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Organization capital and GHG emissions

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A B S T R A C T

This study examines the impact of organization capital on greenhouse gas (GHG) emissions. Utilizing a sample of 3817 firm-year observations of US publicly listed companies over the period from 2002 to 2019, we find that firms with higher organization capital are associated with lower GHG emissions. Our cross-sectional analysis reveals a stronger negative relationship between organizational capital and GHG emissions among firms characterized by better corporate governance and lower financing constraints. Moreover, this negative relationship is more evident for firms operating in carbon sensitive industries and regions that have implemented an emissions trading scheme (ETS). This result survives after applying a range of robustness tests and addressing endogeneity concerns. Further, we disaggregate total GHG emissions into direct and indirect emissions and find that high-organization capital firms tend to reduce both direct and indirect emissions. Taken together, our analysis suggests that organization capital has considerable implications for corporate GHG emissions.

1. Introduction

Over the past decade, climate change has become a crucial global concern, attracting significant attention. The Paris Agreement has established the objective of limiting the rise in global temperatures to well below 2 °C, while making concerted efforts to keep the increase even further below 1.5 °C.[1] The urgency of addressing climate change has led stakeholders worldwide to consider firms' greenhouse gas (GHG) emissions[2] when making decisions, thereby putting high emitters at risk of decreased market value (Matsumura et al., 2014). Consequently, firms that possess superior organization capital, characterized by specialized knowledge, skills, innovative technologies, and efficient logistics, have begun formally integrating carbon reduction initiatives into their production processes (Eiadat et al., 2008). For instance, Microsoft has allocated $1 billion to its Climate Innovation Fund to advance emission reduction logistics. Apple has committed to achieving a carbon-neutral operation by 2030 through renewable energy, low-carbon product design, tree planting, and coastal ecosystem rehabilitation. Coca-Cola has developed a Carbon Scenario Planner for its distribution network. These initiatives signify that organizational capital has significant implications for firms' GHG emissions in the transition to a low-carbon economy.

Anecdotal evidence also highlights the strategic advantage gained by companies like Proctor and Gamble, Goldman Sachs, Dell Inc., Walmart, and Cisco through their investments in organization capital. Leveraging their respective strengths, such as Proctor and Gamble's product differentiation systems, Goldman Sachs' investment banking systems, Dell Inc.'s efficient supply chain management systems, Walmart's inventory management and product provision-based supply chain networks, and Cisco's web-based product mechanisms and safeguarding structures, these companies have positioned themselves favorably in the market and capitalized on their heightened investment in organization capital. In contrast to tangible capital, organization capital is an intangible resource that encompasses firm-specific knowledge that facilitates an efficient connection between personnel and tangible assets, resulting in enhanced productivity and output. Lev et al. (2009) note that "organization capital enables superior operating, investment and innovation performance, represented by the agglomeration of technologies—business practices, processes and designs" (p. 277). Notably, around 50% of the proceeds generated by all intangibles in the US National Income and Product Accounts (NIPA) can be attributed to organization capital (Atkeson and Kehoe, 2005). Organization capital has become increasingly prominent in enhancing a firm's performance, managerial capability, production efficiency and competitive advantage (e.g., Eisfeldt and Papanikolaou, 2014; Eisfeldt and Papanikolaou, 2013; Lev et al., 2009).

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[1] https://cop23.unfccc.int/most-requested/key-aspects-of-the-paris-agreement

[2] We use carbon emissions, GHG emissions and carbon-equivalent emissions interchangeably in the paper.

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Despite the growing recognition and relevance of organization capital, its influence on GHG emissions has received relatively less attention in the academic literature (He et al., 2022a). Our study thus aims to fill this void in the literature and examine the association between organization capital and GHG emissions, while also exploring potential variations based on firm characteristics, industries, and regional institutions. We adopt a multi-theoretical framework to predict the association between organization capital and GHG emissions.

According to the resource-based theory, organization capital is a valuable resource and a catalyst for competitive advantages (Hasan and Cheung, 2018). Therefore, companies with higher organization capital tend to possess novel resources and exceptional competencies (e.g., knowledge, expertise) enabling them to reduce their GHG emissions. From a signaling theory perspective, we propose that firms with higher organization capital have a strong incentive to communicate and signal their outstanding capabilities and potential by actively undertaking carbon reduction initiatives. By doing so, these firms can reduce information asymmetry between the firm and its investors, providing greater transparency regarding their commitment to addressing climate change and reducing their GHG emissions. As a result, we anticipate a negative association between organization capital and GHG emissions, drawing upon the resource-based and signaling theories.

Conversely, we also posit that organization capital can potentially have an opposite impact on GHG emissions, drawing insights from the financing constraints-based argument and agency theory. First, engaging in knowledge-intensive activities such as green research and development (R&D), decarbonization efforts, and developing sustainable value chains can incur substantial costs. Thus, firms with high organization capital may encounter severe constraints in allocating sufficient resources to invest in these initiatives, thereby limiting their ability to effectively reduce their GHG emissions. Second, organization capital is susceptible to agency problems as both the shareholders and key personnel share in the benefits derived from organization capital (Eisfeldt and Papanikolaou, 2013). The potential unequal division of cash flows may incentivize managers of firms with substantial organization capital to prioritize personal economic benefits over carbon reduction. This prioritization can lead to a deterioration in their carbon performance, as efforts to reduce GHG emissions might be compromised. By considering the challenges posed by financing constraints and aggravated agency problems, we anticipate a positive association between organization capital and GHG emissions.

To test these competing arguments, we utilize a sample of 3817 firm-year observations (643 unique firms) of US publicly listed firms over the period 2002–2019. Following previous studies (Eisfeldt and Papanikolaou, 2013; Hasan and Cheung, 2023; Lev et al., 2009; Peters and Taylor, 2017), we calculate organization capital by accruing a portion of historical selling, general and administrative (SG&A) costs. Corporate GHG emissions are sourced from self-reported data in the Refinitiv ESG database.

Our baseline regression results suggest that companies with higher organization capital are associated with lower GHG emissions, suggesting that high-organization capital firms are better equipped to leverage non-replicable resources and capabilities, enabling them to reduce GHG emissions. These results lend support to our resource-based and signaling theory. The findings are also economically significant, with a one-standard-deviation increase in organization capital resulting in a 3.09% decrease in GHG emissions compared to the sample mean, which can be interpreted as a reduction in total emissions of 113,126 t. These results hold consistent across a range of robustness tests and addressing endogeneity problems.

Our cross-sectional analyses demonstrate that the negative association is more prominent for companies with higher institutional ownership, greater board independence and lower financing constraints. This suggests that firms with better corporate governance and greater financial flexibility are better positioned to leverage their organization capital in reducing GHG emissions effectively. In addition, the negative association is particularly notable for firms that operate in carbon-sensitive industries. These industries typically have a higher climate change impact, which amplifies the significance of the emission reduction efforts undertaken by firms with higher levels of organization capital. Furthermore, we observe that the negative association is also reinforced in regions that have implemented an emission trading system (ETS). The presence of an ETS provides a regulatory framework and market incentives for firms to actively reduce their GHG emissions. As a result, firms in these regions tend to leverage their organization capital effectively to mitigate the carbon risks and seize the carbon opportunities, leading to a reduction in GHG emissions.

Finally, we disaggregate total GHG emissions into direct and indirect emissions to gain a deeper understanding of the specific areas where organization capital has an impact. Our results reveal that organizational capital demonstrates effectiveness in reducing both direct and indirect GHG emissions. The findings suggest that high-organization capital firms are adept at mitigating their climate change impact across various aspects of their operations.

Our study complements the existing literature and makes incremental contributions in the following ways. First, our study contributes to the existing literature on organization capital. Previous research has documented the positive impact of organization capital in value creation and the underlying processes that contribute to value formation (e.g., Eisfeldt and Papanikolaou, 2013; Leung et al., 2018; Li et al., 2018). Recent studies have also demonstrated the significance of organization capital in influencing cash holdings, dividend payouts, and access to finance (e.g., Attig and Cleary, 2014; Hasan and Uddin, 2022; Marwick et al., 2020). In contrast to these previous studies, our findings offer novel and unique insights into the contribution of organization capital to non-financial performance, specifically focusing on GHG emissions. We reveal that organization capital significantly affects firms' levels of GHG emissions. The finding extends our understanding that organizational capital not only has an impact on financial performance but also non-financial performance (e.g., GHG emissions).

Second, we further provide nuanced empirical evidence regarding the specific circumstances that can influence how organizational capital impacts GHG emissions. Our findings unveil a complex interplay of factors, shedding light on the various elements that shape this relationship. Notably, we find that sound governance practices facilitate the alignment of organizational goals and strategies with climate change objectives, thereby reinforcing the positive impact of organizational capital on addressing climate change. Moreover, we reveal that organization capital's impact on GHG emissions varies across the industry dynamics. Furthermore, the influence of regional institutions cannot be understated as the regulatory and policy frameworks set by regional bodies significantly affect how firms operate and strategize their emission reduction efforts. Overall, understanding how corporate governance, industry characteristics, and regional institutions modulate the relationship between organizational capital and GHG emissions is crucial for tailoring effective strategies to reduce emissions and foster sustainable practices within firms.

Third, we contribute to the growing body of literature on GHG emissions by highlighting the substantial role of organization capital as a significant intangible factor. While prior research has primarily focused on firm-level or country-level factors such as corporate governance and management (Haque, 2017; Luo and Tang, 2021; Tang and Luo, 2014), emissions reduction commitment and initiatives (Haque and Ntim, 2022; Lee, 2012), mandatory and voluntary carbon disclosure (Bartram et al., 2022; Downar et al., 2021; Qian and Schaltegger, 2017; Tomar, 2023), energy taxes (Jeffrey and Perkins, 2015) and national culture (Luo and Tang, 2022), our study offers a fresh perspective by illuminating the significant impact of organizational capital in the context of reducing GHG emissions. This paper thus extends this literature by showing that organization capital, as an unobservable and intangible factor, can synergistically work together with other tangible factors to mitigate a firm's overall GHG emissions.

Finally, this study provides valuable insights from a multi-theoretical lens, incorporating resource-based theory, signaling theory, agency theory, and considering arguments related to financial constraints. By adopting this comprehensive approach, we establish a robust foundation for understanding the mechanisms through which organization capital influences GHG emissions. Our empirical findings further reinforce the validity and applicability of this theoretical framework, shedding light on the complex interplay between organization capital and GHG emissions.

The rest of our study is organized as follows. Section 2 reviews prior literature on organization capital and GHG emissions; Section 3 develops our hypotheses. Section 4 explains the research design. Section 5 outlines the empirical analyses and Section 6 concludes the study.

2. Literature review

2.1. Organization capital

Organization capital represents the knowledge base, know-how and systems that integrate human talents and tangible resources for the creation and delivery of superior goods and services (Evenson and Westphal, 1995). Lev et al. (2009) describe organization capital as the primary driver of operational performance, resulting from the accumulation of know-how, processes, and practices. In the current knowledge-intensive economy, organization capital is a crucial operational factor that enhances strategic competency. Several studies (Eisfeldt and Papanikolaou, 2013, 2014; Leung et al., 2018) support this notion. Specifically, Eisfeldt and Papanikolaou (2013) contend that organization capital possesses two defining characteristics that differentiate it from other intangible assets. First, it is reflected in highly skilled labor resources, represented by key talents that are distinct from physical capital. Secondly, the firm-specific nature of organization capital makes it unique and sets it apart from general human capital.

There are two prevailing schools of thought regarding organization capital. The first school emphasizes the transient nature of organization capital, suggesting that it resides in the firm's key personnel and can be lost if they leave the firm. The second school of thought argues that organization capital sustains within the firm through its systems and processes, making it durable even after key talents depart. Evenson and Westphal (1995) supports that this second view is more pertinent, as a significant portion of the knowledge required for basic operations and system integration is implicit and not easily codifiable or transferable.

Prior studies indicate that organization capital is a valuable and inimitable resource that contributes to achieving a sustained competitive advantage (Barney, 1991, 1996). A plethora of studies support this view and show that organization capital is a major driver of competitive edge (Gao et al., 2021; Lev et al., 2009). Lev and Radhakrishnan (2005) suggest that high-organization capital firms tend to outperform their competitors, resulting in efficient production, stable transactions, and reduced environmental risks. Hasan and Cheung (2018) show that organization capital drives a company's growth through different stages of its lifecycle, while Francis et al. (2021) demonstrate that organization capital fosters innovation, which is crucial for excellent firm performance. In addition, organization capital facilitates optimal resource planning (Venieris et al., 2015), reduces cash holdings (Marwick et al., 2020), improves operational and financial market effectiveness (Lev et al., 2009) and reduces sensitivity to underinvestment and overinvestment (Attig and Cleary, 2014). Overall, organization capital is a distinctive resource that can significantly enhance a firm's growth potential and create superior value.

Although organization capital is a dominant factor in value creation, expansion and innovation, it is not typically recorded in financial systems or tracked by firm (Lev et al., 2009). A considerable proportion of organization capital is not reflected in the fair market value and thus does not appear in the financial statements of a company. As a result, organization capital is often ambiguous, idiosyncratic and complex, making it challenging to assess. Since organization capital is an unreported balance sheet element and involves more intricate concepts than conventional assets, it can introduce valuation ambiguity and thus lead to information asymmetry between managers and external investors.

Previous research indicates that organization capital is embedded within the organization and its key personnel, granting both shareholders and key personnel entitlement to the resulting cash flows (Eisfeldt and Papanikolaou, 2013). Eisfeldt and Papanikolaou (2013) note that key talents are incentivized to invest more in organization capital and undertake additional initiatives to enhance their labor market prospects or maximize their personal benefits, particularly when the costs and rewards associated with organization capital are not equitably distributed among core personnel and shareholders. This exacerbates the agency conflict arising from the unequal distribution of income between key personnel and shareholders. Leung et al. (2018) and Eisfeldt and Papanikolaou (2013) provide support for this notion by documenting that shareholders seek a higher risk premium when investing in firms with greater organization capital.

2.2. Research on GHG emissions

We categorize the research on carbon performance into two main streams: the determinants and the consequences. The first stream of the literature focuses on identifying the determinants that influence GHG emissions (e.g., Haque, 2017; Haque and Ntim, 2022; Luo and Tang, 2014; Moussa et al., 2019; Qian et al., 2020). For instance, Haque and Ntim (2022) show that corporate sustainability initiatives contribute to reducing GHG emissions and improving carbon performance. Similarly, Haque (2017) reveals that board attributes and environmental social and governance (ESG)-based compensation schemes have a discernible impact on process-oriented carbon reduction initiatives but not on outcome-oriented GHG emissions. Luo and Tang (2021) reveal that corporate governance quality significantly influences a company's carbon performance, as indicated by their GHG emissions relative to industry benchmarks and the previous year. Tomar (2023) shows a positive impact of the US Greenhouse Gas Reporting Program (GHGRP) on GHG emission reductions. Zhang et al. (2017) suggest that knowledge innovation, particularly knowledge spillover, plays a crucial role in carbon emission abatement in China. Other studies also highlight that carbon emission reduction commitments and initiatives (Haque and Ntim, 2022; Lee, 2012), carbon disclosure (Qian and Schaltegger, 2017), carbon strategies (Moussa et al., 2019), and well-functioning carbon management systems (Tang and Luo, 2014) also have a significant influence on a firm's level of GHG emissions or emission reduction.

Another stream of literature investigates the capital market impact of GHG emissions such as firm value and the cost of capital (Bolton and Kacperczyk, 2021; Chapple et al., 2013; Choi and Luo, 2021; Choi et al., 2021; Griffin et al., 2017; Jung et al., 2018; Matsumura et al., 2014). These studies consistently find that a higher level of GHG emissions reduces firm value. For example, Matsumura et al. (2014) analyze 550 US firm-year observations and estimate a decrease of US$212 in equity value per metric ton of carbon dioxide equivalent. Chapple et al. (2013) report similar findings in an Australian context, while Kim et al. (2015) observe that the cost of equity increases with higher GHG emission intensity in the Korean market.

3. Hypothesis development

We draw upon a multi-theoretical framework from the resource-based theory, signaling theory, financial constraint theory, and agency theory to predict the association between organization capital and GHG emissions.

The resource-based theory and signaling theory suggest a negative association between organization capital and GHG emissions. Specifically, the resource-based theory argues that organization capital is a critical factor for attaining competitive advantage as it enables the development of excellent business systems, stable operational processes, innovation capability and exceptional manufacturing techniques (Francis et al., 2021; Lev et al., 2009). According to this perspective, organization capital has the potential to enhance a firm's innovative capacity and facilitates its engagement and investment in environmentally sustainable projects. These projects may involve the use of emission-reducing technologies, the implementation of energy-efficient strategies or the development of green R&D concepts. For instance, technologies like carbon capture and storage have demonstrated their effectiveness in reducing GHG emissions, while green research and development initiatives align with global endeavors to mitigate emissions (Lee and Min, 2015). Consequently, firms with higher levels of organization capital are better positioned to leverage their unique and inimitable capabilities to adopt low-carbon production practices and ultimately reduce their GHG emissions. In summary, based on the resource-based theory, organization capital empowers firms to leverage their resource-based advantages and innovative capabilities, thereby enhancing their ability to reduce GHG emissions.

The signaling theory suggests that since organization capital is not readily observable and known by investors, enhanced carbon performance can act as an effective mechanism to signal a firm's underlying superior quality, which encompasses various intangible assets, knowledge, processes, and relationships within the organization. Prior studies indicate that firms with more organization capital face greater informational complexity, leading to increased uncertainty and information asymmetry (Lev et al., 2009). This poses a challenge for investors to identify and differentiate such firms from those with lower organization capital. Thus, the level of GHG emission reduction achieved by a firm can provide valuable information about its internal resources, capabilities, and strategic positioning, which are not easily observable to external investors or other stakeholders. By demonstrating significant reductions in GHG emissions, firm' signals to investors that they possess the necessary internal resources and capabilities to effectively manage and reduce these GHG emissions. This signal helps investors assess the firms' potential for sustainable competitive advantage, long-term value creation, and their commitment to environmental sustainability. Overall, signaling theory suggests that firms with higher organization capital could leverage their GHG emission levels and reduction outcome as a means to signal their superior prospects and reduce information asymmetry.

In contrast, the financial constraint and agency theory suggest a positive relationship between organization capital and GHG emissions, indicating that financial constraints and agency conflicts can hinder firms with greater organization capital from reducing their GHG emissions. Specifically, financial constraint perspective emphasizes that investment in organization capital to reduce GHG emissions requires firms to redesign their production process, which often involves the adoption of costly energy-efficient technologies such as renewable low-carbon fuels. Carbon control efforts are highly risky and subject to technological obsolescence, market risks and uncertainties, and require substantial upfront capital and ongoing expenses for monitoring, coordination and maintenance (Ghisetti and Rennings, 2014; Ghisetti and Pontoni, 2015; He et al., 2022b). Current literature suggests that firms with a high level of organization capital may face difficulty in securing external financing due to the non-redeployable nature of organization capital, which precludes it from being used as collateral (Marwick et al., 2020). These financing constraints may impede the ability of high organization capital firms to undertake and implement carbon control projects, making it challenging for them to afford the costs associated with reducing their GHG emissions. Consequently, firms with high levels of organization capital may face limited options and thus are less inclined to lower their GHG emissions.

In addition, agency theory argues that organization capital can give rise to agency problems, as both investors and key personnel (e.g., managers) have a stake in the income generated by the organization's capital (Eisfeldt and Papanikolaou, 2013). This situation creates an

Table 1
Sample selection process and distribution.

Panel A: Sample selection process

Description	Total number of observations
Initial sample from CRSP/Compustat merged file (2002–2019)	223,390
Less: duplicate with respect to GVKEY and FYEAR	(22,001)
Less: observations from utility sectors [SIC 4900–4999]	(6894)
Less: observations from financial sectors [SIC 6000–6999]	(67,253)
Less: observations with missing organization capital, GHG emissions and control variables	(123,425)
Final sample	**3817**
Number of unique firms	643

Panel B: Industry-wise distribution of the sample

Industry	Frequency	Percentage (%)
Consumer nondurables	380	9.96
Consumer durables	145	3.80
Manufacturing	684	17.92
Oil, gas and coal extraction and products	287	7.52
Chemicals and allied products	311	8.15
Business equipment	776	20.33
Telephone and television transmission	68	1.78
Wholesale, retail and some services	371	9.72
Healthcare, medical equipment and drugs	356	9.33
Other	439	11.50
Total sample	**3817**	**100.00**

Panel A of this table exhibits the sample selection procedure and Panel B outlines the sample distribution by industry (Fama-French twelve industry classification).

incentive for key personnel to prioritize their personal interests over the long-term objectives of the firm. For instance, managers of firms with high organization capital may opt to invest in short-term projects that yield immediate economic benefits or prioritize initiatives that align with their personal interests rather than those that promote environmental sustainability. Overall, due to agency problems, firms with more organization capital are less motivated to reduce GHG emissions, implying a positive relationship between organization capital and GHG emissions.

In light of the aforementioned competing arguments, we propose a non-directional hypothesis as follows:

H1. There is an association between organization capital and GHG emissions.

Literature suggests that strong governance plays a strategic role in controlling and reducing GHG emissions (Galbreath, 2010; Haque, 2017). First, robust governance helps companies understand and comply with evolving climate change regulations and standards related to GHG emissions. In turn, firms can effectively allocate resources for compliance measures, technology upgrades, and initiatives aimed at reducing GHG emissions to meet regulatory requirements. Second, a company with stakeholder-oriented governance mechanisms is more likely to integrate climate change considerations into strategic decision-making, influencing the way they utilize resources for GHG emission reduction efforts. This integration also helps establish appropriate incentive and rewarding mechanisms to better align managerial interests with shareholder objectives regarding climate change strategies and performance (Luo et al., 2021). Third, better governance emphasizes transparency and accountability (Liao et al., 2015). When it comes to GHG emissions, firms with better governance are more likely to accurately measure, report, and disclose their emissions, which facilitates firms' achievement of real effect in GHG emission reduction (e.g., Tomar, 2023). Fourth, companies with strong governance tend to garner favor from stakeholders and are frequently in the media spotlight. However, they also face heightened scrutiny from these stakeholders concerning their efforts to address climate change issues. As stakeholders, including investors, place greater value on a firm's GHG emissions, we anticipate that organizational capital plays a more significant role in the presence of strong corporate governance in facilitating firms' GHG emission reduction efforts, meeting stakeholder expectations and upholding a positive reputation (Choi and Luo, 2021; Krueger et al., 2020; Ilhan et al., 2023). Therefore, we establish our second hypothesis below:

H2. The association between organization capital and GHG emissions varies with corporate governance factors.

Studies suggest that financing constraints can act as a significant bottleneck in implementing environmental policies aimed at reducing GHG emissions (Wang et al., 2021). For example, financing constraints can hinder firms' ability to invest in clean technologies, infrastructure, low-carbon energy and transportation systems for reducing GHG emissions (Wang et al., 2021). In this connection, Bartram et al. (2022) show that financially constrained firms experience a rise in their overall emissions following the implementation of the cap-and-trade regulation, thereby compromising the efficacy of the policy. Therefore, we anticipate that the relationship between organization capital and GHG emissions would be more evident for firms with lower financing constraints.

H3. The association between organization capital and GHG emissions varies with financial constraints.

Firms in carbon-sensitive industries (e.g., energy, manufacturing, materials) inherently involve processes that emit significant GHG emissions and, consistently, report higher average GHG emissions than other industries (Choi et al., 2021). As a result, these industries are frequently subject to various climate change-related policies, legislations, and restrictions (Chapple et al., 2013; He et al., 2022b; Luo, 2019). This highlights the imperative for firms to focus on reducing GHG emissions and strategically leverage their organizational capital for initiatives aimed at emission reduction in order to meet these regulatory requirements. However, the reduction of GHG emissions in carbon-intensive sectors typically requires significant investments in advanced, low-carbon technologies and firm infrastructure. Thus, effectively leveraging organizational capital becomes pivotal for firms operating in these industries. Building upon these arguments, we predict that the relationship between organization capital and carbon emissions is contingent on firms' affiliation to carbon sensitive industries. Therefore, our third hypothesis is established below:

H4. The association between organization capital and GHG emissions varies with industry.

ETS establishes a market-based mechanism where companies receive economic incentives for reducing GHG emissions below their allocated caps and penalties for exceeding them (Choi and Luo, 2021). As a result, companies operating within an ETS region must grapple with GHG

Table 2
Summary statistics.

Variables	N	Mean	SD	P25	Median	p75	p99
Dependent variable							
EMIS(Ln)	3817	13.102	2.047	11.659	13.077	14.543	17.947
EMIS (Million Tonnes)	3817	3.660	12.241	0.116	0.478	2.071	63.000
Independent variable							
OC/TA	3817	0.216	0.199	0.079	0.158	0.280	1.026
Control variables							
SIZE	3817	9.056	1.308	8.142	8.959	9.882	12.313
LEV	3817	0.248	0.152	0.143	0.229	0.338	0.707
ROA	3817	0.151	0.072	0.108	0.145	0.188	0.368
TOBINQ	3817	1.429	1.119	0.676	1.151	1.841	5.868
ASSET_NEW	3817	0.491	0.134	0.396	0.474	0.578	0.845
CAPEX	3817	0.046	0.038	0.021	0.035	0.057	0.245
EARN_VOL	3817	0.032	0.033	0.013	0.023	0.039	0.199
INST_OWN	3817	0.787	0.158	0.701	0.816	0.898	1.000
Variables used in other tests							
R&D_INTENSITY	3817	0.031	0.045	0.000	0.011	0.044	0.216
LIQUIDITY	3378	56.425	218.895	1.336	4.107	15.664	1594.273
MGR_ABILITY	3768	0.056	0.189	−0.082	0.008	0.154	0.570
ATO	3817	0.968	0.628	0.541	0.805	1.215	3.467
DUALITY	3247	0.593	0.491	0.000	1.000	1.000	1.000
IND_DIR	3247	0.725	0.289	0.727	0.833	0.900	0.929
SA_INDEX	3807	−3.195	0.133	−3.277	−3.239	−3.164	−2.652
Const_Words	2843	0.008	0.002	0.006	0.007	0.008	0.012
SENSITIVE	3817	0.130	0.337	0.000	0.000	0.000	1.000
ETS	4817	0.159	0.366	0.000	0.000	0.000	1.000
EMIS/SALE	3817	2.010	4.193	0.197	0.471	1.779	26.295
EMIS_SECTOR(Ln)	3817	−0.001	1.358	−0.912	0.000	0.802	3.440
EMIS_GROWTH(Ln)	3133	0.000	0.016	−0.005	−0.000	0.004	0.065
DIR_EMIS(Ln)	3186	11.890	2.708	10.193	11.859	13.692	17.838
DIR_EMIS_SECTOR(Ln)	3186	−0.006	1.632	−0.941	0.000	0.899	4.026
DIR_EMIS_GROWTH(Ln)	2553	0.002	0.026	−0.006	0.000	0.007	0.115
INDIR_EMIS(Ln)	3155	12.351	1.800	11.177	12.505	13.629	16.030
INDIR_EMIS_SECTOR(Ln)	3155	−0.018	1.406	−0.849	0.000	0.843	3.518
INDIR_EMIS_GROWTH(Ln)	2512	−0.001	0.020	−0.006	−0.001	0.004	0.074
OC/PPE	3817	0.634	0.651	0.135	0.474	0.903	3.317
OC/TA_EPW	2661	0.208	0.171	0.077	0.159	0.295	0.766
OC/TA_EP	3817	1.068	0.898	0.408	0.841	1.472	4.556

This table presents summary statistics of variables. Detailed definitions of variables are provided in Appendix A. Here, N signifies the number of firm-year observations, SD symbolizes standard deviation, while p25, p75 and p99 indicate the 25th, 75th and 99th percentiles of the variables, respectively.

Table 3
Correlation matrix ($N = 3817$).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) EMIS(Ln)	1.000									
(2) OC/TA	−0.219*	1.000								
(3) SIZE	0.621*	−0.020	1.000							
(4) LEV	0.063*	−0.047*	−0.072*	1.000						
(5) ROA	0.055*	0.236*	0.155*	−0.077*	1.000					
(6) TOBINQ	−0.239*	0.128*	−0.085*	0.046*	0.498*	1.000				
(7) ASSET_NEW	0.217*	−0.289*	0.085*	0.111*	−0.105*	0.046*	1.000			
(8) CAPEX	0.365*	−0.121*	0.023	0.026	0.128*	−0.048*	0.255*	1.000		
(9) EARN_VOL	0.022	−0.151*	−0.161*	−0.009	−0.005	0.075*	0.070*	0.296*	1.000	
(10) INST_OWN	−0.246*	0.002	−0.295*	0.033	−0.129*	−0.090*	−0.040	−0.045*	−0.026	1.000

This table exhibits the pairwise correlation matrix of the variables used in the main analysis. * denotes the statistical significance at the 0.01 level. Detailed definitions of variables are provided in Appendix A.

Table 4
Baseline regression: Organization capital and GHG emissions.

	(1)	(2)
Dep. Var. =	EMIS(Ln)	EMIS(Ln)
OC/TA	**−2.035*** [0.336]**	**−1.127*** [0.366]**
SIZE		0.882*** [0.039]
LEV		0.585** [0.270]
ROA		0.461 [0.643]
TOBINQ		−0.241*** [0.042]
ASSET_NEW		−0.866** [0.438]
CAPEX		10.457*** [1.907]
EARN_VOL		−1.310 [1.351]
INST_OWN		−0.070 [0.249]
Constant	15.946*** [0.204]	7.578*** [0.560]
Year effects	Yes	Yes
Industry effects	Yes	Yes
Observations	3817	3817
Number of unique firms	643	643
Adj. R-squared	0.54	0.78

This table presents baseline regression results illuminating the effect of organization capital (OC/TA) on GHG emissions (EMIS(Ln)). Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

emission constraints, compelling them to actively pursue emission reduction strategies. We argue that the role of organizational capital in shaping a company's competitiveness is more pronounced within the framework of ETS than firms that operate in a non-ETS region. This is because, organizational capital provides the intangible resources crucial for investment in cleaner and more efficient technologies. This includes upgrading manufacturing equipment, retrofitting facilities for energy efficiency, and implementing waste reduction strategies. Thus, companies can optimize existing processes and upgrade facilities to make them more environmentally friendly and carbon neutral. In addition, organizational capital enables the establishment of robust monitoring and reporting systems to accurately measure and report GHG emissions. This allows firms to better comprehend their emission patterns, identify areas for improvement, and implement targeted strategies to reduce emissions effectively. In sum, companies can leverage organizational capital towards implementing clean technologies, promoting green innovation and more advanced measuring, monitoring and control system. This not only helps them stay within emission limits within the ETS market but also facilitate a significant reduction in GHG emissions (Borghesi et al., 2015; Zhu et al., 2019). These arguments thus imply that the association between organization capital and carbon emissions is moderated on the presence of an ETS. Therefore, our final hypothesis is established below:

H5. The association between organization capital and GHG emissions varies on the presence of ETS.

4. Research design

4.1. Data and sample

Our analysis focuses on US public companies, and we collect GHG emissions data from the Refinitiv ESG database spanning the years 2002 to 2019. The sample period begins in 2002 as GHG emissions data are accessible from this year and ends in 2019 to avoid any potential influence from the COVID-19 pandemic. Financial data is sourced from Compustat, organization capital data from WRDS (Peters and Taylor Total Q), and institutional shareholding data from the 13F database.

Panel A of Table 1 presents the sample selection process. Initially, we begin with 223,390 firm-year observations sourced from the CRSP/Compustat merged datafile. After removing duplicates (22,001 observations) and excluding financial and utility sector firms (74,147 observations), we discard observations with missing values (123,425 observations) for GHG emissions, organization capital, and control variables. The final sample consists of 3817 firm-year observations, representing 643 distinct firms. Finally, we winsorize the continuous variables at the 1% level (both sides) to mitigate concerns about outliers.

Panel B of Table 1 demonstrates the sample distribution based on the Fama-French twelve industry classification. We observe that the business equipment industry represents 20.33% of the sample, followed by manufacturing (17.92%) and other industry (11.5%).

4.2. Measurement of independent variable

Our key independent variable is organization capital. We conceptualize organization capital as a key cornerstone for achieving competitive advantage that is developed through the integration of human capabilities, corporate culture, business practices, processes, and know-how, interacting synergistically with physical assets in the production and distribution of goods and services. Following Peters and Taylor (2017), we employ a fraction of SG&A expenditures to estimate organization capital. This is because most of the expenses for developing organization capital are recorded under the SG&A. Adopting the perpetual inventory approach, we assess the stock of organization capital by accruing a fraction of past SG&A expenses of a firm (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017):

$$OC_{i,t} = (1-\delta_0)\, OC_{i,t-1} + \left(SG\&A_{i,t} \times \theta_0\right) \tag{1.1}$$

We compute the initial inventory of organization capital as follows:

Table 5
Cross-sectional analyses.

Panel A: The role of corporate governance

	(1)	(2)	(3)	(4)
	Institutional shareholding		CEO-chair duality	
	Institutional ownership > Sample median	Institutional ownership < Sample median	Duality = Yes (1)	Duality = No (0)
Dep. Var. =	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)
OC/TA	**−1.623***** **[0.420]**	**−0.078** **[0.437]**	**−0.940**** **[0.462]**	**−1.582***** **[0.421]**
Constant	8.543*** [1.026]	7.044*** [0.614]	8.063*** [0.789]	6.527*** [0.886]
Other controls	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes
Observations	1919	1898	1926	1321
Adjusted R-squared	0.72	0.82	0.8	0.76
Difference in sample coefficients on OC/TA between low vs high corporate governance subsamples:				
OC/TA	$\chi2 = 31.08$ ($p = 0.000$) ***		$\chi2 = 5.11$ ($p = 0.0237$) **	

Panel B: The role of financing constraints

	(1)	(2)	(3)	(4)
	SA Index		% of constraining words in 10-K file	
	SA_INDEX> Sample median	SA_INDEX < Sample median	Const_Words> Sample median	Const_Words< Sample median
Dep. Var.=	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)
OC/TA	**−0.147** **[0.488]**	**−2.042***** **[0.419]**	**−0.382** **[0.440]**	**−1.677***** **[0.440]**
Constant	6.034*** [0.637]	3.661*** [0.992]	7.937*** [0.751]	7.823*** [0.819]
Other controls	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes
Observations	1893	1914	1717	1126
Adj. R-squared	0.83	0.71	0.79	0.81
Difference in coefficients on OC/TA between low vs high financing constraints subsamples:				
OC/TA	$\chi2 = 30.97$ ($p = 0.000$) ***		$\chi2 = 18.95$ ($p = 0.000$) ***	

Panel C: The role of carbon sensitivity of the industry and regional ETS

	(1)	(2)	(3)	(4)
	Carbon sensitive and non-sensitive industries		ETS and Non-ETS regions	
	Carbon sensitive = 1	Carbon sensitive = 0	ETS = Yes (1)	ETS = No (0)
Dep. Var. =	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)
OC/TA	**−5.245***** **[1.607]**	**−1.158***** **[0.369]**	**−2.086**** **[1.007]**	**−0.974***** **[0.355]**
Constant	7.941*** [1.019]	7.446*** [0.618]	7.443*** [1.363]	7.768*** [0.619]
Other controls	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes
Observations	498	3319	607	3210
Adjusted R-squared	0.76	0.75	0.81	0.75
Difference in sample coefficients on OC/TA for carbon sensitive industries vs carbon non-sensitive industries and ETS regions vs non-ETS regions subsamples:				
OC/TA	$\chi2 = 39.75$ ($p = 0.000$) ***		$\chi2 = 5.97$ ($p = 0.015$) **	

This table illustrates the results of cross-sectional analyses which examine whether the relationship between organization capital and GHG emissions is moderated by corporate governance mechanisms (Panel A), financing constraints (Panel B), carbon sensitivity of the industry and regional ETS (Panel C). Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

$$OC_{i,0} = \frac{SG\&A_{i,t} \times \theta_0}{g + \delta_0} \qquad (1.2)$$

where $OC_{i,t}$ indicates organization capital of firm i at time t, δ_0 indicates the depreciation rate of organization capital, $SG\&A_{i,t}$ indicates SG&A expenditures of i at time t, θ_0 signifies the proportion of SG&A expenditure that is invested in organization capital, and g indicates the average growth rate of SG&A expenses at the firm-level. Following the preceding literature (Peters and Taylor, 2017), we employ 30% of SG&A to estimate the stock of organization capital (i.e., $\theta_0 = 0.30$).In addition, we use a depreciation rate of 20% (i.e., $\delta_0 = 0.20$) [3] (Peters and Taylor, 2017). We then divide the stock of organization capital by total assets (OC/TA).

[3] Peters and Taylor (2017) validate that the applications of various proportions of SG&A expenditure (θ_0) and depreciation rates (δ_0) have no impact on their outcomes.

4.3. Baseline regression model

We test the association between organization capital and GHG emissions using the ordinary least squares (OLS) regression model[4] as specified in the Eq. (2) below:

$$GHG_{i,t} = \alpha_0 + \beta_1 OC/TA_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 LEV_{i,t} + \beta_4 ROA_{i,t} + \beta_5 TOBINQ_{i,t} + \beta_6 ASSET\_NEW_{i,t} + \beta_7 CAPEX_{i,t} + \beta_8 EARN\_VOL_{i,t} + \beta_9 INST\_OWN_{i,t} + YEAR\ EFFECTS + INDUSTRY\ EFFECTS + \varepsilon_{i,t} \tag{2}$$

where the subscripts i and t specify firm and year respectively, while ε represents the error term. GHG stands for firm-disclosed GHG emissions, which is the sum of total direct and indirect GHG emissions[5] (Downar et al., 2021; Haque, 2017). Because of the skewed distribution of GHG emission data, we use a natural logarithmic scale, following Clarkson et al. (2011) and Haque (2017). OC/TA represents organization capital divided by book value of total asset, as discussed in Section 4.2. We control for year and industry fixed effects and cluster standard errors at the firm level.

Following the prior studies, we include several firm-level controls in our regression model (e.g., Clarkson et al., 2011; Haque, 2017; Luo and Tang, 2021; Luo and Tang, 2016; Matsumura et al., 2014; Qian and Schaltegger, 2017). First, we include the logarithmic transformation of total revenue as a proxy for firm size (SIZE) (Luo and Tang, 2016). Studies suggest that large corporations may not improve their carbon performance due to the heightened political costs (Haque and Ntim, 2022). Profitable companies are more capable of investing in carbon emission tracking, monitoring and removal technologies (Clarkson et al., 2008; Luo, 2019; Nadeem et al., 2021). Therefore, we control the return on assets (ROA) in the regression model. Financial leverage (LEV), representing long-term debt scaled by total assets, is included to account for the impact of financing policy on environmental initiatives (Haque and Ntim, 2022; Luo and Tang, 2014).

In addition, growth firms may have limited ability to implement climate-change related strategies (Dhaliwal et al., 2011). To control the effect of corporate growth, we include Tobin's Q (TOBINQ), which is measured as the ratio of market value of assets to book assets. Asset newness (ASSETNEW), calculated as net property, plant, and equipment scaled by gross property, plant, and equipment, is considered to capture the influence of asset characteristics on GHG emissions (Qian and Schaltegger, 2017). Capital intensity, measured as the proportion of capital expenditure to total assets (CAPEX), is included to account for the predisposition of firms with significant capital expenditures to engage in environmental projects and innovation (Nadeem et al., 2021). We control for institutional ownership (INST_OWN), reflecting the percentage of institutional investors, as it affects managerial decision-making on climate change policies (Luo and Tang, 2016; Safiullah et al., 2022). Finally, we include earnings volatility (EARN_VOL) since carbon performance enhancement tends to be impeded by substantial earnings volatility of a firm (Francis et al., 2021).

5. Empirical results

5.1. Summary statistics

Table 2 presents key descriptive statistics for the study. The average annual firm-disclosed GHG emissions (EMIS(Ln)) in our sample is 13.102, with a standard deviation of 2.047, aligning with Haque (2017). OC/TA has a mean (median) value of 0.216 (0.158), with a standard deviation of 0.199, consistent with Marwick et al. (2020). In addition, the mean (median) value of SIZE is 9.056 (8.959), suggesting that our sample represents larger firms in line with the reported results of Luo and Tang (2016). Also consistent with Luo and Tang (2021) findings, the mean leverage (LEV) is 0.248, which implies that the sample firms are moderately leveraged. The sample firms exhibit an average profitability (ROA) of 15.1% and capital expenditure (CAPEX) of 4.6% of total assets. Institutional ownership (INST_OWN), estimated as the percentage of shares held by the institutional investors, is 78.7% on average. Finally, the variables including Tobin's Q (TOBINQ), asset newness (ASSET-NEW) and earning volatility (EARN_VOL) demonstrate mean values of 1.429, 0.491 and 0.032 respectively. Overall, these summary statistics align with previous literature (Luo and Tang, 2021; Marwick et al., 2020; Qian and Schaltegger, 2017).

5.2. Correlation matrix

The pairwise correlation matrix among the variables is shown in Table 3. The correlation between OC/TA and EMIS(Ln) is negative and significant (correlation coefficient = −0.22; $p < 0.01$). This result manifests a preliminary basis, supporting our hypothesis that organization capital is negatively correlated with GHG emissions. We also find that the correlation between SIZE and EMIS(Ln) is positive and moderately strong (correlation coefficient = 0.62; $p < 0.01$). There is a similar positive and significant correlation between LEV and EMIS(Ln) (correlation coefficient = 0.06; $p < 0.01$). In addition, EMIS(Ln) tends to be significantly and positively correlated with ASSETNEW and CAPEX ($p <$ 0.01 in both cases). Finally, the correlation between the explanatory variables does not exceed 0.62, indicating a statistically stable analysis and ruling out the concern of severe multicollinearity.

5.3. Baseline regression result

Table 4 exhibits the OLS regression estimates on the relationship between organization capital and GHG emissions (H1). In column (1), the relationship between organization capital and GHG emissions is examined without including control variables. We find that the coefficient of OC/TA is negative (coefficient = −2.035) and statistically significant at the 1% level. This result is also economically significant, suggesting that a one-standard-deviation increase in organization capital (SD = 0.199) leads to a decrease in total GHG emissions by 3.09% (i.e., (0.199*–2.035)/13.102) compared to the average value. This economic significance can be interpreted further as a reduction in total emissions of 113,126 t (i.e., 3.09% *3.66 million tonnes). The evidence thus supports our hypothesis 1 that organization capital is negatively associated with GHG emissions. In column (2), when all firm-specific control variables are encapsulated, the sign, significance and economic effect of organization capital in reducing GHG emissions remain analogous to the findings documented in Column (1). In particular, total GHG emissions reduce by 1.71% (i.e., (0.199*–1.127)/13.102) compared to its mean owing to a one-standard-deviation rise in

[4] In our dataset OC/TA exhibits persistence over time and exhibits higher cross-sectional variation (=0.196) than within-firm variation (=0.043). Therefore, following the guidance of prior studies (e.g., Allison, 2009; Boutchkova et al., 2022), we opt for an OLS regression for our analysis. This regression model is also consistent with extant literature that uses OC/TA as the key independent variable (see e.g., Boubaker et al., 2022; Danielova et al., 2023; Li et al., 2018). Further, prior studies consistently suggest that GHG emissions are a result of firms' production processes or energy consumption, which are most likely to be homogeneous within the industry (e.g., Nguyen et al., 2021; Talaei et al., 2020), emphasizing the role of industry-specific factors in GHG emissions. Therefore, controlling for industry-specific effects is consistent with prior studies examining determinants of GHG emissions (Hossain et al., 2023; Tomar, 2023).

[5] In our main analysis, we employ firm disclosed GHG emissions. Direct emissions are scope 1 emissions generated from company-possessed or managed sources and consist of on-site discharges from fossil fuels, leased cars belonging to the company, as well as other similar sources. In contrast to direct emissions, indirect emissions, known as scope 2 emissions, originate through bought energy, heating up, freezing, or steaming, together with the transmission and circulation deficits from procured services.

Table 6
Sensitivity tests.

Panel A: Alternative measures of GHG emissions

	(1)	(2)	(3)	(4)
Dep. Var. =	Est. EMIS (Ln)	EMIS/ SALE	EMIS_SECTOR (Ln)	EMIS_GROWTH (Ln)
OC/TA	**−1.162*** [0.369]**	**−3.354*** [0.989]**	**−1.067*** [0.358]**	**−0.010*** [0.002]**
Constant	7.176*** [0.551]	7.441*** [1.690]	−7.081*** [0.540]	0.007 [0.007]
Other controls	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes
Observations	3564	3817	3817	3133
Adj. R-squared	0.77	0.42	0.53	0.05

Panel B: Alternative scaling and measures of organization capital

	(1)	(2)	(3)
Dep Var. =	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)
OC/PPE	**−0.712*** [0.098]**		
OC/TA_EP		**−0.280*** [0.078]**	
OC/TA_EPW			**−1.368*** [0.430]**
Constant	7.584*** [0.533]	7.761*** [0.569]	7.973*** [0.678]
Other controls	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes
Observations	3817	3817	2661
Adj. R-squared	0.80	0.78	0.78

Panel C: Lagged regression

	(1)	(2)
Dep. Var. =	EMIS (Ln)	Est. EMIS (Ln)
$OC/TA_{t\text{-}1}$	**−1.334*** [0.374]**	**−1.352*** [0.378]**
Constant	7.974*** [0.583]	7.547*** [0.589]
Other $controls_{t\text{-}1}$	Yes	Yes
Year and Industry effects	Yes	Yes
Observations	3075	2922
Adj. R-squared	0.79	0.79

This table reports the sensitivity tests results with respect to the use of alternative specifications of GHG emissions (Panel A) and organization capital (Panel B). Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

organization capital, which can be interpreted as a reduction in total emissions of 62,586 t (i.e., 1.71% *3.66 million tonnes).

Column (2) shows that carbon emission is associated negatively with Tobin's Q and asset newness, while it is related positively with firm size, leverage, and capital expenditure in line with prior literature. For example, the significant negative relationship between TOBINQ and EMIS(Ln) (coefficient = −0.241) is consistent with prior research findings (Busch and Hoffmann, 2011; Luo and Tang, 2021). Similarly, the negative and significant relationship between ASSETNEW and EMIS(Ln) (i.e., coefficient = −0.866, $p < 0.05$) is consistent with Qian and Schaltegger (2017). Further, the positive and significant coefficient on SIZE and CAPEX corroborates the findings of Luo and Tang (2021) and Qian and Schaltegger (2017), respectively.

Taken together, Table 4 provides robust evidence that organization capital is negatively related to GHG emissions, and this endorses the resource-based and signaling theory of organization capital.

5.4. Cross-sectional tests

5.4.1. The role of corporate governance

In this section, we examine the role of corporate governance on the relationship between organization capital and GHG emissions (H2). Following prior studies, we use institutional ownership (INST_OWN) and CEO-Chair duality (DUALITY) to assess the strength of corporate governance mechanisms (e.g., Choi and Luo, 2021; Iqbal et al., 2022; Narsa Goud, 2022). Higher institutional shareholding and the absence of CEO-Chair duality indicate stronger corporate governance structures. We classify the entire sample into high (low) institutional shareholding subsamples if the firm has a greater (lower) than sample median institutional shareholding. We also use a subsample based on whether the CEO-Chair position is held by the same person (DUALITY = Yes) or not (DUALITY = No). We then re-evaluate the main regression model to identify the moderating role of corporate governance.

In Panel A of Table 5, columns (1) and (2) exhibit the results for high and low institutional shareholding subsamples. The coefficient of OC/TA is negative and significant for the high institutional shareholding subsample (INST_OWN > sample median). A χ^2 test confirms the statistical significance of the differences in OC/TA coefficients between the high and low institutional shareholding subgroups ($p < 0.01$). Similarly, in columns (3) and (4), the magnitude of the coefficient in the non-duality subsample is significantly greater than in the duality subsample.[6] These findings support our prediction that effective corporate governance mechanisms strengthen the negative link between organization capital and GHG emissions.

5.4.2. The role of financing constraints

To examine the potential moderating effect of financing constraints on the organization capital-GHG emissions nexus, we conduct subsample analyses based on two measures of financial constraints: the SA index (SA_INDEX) (Hadlock and Pierce, 2010) and text-based measure of financing constraints (Const_Words) (Bodnaruk et al., 2015). It is worth noting that firms with higher values of SA index and higher proportion of constraining words are more financially constrained. For the empirical analysis, firms are partitioned into a high (low) financial constraint group if the SA index and Const_Words stands above (below) than the sample median. Next, we re-estimate the baseline regression for two subsamples and report the estimates in Panel B of Table 5.

We observe that the coefficients of OC/TA are negative and significant for companies with low financing constraints (Columns (2) and (4)). However, the coefficients of OC/TA are insignificant for subsamples of firms with more financing constraints (Columns (1) and (3)). Importantly, a chi-square test confirms that the variations in OC/TA coefficients between low and high financing constraint subsamples are statistically different. These findings thus suggest that acute financing constraints weaken the negative relationship between organization capital and GHG emissions.

5.4.3. The role of the industry

To test our prediction that the negative relationship between organization capital and GHG emissions is more pronounced for firms

[6] We acknowledge that the combined sample size of the columns (3) and columns (4) in panel A of Table 5 is only 3247, while the baseline regression in the study has a sample size of 3817. This disparity emerges due to the unavailability of duality data for the entire baseline sample. Nonetheless, to mitigate the concerns about the discrepancy in sample between the baseline regression and the cross-sectional analysis in Panel A of Table 5, we restrict our baseline regression to the subset of data with available CEO-Chair duality data and obtain qualitatively similar results (untabulated).

Table 7
Causal identification (i): Additional controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var. =	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)	EMIS(Ln)
OC/TA	**−1.162***** **[0.379]**	**−1.236***** **[0.378]**	**−1.075***** **[0.333]**	**−0.881**** **[0.379]**	**−1.222***** **[0.369]**	**−1.201***** **[0.365]**	**−1.118***** **[0.381]**
R&D_INTENSITY	−5.824*** [1.253]						−6.290*** [1.310]
LIQUIDITY		−0.0003*** [0.000]					−0.000*** [0.000]
MGR_ABILITY			−1.318*** [0.236]				−0.850*** [0.230]
ATO				−0.269** [0.104]			−0.307*** [0.109]
DUALITY					0.082 [0.072]		−0.030 [0.072]
IND_DIR						0.394** [0.175]	0.394** [0.178]
Constant	8.148*** [0.562]	7.568*** [0.561]	6.642*** [0.568]	7.565*** [0.559]	8.250*** [0.669]	7.993*** [0.680]	7.798*** [0.666]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3817	3378	3768	3817	3247	3247	2817
Adj. R-squared	0.79	0.78	0.78	0.78	0.79	0.79	0.81

This table exhibits the results of the effect of organization capital on GHG emissions after incorporating additional controls. Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

Table 8
Causal identification (ii): ITCV analysis.

	(1)	(2)
	Impact	Impact
	(Raw)	(Partial)
	OC/TA	
ROA	0.0131	0.0092
INST_OWN	−0.0005	−0.0004
LEV	−0.003	−0.0017
EARN_VOL	−0.0033	−0.0065
TOBINQ	−0.0306	−0.0104
CAPEX	−0.0442	−0.015
SIZE	−0.0121	−0.0277
ASSET_NEW	−0.0625	−0.0303
Benchmark value		
The required correlations between organization capital and carbon performance with unknown confounding factor to reverse the main result	0.137	

This table presents the estimates of ITCV technique. Detailed definitions of variables are provided in Appendix A.

belonging to carbon sensitive industries, we divide the sample into two sub-groups based on the nature of the firm's industry. In particular, we classify firms as belonging to carbon sensitive industries (SENSITIVE = 1), if they belong to the utilities, paper, petroleum refining, oil exploration, chemical and allied products, metals or mining sectors. The rest of the sample is categorized as carbon non-sensitive industries (SENSITIVE = 0). We then repeat the baseline regression to examine the moderating role of carbon sensitivity. We present the outcomes from this analysis in Panel C of Table 5 (columns 1 & 2). We observe that the coefficient of OC/TA is significant and negative for both carbon-sensitive (column 1) and carbon non-sensitive (column 2) subsamples. However, the magnitude of the relationship is significantly more pronounced for the carbon-sensitive subsample ($\chi^2 = 39.75$; $p < 0.01$). This evidence thus signifies that carbon intensive industry magnifies the negative relationship between organization capital and GHG emissions.

5.4.4. The role of ETS

To empirically test the moderating role of ETS, we split firms into an ETS and a non-ETS subsample (see Appendix B). Specifically, a firm is treated as belonging to the ETS regions (ETS = 1) if it operates under the regional ETS in the USA. Firms in the remaining sample are classified as in non-ETS regions (ETS = 0). We then re-estimate the baseline regression for the two subsamples separately and report the estimates in Panel C of Table 5. Column (3) concentrates on the ETS subsample while the non-ETS subsample is featured in column (4). We find that the coefficients of OC/TA are negative and statistically significant both for ETS and non-ETS subsamples. Nevertheless, it is evident that the magnitude of the negative association between organization capital and GHG emissions is more salient in the ETS subsample. Moreover, a chi-square test validates this finding. Overall, findings from cross-sectional tests suggest that the role of organization capital in reducing GHG emissions is more evident for firms with sound corporate governance mechanisms, lower financing limitations, more carbon sensitivity and in regions with an established ETS.

5.5. Sensitivity tests

5.5.1. Alternative measures of GHG emissions

To examine the sensitivity of our key finding, we employ four alternative specifications of GHG emissions: (i) the natural logarithm of the *estimated* total GHG emissions in tonnes (Est. EMIS (Ln)); (ii) total GHG emissions over total revenue (EMIS/SALE) to capture carbon emission intensity (Luo, 2019; Clarkson et al., 2008); (iii) the sector-adjusted measure of GHG emissions, which is computed as total GHG emissions of a firm in a given year minus mean total emissions of the respective sector (i.e., 2-digit SIC codes) (Luo, 2019; Tang and Luo, 2014;), and (iv) the growth-adjusted measure of total emissions, which captures the difference in total GHG emissions (EMIS(Ln)) between current year and preceding year[7] (Qian and Schaltegger, 2017).

Using these alternative specifications of GHG emissions, we re-estimate the main regression and report the results in Panel A of Table 6. Columns (1) to (4) exhibit that the coefficient of OC/TA remains negative and significant for each measure of GHG emissions (coefficient

[7] Specifically, growth-adjusted carbon performance is determined as $\text{EMIS\_GROWTH}_{i,t} = \left[\text{EMIS(LnLn)}_{i,t} - \text{EMIS(LnLn)}_{i,t-1}\right] \; / \; \text{EMIS(LnLn)}_{i,t-1}$; where $\text{EMIS(LnLn)}_{i,t}$ and $\text{EMIS(LnLn)}_{i,t-1}$ represent total GHG emissions of current and previous year, respectively.

Table 9
Causal identification (iii): 2SLS regression estimates.

	Instrumental variable regression		Lewbel (2012) methodology
	(1)	(2)	(3)
Variables	OC/TA	EMIS(Ln)	EMIS(Ln)
OC/TA		**−1.490*** [0.507]**	**−3.082*** [0.736]**
PEER_OC_RES	**0.926*** [0.102]**		
SIZE	−0.011** [0.004]	0.875*** [0.038]	0.841*** [0.044]
LEV	0.011 [0.031]	0.596** [0.266]	0.647** [0.273]
ROA	0.132* [0.067]	0.577 [0.637]	1.083 [0.695]
TOBINQ	0.010** [0.005]	−0.234*** [0.041]	−0.204*** [0.042]
ASSET_NEW	−0.223*** [0.039]	−0.994** [0.446]	−1.558*** [0.499]
CAPEX	0.12 [0.113]	10.485*** [1.883]	10.610*** [1.879]
EARN_VOL	−0.112 [0.110]	−1.442 [1.338]	−2.023 [1.370]
INST_OWN	−0.010 [0.031]	−0.080 [0.244]	−0.123 [0.254]
Observations	3817	3817	3817
Year effects	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Under-identification test:			
Kleibergen-Paap rk LM statistic	39.88		13.485
p-value	0.000		0.036
Weak identification test:			
Cragg-Donald Wald F statistic	2519.99		132.518
Stock and Yogo (2005) critical value	16.38		29.18
Overidentification test:			
Hanson J statistics (*p*-value)			1.431 (0.921)

This table displays the results of two-stage least-squares estimations of the impact of organization capital on GHG emissions. Columns (1) and (2) report instrumental variable regression employing external instrumental variable, whereas Column (3) presents regression result adopting Lewbel (2012) methodology[a]. Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10,0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

[a] For brevity, we do not report the results of the first-stage regression.

= −1.162; $p < 0.01$ for Est. EMIS(Ln); −3.354; $p < 0.01$ for EMIS/SALE; coefficient = −1.067; $p < 0.01$ for EMIS_SECTOR(Ln); and coefficient = −0.010; $p < 0.01$ for EMIS_GROWTH(Ln)). These findings suggest that inference from our study is not sensitive to the use of specific measures of GHG emissions.

5.5.2. *Alternative scaling and measures of organization capital*

Next, we consider one alternative scaling and two alternative measures of organization capital to address concerns about measurement bias related to organizational capital. The estimates from this analysis are presented in Panel B of Table 6.

In column (1), we scale the stock of organization capital by a firm's physical asset (OC/PPE) (Hasan and Cheung, 2018). This variable captures the extent of organization capital (intangible assets) in proportion to the property, plant, and equipment (tangible assets). We document that the coefficient of OC/PPE remains negative and significant (coefficient = −0.712; $p < 0.01$). In column (2), we employ the organization capital measure of Eisfeldt and Papanikolaou (2013). This measure differs from that of Peters and Taylor (2017) in two ways. First, Eisfeldt and Papanikolaou (2013) model considers SG&A expenses to be deflated by the consumer price index (CPI). Secondly, this model utilizes the aggregate SG&A expenses instead of a fraction of these expenditures. Despite these differences, the coefficient of OC/TA_EP remains negative and significant (coefficient = −0.280; $p < 0.01$).

Furthermore, it is probable that in different industries there is a varied allocation of SG&A expenses to the integration of organization capital and its depreciation rates. Therefore, in column (3), we adopt the organization capital measure of Ewens et al. (2020) that uses industry-specific parameters in estimating organization capital (OC/TA_EPW). We document consistent negative and significant coefficient of OC/TA_EPW (coefficient = −1.368; $p < 0.01$).

5.5.3. *Lagged regression*

There may be a concern that emissions data could suffer from reporting delays if the firm discloses them, or that these emissions data could be based on lagged firm-level fundamentals if vendors estimate them. Therefore, using a contemporaneous regression could limit the impact of organizational capital on a firm's actual GHG emissions. To alleviate this concern, we separately regress firm-disclosed and estimated GHG emissions on lagged OC/TA and controls.

The estimates derived from this analysis are presented in Panel C of Table 6. We continue to observe a negative and significant coefficient of OC/TA_{t-1} ($p < 0.01$), reinforcing the robustness of our findings.

5.6. *Causal identification issues and strategies*

In this subsection, we use four causal identification techniques to account for possible endogeneity problems resulting from omitted variable bias, selection bias, and reverse causality.

5.6.1. *Inclusion of additional controls*

To mitigate the endogeneity arising from omitted variable bias, we include a number of additional controls. Following extant literature (Alam et al., 2019; Haque and Ntim, 2022; Nadeem et al., 2021; Qian and Schaltegger, 2017), we include six additional controls: R&D expenses over total asset (R&D_INTENSITY), liquidity, managerial ability score of Demerjian et al. (2012) (MGR_ABILITY), asset turnover measured as the total sales divided by total assets (ATO), CEO-chair duality (DUALITY) and the proportion of independent directors on the board (IND_DIR).

Literature suggests that investing in R&D can enhance a firm's ability to innovate and improve its production processes to reduce GHG emissions (Lee et al., 2015). We control for ATO to capture the efficient deployment of a firm's assets and LIQUIDITY to control for a firm's capacity to fulfill its current obligations as more liquid firms are better able to boost their carbon performance (Haque and Ntim, 2022; Qian and Schaltegger, 2017). Furthermore, we include MGR_ABILITY because companies with higher managerial ability may pursue environmentally sound practices to reduce GHG emissions (Sharma and Vredenburg, 1998). Finally, following earlier literature (e.g., Nadeem et al., 2021), we incorporate IND_DIR and DUALITY to control the impact of corporate governance on GHG emissions.

In Table 7, we present the estimates from this analysis. Even after accounting for the aforementioned controls, both separately (columns 1–6) and collectively (column 7), the relationship between organization capital and GHG emissions remains negative and significant ($p < 0.01$). Thus, we argue that omitted variable bias is not a major concern for our analysis.[8]

5.6.2. *Impact threshold of a confounding variable (ITCV)*

To further alleviate concerns about the omitted variable bias, we apply the ITCV method as per prior studies (Frank, 2000; Larcker and Rusticus, 2010). Since the confounding variable continues to be

[8] We do not include these additional controls in main regression as their inclusion reduce the sample size by >25%.

Table 10
Causal identification (iv): Entropy balancing estimates.

Panel A: Covariate balance (OC/TA)

	Before: Without weighting						After: With weighting					
	Treat			Control			Treat			Control		
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
SIZE	8.974	1.646	0.294	9.144	1.765	0.230	8.974	1.646	0.294	8.974	1.646	0.294
LEV	0.238	0.022	0.597	0.259	0.024	0.657	0.238	0.022	0.597	0.238	0.022	0.597
ROA	0.164	0.005	0.339	0.138	0.005	0.339	0.164	0.005	0.339	0.164	0.005	0.339
TOBINQ	1.624	1.401	1.326	1.221	1.012	2.150	1.624	1.401	1.326	1.624	1.401	1.326
ASSET_NEW	0.449	0.013	0.486	0.536	0.019	0.250	0.449	0.013	0.486	0.449	0.013	0.486
CAPEX	0.038	0.001	1.935	0.055	0.002	1.596	0.038	0.001	1.935	0.038	0.001	1.935
EARN_VOL	0.026	0.000	3.396	0.039	0.001	2.529	0.026	0.000	3.396	0.026	0.000	3.396
INST_OWN	0.782	0.025	−1.173	0.791	0.024	−1.198	0.782	0.025	−1.173	0.782	0.025	−1.173

Panel B: Regression result using entropy-balanced sample

Dep. Var. =	EMIS(Ln)
OC/TA	**−1.310***** **[0.360]**
Constant	7.524*** [0.690]
Other controls	Yes
Year and Industry effects	Yes
Observations	3817
Adj. R-squared	0.77

This table shows the results of entropy balancing estimates to deal with potential endogeneity. Panel A describes the variation of the mean, variance, and skewness of the variables across the treatment and control groups, whereas Panel B outlines the regression result on the basis of entropy-balanced sample. Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

Table 11
Decomposition of total GHG emissions.

	Direct (Scope 1) GHG emissions			Indirect (Scope 2) GHG emissions		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var. =	DIR_ EMIS(Ln)	DIR_EMIS_ SECTOR (Ln)	DIR_EMIS_ GROWTH (Ln)	INDIR_ EMIS (Ln)	INDIR_EMIS_SECTOR (Ln)	INDIR_EMIS_ GROWTH (Ln)
OC/TA	**−1.324***** **[0.477]**	**−1.222***** **[0.458]**	**−0.015***** **[0.004]**	**−0.795**** **[0.377]**	**−0.799**** **[0.361]**	**−0.010***** **[0.004]**
Constant	6.349*** [0.814]	−8.033*** [0.800]	0.000 [0.009]	5.989*** [0.773]	−7.531*** [0.631]	0.004 [0.013]
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year and Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3186	3186	2553	3155	3155	2512
Adj. R-squared	0.78	0.43	0.02	0.68	0.51	0.03

This table presents how organization capital affects both direct GHG emissions (Columns 1 to 3) and indirect GHG emissions (Columns 4 to 6). Standard errors are provided in brackets below the estimated coefficients and are clustered by firm. *, **, *** articulate the statistical significance levels at 0.10, 0.05, and 0.01, respectively (two-tailed). Detailed definitions of variables are provided in Appendix A.

unexplained, and may not be even observable, it is legitimate to adopt this critical technique to validate the main regression result. Table 8 details the results of the ITCV analysis. The ITCV is determined by the least multiplication of partial correlation between organization capital and other firm-level controls. In order to nullify the inferences, the magnitude of correlation between organization capital and GHG emissions along with an unseen confounding variable must be 0.137 for OC/TA. Intriguingly, the greatest impact variable in ITCV analysis is ROA, which holds a partial impact factor of 0.0092, implying that an unobservable confounding variable should be a minimum 14.89-fold higher than the impact of ROA to invalidate our inferences. Therefore, we conclude that our baseline finding is not susceptible to the influence of unobserved confounding variables.

5.6.3. Two-stage least-squares (2SLS) regression

It is possible that companies with lower GHG emissions have greater access to resources, allowing them to invest more in organization capital. This could result in reverse causality issue. To shed further light in dealing with endogeneity resulting from omitted variables and reverse causality, we rely on instrumental variable estimation. Following Marwick et al. (2020), we consider industry (3-digit SIC)-year level median organization capital (PEER_OC) as the instrumental variable in 2SLS regression analysis. The literature indicates that a firm is incentivized to invest in developing organizational capital when it observes its industry peers possessing a higher level of organizational capital. Furthermore, a company's economic decisions are influenced to a large extent by its industry counterparts (Leary and Roberts, 2014). In line with this notion, Hasan and Cheung (2018) show that organizational capital remains relatively consistent among corporations operating within the same sectors. Consequently, a firm's organizational capital is likely to be directly linked to the industry-level organizational capital.

Although our instrumental variable (i.e., PEER_OC) meets the relevance condition, the exclusion restriction is a natural limitation of any instrumental variable design. For example, it is possible that the overall improvement in industry-level organizational capital may encourage firms with relatively lower levels of organizational capital to invest more and align themselves with industry standards, thereby leading to a reduction in GHG emissions. To address this concern, following recent literature (e.g., Amin et al., 2023; Francis et al., 2021; Hasan and Uddin, 2022) we adopt steps to isolate the influence of industry-level organization capital on GHG emission. In particular, we first estimate the industry-level GHG emissions for the firms in each year. Subsequently, we employ the following regression for each industry:

$$PEER\_OC_{f,t} = \propto_0 + \propto_1 GHG_{f,t} + \epsilon_{f,t} \quad (3)$$

In this specification, "*f*" denotes industry and "*t*" denotes time. The residuals derived from the above regression (i.e., *PEER_OC_RES*) signifies industry-level organization capital unexplained by GHG emissions. We employ this variable as our instrument in the 2SLS regression.

Columns (1) and (2) of Table 9 present the results of 2SLS regression. The first-stage regression results in column (1) show that our instrument (i.e., PEER_OC_RES) is positively and significantly correlated with OC/TA (Coefficient = 0.926; $p < 0.01$), corroborating our prediction. The second-stage regression result in column (2) shows that the coefficient of OC/TA is negative and significant ($p < 0.01$), which is consistent with the baseline result. We also observe that our estimation is not affected by under-identification bias. Furthermore, the Cragg-Donald Wald *F* statistic for the weak-identification test far exceeds the Stock and Yogo (2005)-specified threshold level of 16.38, implying that weak identification does not seem to be a concern for our analysis.

In addition to the above 2SLS regression, we also adopt the novel 2SLS regression technique of Lewbel (2012) to circumvent potential endogeneity issues. In lieu of using an external instrument, this methodology constructs instrumental variables based on heterogeneity in the data. This technique has been shown to perform well and this is particularly useful in the absence of conventional suitable instruments (Hasan et al., 2021; Schlueter et al., 2015).

The results of the 2SLS estimation using Lewbel (2012) methodology are presented in column (3) of Table 9. The instrumented organization capital continues to be negatively and significantly correlated with GHG emissions ($p < 0.01$) in column (3), implying that our baseline finding is not susceptible to the endogeneity problem. Moreover, the instruments constructed utilizing Lewbel's method are not prone to weak identification issue as well as under-identification and over-identification biases. Overall, the findings from the above analyses reinforce that our main result remains robust and is unlikely to be driven by endogeneity concerns.

5.6.4. Entropy balancing approach

In order to alleviate the concern that our baseline result is influenced by design choices, we adopt entropy balancing estimates. This cutting-edge method has gained recognition in contemporary literature to tackle endogeneity concerns (e.g., Ashraf et al., 2020; Jiang et al., 2018). To employ this technique, we partition the sample into two categories: a treatment (firms with more than the sample median organization capital) and the control group (firms with less than the sample median organization capital). To ensure that the skewness, mean and standard deviation of all covariates are comparable between the treated and control firms, this method uses a re-weighting scheme.

Panel A of Table 10 exhibits the results of the covariate balance. Intriguingly, after re-weighting of the covariate distribution, both treatment and control groups possess identical features with respect to their firm-level controls (Hainmueller, 2012). Subsequently, we re-estimate the regression incorporating entropy-balanced sample and report the findings in Panel B of Table 10. We document that the coefficient of OC/TA is negative and statistically significant ($p < 0.01$), substantiating the finding of the baseline regression (see Table 4).

5.7. Additional analysis

Our baseline regression measures the total GHG emissions as the sum of total direct (Scope 1) and indirect (Scope 2) emissions. To present additional insight into the relationship, we examine whether organizational capital has a varying impact on these two sources of GHG emissions. We extract direct (Scope 1) and indirect (Scope 2) emissions data from Refinitiv ESG database. Scope 1 emissions are a direct outcome of a firm's controlled or owned resources, encompassing emissions from activities such as on-site combustion of fossil fuels (e.g., company-owned vehicles and boilers) and emissions arising from chemical reactions during production processes. In contrast, Scope 2 emissions comprise indirect greenhouse gas emissions associated with the purchase of electricity, heat, or steam from external suppliers, originating during the production of the acquired energy and arising from activities beyond the control of the reporting entity.[9] Thus, direct and indirect emissions often have different sources and characteristics. By breaking down total emissions into these components, we can conduct a more targeted analysis of how organizational capital influences each source of emissions. Therefore, this analysis is essential for tailoring effective corporate strategies, making informed decisions, and implementing targeted interventions to mitigate an organization's GHG emissions.

The estimates from this analysis are presented in Table 11. In columns (1) and (4), we observe that the coefficients of OC/TA continue to be negative and significant for logarithm form of direct and indirect emissions with *p*-values at least <0.05. Further, sector-adjusted and growth-adjusted direct (Columns 2 and 3, respectively) and indirect (Columns 5 and 6, respectively) GHG emissions demonstrate qualitatively similar results, corroborating our main finding. Thus, the results in Table 11 imply that the baseline result is driven by both direct and indirect GHG emissions. Our analysis highlights the broad influence of organizational capital across diverse emission sources.

6. Conclusion

We explore whether organization capital has any relationship with a firm's GHG emissions. We find strong evidence endorsing resource-based and signaling theory-grounded hypothesis that firms with high organizational capital exhibit lower GHG emissions. This result holds true across various sensitivity tests and identification strategies to address endogeneity concerns. Further analysis reveals that the documented negative association between organization capital and GHG emissions is more salient for firms with effective corporate governance mechanisms and sound financial conditions, operating in carbon sensitive industries and in regions with an established ETS. Finally, our key result holds for both direct and indirect GHG emissions.

This study contributes significantly to the literature on organization capital and GHG emissions, offering policy implications for corporate managers and policymakers. For example, in response to stakeholder pressure and climate activism, top management teams can strategically invest in intellectual assets (organization capital) to enhance legitimacy and demonstrate environmental responsibility. In addition, as the extent of this relationship varies contingent on the corporations' corporate governance structures and financial conditions, managers should undertake vigilant actions and implement policies accordingly that have far-reaching effect on firm's climate-related activism.

CRediT authorship contribution statement

Sagira Sultana Provaty: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft,

[9] It is worth noting that as Scope 3 emissions encompass all additional indirect emissions resulting from a firm's supply chain, it is not considered in our estimation.

Writing – review & editing. **Mostafa Monzur Hasan:** Conceptualization, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing. **Le Luo:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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Appendix A. Description of variables

Variables	Definition and measurement
Dependent variable	
EMIS(Ln)	Total GHG emissions, calculated as the natural logarithm of one plus total GHG emissions (En_En_ER_DP023) in tonnes. The higher the EMIS(Ln), the lower the carbon performance and vice versa.
EMIS (Million Tonnes)	Total GHG emissions (En_En_ER_DP023) expressed in million tonnes.
Main independent variable	
OC/TA	The ratio of a firm's stock of organization capital (OC) to total assets (AT). Based on the perpetual inventory approach, a fraction of previous SG&A expenses is used to calculate the stock of organization capital.
Control variables	
SIZE	The natural logarithm of a firm's total revenue (SALE).
LEV	Financial leverage, computed as the ratio of long-term debts (DLTT) to total assets (AT).
ROA	Return on assets, measured as the operating income before depreciation (OIBDP) scaled by total assets (AT).
TOBINQ	Tobin's Q ratio, calculated as the ratio of market value of equity (PRCC_F*CSHO) plus long-term debts (DLTT) plus short-term debts (DLC) minus current assets (ACT) to total assets (AT).
ASSET_NEW	Asset newness, measured as the proportion of net property, plant and equipment (PPENT) divided by gross property, plant and equipment (PPEGT) at the year-end.
CAPEX	Capital expenditure, measured as the ratio of capital expenditure (CAPX) to total assets (AT).
EARN_VOL	Earnings volatility, measured as the standard deviation of the operating income before depreciation scaled by total assets (AT) over year $t + 1$ through year $t + 5$.
INST_OWN	Percentage of institutional shareholdings.
Variables used in further analysis	
SA_INDEX	Hadlock and Pierce (2010)'s proxy for financing constraint.
Const_Words	A text-based measure of financing constraints that captures the number of constraining words in 10-K disclosures (Bodnaruk et al., 2015).
ETS	An indicator variable equals 1 for firms subject to emissions trading schemes, while the remaining firms are denoted by 0. Source: https://icapcarbonaction.com/en/ets-map
SENSITIVE	An indicator variable representing carbon sensitive firms. Firms from utilities, energy, and materials sectors are classified as carbon-sensitive and the remaining firms are classified as carbon non-sensitive.
OC/PPE	The stock of organization capital (OC) to gross property, plant and equipment (PPEGT).
OC/TA_EP	Eisfeldt and Papanikolaou (2013) stock of organization capital (OC), which is divided by total assets (AT).
OC/TA_EPW	Ewens et al. (2020) stock of organization capital (OC) that incorporates sector-specific parameters for estimation. We standardize this variable by dividing it by total assets (AT).
EMIS/SALE	GHG emissions intensity, measured as total GHG emissions (En_En_ER_DP023) divided by total sales (SALE).
EMIS_SECTOR(Ln)	Sector-adjusted total GHG emissions calculated using EMIS(Ln) minus their sector mean.
EMIS_GROWTH(Ln)	The difference in total GHG emissions for current year and previous year.
DIR_EMIS(Ln)	The natural logarithm of one plus direct (Scope 1) GHG emissions.
INDIR_EMIS(Ln)	The natural logarithm of one plus indirect (Scope 2) GHG emissions.
DIR_EMIS_SECTOR(Ln)	Sector-adjusted direct (SCOPE 1) GHG emissions calculated using DIR_EMIS(Ln) minus their sector mean.
INDIR_EMIS_SECTOR(Ln)	Sector-adjusted indirect (SCOPE 2) GHG emissions, calculated using INDIR_EMIS(Ln) minus their sector mean.
DIR_EMIS_GROWTH(Ln)	The difference in direct (SCOPE 1) GHG emissions for current year and previous year.
INDIR_EMIS_GROWTH (Ln)	The difference in indirect (SCOPE 2) GHG emissions for current year and previous year.
MGR_ABILITY	The managerial ability score of Demerjian et al. (2012).
LIQUIDITY	Cash and equivalents (CHE) scaled by total current liabilities (DLC).
DUALITY	An indicator variable denotes CEO duality, taking the value of 1 when the CEO retains the chair position and 0 otherwise.
IND_DIR	The percentage of independent directors on the board.
R&D_INTENSITY	R&D expenditures (XRD) scaled by total assets (AT).

Appendix B. Regional emissions trading schemes - USA

Name of regional ETS	Type	Status	Inception year
California Emissions Trading Scheme	Mandatory	Under operation	2013
Regional Greenhouse Gas Initiative (RGGI)	Mandatory	Under operation	2009
Western Climate Initiative (WCI)	Voluntary	Under operation	2013

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107372.

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