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Organisation capital: A key asset for mitigating firm-level climate change exposure

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ABSTRACT

Despite growing evidence of the importance of organisation capital, its impact on corporate resilience remains underexplored. This study investigates whether organisation capital provides firms with greater resilience and reduces their exposure to climate change. By analysing a sample of 3,622 US firms from 2001 to 2021, we found that firms with high organisation capital experienced less climate change exposure. This result remained robust across various tests and methods to address endogeneity concerns. Furthermore, organisation capital was found to act as a mediator or suppressor in the relationship between firm-specific factors – such as financial constraints, analyst forecast quality, agency costs, financial leverage, corporate governance, firm performance, efficiency, operating performance, product market competition, and environmental commitment and initiative – and climate change exposure. Overall, our results underscore the resilience benefits provided by organisation capital and highlight its critical role in mitigating climate-related risks.

1. Introduction

Climate change has become a pressing issue in recent decades, affecting not only the global economy and financial markets but also individual firms' performance and the financial and investment risks they face. For instance, according to the NOAA National Centers for Environmental Information (NCEI), the US experienced 341 climate and weather disasters from 1980 to the present, resulting in total costs exceeding $2.475 trillion. In 2022 alone, 18 events each caused over $1 billion in damages (NOAA, 2023). In addition to its wide impact on the economy, climate risk has become detrimental to firm performance and has increased firms' risk. For example, PG&E became the first corporation to file for bankruptcy due to climate change and California's wildfire in 2019. Furthermore, investors are increasingly influenced by climate risk in their decisions. According to The New York Times, Mr. Larry Fink, the founder and CEO of BlackRock, announced that BlackRock would exit investments with 'high sustainability-related risk'. Ørsted, once one of the most coal-intensive energy companies in Europe, successfully shifted its business model from fossil fuels to renewable energy by making substantial investments in offshore wind farms. This proactive approach to addressing climate risks was recognized and rewarded by investors and customers, leading to significantly improved financial performance following its green transformation.[1]

Academic research has also investigated the impact of climate change on firm performance and risk and stock market performance, which is manifested by affecting investors' attitudes towards firm performance. Pankratz et al. (2023) reported that extreme high

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[1] See Ørsted's green energy transformation at https://orsted.com.au/about-us/our-green-energy-transformation for more information.

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temperatures and increased heat exposure affect firms' productivities and negatively impact firms' revenues and operating incomes. Capasso et al. (2020) reported that firms with high carbon footprint have shorter distance to default. Huang et al. (2018) reported that climate risk has been meticulously considered in firms' financial policies and decisions, as firms facing more climate-related risks tend to have more volatile earnings, hold more cash but pay lower dividends, and rely on more long-term borrowing but less short-term borrowing. Huang et al. (2022) reported that firms with higher climate risk exposure face unfavourable bank loan terms.

With numerous empirical studies highlighting the severe impact of climate risk, mitigating firm-level climate change exposure has become an issue of first-order importance. Huang et al. (2018) highlighted the importance of organisational resilience against climate risk threat, stating that holding more cash can help firms to build organisational resilience. According to Fiksel (2006, p.16), organisational resilience is defined as 'the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change' in the business context. This prompts the question: What business practices should companies adopt to develop organisational resilience and effectively respond to adversity? Organisation capital (OC), described by Lev et al. (2009, p.277) as an 'agglomeration of technologies—business practices, processes, and designs', is believed to provide firms with greater resilience to cope with adversity and threat in the industry and economy. Uddin et al. (2022) reported that firms investing in intangibles (mainly internally generated knowledge capital and OC) have developed corporate resilience to pandemic shocks from infectious diseases. However, research on the corporate resilience benefits of OC against firm risks and new threats remains underdeveloped. To address this gap in the literature, we attempt to investigate whether a firm's accumulated OC can provide resilience benefits by mitigating/reducing firm-level climate change exposure.

Two main theories regarding OC are discussed in the literature: the agency view and the resource-based view (RBV). The agency view suggests that OC exacerbates agency problems because both shareholders and key employees have claims on cash flows generated by OC, which may be appropriated by key talent for personal benefits (Eisfeldt and Papanikolaou, 2013; Venieris et al., 2015). In contrast, RBV sees a firm's unique OC as a source of sustainable competitive advantage, enhancing firm value, fostering growth, and promoting long-term survival (Youndt et al., 2004; Lev et al., 2009; Lev et al., 2016). Our study is primarily motivated by RBV, aiming to investigate whether firms with high OC exhibit greater resilience and a stronger sustainable competitive advantage against external risks, such as climate exposure, as opposed to internal firm-specific risks, than those with low OC.

Based on a sample of 3622 US firms and 31,580 firm-year observations from 2001 to 2021, we found that firms with high OC were exposed to less climate change. This relationship remained negative and significant when we used alternative proxies for OC and climate change exposure. To address endogeneity issues, we conducted several tests, such as the two-stage least squares (2SLS) with Lewbel's (2012) approach and entropy balancing estimates. The endogeneity test results were in line with our previous findings. To further validate our main results, we conducted several robustness checks and reran the regressions with additional control variables and alternative measures of OC and climate change exposure. We also reran our baseline model by excluding the crisis period, restricting the main sample to a crisis period, or limiting it to firms with positive climate change exposure (i.e. excluding firms with zero exposure). Our results were consistent with the main findings, suggesting that OC provides corporate resilience and plays a pivotal role in reducing firm-level exposure to climate change. Furthermore, we examined how OC influences the relationship between firm-specific factors and firm-level climate change exposure. Through a mediation analysis, we found that OC mediates the effects of financial constraints, corporate governance, firm performance, efficiency, operating performance, shareholder base on a firm's climate change exposure. In addition to its mediation effect, OC also has a beneficial suppression effect in the relationship between analyst forecast quality, environmental commitment and initiative and climate change exposure. Lastly, we find that for firms with high institutional ownership, financial leverage, or those operating in highly competitive markets, the suppression effect of OC appears less effective, as the reduction in climate change exposure would have been more pronounced without such investment.

This study contributes to existing literature in several ways. First, it contributes to the emerging body of research on climate change exposure. While many studies have emphasised the importance of climate change exposure and its effects on financial performance, firm decisions, and risk (e.g., Javadi et al., 2023), the question of how to mitigate firms' climate change exposure still deserves further investigation. This study significantly advances the literature on climate change by highlighting the considerable influence of OC as a key intangible factor. By showing how OC can work in tandem with other tangible factors to effectively reduce firms' climate change exposure, this study makes a noteworthy addition to the existing body of work. Second, it contributes to the literature on OC. Prior studies have highlighted the beneficial role of OC in value creation and firm performance (Eisfeldt and Papanikolaou, 2013; Lev et al., 2009). Recent research has shown the importance of OC in influencing cash holdings, dividend distributions, and the cost of capital (Marwick et al., 2020; Hasan and Uddin, 2022; Attig and El Ghoul, 2018; Attig and Cleary, 2014; Danielova et al., 2023). Despite the growing evidence and various arguments on OC in recent years, the resilience benefits of OC against immediate and unexpected challenges and threats have rarely been studied. To the best of our knowledge, this study is the first to investigate the resilience benefits provided by OC in mitigating climate change exposure, thus making a novel contribution to the literature. This finding enhances our understanding that OC impacts not only financial performance but also non-financial aspects such as climate change exposure. Third, we offer nuanced empirical evidence that OC plays a complex role, acting not only as a mediator but also as a suppressor in shaping the relationship between firm-specific characteristics and climate change exposure. Specifically, we show how investment in OC can mediate or suppress the effects of financial constraints, analyst forecast quality, agency costs, corporate governance, firm performance, efficiency, operating performance, and environmental commitment and initiative on climate change exposure, issues that have not been previously explored. Additionally, in certain contexts, the benefit of OC may be marginal or insignificant.

Our study builds on the work of Provaty et al. (2024) who found that firms with higher OC tend to have lower greenhouse gas (GHG) emissions. However, our study adopts a broader approach by focusing on climate change exposure, which encompasses a range of risks and opportunities related to a firm's vulnerability to climate change. While GHG emissions measures concentrate on monitoring and managing a firm's emissions to minimise environmental impacts, climate change exposure captures a wider set of potential challenges and benefits for firms in the context of climate change. Moreover, whereas Refinitiv ESG database's GHG emissions data rely on quantifiable 'hard' information, our analysis of firm-level climate change exposure utilises 'soft' information extracted from earnings conference call transcripts. This distinction allows us to uncover additional economic insights that complement those obtained from existing firm-level exposure measures based on 'hard' information.

This paper is related to Almaghrabi (2023) and Kanagaretnam et al. (2022). Almaghrabi (2023) demonstrates that higher managerial ability can alleviate the adverse impacts of climate change risk on financial performance and cash flow volatility. Our study extends this research by exploring the influence of a broader concept, OC, on firm-level exposure to climate change. While managerial ability is a key component of OC, the latter encompasses a firm's internally accumulated knowledge, expertise, business processes, systems, and culture. Furthermore, while Almaghrabi (2023) investigates how managerial ability moderates the relationship between climate change exposure and firm performance, our study focuses on the direct effect of OC on climate change exposure at the firm level.

Kanagaretnam et al. (2022) explore the relationship between OC, physical capital, and a firm's exposure to climate risk. Our study differs from their study in two ways. Their study treats climate risk as a key factor influencing firm investments in physical capital and OC. They argue that increased investment in physical capital to address climate change may lead to reduced investment in OC. In contrast, our study adopts a different approach by using OC as an explanatory variable rather than a dependent variable. We focus on firms with significant investments in OC and investigate the effects of accumulated OC on firm-level exposure to climate change. Additionally, while their climate risk data from German Watch provides a country-level measure of climate risk, our measure is derived from the transcripts of earnings conference calls, offering a firm-level perspective on climate exposure.

The remainder of this paper is organised as follows. Section 2 presents the literature review and hypothesis development. Section 3 discusses sample data, different measures of variables, and the methodology. Section 4 presents the baseline regression results and methods used to address the endogeneity issue. Section 5 discusses the mediation and suppression results for OC. Section 6 presents the results of the robustness checks. Section 7 provides the concluding remarks of the study.

2. Literature review and hypothesis development

Climate change, including more frequent and intense extreme weather events (e.g. floods, droughts, fires, tropical cyclones, and heatwaves), has caused widespread damage and significant losses to nature, communities, and people (IPCC, 2022). Prior research has found that climate risk poses dangerous threats to corporate operations and performance by significantly disrupting their production processes and substantially damaging their investments, earnings, sales, supply chains, and cash flows (Barrot and Sauvagnat, 2016; Huang et al., 2018; Brown et al., 2021; Huynh and Xia, 2021). Climate risk is generally classified as physical, regulatory, and transitional risk (Javadi and Masum, 2021). Physical risk refers to direct costs and physical damage associated with extreme weather events and natural disasters. Regulatory risk is driven by tightening environmental policies and regulations to reduce CO_2 emissions and minimise climate-related concerns. Transitional risk stems from climate-oriented innovations and changes in business models that can disrupt certain industries during the shift to a low-carbon economy. Investors and lenders increasingly perceive climate change as a material risk factor, and hence incorporate it into their asset pricing models. Consistent with this view, a fast-growing literature documented that climate risk substantially increases the costs of bank loans (Javadi and Masum, 2021; Do et al., 2021), issuing municipal bonds (Painter, 2020), and mortgage credit (Nguyen et al., 2022). Similar findings have been reported for equity capital. Hong et al. (2019) and Huynh et al. (2020) reported that climate risk increases the cost of equity due to elevated business disruption caused by droughts conditions.

A firm's climate change exposure may be influenced by both voluntary and strategic actions. Voluntary actions are often driven by altruistic motives, where companies act on core values and broader missions that prioritize the well-being of future generations, even if these actions do not provide immediate financial gains (Wu and Shen, 2013). Additionally, such voluntary initiatives offer moral satisfaction to firms and their leaders by aligning corporate actions with personal and organisational ethics. In contrast, Baron (2009) posits that strategic corporate social responsibility (CSR) enables firms to differentiate their products, minimize price competition, and allow ethically managed companies to charge a premium. Hence, strategic choices aimed at mitigating climate risk can provide a competitive edge by differentiating a firm in the marketplace. For instance, firms that lead in renewable energy technologies or sustainable construction can outpace competitors reliant on traditional, carbon-intensive practices.[2]

While there is no consensus on the definition of OC,[3] it encompasses a firm's stock of knowledge, capabilities, culture, business

[2] NextEra Energy, a leading U.S. electric utility company in the Electric, Gas, and Sanitary Services industry – identified as having the highest climate change exposure (Sautner et al., 2023) – serves as another example of OC at work. The company leverages its OC, including strong leadership, a culture of innovation, and advanced risk management, to drive its shift towards renewable energy, particularly wind and solar power. This strategic focus reduces NextEra's exposure to regulatory and market risks associated with fossil fuels, allowing it to outperform competitors still reliant on carbon-intensive energy sources. Refer to https://www.investor.nexteraenergy.com/sustainability for more information.

[3] For example, Evenson and Westphal (1995, p.2237) define OC as 'knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products.' Wright et al. (2001) and Youndt et al. (2004) define OC as the codified and tacit knowledge institutionalized within organisation processes, databases, routines, patents, manuals, structures and the like. Lev and Radhakrishnan (2005, p.75) define OC as 'an agglomeration of technologies – business practices, process and designs, and incentive and compensation systems – that together enable some firms to consistently and efficiently extract from a given level of physical and human resources a higher value of product than other firms find possible to attain.' Similarly, according to Lev et al. (2009, p.276), OC is 'the agglomeration of business processes and systems, as well as a unique corporate culture, that enables them to convert factors of production into output more efficiently than competitors.'.

processes, and systems that integrates human skills with physical capital (Eisfeldt and Papanikolaou, 2013). Lev et al. (2016) suggested that OC is multi-faceted, consisting of human capital (Prescott and Visscher, 1980), values and norms (Tomer, 1998), knowledge and expertise (Atkeson and Kehoe, 2005), and business processes and practices (Evenson and Westphal, 1995). Hence, OC is partly firm-specific and partly embodied in a firm's key talent such as managers, scientists, engineers, salespeople, and research employees (Eisfeldt and Papanikolaou, 2013, 2014). Examples of OC include Walmart's supply chain system, Netflix's algorithmic technology, Cisco's Internet-based product installation and maintenance system, and Apple's internal culture.[4]

The literature on OC explores two distinct theories: RBV and agency view. RBV argues that OC is an important source of sustainable competitive advantage, which is considered the cornerstone of its survival. OC enables firms to achieve efficient production and stable business operations and, thereby, provide resilience against adverse exogenous shocks (Hasan and Cheung, 2018; Lev et al., 2009; Uddin et al., 2022). In contrast, agency view suggests that OC is a firm-specific knowledge asset embedded in a firm's key employees; therefore, shareholders and key talents have a claim on the cash flows accruing from OC. Given the risk of key talents leaving firms if the value of external options is greater than the value of staying, cash flow rights related to key talents could fluctuate, thereby increasing the volatility of cash flows and, hence, the firm's risk (Eisfeldt and Papanikolaou, 2013; Danielova et al., 2023). Thus, these two competing arguments regarding OC (i.e. RBV and agency view) would lead to two opposing predictions regarding the relationship between OC and firm-level climate change exposure, as discussed in detail below.

2.1. RBV of OC

RBV argues that fundamental sources and drivers of a firm's competitive advantage and superior performance are associated with the resources and capabilities that the firm controls that are valuable, rare, imperfectly imitable, and not substitutable (Penrose, 1959; Dierickx and Cool, 1989; Barney, 1991; Barney et al., 2001). These resources and capabilities can be considered as bundles of tangible and intangible assets. The literature suggests that intangibles manifesting in a firm's management skills, organisational processes, routines, policies, information systems, knowledge, and culture enhance the firm's capacity to deal with general market movements successfully, making them less susceptible to macroeconomic shocks and systematic risk, such as pandemics (Uddin et al., 2022), and play a role in restoring stability during shocks and restructuring (Mishra, 2014). Furthermore, prior studies have shown that OC captures the largest portion of intangible assets (Corrado et al., 2009), and the nature of climate risk is unpredictable and undiversifiable (Engle et al., 2020).

Extant studies suggest that OC (e.g. business practices, processes, systems, designs, and unique corporate culture) may be viewed as an important firm-specific resource base and can be a source of sustainable competitive advantage (Wernerfelt, 1984; Lev et al., 2009). OC is valuable because it empowers firms to integrate physical and human capital in the most efficient and effective way to create economic value and growth (Lev et al., 2009). Lev et al. (2016) posit that investments in OC ensure productive operations and enhance firms' abilities to adapt to new ways of doing business. Owing to its tacit, idiosyncratic, and proprietary nature, OC (e.g. business processes and practices) cannot be easily imitated by competitors (Prescott and Visscher, 1980), which creates competitive edges for firms. OC, as captured by codified, integrated, and institutionalised firm-specific knowledge of business practices and processes, may help firms to better understand innovative climate mitigation and adaptation technologies and enhance their ability to react and adapt to shifts in the business environment. An anecdotal example of this is Toyota's implementation of lean production through its renowned "Toyota Production System". This approach not only improved efficiency but also reduced the company's carbon footprint by minimizing waste and optimizing energy use.[5]

We expect that firms with high OC will be able to reduce their environmental impact through broad, integrated changes to the production process and demonstrate timely responsiveness and rapid and flexible product innovation. In practice, these changes typically imply that firms adopt production processes that rely on cleaner raw materials and/or use existing inputs more efficiently. Furthermore, OC deepens the resource base or capabilities that enhance a firm's ability to 'integrate, build, and reconfigure internal and external competencies to address rapidly changing environments' (Teece et al., 1997). Under the pressure of stringent environmental regulations and media spotlight, we posit that high OC firms can expand their capacity to understand and assimilate the external knowledge and technical know-how needed to fundamentally transform or re-engineer their production processes (Brown et al., 2022), which would in turn reduce their climate change exposure. Firms with high OC can gain better knowledge about the availability of more complex clean technologies and how to use them efficiently (Hammar and Löfgren, 2010). Taken together, OC not only helps firms develop new processes and product innovation but also promotes their technological absorptive capacity, leading to lower climate change exposure.

Additionally, literature suggests that OC captures superior management practices, capabilities, and skills that may support the implementation of cleaner production measures, primarily by improving the information necessary for the development of new technologies (Attig and El Ghoul, 2018; Frondel et al., 2007). Hence, a better corporate management system can help organisations effectively respond to business risks, including climate change risks. Therefore, from a resource-based perspective, we predict that OC

[4] Anecdotal evidence suggests that OC plays a role in shaping a firm's exposure to climate risk. For instance, Walmart's adaptive supply chain strategies, such as optimizing delivery routes and minimizing energy consumption, help mitigate physical climate risks and maintain operations during environmental disruptions. Similarly, Apple's culture of environmental responsibility drives investments in renewable energy, low-carbon product design, and sustainable manufacturing, enhancing its resilience to climate risks and reducing exposure to regulatory changes.

[5] Refer to the Toyota Production System (TPS) at https://www.toyota-europe.com/about-us/toyota-vision-and-philosophy/toyota-production-system for further information.

is associated with lower firm-level climate risk exposure.

2.2. Agency view of OC

There is, however, reason to expect a positive association between OC and climate risk exposure. Prior literature has attempted to capture intangible capital through market capitalisation (Hall, 2001; Hansen et al., 2005), research and development expenditure (Chan et al., 2001, Hirshleifer et al., 2013), and brand capital (Belo et al., 2014) and has shown a positive link between intangible capital and risk.

Unlike physical capital, in which shareholders own all cash flow rights, the rights are also shared with key talents for investment in OC. Research suggests that OC may escalate agency problems because it is embodied in firms' key talents, shared between the firms and their key talents, and potentially movable across firms through labour mobility, making it riskier than physical capital from the shareholders' perspective (Eisfeldt and Papanikolaou, 2013). The skills gained through knowledge or experience are not specific to one entity or sector and are readily transferable across firms and industries. Hence, this cash flow-sharing motivates key talents to utilise OC to maximise their own benefits (Eisfeldt and Papanikolaou, 2013, 2014). Israelsen and Yonker (2017) suggested that firms with key human capital are riskier because skilled key talents (e.g. scientists who develop high-tech products or managers with crucial relationships with clients or suppliers) possess a larger fraction of the firm's human capital and are difficult, if not impossible, to replace following departure. Importantly, the disproportionate division of cash flows between key talents and shareholders depends on the external options of the key talents. When key talents have better external options, the higher compensation required to retain them reduces the fraction of cash flows that shareholders can extract from OC.

Consistent with this notion, Eisfeldt and Papanikolaou (2013) contended that the superior operating and stock market performance of firms with high OC is a risk premium required by shareholders for the additional risk they take when they invest in those firms. Building on the work of Eisfeldt and Papanikolaou (2013), Boguth et al. (2022) suggested that the fragility of OC, proxied by the size of the top management team, also matters in the stock market. They found that firms with smaller top management teams outperform firms with large teams by 5 % annually, which is attributed to OC concentrated in a smaller number of key talents in small teams being prone to higher risk levels. Furthermore, Leung et al. (2018) found that the positive relationship between OC and expected returns is more pronounced when labour market flexibility allows key talents to take tacit know-how with them and relocate between firms. This finding implies that greater labour mobility and competition in flexible labour markets render OC investment riskier from the shareholders' perspective. Along a similar line, Lustig et al. (2011) demonstrated that because a manager can quit and transfer some of the OC to a new firm, the increased accumulation of OC improves the manager's external options in successful firms. To retain the manager, their compensation needs to be increased in response to positive performance.

Overall, the agency view of OC reveals that firms with high OC, a form of intangible capital, are riskier than those with low OC. Recent studies have highlighted the importance of green innovative technology in mitigating climate change risk, such as by promoting energy efficiency and reducing carbon emission (Sun et al., 2019; Meng et al., 2022; Xin et al., 2022). We conjecture that firms rely on their key talents to build knowledge or increase awareness of climate change within the organisation and utilise OC to develop innovation in climate change mitigation technologies (or green innovation/technology). This assumption is also supported by prior findings by Miao et al. (2021), who discussed the importance of technical innovative talents in improving the efficiency of green innovation, and Sarpong et al. (2023), who presented talented cadres as a key component in producing sustainable innovation. However, the departure of key talents who possess such skills and knowledge of green innovation will be detrimental to these firms, and their long-term activities as key talents cannot be easily replaced within a short period (Israelsen and Yonker, 2017). Therefore, we hypothesise that firms with high levels of OC tend to be associated with higher climate change exposure.

Therefore, based on the above discussion, we developed the following hypotheses regarding the association between OC and firm-level climate change exposure:

Hypothesis 1a: Firms with higher OC have lower exposure to climate change risk

Hypothesis 1b: Firms with higher OC have higher exposure to climate change risk

3. Sample and methods

3.1. Sample selection and data

We used several data sources to construct the dataset for our empirical investigation. We collected financial data from the CRSP-COMPUSTAT merged annual file to construct OC measures and control variables required for the multivariate analyses. The climate change exposure data were taken from the study by Sautner et al. (2023) who conducted a textual analysis of earnings conference call transcripts to measure time-varying firm-level climate change exposure. In addition, we obtained institutional shareholding data from the Thomson Reuters Institutional Holdings (13F) database, governance data from the BoardEx database, analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) database, environmental-related data from the LSEG Refinitiv Workspace database, firm risk data from the WRDS Beta Suite, managerial ability data from Perter Demerjian's website, and product market competition data from the Hoberg-Phillips data library.

The sample period for this study was 2001–2021. The availability of climate change exposure data determined the start year. Our initial sample included all firm-year observations available in the CRSP-COMPUSTAT merged database for 2001–2021 (123,617 firm-years). We then merged the CRSP-COMPUSTAT data with Sautner et al.'s (2023) climate change exposure data and excluded firm-year observations with missing and duplicate values for the dependent, independent, and control variables. These sample criteria yielded unbalanced panel data consisting of 31,580 firm-year observations in the final sample. All continuous variables are winsorised at the 1 % and 99 % level to minimise the effects of outliers. The number of firm-year observations in the regression models varied depending on model-specific data requirements. The sample selection procedure is shown in Panel A of Table 1.

3.2. Measures of OC

Following Peters and Taylor (2017), we estimated OC based on SG&A expenses, which included all non-production costs, i.e. a firm's operating expenses that are not included in the direct costs of production (or cost of goods sold). Extant studies have shown that SG&A expenses contain items that are essential elements to create OC, including employee training, consulting and information technology expenses, marketing, advertising, managerial compensation, research and development, and brand promotion (Eisfeldt and Papanikolaou, 2013; Lev et al., 2009). In other words, a large portion of SG&A expenses is invested into OC through labour expense, which cannot be directly attributed to a particular unit of output and IT, implying that 'any accrued value will be somewhat firm-specific and must be shared with key talent' (Eisfeldt and Papanikolaou, 2013, pp.1380–1381). We followed the method employed by Peters and Taylor (2017) and constructed a firm's stock of OC as the accumulation of a fraction of past SG&A expenditures using the perpetual inventory method, as follows:

$$OC_{i,t} = (1-\delta_0)OC_{i,t-1} + \left(SG\&A_{i,t} \times \lambda_0\right) \tag{1}$$

where $OC_{i,t}$ denotes a firm i's OC at time t, δ_0 denotes the depreciation rate of OC, $SG\&A_{i,t}$ represents the firm i's SG&A expenses at time t, and λ_0 indicates the fraction of SG&A expenses that are invested in OC.

The initial stock of OC was computed as follows:

$$OC_{i,t_0} = \frac{\left(SG\&A_{i,t_0} \times \lambda_0\right)}{g+\delta_0} \tag{2}$$

where g denotes growth in the flow of OC, estimated as the average growth rate of firm-level SG&A expenses. Following prior literature (Eisfeldt and Papanikolaou, 2013; Peters and Taylor, 2017), we used 30 % of SG&A (i.e. $\lambda_0 = 0.30$) to estimate the stock of OC.[6] We also followed the approach used by Peters and Taylor (2017) and used a deprecation rate of 20 % ($\delta_0 = 0.20$). We then scaled the stock of OC by the book value of total assets (*oc_pt_at*) as our proxy for OC in our empirical tests.

As a robustness check, we constructed OC based on Eisfeldt and Papanikolaou's (2013) measure, which involves accumulating the deflated value of SG&A expenses rather than the fraction of past SG&A expenses. Their method was estimated as follows:

$$OC_{i,t} = (1-\delta_{OC})OC_{i,t-1} + \frac{SG\&A_{i,t}}{cpi_t} \tag{3}$$

where cpi_t represents the consumer price index at time t, and the other variables are as defined earlier. OC was then scaled by total assets. In the robustness checks, we used three alternative measures of OC (see Section 6).

3.3. Measures of climate change exposure

We adopted climate change exposure data developed by Sautner et al. (2023) to measure firm-level climate change exposure. These measures capture the occurrence of climate change events or shocks at the firm level and reflect market participants' perceptions of individual companies' exposure to climate change. The measures were constructed using transcripts of earnings conference calls held by publicly listed firms. The authors believe that earnings conference calls are largely forward-looking compared with risk exposure measures that are mainly historical and rely on firms' annual reports. Specifically, a machine learning keyword discovery algorithm was applied to produce different sets of climate change bigrams (word combinations). Each climate change exposure measure was derived using the frequency of certain climate change bigrams in a transcript as a percentage of the total number of bigrams in that transcript, to capture different aspects of climate change risk. Sautner et al. (2023) developed an overall exposure measure and three topic-based measures, i.e. climate-related opportunity and physical and regulatory shocks. In our main analysis, we employed an overall exposure measure, *cc_expo*, and adopted topic-based measures and a more specific risk measure (i.e. *cc_risk*) as alternative proxies, which are discussed in our robustness tests in Section 6. Then, we multiplied the raw data provided Sautner et al. (2023) by 1000 to fit the scale of this measure with the other variables included in the study. Sautner et al.'s (2023) measure is a multi-dimensional, firm-level measure; therefore, it was more capable of capturing climate change exposure than carbon emission, natural disasters, and pollution data (Hossain et al., 2023). This measure has been widely employed by a large contemporary body of climate change research (Hossain et al., 2023; Hossain and Masum, 2022; Mbanyele and Muchenje, 2022).

[6] We follow Peters and Taylor (2017) by using different values of λ, i.e. the percentage of SG&A ranging from 0% to 100%, and find that our results remain qualitatively unchanged.

Table 1
Sample selection, descriptive statistics, and sample distribution.

Panel A: Sample selection procedure	Observations
Firm-year observations from 2001 to 2021 in CRSP-COMPUSTAT Merged Annual file after excluding duplicates	122,313
Firm-year observations from 2001 to 2021 in Sautner, van Lent, Vilkov, and Zhang (2022)'s climate change exposure file after excluding duplicates	62,563
Matched observations after merging the two files above by firm and year	57,243
Less: Missing OC and control variable data	25,663
Final sample	31,580
Final number of unique firms	3,622

Panel B: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	mean	sd	min	p25	p50	p75	max
Dependent variables							
cc_expo ($\times 10^3$)	0.7860	1.9260	0.0000	0.1070	0.2910	0.6840	48.6800
Main independent variable							
oc_pt_at	0.2940	0.3430	0.0000	0.0679	0.1990	0.3870	2.0820
Control variables							
lnat	7.1870	1.9390	2.6980	5.8290	7.1740	8.4950	11.8600
debt	0.2390	0.2190	0.0000	0.0439	0.1990	0.3720	1.0110
cash	0.1890	0.2090	0.0008	0.0341	0.1050	0.2710	0.8760
ppe	0.2080	0.2230	0.0000	0.0432	0.1240	0.2960	0.8980
ebit	0.0412	0.1600	−0.8430	0.0173	0.0638	0.1150	0.3350
capex	0.0381	0.0469	0.0000	0.0010	0.0239	0.0478	0.3020
rd	0.0440	0.0853	0.0000	0.0000	0.0000	0.0530	0.5040
insownship	0.6340	0.2350	0.0113	0.5010	0.6940	0.8100	1.0000
Variables used in additional analysis							
oc_ep_at	0.4790	1.1063	−1.7231	0.0198	0.1144	0.4792	8.2924
oc_pt_ppe	1.6819	2.8106	0.0000	0.2357	0.8159	1.8869	19.2776
oc_indadj	−0.0006	0.3106	−0.3840	−0.1676	−0.0510	0.0481	1.6466
oc_pt_net	0.2212	0.2861	−0.7288	0.0517	0.1495	0.2992	1.7861
cc_risk ($\times 10^3$)	0.0251	0.1046	0.0000	0.0000	0.0000	0.0000	4.6736
rg_expo ($\times 10^3$)	0.0439	0.2587	0.0000	0.0000	0.0000	0.0000	10.3406
ph_expo ($\times 10^3$)	0.0123	0.0816	0.0000	0.0000	0.0000	0.0000	3.0815
sa	−3.0106	0.3155	−3.2964	−3.2427	−3.1270	−2.8832	−1.7802
shr_base	1.2419	1.3573	0.0060	0.1664	0.6704	1.9559	5.6836
roa	0.0797	0.1635	−0.7921	0.0343	0.1047	0.1586	0.3851
tobin's q	2.1201	1.5611	0.6771	1.1678	1.5880	2.4087	9.6363
fra_female_dire	0.1337	0.1150	0.0000	0.0000	0.1250	0.2000	0.4440
prodmktfluid	6.6056	3.4124	0.3284	4.1108	5.9344	8.4034	26.7339
hhi_sale	0.3944	0.2662	0.0000	0.1830	0.3323	0.5245	1.0000
firm_effi	0.3498	0.1837	0.0168	0.2337	0.2923	0.4083	1.0000
opm	0.0431	0.7276	−5.7404	0.0582	0.1336	0.2335	0.6637
duality	0.0206	0.1421	0.0000	0.0000	0.0000	0.0000	1.0000
ma	0.0054	0.1507	−0.2295	−0.0852	−0.0325	0.0481	0.5714
ivol	0.0245	0.0161	0.0022	0.0141	0.0205	0.0301	0.3963
tvol	0.0293	0.0172	0.0022	0.0177	0.0250	0.0360	0.3972
mkt	0.9888	0.4494	−5.8147	0.7227	0.9807	1.2432	4.4077
f_err	4.9068	1.8073	−4.5274	4.0146	5.1049	6.0976	8.3693
e_innov	16.0714	26.8808	0.0000	0.0000	0.0000	27.8261	93.3333
emission	26.0891	31.5636	0.0000	0.0000	9.8684	50.0000	98.0769
e_mgmt	23.4049	36.1548	0.0000	0.0000	0.0000	70.0405	91.3169
e_pillar	25.3507	27.1904	0.0000	0.0000	17.3102	44.7012	90.1498

Panel C: Sample industry distribution and average oc_pt_at by industry

Industry	Sample	%N	Mean oc_pt_at
Consumer nondurables	1,563	4.95	0.3896
Consumer durables	761	2.41	0.2968
Manufacturing	3,520	11.15	0.2482
Oil, gas, and coal extraction and products	1,303	4.13	0.0767
Chemicals and allied products	931	2.95	0.2632
Business equipment	7,055	22.34	0.4054
Telephone and television transmission	760	2.41	0.2343
Utilities	66	0.21	0.0462
Wholesale, retail, and some services	3,460	10.96	0.4343
Healthcare, medical equipment, and drugs	3,409	10.79	0.4321
Finance	4,572	14.48	0.0459
Other	4,180	13.24	0.2391
Total	31,580	100	

Note: Panel A of Table 1 reports sample selection procedure, Panel B presents summary statistics for the variables used in this study, and Panel C shows the sample distribution by Fama-French 12 industry classification and the average value of *oc_pt_at*. The sample period is from 2001 to 2021. Descriptions of the variables are presented in Appendix A.

Research design

To examine the relationship between OC and firm-level climate change exposure, we estimated the following ordinary least-squares (OLS) regression model:

$$cc\_expo_{i,t} = \alpha_0 + \beta_1 oc\_pt\_at_{i,t} + \beta_2 lnat_{i,t} + \beta_3 debt_{i,t} + \beta_4 cash_{i,t} + \beta_5 ppe_{i,t} + \beta_6 ebit_{i,t} + \beta_7 capex_{i,t} + \beta_8 rd_{i,t} + \beta_9 insownship_{i,t} + year + industry + \varepsilon_{i,t} \quad (4)$$

where the dependent variable is climate change exposure (*cc_expo*) (see Section 3.3), and the main independent variable is OC (*oc_pt_at*) (see Section 3.2). We followed the approach taken by Sautner et al. (2023) and included an array of control variables that were found to affect firm-level climate change exposure. Specifically, we controlled for firm size: *lnat*, defined as the natural logarithm of the book value of total assets; *debt*, defined as the sum of the book value of long-term debt and the book value of current liabilities scaled by the book value of total assets; *cash*, measured as the ratio of cash and short-term investments to the book value of total assets; *ppe*, defined as the ratio of property, plant, and equipment to the book value of total assets; *ebit*, proxied by the ratio of earnings before interest and taxes to the book value of assets; *capex*, defined as the ratio of capital expenditure to the book value of total assets; *rd*, measured as the ratio of R&D expenditures to the book value of total assets. We also controlled for institutional investors (*insownship*), measured as the percentage of shares held by institutional investors, since these big investors typically influence climate change disclosure practices (Bolton and Kacperczyk, 2021; Cotter and Najah, 2012; Dyck et al., 2019).[7] The subscripts *i* and *t* indicate the firm and year, respectively. We also included year- and industry-fixed effects to account for time and industry trends. Standard errors are heteroscedasticity-robust in all specifications and are clustered at the firm level. The definition of the variable is presented in Appendix A.

4. Results

4.1. Descriptive statistics

Summary statistics of the variables used in the study are reported in Panel B, Table 1. The mean of climate change exposure (*cc_expo*) was 0.786, with the 25th and 75th percentile values at 0.107 and 0.684, respectively,[8] similar to the findings of Sautner et al. (2023), who reported that the average *cc_expo* is 1.01, with the 25th and 75th percentile values at 0.10 and 0.78, respectively.

Regarding the OC variable, the mean (median) value of OC (*oc_pt_at*) was 0.294 (0.199), and the standard deviation was 0.343. These results are generally comparable to those reported in a prior study by Hasan et al. (2021). The mean (median) value of OC was 0.333 (0.236), and the standard deviation was 0.435 in their study. Regarding the control variables, the mean statistics showed that our sample firms were very large (*lnat* = 7.187), moderately leveraged (*debt* = 0.239), sufficiently liquid (*cash* = 0.189), and somewhat profitable (*ebit* = 0.041). They held an adequate amount of physical assets (*ppe* = 0.208) and had a similar amount of investment in research and development (*rd* = 0.044) and capital expenditure (*capex* = 0.038), along with a high average participation of institutional investors (*insownship* = 0.634) in the sample.

Panel C of Table 1 reports the distribution of our sample across the 12 Fama and French (1997) industry groups. As shown, the business equipment industry (i.e. computers, software, and electronic equipment) comprised the largest share of our sample (22.34 %), and utilities made up the smallest share (0.21 %). Moreover, firms in the wholesale, retail, and service industries had the highest average OC (0.434), whereas those in the highly regulated industries such as utilities and finance had the lowest OC (0.046).

Fig. 1 illustrates the average firm-level climate change exposure (*cc_expo)* for our sample firms from 2001 to 2021. The data reveal a pronounced upward trend in *cc_expo* starting after 2006, consistent with the literature linking this shift to the increased public awareness of climate change following the release of the Stern Review in 2006 (Painter, 2020). Notable spikes in exposure are evident during major external shocks, such as the Global Financial Crisis (GFC) in 2008–2009 and the COVID-19 pandemic in 2020–2021. Starting with an average exposure of 0.45 in 2001, *cc_expo* steadily increased, peaking at 1.42 in 2021. This upward trajectory underscores firms' growing vulnerability to climate-related risks, reflecting heightened sensitivity to both environmental challenges and economic disruptions over the period.

4.2. Correlations and univariate analysis

Panel A of Table 2 presents the Pearson's correlation matrix for the main variables. The pairwise correlations showed negative correlations between our proxies for climate change exposure (*cc_expo*) and OC (*oc_pt_at*), providing preliminary evidence to support Hypothesis 1a. For example, the correlation between *cc_expo* and *oc_pt_at* was −0.0480 and statistically significant at the 1 % level. These negative correlations indicate that firms with high OC have lower exposure to climate change. However, these correlations give a general idea only of the bivariate relations, and do not control for other factors in a rigorous fashion. This underscores the need for

[7] We are grateful to an anonymous reviewer for suggesting this point.

[8] Note that our climate change exposure (*cc_expo*) is multiplied by 10^3, following Sautner et al. (2023). This indicates that the average firm in our sample discussed 'climate change' issues exclusively about 0.0786% of the time during their corporate conference calls.

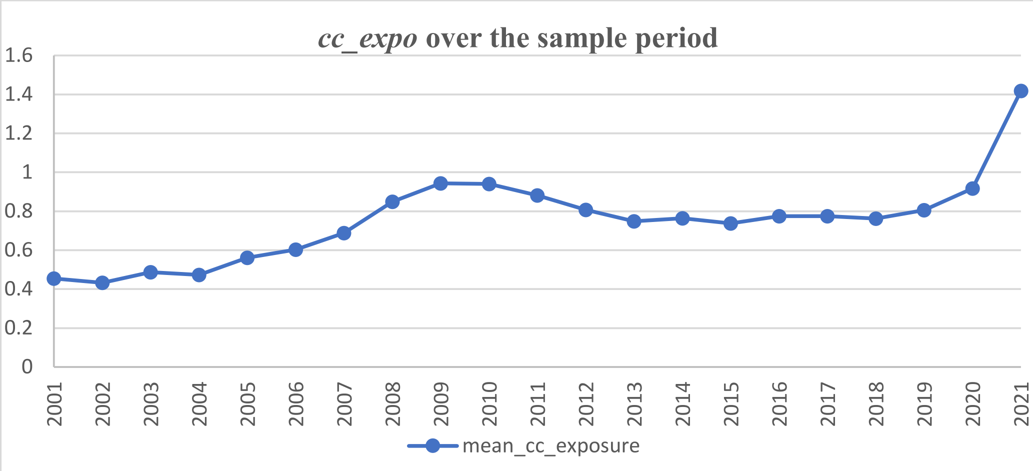

Fig. 1. Fim-level climate change exposure (*cc_expo*) over the sample period.

further analysis, which is addressed through our regression estimates presented in the baseline model.

Furthermore, our results showed that firm size (*lnat*) and profitability (*ebit*) were negatively correlated ($p < 0.01$) with the climate change exposure (*cc_expo*), consistent with Almaghrabi (2023) who showed that climate change exposure had a negative and significant correlation with financial performance and size. We also found that physical assets (*ppe*) and capital expenditure (*capex*) was positively correlated ($p < 0.01$) with climate change exposure (*cc_expo*) whereas research and development (*rd*) showed a negative corelation with *cc_expo*. These findings are consistent with those of Heo (2021). Moreover, in line with findings of Hasan and Cheung (2023), we found that OC (*oc_pt_at*) was strongly negatively correlated ($p < 0.01$) with firm size (*lnat*), leverage (*debt*), physical assets (*ppe*), and profitability (*ebit*) but positively correlated ($p < 0.01$) with liquidity (*cash*) and research and development (*rd*). The negative and significant correlation between institutional ownership (*insownship*) and climate change exposure (*cc_expo*) aligns with findings from previous studies, such as Cotter and Najah (2012). Their research highlights that the influence of institutional investors is positively associated with increased climate change disclosure, which could in turn reduce a firm's exposure to climate-related risks. This suggests that institutional investors play a crucial role in promoting transparency and mitigating a firm's vulnerability to climate change. Lastly, the variance inflation factor (VIF) values reported in the last Column of Table 2, Panel A, are well below the critical value of 10, suggesting that multicollinearity is not a major concern for our study (Wooldridge, 2006).

Panel B of Table 2 presents the univariate mean differences in climate change and control variables between the subsamples of firms with high (*oc_pt_at* > median) and low (*oc_pt_at* < median) OC. *cc_expo* was significantly lower for firms with high OC than for those with low OC, which also supports Hypothesis 1a. Moreover, firms with low OC tended to be larger (*lnat*), more leveraged (*debt*), highly profitable (*ebit*), had more physical assets (*ppe*) and institutional investors (*insownship*), and invested more in capital expenditure (*capex*), whereas they were likely to hold less cash (*cash*) and invest less in research and development (*rd*).

4.3. Baseline results

Panel A of Table 3 presents the regression results for the relationship between OC and climate change exposure. The main independent variable was OC (*oc_pt_at*). We used firm-level climate change exposure as dependent variable (*cc_expo*). The coefficient of *oc_pt_at* was negative and significant at the 1 % level, implying that firms with high OC are exposed to less climate change risk. In terms of economic significance, for example, in Column (3), the coefficient for *oc_pt_at* was −0.2273, which suggests that a one-standard-deviation increase in OC reduces a firm's exposure to climate change by approximately 7.80 % (i.e. -0.2273×0.3430), which may be further interpreted as a decrease in climate change exposure by 9.92 % relative to the average climate change exposure in the sample (0.078/0.7860).[9] Thus, the findings of our regression models are not only statistically significant but also economically meaningful.

Regarding the control variables, we found that more leveraged (*debt*), and more profitable firms (*ebit*) and firms with more institutional investors (*insownship*) were exposed to less climate change risk, whereas firms with more cash holdings (*cash*) and long-term assets (*ppe*) tended to face increased climate change risk.[10] Overall, the results in Table 3 provide strong support for Hypothesis 1a

[9] We multiplied climate change exposure by 10^3 in the raw data from Sautner et al. (2023) to ensure that *cc_expo* is comparable to other variables in our study, following the approach outlined by Sautner et al. (2023). The economic significance of climate change exposure, as interpreted by Sautner et al. (2023), is based on their transformed measure of exposure.

[10] In a robustness check, we also controlled for regulatory shocks related to climate change, as captured in the transcripts of earnings conference calls and calculated by Sautner et al. (2023), to address concerns that our results may be confounded by regulatory changes. Our findings remain qualitatively unchanged. We thank the anonymous reviewer for this suggestion.

Table 2
Correlation and univariate analysis.

Panel A: Correlation matrix

Variables	cc_expo	oc_pt_at	lnat	debt	cash	ppe	ebit	capex	rd	insownship	VIF
cc_expo	1										
oc_pt_at	−0.0480***	1									1.37
lnat	−0.0344***	−0.4610***	1								1.63
debt	−0.0037	−0.1960***	0.2740***	1							1.24
cash	−0.0093	0.2960***	−0.4330***	−0.3470***	1						1.85
ppe	0.1050***	−0.1230***	0.1030***	0.2350***	−0.2920***	1					2.20
ebit	−0.0398***	−0.2660***	0.3510***	0.0393***	−0.3880***	0.1070***	1				1.69
capex	0.0498***	−0.0249***	−0.0222***	0.0388***	−0.1260***	0.6880***	0.0928***	1			2.00
rd	−0.0205***	0.3930***	−0.4020***	−0.1900***	0.6000***	−0.2220***	−0.5940***	−0.1000***	1		2.19
insownship	−0.0454***	−0.2190***	0.3460***	0.0718***	−0.1260***	−0.0138*	0.2900***	0.0012	−0.1780***	1	1.20

Panel B: Univariate analysis

Variables	Low OC (oc_pa_at < median)	High OC (oc_pa_at > median)	Diff.
cc_expo	0.8687	0.7025	0.1661***
lnat	7.9339	6.4397	1.4943***
debt	0.2882	0.1897	0.0985***
cash	0.1307	0.2470	−0.1163***
ppe	0.2474	0.1686	0.0787***
ebit	0.0490	0.0334	0.0155***
capex	0.0408	0.0354	0.0054***
rd	0.0193	0.0687	−0.0493***
insownship	0.6511	0.6165	0.0346***

Note: Panel A of Table 2 reports Pearson correlations between the key variables. Panel B presents mean difference test of variables between high and low organisation capital groups. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively. Variable definitions are provided in the Appendix A.

that OC, as an intangible asset, helps mitigate a firm's climate change exposure substantially.

As discussed in Section 3.2, OC comprises firms' accumulated stock of knowledge, human capital, brand capital, business processes, and systems that improve operational efficiency and firm value. To better understand the driving forces behind the total OC, we followed the approach used by Hasan et al. (2021) and decomposed OC into three components: OC related to brand capital investment (*oc_bc_at*), human capital investment (*oc_hc_at*), and business processes and systems investment (*oc_ps_at*). Following the estimation procedure specified in Equations (1) and (2), we capitalised staff expenses (Compustat item: *xlr*) into the human capital component of OC and advertising expenses (Compustat item: *xad*) into the brand capital component. We then calculated the difference between the total OC (*oc_pt_at*) and sum of *oc_bc_at* and *oc_hc_at* as a proxy for OC due to firm-specific business processes and systems investment (*oc_ps_at*). Our results are presented in Panel B, Table 3. We found a negative and significant ($p < 0.01$) relationship between the different components of OC and climate change exposure across all cases.

4.4. Controlling for endogeneity

Our analysis, so far, provides robust evidence that firms with high OC are exposed to less climate change exposure. However, there may be concerns that our regression models are affected by omitted variables correlated with OC and climate change exposure. A reverse causality issue may also arise, where firms facing lower climate exposure may have more resources to invest in OC. In this section, we attempt to mitigate these issues.

4.4.1. 2SLS regression with Lewbel's (2012) approach

We employed an IV approach using novel heteroscedasticity-based instruments generated using the method proposed by Lewbel (2012). This method does not rely on an external instrument but uses heterogeneity in the error term of the first-stage regression to construct instruments from within the existing model. Lewbel (2012) suggested that this method can address endogeneity issues in the absence of external instruments or when external instruments are weak. More specifically, this technique exploits model heteroscedasticity to generate instruments using available regressors, and identification can be achieved by observing a vector of exogenous regressors that are uncorrelated with the covariance of heteroscedastic errors, which is a feature of many models in which error correlations are due to an unobserved common factor. Lewbel's (2012) technique has been widely employed in recent studies to address the endogeneity problem (Kao et al., 2018; Zheng et al., 2023; Hasan and Cheung, 2023). The simplified version of Lewbel's (2012) approach is as follows:

$$y_1 = X'\theta_1 + y_2\rho + \varepsilon_1 \tag{5}$$

$$y_2 = X'\theta_2 + \varepsilon_2 \tag{6}$$

where y_1 and y_2 are scalars of observed endogenous variables, X is a matrix of observed exogenous regressors, and $\varepsilon = (\varepsilon_1, \varepsilon_2)$ is a (2 × 1) vector of unobserved errors. Assuming that there is no element of X that can be used as an instrument of y_2, Lewbel's (2012) approach provides generated instruments from the sample data that can be constructed by exploiting information contained in the heteroscedasticity of ε_2. Let K be some or all of the elements of X. We obtained θ_1 and θ_2 by estimating an ordinary linear 2SLS regression of y_1 on X and y_2, using X and $(K - \overline{K})\widehat{\varepsilon_2}$ as instruments, where $\overline{K}$ is the sample mean of K. Test of heteroscedasticity, over-identification, and weak instruments can be conducted to validate the quality of the generated instruments.

After generating a set of instruments based on Lewbel's (2012) approach, we selected the instruments from the generated instruments and applied the standard IV estimation method to the selected instruments. Table 4 presents the IV regression results. In the first stage (see Column (1)), when the instruments were generated, we labelled them with **e* and selected *insownship*e* and *debt*e*. These instruments were selected as their coefficients were statistically significant, indicating that they are useful in explaining OC. Moreover, the first-stage *F*-test indicated that weak instrument problem was unlikely ($p < 0.01$). The under-identification test results showed that the instruments were relevant, as the Kliebergen-Paap rk LM statistic was significant at the 1 % level. The second-stage p-value for the Hansen *J*-statistic for over-identification indicated that our instruments were sufficiently uncorrelated with the error term. The results for the second-stage regressions are reported in Column (2), Table 4. We found that the coefficients of *oc_pt_at* remained negative and statistically significant, corroborating the findings of the main analysis.

4.4.2. Entropy balancing estimates

We followed extant research (Hasan and Uddin, 2022; Hossain et al., 2023; Hossain and Masum, 2022; Hasan and Cheung, 2023) and employed entropy balancing estimates to further address endogeneity concerns. This technique is increasingly being utilised in contemporary accounting and finance studies due to two advantages (Hainmueller, 2012): first, this method mitigates the possibility that design choices could affect our results by adjusting for random and systematic inequalities in the variable distribution; second, this approach helps retain the original sample size and improves estimation efficiency. Specifically, we split the sample into treatment (high OC) and control (low OC) groups, based on the sample median *oc_pt_at*. The entropy-balancing technique then reweighs each observation of the control group to achieve a covariate balance in the two groups of high- and low OC firms in terms of the mean, variance, and skewness.

Table 5 presents the results. Panel A shows that the entropy-balanced weight adjustment improved the covariate balance used in our multivariate analysis. In Panel B, we re-estimated the regression using an entropy-balanced sample. *oc_pt_at* was negatively and significantly correlated with *cc_expo* in the matched sample ($p < 0.01$), easing concerns of endogeneity bias.

Table 3
Organisation capital and climate change exposure: Baseline regression results.

Panel A	(1)	(2)	(3)
Variables	cc_expo	cc_expo	cc_expo
oc_pt_at	**−0.4379*****	**−0.2009*****	**−0.2273*****
	(0.032)	(0.033)	(0.034)
lnat	−0.0698***	0.0080	−0.0083
	(0.006)	(0.006)	(0.007)
debt	−0.4160***	−0.0984	−0.2192***
	(0.048)	(0.060)	(0.059)
cash	0.0221	0.5894***	0.5408***
	(0.072)	(0.069)	(0.069)
ppe	1.1796***	1.0747***	1.0218***
	(0.081)	(0.099)	(0.099)
ebit	−0.5766***	−0.8663***	−0.6935***
	(0.105)	(0.094)	(0.095)
capex	−1.3775***	−0.6318	0.0494
	(0.425)	(0.411)	(0.413)
rd	−0.7616***	−1.1765***	−1.0011***
	(0.185)	(0.175)	(0.174)
insownship	−0.2896***	−0.2425***	−0.3172***
	(0.056)	(0.051)	(0.053)
Constant	1.5594***	0.7407***	0.9216***
	(0.075)	(0.060)	(0.063)
Observations	31,580	31,577	31,577
R-squared	0.037	0.344	0.356
Year FE	Yes	No	Yes
Industry FE	No	Yes	Yes

Panel B	(1)	(2)	(3)
Variables	cc_expo	cc_expo	cc_expo
oc_hc_at	**−0.3860*****		
	(0.103)		
oc_bc_at		**−0.7195*****	
		(0.091)	
oc_ps_at			**−0.1617*****
			(0.031)
Observations	29,101	29,101	29,101
R-squared	0.357	0.357	0.357
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Note: Panel A of Table 3 presents the regression estimates analysing Eq. (4) on the relationship between organisation capital and firm-level climate change exposure. In Panel B, we follow the methodology outlined by Hasan et al. (2021) and decompose organisation capital into three components: OC related to human capital investment (*oc_hc_at*), brand capital investment (*oc_bc_at*), and business processes and systems investment (*oc_ps_at*) and then rerun Eq. (4). Robust standard errors are reported in parentheses. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. The variable descriptions are in Appendix 1. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

4.4.3. *Other endogeneity tests*

We conducted two additional tests to mitigate endogeneity concerns. First, following the approach used by Hasan and Uddin (2022), we ran a change regression analysis. This approach reduces potential noise in the regression model by eliminating unobserved fixed effects over time. Therefore, it could be a powerful tool for explaining the incremental effects of OC on firm-level climate change exposure. Panel A of Table 6 shows that an increase in *oc_pt_at* was associated with a decrease in firm-level climate exposure, providing evidence that our estimates are unlikely to be driven by an endogeneity problem.

Second, we conducted a test suggested by Oster (2019) to further mitigate endogeneity concerns arising from omitted variable bias. Using this technique, the stability of the coefficients combined with the R-squares from regressions with and without controls was utilised to construct a new identifiable set. If zero is not present in the identifiable set, then the null hypothesis that an omitted variable bias drives the results can be rejected.

The identified set is defined as $\left[\widetilde{\beta}, \beta^{*'}\right]$, where $\beta^{*'}$ is derived using the following formula:

$$\beta^{*'} = \widetilde{\beta} - \delta\left[\dot{\beta} - \widetilde{\beta}\right]\frac{R_{max} - \widetilde{R}}{\widetilde{R} - \dot{R}} \tag{7}$$

where $\widetilde{\beta}$ and $\widetilde{R}$ are the estimated coefficients of our main variable of interest (*oc_pt_at*) and the R-squared value from the baseline model with all controls, respectively, and $\dot{\beta}$ and $\dot{R}$ are their counterparts for the regression without any control variables and fixed effects.

Table 4
Endogeneity test: Two-stage instrumental-variable estimation.

	Lewbel (2012) approach – First stage (1)	Lewbel (2012) approach – Second stage (2)
Variables	oc_pt_at	cc_expo
*insownship*e*	−1.5545***	
	(0.029)	
*debt*e*	−0.4709***	
	(0.070)	
oc_pt_at		**−0.2479*****
		(0.062)
Control variables	Yes	Yes
Observations	31,577	31,577
R-squared		0.015
First stage F-test	1888.35***	
Underidentification test		
Kliebergen-Paap rk LM statistic		702.255***
Weak identification test		
Cragg-Donald Wald F Statistic		8391.002
Overidentification test		
Hansen *J*-statistic (*p*-value)		0.9424
Year FE	Yes	Yes
Industry FE	Yes	Yes

Note: Table 4 presents the two-stage instrumental-variable regression results of the relationship between organisation capital and firm-level climate change exposure to address endogeneity concerns. In Column (1), we follow Lewbel's (2012) approach and generate instrumental variables. Two exogenous variables are used for this purpose; they are *insownship* and *debt*. The instruments so generated are labelled *insownship*e* and *debt*e*, respectively. Column (2) presents the second-stage results from Lewbel's (2012) approach. Robust standard errors are reported in parentheses. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively. The variable descriptions are in Appendix 1.

Following prior literature (Gao and Huang, 2020; Hasan and Uddin, 2022; Hossain and Masum, 2022), we set $\delta = 1$. In addition, we used the more conservative Mian and Sufi (2014) value of $R_{max} = \min\left(2.2\widetilde{R}, 1\right)$ in the upper panel and the extreme value from Oster (2019) of $R_{max} = 1$ in the lower panel. Panel B of Table 6 shows that our estimated bounded sets for *oc_pt_at* do not include 0, suggesting that inferences from our OLS specifications presented in Table 3 are unlikely to suffer from an omitted variable bias.

5. Mediation and suppression effect of OC

Our findings in the previous sections demonstrate that firms with high OC tend to face lower climate risk than those with low OC. In this section, we further investigated the mediating role of OC, that is, whether it can mediate the potential relationship between firm-specific factors and firm-level climate change exposure. We conduct a mediation test following the established framework proposed by Baron and Kenny (1986), using the following equations:

$$cc\_expo_{i,t} = \beta_0 + \beta_1 Firm\,Factors_{i,t-1} + \eta' control_{i,t-1} + \theta' year_{t-1} + \varepsilon_{i,t-1} \tag{8-1}$$

$$oc\_pt\_at_{i,t-1} = \alpha_0 + \alpha_1 FirmFactors_{i,t-1} + \eta' control_{i,t-1} + \theta' year_{t-1} + \varepsilon_{i,t-1} \tag{8-2}$$

$$cc\_expo_{i,t} = \beta_0' + \beta_1' FirmFactors_{i,t-1} + \beta_2 oc\_pt\_at_{i,t-1} + \eta' control_{i,t-1} + \theta' year_{t-1} + \varepsilon_{i,t-1} \tag{8-3}$$

where all control variables were the same as those defined in baseline Equation (4). The variable *Firm Factors* represented the ten firm-specific factors tested: financial constraints, analyst forecast quality, agency cost, financial leverage, corporate governance, firm performance, efficiency, operating performance, product market competition, environmental commitment and initiative. Equation (8-1) shows the total effect of these ten tested firm-specific factors on climate exchange exposure (measured by β_1). Equation (8-2) shows the direct relationship between these firm-specific factors and the mediator OC (measured by α_1). Lastly, Equation (8-3) shows the direct effect of these ten characteristics on climate change exposure while controlling for OC (measured by β_1') and the relationship between the mediator OC and climate change exposure (measured by β_2). A complete mediation occurs when the effect of *Firm Factors* on *cc_expo* decreases to zero with OC in the model ($\beta_1' = 0$), while a partial medication occurs when the effect of *Firm Factors* on *cc_expo* decreases by a nontrivial amount when OC is included in the model.

To confirm the mediation effect, we further examine our results through Sobel tests. The null hypothesis for the Sobel test indicates the indirect effect of OC on the potential impact of *Firm Factors* and *cc_expo* ($a_1 \times \beta_2$) is zero (or equivalent, $\beta_1 - \beta_1' = 0$). The rejection of a null hypothesis in the Sobel test would confirm the existence of a mediation effect based on Baron and Kenny (1986)'s approach. Following prior research (e.g., Zhang et al., 2024), we lag firm-specific factors, OC, and control variables by one period. This temporal adjustment ensures that firm-specific factors precede climate change exposure (i.e. past values of firm-specific variables influence current climate change exposure), thereby reducing the risk of simultaneity bias and improving causal inference. However, our

Table 5
Endogeneity test: Entropy balancing estimate.

Panel A: Covariate balance

Before balancing

	Treat (High OC)			Control (Low OC)		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
lnat	6.4680	3.3880	0.3148	7.9050	3.0990	−0.0067
debt	0.1931	0.0441	1.3720	0.2848	0.0478	0.7195
cash	0.2476	0.0476	0.9851	0.1302	0.0325	2.3530
ppe	0.1682	0.0215	1.6280	0.2478	0.0744	0.9616
ebit	0.0325	0.0363	−2.2250	0.0499	0.0147	−3.4300
capex	0.0352	0.0011	2.7580	0.0410	0.0033	2.4590
rd	0.0687	0.0094	2.1670	0.0193	0.0039	5.4620
insownship	0.6185	0.0602	−0.7789	0.6490	0.0496	−0.9192

After balancing

	Treat (High OC)			Control (Low OC)		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness
lnat	6.4680	3.3880	0.3148	6.4680	3.3880	0.3148
debt	0.1931	0.0441	1.3720	0.1931	0.0441	1.3720
cash	0.2476	0.0476	0.9851	0.2476	0.0476	0.9851
ppe	0.1682	0.0215	1.6280	0.1682	0.0215	1.6280
ebit	0.0325	0.0363	−2.2250	0.0325	0.0363	−2.2250
capex	0.0352	0.0011	2.7580	0.0352	0.0011	2.7580
rd	0.0687	0.0094	2.1670	0.0687	0.0094	2.1670
insownship	0.6185	0.0602	−0.7789	0.6185	0.0602	−0.7789

Panel B: Regression results based on the entropy balanced sample

Variables	(1) cc_expo	(2) cc_expo	(3) cc_expo
oc_pt_at	**−0.5996*****	**−0.1997*****	**−0.2609*****
	(0.081)	(0.065)	(0.065)
lnat	−0.0389***	0.0145	−0.0016
	(0.012)	(0.014)	(0.015)
debt	−0.6593***	−0.2814***	−0.3505***
	(0.095)	(0.087)	(0.083)
cash	0.1476	0.7894***	0.7742***
	(0.144)	(0.139)	(0.137)
ppe	1.2305***	1.2432***	1.2289***
	(0.210)	(0.252)	(0.242)
ebit	−1.2052***	−1.0134***	−0.9009***
	(0.300)	(0.185)	(0.189)
capex	−0.1987	−0.6213	0.1810
	(0.851)	(0.797)	(0.753)
rd	−2.2529***	−1.5521***	−1.3893***
	(0.368)	(0.311)	(0.317)
insownship	−0.4326***	−0.3293***	−0.3796***
	(0.113)	(0.097)	(0.097)
Constant	1.6530***	0.8457***	0.9766***
	(0.146)	(0.143)	(0.145)
Observations	31,580	31,577	31,577
R-squared	0.038	0.352	0.361
Year FE	Yes	No	Yes
Industry FE	No	Yes	Yes

Note: Table 5 presents the entropy balancing regression estimates. Panel A reports the diagnostics test to show that convergence is achieved in all three dimensions (e.g., mean, variance, and skewness) following Hainmueller (2012). Panel B reports the regression results based on the entropy balanced sample. Robust standard errors are reported in parentheses. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. The variable descriptions are in Appendix 1. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

analyses reveal that the direct effects of certain firm-specific factors on climate change exposure become stronger when OC is included in the model. This suggests that OC functions as a suppressor variable, rather than a mediator, in these relationships. According to Conger (1974, p.36–37): “a suppressor variable is defined to be a variable which increases the predictive validity of another variable (or set of variables) by its inclusion in a regression equation.” This is the opposite of a mediator as the magnitude of the relationship becomes larger when a third variable is included in the model (MacKinnon et al., 2000; De Blick et al., 2024). Results of mediation and suppression analyses are presented in Table 7.

Table 6
Other endogeneity tests.

Panel A: Change regression analysis			
Variables	(1) Δcc_expo	(2) Δcc_expo	(3) Δcc_expo
Δoc_pt_at	**−0.2493*****	**−0.2242*****	**−0.2185*****
	(0.076)	(0.076)	(0.076)
Δlnat	−0.1581***	−0.1291***	−0.1453***
	(0.035)	(0.035)	(0.036)
Δdebt	−0.0215	−0.0410	−0.0154
	(0.071)	(0.073)	(0.073)
Δcash	0.0528	0.0024	0.0392
	(0.087)	(0.086)	(0.087)
Δppe	−0.2080	−0.3102	−0.1859
	(0.213)	(0.213)	(0.214)
Δebit	0.0070	0.0806	0.0131
	(0.085)	(0.085)	(0.085)
Δcapex	0.1835	0.2812	0.1846
	(0.242)	(0.245)	(0.247)
Δrd	−0.0392	0.0780	−0.0660
	(0.194)	(0.194)	(0.195)
Δinsownship	0.1583***	0.0574	0.1732***
	(0.057)	(0.056)	(0.058)
Constant	0.0695***	0.0684***	0.0681***
	(0.006)	(0.006)	(0.006)
Observations	27,460	27,456	27,456
R-squared	0.023	0.018	0.039
Year FE	Yes	No	Yes
Industry	No	Yes	Yes

Panel B: Tests for omitted variable bias using Oster (2019)			
	Dependent variable		
	(1)	(2)	(3)
Variable of Interest: oc_pt_at	cc_expo	cc_expo	cc_expo
Without controls			
Beta	−0.0378	−0.0335	−0.0047
R-squared	0.0132	0.3349	0.3468
With controls			
Beta	−0.0740	−0.0650	−0.0363
R-squared	0.0339	0.3444	0.3558
Rmax	0.0746	0.7577	0.7828
Oster condition	Assume δ=1; RMAX=min (2.2 $\tilde{R}$,1)		
Identified set	[-0.2698, −0.4379]	[-0.2698, −0.2009]	[-0.2698, −0.2273]
Includes zero?	No	No	No
Year FE	Yes	No	Yes
Industry FE	No	Yes	Yes

Note: Panel A of Table 6 reports results of the change in the level of climate change exposure on change in organisation capital and change in control variables. Panel B presents the Oster (2019) bounds for our variable of interest as depicted in our baseline regression in Table 3. We present results based on the Mian and Sufi (2014) assumptions of Oster bounds using $\delta = 1$ and RMAX = min (2.2 $\tilde{R}$,1). Robust standard errors are reported in parentheses. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. The variable descriptions are in Appendix 1. *, **, and *** represent significance at the 10 %, 5 % and 1 % level, respectively.

5.1. *Financial constraints and corporate governance*

Financial constraints are measured using the *Size-Age* (*sa*) index (Hadlock and Pierce, 2010). Higher *sa* index indicates greater financial constraints. Panel A, Columns (1) – (3) present the results for the financial constraints. Column (1) shows the total effect of financial constraints on exposure to climate change. The estimated coefficient for financial constraints (i.e. β_1) was negative and significant. While it might seem counterintuitive, the negative association between financial constraints and climate change exposure can be explained by the distinctive environmental innovation behaviors of financially constrained firms. These firms are typically smaller in size and face greater difficulty in accessing external financing (Kaplan and Zingales, 1997; Chang et al., 2024). However, the absence of external funding does not appear to be a major barrier to eco-innovation (Cecere et al., 2020). On the contrary, many eco-innovative solutions are driven by small and medium-sized enterprises (SMEs), which play a strategic role in advancing sustainable development (Ghisetti et al., 2017). These findings suggest that financially constrained firms may experience lower climate risk, potentially due to their proactive adoption of environmental innovations. Column (2) reports the direct relationship between financial constraints and OC. We found a positive and significant relationship (i.e. α_1), supporting the notion that financially constrained firms tend to invest more in OC, so as to be perceived optimistically by the market (Kim et al., 2021). By making visible and hard-to-imitate investments, a firm can send a positive signal to external stakeholders about its prospects and capabilities. Column (3) presents the mediation results. We found a weakly significant (at the 10 % level) direct effect of financial constraint on exposure to climate change (i.e. β_1') and a negative and statistically significant effect of OC on exposure to climate change (i.e. β_2), implying a partial mediation effect of OC. In terms of magnitude, the direct effect is -0.1846 but decreases to -0.3382 for the total effect. This suggests that investment in OC enables financial constrained firms to further reduce their climate change exposure. The significant Sobel test z-values at the 1 % level also confirmed the presence of partial mediation.

Following Gull et al. (2023), we use the proportion of female directors (*fra_female_dire*), representing the fraction of female directors on a board, to measure corporate governance. Table 7, Panel A, Columns (4) – (6) present the results for corporate governance. Column (4) shows that the total effect of *fra_female_dire* on *cc_expo* was negative and significant (i.e. β_1). This finding is consistent with prior studies (e.g., Atif et al., 2021), which note that board gender diversity enhances corporate environmental performance. As shown in Column (5), we found a positive and significant relationship (i.e. α_1) between *fra_female_dire* and OC, suggesting that firms with strong corporate governance are more likely to invest in OC. As can be seen in Column (6), we observed a negative and significant direct effect of *fra_female_dire* on *cc_expo* (i.e. β_1') and a negative and statistically significant effect of OC on *cc_expo* at the 1 % level (i.e. β_2). The stronger negative total effect (i.e. β_1) compared to the direct effect (i.e. β_1') shows that OC investment in firms with effective corporate governance can further amplify the reduction in climate change exposure. The results indicate that OC partially mediates the relationship between corporate governance and climate change exposure. This finding is further supported by significant Sobel test z-values at the 1 % level.

5.2. Firm performance

To measure firms' financial performance, we adopted *roa* and *tobin's q*. Panel B presents the results for firm performance. As shown in Columns (1) and (4), the total effects of *roa* and *tobin's q* on climate change exposure were negative and significant (i.e. β_1), consistent with the literature suggesting that more profitable firms are likely to provide greater ESG or climate disclosure (Yu et al., 2018), which can lead to lower climate change exposure. As shown in Columns (2) and (5), we found a positive and significant relationship (i.e. α_1) between firm performance (measured by both *roa* and *tobin's q*) and OC. This finding implies that profitable firms invest more in OC. The mediation results in Columns (3) and (6) show a negative and significant direct effect of *roa* and *tobin's q* on climate change exposure (i.e. β_1'). The direct versus total effect comparisons indicate that the mediating role of OC results in greater reductions in climate change exposure. More importantly, we observed a negative and statistically significant effect of OC on climate change exposure at the 1 % level (i.e. β_2), implying that profitable firms consider OC as a mediator to alleviate their climate change exposure. The significant Sobel test z-values at the 1 % level indicate a partial mediation effect of OC on the relationship between firm performance and climate change exposure.

5.3. Financial efficiency and operating performance

Firm efficiency data is sourced from Demerjian et al. (2012), who employed the Data Envelopment Analysis (DEA) technique to calculate firms' overall operational efficiency (*firm_effi*).[11] We use operating profit margin (*opm*), calculated as the ratio of operating income before depreciation to total sales, to proxy for operating performance.

Panel C of Table 7 presents the results. As shown in Columns (1) and (4), the total effects of *firm_effi* and *opm* on exposure to climate change were negative and significant (i.e. β_1). We argue that firms that maximize efficiency and maintain strong operating performance are better equipped to mitigate the physical, regulatory, and transitional risks associated with climate-related disruptions. Efficient and productive firms have greater financial flexibility and slack resources, enabling them to invest in environmental initiatives that address these risks. Supporting this view, a substantial body of research shows that firms with stronger financial performance are more likely to allocate resources toward CSR activities (McGuire et al., 1988; Waddock and Graves, 1997). Columns (2) and (5) report the direct relationship between *firm_effi* and OC, and between *opm* and OC, respectively. We found a positive and significant relationship (i.e. α_1), indicating that efficient and productive firms are more likely to invest in OC. Columns (3) and (6) present the mediation results. We observed a negative and significant direct effect of *firm_effi* and *opm* on exposure to climate change (i.e. β_1') and a negative and statistically significant effect of OC on exposure to climate change (i.e. β_2), implying a partial mediation effect of OC. As mentioned in Section 5.2, a stronger negative total effect further suggests that the reduction in climate change exposure is amplified by the mediating role of OC. The significant Sobel test z-values at the 1 % level also confirmed the presence of partial mediation.

5.4. Agency costs

To measure agency costs, we first considered the shareholder base (*shr-base*), calculated as the natural logarithm of one plus

[11] DEA is a nonparametric linear programming method used to calculate the efficiency of decision-making units (DMUs) by assessing the quantity of output produced given certain levels of input. DEA allows for multiple comparisons between a set of homogeneous units and does not assume any specific functional relationship between inputs and outputs, making it a flexible tool for measuring efficiency without requiring a predefined model of the input–output relationship.

Table 7
The mediation effect of organisation capital.

Panel A: Financial constraints and corporate governance

Variables	cc_expo_t sa_{t-1} (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t $fra\_female\_dire_{t-1}$ (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
sa_{t-1}/$fra\_female\_dire_{t-1}$	−0.3382*** (0.110)	0.3230*** (0.016)	−0.1846* (0.111)	−1.0370*** (0.127)	0.4736*** (0.018)	−0.8459*** (0.128)
$oc\_pt\_at_{t-1}$			−0.4755*** (0.055)			−0.4036*** (0.044)
Sobel test	$\beta_1 = -0.3382^{***}\alpha_1 = 0.3230^{***},\beta_2 = -0.4755^{***}\beta_1' = -0.1846^{*}$Sobel test z-stat = -7.997***			$\beta_1 = -1.0370^{***}\alpha_1 = 0.4736^{***},\beta_2 = -0.4036^{***}\beta_1' = -0.8459^{***}$Sobel test z-stat = -8.616 ***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Mediation effect	Partial mediation			Partial mediation		
Observations	16,201			25,393		

Panel B: Firm performance

Variables	cc_expo_t tobin's q_{t-1} (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t roa_{t-1} (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
tobin's q_{t-1}/roa_{t-1}	−0.0279*** (0.009)	0.0129*** (0.001)	−0.0224** (0.009)	−2.7495*** (0.484)	2.1167*** (0.071)	−1.8161*** (0.491)
$oc\_pt\_at_{t-1}$			−0.4261*** (0.040)			−0.4410*** (0.042)
Sobel test	$\beta_1 = -0.0279^{***}\alpha_1 = 0.0129^{***},\beta_2 = -0.4261^{***}\beta_1' = -0.0224^{**}$Sobel test z-stat = −6.956***			$\beta_1 = -2.7495^{***}\alpha_1 = 2.1167^{***},\beta_2 = -0.4410^{***}\beta_1' = -1.8161^{***}$Sobel test z-stat = −9.855***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Mediation effect	Partial mediation			Partial mediation		
Observations	27,357			26,169		

Panel C: Firm efficiency and operating performance

Variables	cc_expo_t $firm\_effi_{t-1}$ (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t opm_{t-1} (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
$firm\_effi_{t-1}$/opm_{t-1}	−0.6660*** (0.108)	0.3104*** (0.016)	−0.5321*** (0.109)	−0.2173*** (0.024)	0.0344*** (0.004)	−0.2012*** (0.024)
$oc\_pt\_at_{t-1}$			−0.4312*** (0.054)			−0.4661*** (0.042)
Sobel test	$\beta_1 = -0.6660^{***}\alpha_1 = 0.3104^{***},\beta_2 = -0.4312^{***}\beta_1' = -0.5321^{***}$Sobel test z-stat = −7.352***			$\beta_1 = -0.2173^{***}\alpha_1 = 0.0344^{***},\beta_2 = -0.4661^{***}\beta_1' = -0.2012^{***}$Sobel test z-stat = −7.258***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Mediation effect	Partial mediation			Partial mediation		
Observations	15,249			26,001		

Panel D: Agency costs

Variables	cc_expo_t shr_base_{t-1} (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t $insownship_{t-1}$ (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
shr_base_{t-1}/$insownship_{t-1}$	−0.0210** (0.011)	0.0323*** (0.002)	−0.0045 (0.011)	−0.2521*** (0.056)	−0.0955*** (0.008)	−0.2934*** (0.056)
$oc\_pt\_at_{t-1}$			−0.5123*** (0.042)			−0.4317*** (0.040)
Sobel test	$\beta_1 = -0.0210^{**}\alpha_1 = 0.0323^{***},\beta_2 = -0.5123^{***}\beta_1' = -0.0045$Sobel test z-stat = −10.414***			$\beta_1 = -0.2521^{***}\alpha_1 = -0.0955^{***},\beta_2 = -0.4317^{***}\beta_1' = -0.2934^{***}$Sobel test z-stat = 7.830***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Mediation/suppression effect	Complete mediation			Suppression effect, OC is less effective		
Observations	25,848			27,374		

Panel E: Analyst forecast quality and financial leverage

Variables	cc_expo_t f_err_{t-1} (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t lev_{t-1} (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
f_err_{t-1}/ lev_{-1}	0.0812*** (0.011)	0.0078*** (0.002)	0.0842*** (0.011)	−0.3530*** (0.060)	−0.1126*** (0.009)	−0.4016*** (0.060)

(*continued on next page*)

Table 7 (*continued*)

Panel E: Analyst forecast quality and financial leverage

Variables	cc_expo_t f_err_{t-1} (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t lev_{t-1} (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
$oc\_pt\_at_{t-1}$			−0.3959***			−0.4317***
			(0.056)			(0.040)
Sobel test	$\beta_1 = 0.0812^{***}\alpha_1 = 0.0078^{***}, \beta_2 = -0.3959^{***}\beta_1' = 0.0842^{***}$ Sobel test z-stat = −4.107***			$\beta_1 = -0.3530^{***}\alpha_1 = -0.1126^{***}, \beta_2 = -0.4317^{***}\beta_1' = -0.4016^{***}$ Sobel test z-stat = 8.134***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Suppression effect	Suppression effect, OC is beneficial			Suppression effect, OC is less effective		
Observations	15,905			27,374		

Panel F: Product market competition

Variables	cc_expo_t prodmktfluid (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t hhi (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
$prodmktfluid_{t-1}/hhi_{t-1}$	−0.0302***	−0.0181***	−0.0394***	−0.6575***	−0.1595***	−0.7417***
	(0.004)	(0.001)	(0.004)	(0.045)	(0.007)	(0.045)
$oc\_pt\_at_{t-1}$			−0.5071***			−0.5279***
			(0.043)			(0.041)
Sobel test	$\beta_1 = -0.0302^{***}\alpha_1 = -0.0181^{***}, \beta_2 = -0.5071^{***}\beta_1' = -0.0394^{***}$ Sobel test z-stat = 11.037***			$\beta_1 = -0.6575^{***}\alpha_1 = -0.1595^{***}, \beta_2 = -0.5279^{***}\beta_1' = -0.7417^{***}$ Sobel test z-stat = 11.456***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Suppression effect	Suppression effect, OC is less effective			Suppression effect, OC is less effective		
Observations	22,962			27,374		

Panel G: Environmental commitment and initiative I

Variables	cc_expo_t e_innov (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t emission (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
$e\_innov_{t-1}/emission_{t-1}$	0.0136***	0.0006***	0.0140***	0.0040***	0.0014***	0.0048***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
$oc\_pt\_at_{t-1}$			−0.6547***			−0.6154***
			(0.071)			(0.073)
Sobel test	$\beta_1 = 0.0136^{***}\alpha_1 = 0.0006^{***}, \beta_2 = -0.6547^{***}\beta_1' = 0.0140^{***}$ Sobel test z-stat = −5.993***			$\beta_1 = 0.0040^{***}\alpha_1 = 0.0014^{***}, \beta_2 = -0.6154^{***}\beta_1' = 0.0048^{***}$ Sobel test z-stat = −7.473***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Suppression effect	Suppression effect, OC is beneficial			Suppression effect, OC is beneficial		
Observations	11,065			11,065		

Panel H: Environmental commitment and initiative II

Variables	cc_expo_t e_mgmt (1)	$oc\_pt\_at_{t-1}$ (2)	cc_expo_t (3)	cc_expo_t e_pillar (4)	$oc\_pt\_at_{t-1}$ (5)	cc_expo_t (6)
$e\_mgmt_{t-1}/e\_pillar_{t-1}$	0.0019***	0.0005***	0.0022***	0.0095***	0.0016***	0.0106***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
$oc\_pt\_at_{t-1}$			−0.6726***			−0.6902***
			(0.078)			(0.073)
Sobel test	$\beta_1 = 0.0019^{***}\alpha_1 = 0.0005^{***}, \beta_2 = -0.6726^{***}\beta_1' = 0.0022^{***}$ Sobel test z-stat = −5.707***			$\beta_1 = 0.0095^{***}\alpha_1 = 0.0016^{***}, \beta_2 = -0.6902^{***}\beta_1' = 0.0106^{***}$ Sobel test z-stat = −8.225***		
$Controls_{t-1}$	Yes			Yes		
Year dummy	Yes			Yes		
Suppression effect	Suppression effect, OC is beneficial			Suppression effect, OC is beneficial		
Observations	10,773			11,065		

Note: Table 7 presents the results of the mediation analysis estimated in Eq. (8–1) – (8–3) examining the mediation effect of organisation capital on the relationship between financial constraints and corporate governance (Panel A), firm performance (Panel B), firm efficiency and operating performance (Panel C), agency costs (Panel D), analyst forecast quality and financial leverage (Panel E), product market competition (Panel F), environmental commitment and initiative (Panels G and H), and climate change exposure. We use the *sa* index (Hadlock and Pierce, 2010) to measure financial constraints. We measure corporate governance using *fra_female_dire*, which is calculated as the fraction of female directors on a board. Firm performance is proxied by accounting-based measure *roa* and market-based measure *tobin's q*. Firm efficiency (*firm_effi*) is sourced from Demerjian et al. (2012) and operating performance is proxied by operating profit margin (*opm*), calculated as the ratio of operating income before depreciation to total sales. We use the shareholder base (*shr_base*) and institutional shareholdings (*insownship*) to measure the extent to which a firm is exposed to agency costs. We use *f_err*, measured by the absolute value of the difference between the mean earnings forecast and the actual earnings per share (EPS) each month divided by the stock price in that month, then average over the year, to proxy for analyst forecast quality. We measure financial leverage (*lev*) using the ratio of the sum of the book value of long-term debt and current liabilities to total assets. Product market competition is proxied by Hoberg et al.'s (2014) market fluidity score (*prodmktfluid*) and the Herfindahl-Hirschman Index (*hhi*). Environmental commitment and initiative are proxied by four variables: *e_innov* reflects a firm's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products; *emission* is defined as a firm's commitment and effectiveness in reducing environmental emissions during production and operational processes; *e_mgmt* measures how responsible the team is, including employees who are involved in day-to-day operations and are tasked with implementing the environmental strategy; and *e_pillar* reflects how effectively a firm employs best management practices to mitigate environmental risks and capitalize on environmental opportunities. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. The variable descriptions are in Appendix 1. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

common/ordinary shareholders. The literature yields mixed evidence regarding the relationship between the shareholder base and agency problems. On the one hand, a larger shareholder base may signal greater agency problems (Hasan and Uddin, 2022), as it becomes more difficult for shareholders to coordinate their actions, which increases the potential for managerial opportunism and reduces effective oversight, thereby elevating exposure to climate change risks. On the other hand, a larger and more dispersed shareholder base can help mitigate agency problems by improving corporate governance mechanisms and limiting managerial discretion (Demsetz and Lehn, 1985). This could, in turn, lead to reduced climate change exposure. Second, we included the percentage of shares held by institutional investors (*insownship*) as an alternative measure, as higher institutional holdings tend to reduce agency problems and mitigate climate change risks (Shleifer and Vishny, 1986; Crutchley et al., 1999; Cotter and Najah, 2012; Dyck et al., 2019). Table 7, Panel D presents the results for agency costs. As shown in Columns (1) and (4), the total effects coefficient (i.e. β_1) were negative and significant for *shr_base* and *insownship*. This finding suggests that firms with a larger shareholder base may have lower agency costs, which, in turn, could reduce their exposure to climate change. In addition, Flammer et al. (2021) and Ilhan et al. (2023) document that institutional investors demand the disclosure of climate risk, and their pressure potentially helps firms to reduce climate change exposure. As shown in Columns (2) and (5), we found a positive and significant relationship between *shr_base* and OC but a negative and significant relationship between *insownship* and OC (i.e. α_1).

As shown in Column (3), we found that the direct effect of agency cost measured by *shr_base* on climate change exposure (i.e. β_1') was insignificant. The comparison of an insignificant direct effect with a significant and stronger negative total effect suggests that firms with larger and more dispersed shareholder bases could reduce their exposure to climate change by investing in OC. The significant Sobel test z-values at the 1 % level indicates that OC has a complete mediation effect in this relationship. Column (6) shows that the direct effect of agency cost measured by *insownship* was negative and significant for climate change exposure. However, we observed that the direct effect of *insownship* is stronger than its total effect (i.e., $\beta_1' > \beta_1$). This suggests that firms with high institutional ownership may not derive additional benefits in reducing climate change exposure through investments in OC. High institutional ownership typically signifies active monitoring and effective oversight, which already contributes significantly to mitigating climate change exposure. As a result, further investment in OC becomes redundant in these cases and potentially suppresses climate change exposure reduction. This is also consistent with the findings in Column (5), which indicate that firms with high institutional ownership tend to invest less in OC.

5.5. Analyst forecast quality and financial leverage

We follow prior literature (e.g., Krishnaswami and Subramaniam, 1999; Lee and Liu, 2011; Shan et al., 2023) and use analyst earnings forecast error (*f_err*) to measure analyst forecast quality. High analyst forecast quality is associated with a low level of earnings forecast error. We obtain analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) database. Following the methodology of Lee and Liu (2011) and Shan et al. (2023), each month we compute forecast error as the absolute value of the difference between the mean earnings forecast for the next fiscal year and the actual EPS, scaled by the stock price in that month; we then average the monthly forecast errors over the year. We apply the following transformation: $f\_err = \log(0.0001 + \text{average forecast error during year } t)$.

Table 7, Panel E, Columns (1) – (3) present the results of analyst forecast quality. Column (1) indicates that the total effect of analyst earnings forecast error on climate change exposure was positive and significant (i.e. β_1), suggesting that firms with high earnings forecast error tend to exhibit higher climate change exposure. This finding aligns with previous research (e.g., Benlemlih et al., 2024), which suggests that financial analysts play a vital monitoring role, pressuring managers to enhance environmental transparency. Accordingly, more accurate analysts are better positioned to monitor firms' environmental strategies and policies, thereby playing a key role in reducing climate change exposure. As shown in Column (2), we observed a positive and significant relationship (i.e. α_1) between analyst earnings forecast error and OC, implying that firms with high forecast errors tend to invest more in intangible assets, which are difficult to quantify and often do not appear clearly in financial statements. As shown in Column (3), we found a positive and significant direct effect of analyst earnings forecast error on climate change exposure (i.e. β_1') but a negative and statistically significant effect of OC on climate change exposure at the 1 % level (i.e. β_2), as confirmed by the significant Sobel test z-values at the 1 % level. The decrease in the magnitude of total effects (i.e. $\beta_1 = 0.0812$) compared to the direct effect (i.e. $\beta_1' = 0.0842$) further shows that OC suppresses the positive adverse impact of earnings forecast error on climate change exposure. Although OC acts as a suppressor, this finding underscores its beneficial role in mitigating climate change exposure. In the absence of OC investment, the adverse impact of analyst forecast error on climate change exposure would have been even more pronounced (i.e. direct effect $\beta_1' = 0.0842$).

Next, we measure financial leverage (*lev*) using the ratio of the sum of long-term debt and current liabilities to total assets. Panel E, Columns (4) – (6) present the results. As shown in Column (4), the total effect of *lev* on *cc_expo* was negative and significant (i.e. β_1), indicating that firms with higher financial leverage tend to exhibit lower climate change exposure, possibly due to stricter financial oversight and enhanced risk management practices driven by the potential risks associated with elevated debt levels. This finding aligns with prior literature, such as Ginglinger and Moreau (2023), which suggests a negative association between climate risk and leverage. In Column (5), we found a negative and significant relationship (i.e. α_1) between *lev* and OC, in line with the findings of Norkio (2024). This negative relationship suggests that highly leveraged firms tend to invest less in OC, potentially due to the prioritization of short-term liquidity needs over long-term intangible investments. Additionally, a highly leveraged firm carries a substantial debt burden, requiring significant interest payments, which can limit the resources available for investment in OC. Column (6) presents a significant and more pronounced negative direct effect of *lev* on *cc_expo* (i.e. β_1') compared to the total effect (i.e. β_1) in Column (4). This outcome could be attributed to heightened scrutiny and stricter regulatory oversight faced by highly leveraged firms, which drive them to monitor and manage their risks over time. The reduced magnitude of total effects (i.e. $\beta_1 = -0.3530$) compared to the direct effect (i.e. $\beta_1' = -0.4016$) further shows that the potential contribution of OC to achieve additional reductions in climate change exposure is limited in highly leveraged firms. The significant Sobel test z-values at the 1 % level confirm that OC acts as a suppressor. This finding suggests that in highly leverage firms, further investment in OC may be less effective as the reduction in climate change exposure would have been even greater in the absence of OC investment.

5.6. Product market competition

Building on prior studies (e.g., Hoberg et al., 2014; Aslan and Kumar, 2016; Atawnah et al., 2024), we employ the widely recognized market fluidity score (*prodmktfluid*) and the Herfindahl-Hirschman Index (*HHI*) as measures of product market competition. A higher value of *prodmktfluid* indicates that firms are operating in more fluid product markets with greater competitive threats. This measure is particularly advantageous because it serves as an ex-ante indicator, capturing competitive threats at the firm level (Babar and Habib, 2021). *HHI* is computed as the sum of squared markets shares of firms within an industry for each year: $HHI_{it} = \sum_{n=1}^{N_i} s_{nit}^2$, where s_{nit}^2 is the market share of firm *i* in industry *n* in year *t*. Market share is calculated by dividing a firm's sales by the total sales in the industry. Higher *HHI* indicates lower product market risk. For ease of interpretation, we multiply *HHI* by -1 so that a higher *HHI* indicates higher market competition.

Panel F of Table 7 reports the results. Columns (1) and (4) show that, the total effect of *prodmktfluid* and *hhi* on climate change exposure were negative and statistically significant at the 1 % level (i.e. β_1). This finding suggests that firms operating in highly competitive markets may face pressure to innovate, manage risks effectively, and respond to evolving consumer preferences. These factors can drive behaviors and strategies that reduce their climate change exposure. Babar and Habib (2021) also argue that higher market competition requires firms to provide more information to stakeholders as they can easily benchmark the company against other industry peers easily and evaluate its performance. In Columns (2) and (5), we observed a negative and significant relationship (i.e. α_1) between *prodmktfluid* and OC, and between *hhi* and OC, respectively. This is because heightened competition often reduces profitability while simultaneously increasing cash flow volatility (Hoberg et al., 2014; Bustamante and Donangelo, 2017). Consequently, firms operating in such environments may have fewer financial resources to invest in costly, long-term intangible assets like OC. As shown in Columns (3) and (6), we found a negative and significant direct effect of *prodmktfluid* and *hhi* on climate change exposure (i.e. β_1') and a negative and statistically significant effect of OC on climate change exposure at the 1 % level (i.e. β_2). The direct effects of *prodmktfluid* and *hhi* on climate change exposure are stronger than their respective total effects. This suggests OC may not contribute additional mitigation of climate change exposure and instead it suppresses the extent of climate change exposure reduction. Firms operating in highly competitive markets are likely to implement sustainability innovation, such as reduced emissions, waste reduction, environment management, in order to remain competitive (Hermundsdottir and Aspelund, 2021), which may have already resulted in significant reductions in climate change exposure, even without investment in OC. The significant Sobel test z-values at the 1 % level further confirm the existence of a suppressor role of OC in this relationship.

5.7. Environmental commitment and initiative

In this section, we examine whether OC mediates the relationship between environmental innovation (*e_innov*), emission management policies (*emission*), environmental management team score (*e_mgmt*), and environmental pillar score (*e_pillar*), and climate change exposure. All environmental-related data is sourced from the LSEG Refinitiv Workspace database. Environmental innovation score (*e_innov*) reflects a firm's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products. We use the emission score (*emission*), defined as a firm's commitment and effectiveness in reducing environmental emissions during production and operational processes, to capture the announcement of emission reduction policies. The environmental management team score (*e_mgmt*) and the environmental pillar score (*e_pillar*) are used to assess the effectiveness of environmental management teams and practices, respectively. The former measures how responsible the team is, including employees who are involved in day-to-day operations and are tasked with implementing the environmental strategy, while the latter reflects how effectively a firm employs best management practices to mitigate environmental risks and capitalize on environmental opportunities.

Panels G and H of Table 7 present the results. Columns (1) and (4) show that the total effects of environmental commitment and initiative variables on climate change exposure were positive and significant (i.e. β_1). This positive association suggests that firms may be engaging in greenwashing or sustainability window-dressing, where they project an exaggerated or misleading commitment to environmental responsibility without implementing substantive operational changes to reduce their actual climate risk exposure

(Christmann and Taylor, 2006). As shown in Columns (2) and (5), we observed a positive and statistically significant relationship (i.e. α_1) between environmental commitment and initiative variables and OC, indicating that firms demonstrating greater environmental commitment and proactive engagement in sustainability initiatives are more likely to invest in OC. As shown in Columns (3) and (6), we found a positive and significant direct effect of environmental commitment and initiative variables on climate change exposure (i.e. β_1') but a negative and statistically significant effect of OC on climate change exposure at the 1 % level (i.e. β_2). Although firms may engage in exaggerated or misleading commitments to environmental responsibility that do not necessarily reduce climate change exposure, the slight decrease in the total effect (i.e. β_1) compared to the direct effect (i.e. β_1') suggests that investment in OC acts as a suppressor and could help such firms mitigate the adverse impact of their misleading commitments on climate change exposure. The significant Sobel test z-values at the 1 % level confirm the suppressor role of OC, highlighting its beneficial impact.

6. Robustness checks

In this section, we conducted several robustness checks to validate our results. First, one may argue that our analyses omitted some additional controls related to both climate change exposure and OC. To address this legitimate concern, we followed prior literature (e.g., Hossain and Masum, 2022; Hasan and Cheung, 2023) and additionally controlled for the CEO power, proxied by CEO-Chair duality (*duality*); managerial ability score (*ma*) of Demerjian et al. (2012); and firm risk, measured as idiosyncratic risk (*ivol*), systematic risk (*mkt*), and total risk (*tvol*). As shown in Columns (1) – (3) of Panel A of Table 8, we found robust evidence that OC is negatively correlated (significant at $p < 0.01$) with *cc_expo*. These results were noted even when we included all additional controls together in Column (4).

Second, we tested the sensitivity of our documented results using four alternative measures of OC. For example, we used Eisfeldt and Papanikolaou's (2013) OC measure (*oc_ep_at*), which is similar to that of Peters and Taylor (2017), except that it uses the deflated values of SG&A expenses rather than a fraction of past SG&A expenses (see Section 3.2, Equation (3) for a detailed estimation method). Column (1), Panel B of Table 8 shows that the result using this alternative measure of OC corroborated those of our baseline analysis. Following the approach used by Hasan et al. (2021), we scaled the stock of OC by physical assets (*oc_pt_ppe*) instead of total assets; the finding is presented in Column (2), Panel B. We found that the estimated relationship between *oc_pt_ppe* and *cc_expo* remained negative and significant. Next, we followed the approach taken by Li et al. (2018) and used the industry-median adjusted ratio of OC to total assets (*oc_indadj*) as an alternative measure to address the concern that the stock of OC may vary across industries. In Panel B, Column (3) shows that *oc_indadj* was negatively and significantly ($p < 0.01$) associated with *cc_expo*, consistent with the findings reported in Table 3. Finally, following the approach used by Enache and Srivastava (2018), we subtracted R&D and advertising expenses from SG&A expenses to obtain the net SG&A expenses. We then used the same procedure specified in Equations (1) and (2) to estimate an alternative proxy for the stock of the firm's OC scaled by total assets (*oc_pt_net*). As Column (4) of Panel B shows, the coefficients of *oc_pt_net* remain negative and significant ($p < 0.01$) for *cc_expo*.

In our baseline regression analysis, we initially used overall climate change exposure (*cc_expo*) as a proxy. To refine our analysis, we introduced a more specific measure, climate risk exposure (*cc_risk*), and reran the regression. The results, shown in Column (1) of Table 8 Panel C, reveal that the negative and significant coefficient for *op_pt_at* is sustained. Next, we employed the regulatory and physical climate change exposure subcomponents from Sautner et al. (2023) to examine the sensitivity of our findings. The variables *re_expo* and *ph_expo* represent regulatory and physical aspects of climate change exposure, respectively. Results for these subcomponents are displayed in Columns (2) and (3), Panel C of Table 8. As shown, the coefficient for the regulatory subcomponent (*rg_expo*) remains negative and statistically significant; however, the coefficient for the physical exposure (*ph_expo*) is insignificant. These results are not surprising because transition risks are often related to changes in policies, technology, market preferences, and regulatory landscapes as we transition towards a low-carbon economy. Such risks are largely influenced by human decisions, culture, and innovation, where high OC can significantly mitigate impacts. In contrast, physical risks arise from the tangible effects of climate change, such as extreme weather events and natural disasters. These are less controllable at the firm level, though firms can still plan for resilience and recovery. Overall, this finding enhances our understanding of the distinct role OC plays in reducing various types of firms' exposure to climate change.

Furthermore, to demonstrate the robustness of our findings, we reran our baseline model by restricting the sample period to within the window of the global financial crisis (i.e. 2007–2009) and COVID-19 (i.e. 2020 and 2021). Our findings were robust when using short-window data, although the sample size dropped to 5257 and 3890 firm-year observations, respectively (see Columns (1) and (2) of Panel D in Table 8). Additionally, we excluded the GFC and/or COVID-19 periods and reran our baseline model in Columns (3) – (5). Our main results still hold: the coefficient estimates on *op_pt_at* are negative and statistically significant ($p < 0.01$).

The relationship between OC and exposure to climate change may be more significant in certain industries. For example, sectors such as oil and gas, coal mining, steel, cement, and chemicals are more directly impacted by climate change than industries like software development or consulting. Therefore, OC's role in mitigating exposure could vary significantly across different sectors. Following Sautner et al. (2023), we categorized our sample into high climate change exposure industries (i.e. the top 10 industries for *cc_expo*) and low climate change exposure industries (i.e. those outside the top 10 industries for *cc_expo*).[12] Panel E of Table 8 presents

[12] Top 10 *cc_expo* industries are: (1) Electric, Gas, & Sanitary Services; (2) Heavy Construction, Except Building; (3) Construction; (4) Transportation Equipment; (5) Electronic & Other Electric Equipment; (6) Coal Mining; (7) Petroleum Refining; (8) Local & Suburban Transit; (9) Automative Dealers & Service Stations; and (10) Primary Metal.

Table 8
Robustness checks.

Panel A: Additional controls

Variables	(1) cc_expo CEO power	(2) cc_expo Managerial ability	(3) cc_expo Firm risk	(4) cc_expo All
oc_pt_at	**−0.2569*****	**−0.2467*****	**−0.2349*****	**−0.2883*****
	(0.036)	(0.039)	(0.034)	(0.043)
duality	−0.1019*			−0.1279**
	(0.057)			(0.062)
ma		−0.3272***		−0.2858***
		(0.073)		(0.076)
ivol			3.1042	2.6081
			(3.504)	(4.912)
tvol			−1.9363	−2.8268
			(3.434)	(4.695)
mkt			0.0700**	0.1055***
			(0.032)	(0.038)
lnat	−0.0027	−0.0063	−0.0072	−0.0076
	(0.007)	(0.008)	(0.007)	(0.008)
debt	−0.3247***	−0.3021***	−0.2422***	−0.4026***
	(0.055)	(0.065)	(0.060)	(0.067)
cash	0.5924***	0.6272***	0.5418***	0.6856***
	(0.072)	(0.081)	(0.070)	(0.086)
ppe	1.1603***	1.0353***	1.0144***	1.1377***
	(0.104)	(0.113)	(0.098)	(0.118)
ebit	−0.7655***	−0.6498***	−0.6385***	−0.7174***
	(0.104)	(0.114)	(0.097)	(0.130)
capex	−0.2078	0.3463	0.0144	0.3133
	(0.371)	(0.408)	(0.415)	(0.375)
rd	−1.0662***	−0.7514***	−0.9976***	−0.8997***
	(0.181)	(0.193)	(0.175)	(0.200)
insownship	−0.3332***	−0.4124***	−0.3292***	−0.4762***
	(0.056)	(0.065)	(0.055)	(0.072)
Constant	0.9134***	0.9440***	0.8409***	0.9348***
	(0.066)	(0.074)	(0.074)	(0.093)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	29,581	24,410	31,310	22,652
R-squared	0.370	0.335	0.355	0.348

Panel B: Alternative measures of organisation capital

Variables	(1) cc_expo	(2) cc_expo	(3) cc_expo	(4) cc_expo
oc_ep_at	**−0.0363*****			
	(0.009)			
oc_pt_ppe		**−0.0099****		
		(0.004)		
oc_indadj			**−0.1391*****	
			(0.030)	
oc_pt_net				**−0.2079*****
				(0.037)
lnat	−0.0018	−0.0015	−0.0042	−0.0065
	(0.007)	(0.007)	(0.007)	(0.007)
debt	−0.2098***	−0.2527***	−0.2171***	−0.2220***
	(0.059)	(0.063)	(0.059)	(0.059)
cash	0.5561***	0.5937***	0.5494***	0.5404***
	(0.069)	(0.073)	(0.069)	(0.069)
ppe	1.0216***	1.0040***	1.0256***	1.0264***
	(0.099)	(0.104)	(0.099)	(0.099)
ebit	−0.6922***	−0.6924***	−0.6843***	−0.6799***
	(0.096)	(0.098)	(0.095)	(0.095)
capex	0.0666	0.0835	0.0514	0.0479
	(0.414)	(0.419)	(0.414)	(0.413)
rd	−1.2252***	−1.3226***	−1.1184***	−1.2580***
	(0.177)	(0.181)	(0.178)	(0.176)
insownship	−0.3070***	−0.3157***	−0.3046***	−0.3123***
	(0.052)	(0.056)	(0.052)	(0.053)
Constant	0.8228***	0.8749***	0.8194***	0.8950***
	(0.058)	(0.067)	(0.058)	(0.062)

(*continued on next page*)

Table 8 (*continued*)

Panel B: Alternative measures of organisation capital

Variables	(1) cc_expo	(2) cc_expo	(3) cc_expo	(4) cc_expo
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	31,577	27,929	31,577	31,577
R-squared	0.356	0.353	0.356	0.356

Panel C: Alternative measures of climate change exposure

Variables	(1) cc_risk	(2) rg_expo	(3) ph_expo
oc_pt_at	**−0.0106*****	**−0.0182*****	**−0.0012**
	(0.002)	(0.005)	(0.002)
lnat	−0.0001	−0.0004	−0.0016***
	(0.000)	(0.001)	(0.000)
debt	−0.0139***	−0.0162*	−0.0100***
	(0.003)	(0.008)	(0.003)
cash	0.0093**	0.0519***	−0.0020
	(0.004)	(0.009)	(0.003)
ppe	0.0418***	0.0972***	0.0176***
	(0.006)	(0.016)	(0.005)
ebit	−0.0178***	−0.0536***	0.0046
	(0.005)	(0.013)	(0.004)
capex	−0.0413*	−0.1597***	−0.0045
	(0.022)	(0.057)	(0.017)
rd	−0.0096	−0.0692***	0.0025
	(0.011)	(0.027)	(0.008)
insownship	−0.0110***	−0.0313***	−0.0017
	(0.003)	(0.007)	(0.002)
Constant	0.0316***	0.0570***	0.0240***
	(0.004)	(0.010)	(0.003)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	31,577	31,577	31,577
R-squared	0.121	0.233	0.106

Panel D: Global Financial Crisis (GFC) and COVID-19

Variables	(1) cc_expo GFC only	(2) cc_expo COVID only	(3) cc_expo Excluding GFC	(4) cc_expo Excluding COVID	(5) cc_expo Excluding both GFC and COVID
oc_pt_at	**−0.3274*****	**−0.2136****	**−0.2028*****	**−0.2454*****	**−0.2169*****
	(0.084)	(0.092)	(0.036)	(0.036)	(0.040)
lnat	−0.0038	0.0856***	−0.0089	−0.0162**	−0.0192***
	(0.015)	(0.024)	(0.007)	(0.007)	(0.007)
debt	−0.2975**	−0.2144	−0.1804***	−0.2205***	−0.1711***
	(0.124)	(0.242)	(0.067)	(0.055)	(0.061)
cash	0.8540***	0.6671***	0.4763***	0.5746***	0.5037***
	(0.194)	(0.193)	(0.073)	(0.074)	(0.080)
ppe	0.6708***	1.1470***	1.0595***	0.9312***	0.9856***
	(0.220)	(0.377)	(0.110)	(0.101)	(0.114)
ebit	−1.0435***	−1.2618***	−0.6309***	−0.6479***	−0.5641***
	(0.255)	(0.310)	(0.102)	(0.100)	(0.108)
capex	1.4334	1.1046	−0.1490	0.4537	0.2040
	(0.991)	(2.891)	(0.459)	(0.397)	(0.429)
rd	−1.8590***	−1.8965***	−0.8385***	−0.9318***	−0.7203***
	(0.484)	(0.479)	(0.186)	(0.185)	(0.200)
insownship	−0.3896***	−0.3313*	−0.3016***	−0.3394***	−0.3257***
	(0.128)	(0.184)	(0.058)	(0.055)	(0.061)
Constant	1.0181***	0.5429**	0.8962***	0.9360***	0.9103***
	(0.126)	(0.213)	(0.071)	(0.064)	(0.074)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	5,257	3,890	26,308	27,685	22,416
R-squared	0.472	0.485	0.344	0.361	0.343

Panel E: Climate change exposure by industry

Variables	(1) cc_expo High climate change exposure industry	(2) cc_expo Low climate change exposure industry
oc_pt_at	**−1.7168*****	**−0.0419**

(*continued on next page*)

Table 8 (*continued*)

Panel E: Climate change exposure by industry

Variables	(1) cc_expo High climate change exposure industry	(2) cc_expo Low climate change exposure industry
	(0.281)	(0.026)
lnat	0.0616**	−0.0287***
	(0.031)	(0.005)
debt	−1.3954***	−0.0213
	(0.316)	(0.046)
cash	2.3636***	0.1781***
	(0.338)	(0.050)
ppe	2.3046***	0.6916***
	(0.507)	(0.076)
ebit	−3.2896***	−0.3396***
	(0.575)	(0.062)
capex	2.4831	−0.6218*
	(1.963)	(0.359)
rd	−0.7819	−0.8081***
	(0.843)	(0.149)
insownship	−1.3174***	−0.0584*
	(0.268)	(0.032)
Constant	2.1902***	0.7180***
	(0.305)	(0.050)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,992	26,575
R-squared	0.367	0.310

Panel F: Other robustness checks

Variables	(1) cc_expo cc_expo>0	(2) cc_expo High dimensional FE	(3) cc_expo Excluding utility and financial firms
oc_pt_at	**−0.3031******	**−0.2236******	**−0.2100******
	(0.045)	(0.035)	(0.033)
lnat	−0.0344***	0.0008	−0.0107
	(0.008)	(0.006)	(0.007)
debt	−0.2592***	−0.1732***	−0.2639***
	(0.073)	(0.063)	(0.066)
cash	0.6303***	0.6016***	0.5872***
	(0.086)	(0.071)	(0.075)
ppe	1.1364***	0.9657***	1.1203***
	(0.114)	(0.111)	(0.113)
ebit	−0.8279***	−0.8492***	−0.6726***
	(0.119)	(0.102)	(0.098)
capex	0.0562	0.4307	0.1571
	(0.500)	(0.494)	(0.431)
rd	−1.3118***	−1.3112***	−1.0438***
	(0.220)	(0.175)	(0.179)
insownship	−0.5022***	−0.3610***	−0.3474***
	(0.066)	(0.057)	(0.060)
Constant	1.4053***	0.8729***	0.9772***
	(0.081)	(0.062)	(0.071)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Industry x Year FE	No	Yes	No
Observations	26,117	29,679	26,940
R-squared	0.360	0.458	0.352

Note: Table 8 reports regression results of the relationship between organisation capital and firm-level climate change exposure with additional controls (Panel A), alternative measures of organisation capital and climate change exposure (Panels B and C), the Global Financial Crisis (GFC) and COVID-19 periods only; and specifications excluding either the GFC or COVID-19 periods, or both (Panel D), top 10 vs. non-top 10 climate change exposure industries (Panel E), and other robustness checks, i.e. a subsample of firm-year observations where climate change exposure is positive, high dimensional FE, and a subsample of firm-year observations where utility and financial firms are excluded (Panel F). Robust standard errors are reported in parentheses. Climate change exposure is proxied by *cc_expo*. Organisation capital is measured by *oc_pt_at*. The variable descriptions are in Appendix 1. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

the results. As shown, the coefficient for *oc_pt_at* on *cc_expo* is negative and statistically significant for firms in the top 10 industries, while it is insignificant for firms in other industries, suggesting that OC plays a critical role in mitigating climate change exposure in more affected sectors.

Sautner et al.'s (2023) climate change data contained a large portion of the zero values of climate change exposure. To alleviate the concern that our findings may have taken advantage of zero *cc_expo* firms, we reran our baseline regression with *cc_expo* > 0 samples only. In Table 8, Panel F, Column (1) shows that OC was negatively and significantly ($p < 0.01$) correlated with climate change exposure. In addition, we used a high-dimensional fixed-effects model (i.e. industry × year); the results are presented in Column (2), Panel F. We found that the inferences from our analysis remained qualitatively similar when employing this alternative estimation model. Finally, to mitigate the concern that financial and utility firms are subject to substantially different accounting practices and regulations, we reran the baseline model after excluding these two industries from our sample in Column (3) of Panel F. Again, we obtained qualitatively very similar results.

7. Conclusion

As climate risk has become an urgent global concern, we examined whether OC, which encompasses a firm's systems, processes, and culture, provides resilience against climate-related threats. The findings indicate that firms with higher OC are better equipped to mitigate the risks associated with climate change exposure. OC serves as a key intangible asset that enhances corporate resilience, allowing firms to manage climate risk more effectively. Our study also demonstrates that OC mediates the relationship between firm-specific characteristics, including financial constraints, corporate governance, firm performance, firm efficiency, operating performance, shareholder base and climate change exposure. In the relationship between analyst forecast quality, environmental commitment and initiative and climate change exposure, although OC acts as a suppressor, it reduces the positive adverse impact of these firm-specific factors on climate change exposure. Lastly, we find that in firms with high institutional ownership and financial leverage, and those operate in highly competitive markets, additional investment in OC could be less effective as the reduction in climate change exposure would have been stronger in the absence of OC investment. Overall, our study emphasises the importance of strategic investments in OC for enhancing firms' resilience and long-term sustainability in the face of climate change risk.

This study significantly advances the literature on OC and climate change exposure and provides actionable insights for corporate managers and policymakers. Corporate managers can use these insights to shape policies and practices that prioritise building OC, such as investing in employee training, knowledge management, and process innovation. Policymakers can also leverage these findings to design supportive regulations and incentives that encourage businesses to strengthen their OC and promote sustainable practices and resilience to climate change. Future research could explore the nuances of this relationship and investigate other potential factors that may influence firm-level climate change exposure. By advancing our understanding of how OC can serve as a source of competitive advantage in addressing climate risks, businesses can better prepare for the challenges and opportunities posed by a changing climate.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Definition of variables

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Variable	Definition	Source
Dependent variables		
cc_expo	Relative frequency with which bigrams related to climate change occur in the transcripts of earnings conference calls. It is measured as the number of such bigrams divided by the total number of bigrams in the transcripts. A higher *cc_expo* score indicates a higher susceptibility to the climate change exposure.	Sautner et al. (2023)
Independent variables and control variables		
oc_pt_at	Organisation capital measure of Peters and Taylor (2017) divided by total assets (see Section 3.2 for details).	Self-constructed based on Peters and Taylor (2017)
lnat	The natural logarithm of total assets (AT).	CRSP-COMPUSTAT
debt	The sum of the book value of long-term debt (DLTT) and the book value of current liabilities (DLC) divided by total assets (AT).	CRSP-COMPUSTAT
cash	Cash and short-term investments (CHE) divided by total assets (AT).	CRSP-COMPUSTAT
ppe	Property, plant, and equipment (PPENT) divided by total assets (AT).	CRSP-COMPUSTAT
ebit	Earnings before interest and taxes (EBIT) divided by total assets (AT).	CRSP-COMPUSTAT
capex	Capital expenditures (CAPX) divided by total assets (AT).	CRSP-COMPUSTAT
rd	R&D expenditures (XRD) divided by total assets (AT).	CRSP-COMPUSTAT

(*continued on next page*)

(*continued*)

Variable	Definition	Source
insownship	Percentage of shares held by institutional investors. A higher *insownship* is associated with lower agency problems.	Thomson/Refinitiv 13F
Other variables		
oc_ep_at	Organisation capital measure of Eisfeldt and Papanikolaou (2013).	Self-constructed following Eisfeldt and Papanikolaou (2013)
oc_pt_ppe	Organisation capital measure of Peters and Taylor (2017) divided by property, plant and equipment (PPEGT).	Self-constructed based on Peters and Taylor (2017)
oc_indadj	Industry-median adjusted ratio of Peters and Taylor (2017)'s organisation capital to total assets.	Self-constructed following Li et al. (2018)
oc_pt_net	Organisation capital measure of Enache and Srivastava (2018) divided by total assets.	Self-constructed following Enache and Srivastava (2018)
cc_risk	Relative frequency with which bigrams related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of earnings conference calls.	Sautner et al. (2023)
rg_expo	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls.	Sautner et al. (2023)
ph_expo	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls.	Sautner et al. (2023)
sa	Financial constraints measure of Hadlock and Pierce (2010). A higher *sa* index suggests greater financial constraints.	Self-constructed following Hadlock and Pierce (2010)
shr_base	Shareholder base, measured as the natural logarithm of one plus common/ordinary shareholders (CSHR).	CRSP-COMPUSTAT
opm	The ratio of operating income before depreciation (OIBDP) to total sales (SALE).	CRSP-COMPUSTAT
roa	Operating income before depreciation (OIBDP) divided by total assets (AT).	CRSP-COMPUSTAT
tobin's q	Total assets (AT) minus the book value of equity (CEQ) plus the market value of equity (CSHO*PRCC_C), all divided by total assets (AT).	CRSP-COMPUSTAT
duality	A dummy variable equal to one when the CEO and Chair of the Board of Directors are the same person, zero otherwise.	BoardEx
ma	Managerial ability measure following Demerjian et al. (2012).	Peter Demerjian's Website
ivol	Idiosyncratic volatility estimated from Fama-French (1993) three-factor model.	WRDS Beta Suite
mkt	Systematic risk estimated from Fama-French (1993) three-factor model.	WRDS Beta Suite
tvol	Total risk, estimated as standard deviation of firm-specific daily returns over the year.	WRDS Beta Suite
fra_female_dire	The fraction of female directors on a board.	BoardEx
prodmktfluid	Product market competition following Hoberg et al. (2014). A higher *prodmktfluid* value reflects more fluid product markets with greater competitive threats.	Hoberg-Phillips Data Library
hhi_sale	Measured by the Herfindahl-Hirschman Index using sales. HHI is multiplied by −1 so that a higher HHI reflects greater product market competition and vice versa.	Self-constructed
firm_effi	Firm efficiency measure following Demerjian et al. (2012).	Peter Demerjian's Website
f_err	Measured by the absolute value of the difference between the mean earnings forecast and the actual earnings per share (EPS) each month divided by the stock price in that month, then average over the year. A lower *f_err* value suggests higher analyst forecast quality.	I/B/E/S
e_innov	Environmental innovation score, reflects a firm's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.	LSEG Refinitiv Workspace database
emission	Emission score, defined as a firm's commitment and effectiveness in reducing environmental emissions during production and operational processes.	LSEG Refinitiv Workspace database
e_mgmt	Environmental management team score, measures how responsible the team is, including employees who are involved in day-to-day operations and are tasked with implementing the environmental strategy.	LSEG Refinitiv Workspace database
e_pillar	Environmental pillar score, reflects how effectively a firm employs best management practices to mitigate environmental risks and capitalize on environmental opportunities.	LSEG Refinitiv Workspace database

Data availability

Data will be made available on request.

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