Y	Y	Y

Table A.3 Instrument variable regressions

This table reports instrumental variable regression results examining the relationship between carbon emissions and the share of decarbonization-related talent (*ShareDecarbTalent*), using *CarbonEdu*₂₀₁₀ as an instrument. *CarbonEdu*₂₀₁₀ is defined as the share of a firm's employees in 2010 who graduated from universities specializing in carbon reduction-related fields, identified based on university rankings in Energy Science & Engineering from the Academic Ranking of World Universities (ARWU). Columns (1)-(2) and (5)-(6) present the first-stage regression results, where the dependent variables are *ShareDecarbTalent* and *ShareDecarbTalen*×*Post*, respectively. Columns (3)-(4) and (7)-(8) report the corresponding second-stage regression results. The dependent variable in Columns (3) and (7) is *Log*(Emission), while Columns (4) and (8) use *Log*(Emission/Total Assets). Emissions are measured using Scope 1 emissions, Scope 2 emissions, and the summation of Scope 1 and 2. All specifications include the firm-level control variables used in Table 2. All firm-level continuous variables, except *ShareDecarbTalent* and log-transformed variables, are winsorized at the 1 percent level to mitigate the influence of outliers. Columns (1)-(4) include state-by-year fixed effects, while Columns (5)-(8) incorporate industry-by-year fixed effects. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ShareDecarbTalent	ShareDecarbTalent ×Post	Log (Emission)	Log (Emission/total assets)	ShareDecarbTalent	ShareDecarbTalent ×Post	Log (Emission)	Log (Emission/total assets)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CarbonEdu ₂₀₁₀	0.2680*** (3.194)	−0.0395*** (−2.924)			0.3451*** (4.042)	−0.0169 (−1.059)		
CarbonEdu ₂₀₁₀ ×Post	−0.2393*** (−2.859)	0.0757*** (3.422)			−0.2894*** (−3.361)	0.0762*** (3.169)		
ShareDecarbTalent			−11.2282** (−2.044)	−11.2211** (−2.015)			−11.4863** (−2.555)	−10.6278** (−2.353)
ShareDecarbTalent× Post			−51.5992*** (−2.719)	−55.4336*** (−2.862)			−20.6239 (−1.387)	−22.6237 (−1.522)
Controls	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2	Control variables in Table 2
Observations	9,758	9,758	9,758	9,758	9,758	9,758	9,758	9,758
Adjusted R ²	0.216	0.232	0.683	0.437	0.126	0.124	0.614	0.338
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Industry×Year FE	Y	Y	Y	Y	N	N	N	N
State×Year FE	N	N	N	N	Y	Y	Y	Y