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Climate change exposure and internal carbon pricing adoption

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Abstract

Governments and corporations around the world are increasingly pressured to manage climate-related business risks and reduce their carbon footprint. Consequently, a growing number of corporations have started implementing internal carbon pricing (ICP) programs, assigning a monetary value to their carbon emissions as a mitigation and adaptation mechanism. This paper explores the motives underlying voluntary ICP adoption and examines whether a firm's exposure to climate-related risks is a relevant driver of ICP adoption. Using a worldwide sample of firms reporting to the Carbon Disclosure Project between 2016 and 2018, we find that firm-level climate change exposure is significantly and positively related to the likelihood of ICP adoption. More specifically, the probability of adoption is largely linked to regulatory shocks and opportunity exposure. Moreover, we find that board independence acts as a moderator in the climate change exposure–ICP adoption relation. The findings of this study shed light on the factors contributing to the acceleration in ICP implementation in the context of a coordinated effort between public and private sectors to reduce global emissions.

Keywords: Internal carbon price, climate change exposure, GHG emissions, environmental policy, sustainability, self-regulation.

1. Introduction

The 2018 special report¹ of the Intergovernmental Panel on Climate Change asserted that global warming of 1.5°C above preindustrial levels could trigger irreversible changes to the Earth's climate, exposing corporations, investors, and global economies to significant financial risks. The physical impacts of recurring severe extreme weather events may result in significant disruptions to supply chains and asset destruction in several corporations. Further, the rising level of regulatory pressures toward a transition to a net-zero carbon economy could threaten business models' viability in carbon-intensive industries. While numerous studies in the natural sciences have focused on the consequences of climate change, its potential mitigation is still a burning issue.

Over the past decade, the topic of climate change has gained momentum and caught the attention of the corporate world (Linnenluecke et al., 2013). Karstensen et al. (2018) suggest that one way to address the issue of climate change and control CO₂ emissions is to put an external price on greenhouse gases (GHG; see (Aldy & Stavins, 2012). Cadez and Czerny (2016) show that carbon reduction strategies implemented by carbon-intensive firms could include process emissions reduction, combustion emissions reduction, external measures, lowering product output, and emissions trading. The authors argue that firms usually emphasize a single climate mitigation strategy rather than using several concurrently and that emissions trading is the most widely deployed tool.

According to the environmental economics literature (Bonilla et al., 2012; Calzadilla et al., 2011), carbon pricing is one of the most important tools for reducing GHG emissions (Fan et al., 2021; Karstensen et al., 2018). Compared to other types of instruments, carbon pricing

¹ See <https://www.ipcc.ch/2018/10/08/summary-for-policymakers-of-ipcc-special-report-on-global-warming-of-1-5c-approved-by-governments>.

can address the vast heterogeneity of GHG emitters and help minimize the cost of pollution control (Baranzini et al., 2017). Gollier and Tirole (2015) assert that a coherent carbon pricing program is the only effective strategy for achieving emissions reduction targets. In addition to sometimes inefficient government regulations, self-regulation mechanisms could become a useful and complementary tool to reach environmental objectives (Stoeckl, 2004). According to the 2017 Carbon Disclosure Project (CDP) report (Bartlett et al., 2017), almost 1,400 firms had adopted an internal carbon price (ICP) within their business plans, representing an eight-fold increase over four years. ICP is defined as a firm's voluntary setting of a value to internalize the economic cost of its GHG emissions (I4CE, 2016). A recent World Bank study reveals that almost half of the largest 500 global companies are already using ICP or have the intention to use ICP within the next two years (World Bank, 2021).

Companies generally rely on three different approaches, either in isolation or combination, to report on ICP programs: 1) an internal carbon fee, 2) a shadow price, and 3) an implicit price (Bartlett et al. 2017). An internal carbon fee is a monetary value assigned to each ton of carbon emissions, which constitutes a dedicated revenue or investment stream to fund a company's emissions reduction objectives, whereas a shadow price is a theoretical price on carbon that can help support investment strategies and long-term business planning. It favors the selection of low-carbon investments and helps companies prepare for future carbon regulations. Finally, an implicit carbon price is based on how much a company spends to reduce GHG emissions and/or the cost of complying with government regulations. For instance, this can be the amount a company spends on renewable energy purchases or compliance with fuel economy standards. It helps companies identify and minimize these costs and to use the information thus gained to understand their own carbon footprint (Ahluwalia, 2017).

Although the use of ICP mechanisms has accelerated over the recent years, we still know little about the drivers of their implementation. First, companies could set up ICP to reach their emissions reduction targets more effectively. Carbon emissions reduction is most likely to be effective when corporations adopt proactive and creative strategies (Bui & de Villiers 2017). Second, an increasing number of companies are using ICP as a strategy to proactively manage climate-related business risks, since government carbon pricing regimes have come into play. When corporations are exposed to or foresee higher regulatory and financial risks related to climate change potentially affecting their businesses, they strive to quantify, model, and cope with such risks. Third, companies can also look to gain a competitive advantage in a future in which climate policies could affect operating conditions or technical systems. Finally, ICP adoption could trigger and drive investments toward low-carbon technologies, identifying new markets and factoring ICP into capital allocation decisions among investments generating significant GHG emissions (Abe, 2015; Bartlett et al., 2017; Bianchini & Gianfrate, 2018; I4CE, 2016).

To our knowledge, while recent research works have started to look at the impact of ICP on financial performance (Ma & Kuo, 2021), the precise drivers of ICP adoption have not yet been specifically investigated. Our study aims to fill this gap and to provide new insights on the factors explaining a company's decision to use ICP as a corporate strategy. One of the most frequently stated reasons for adopting climate change mitigation policies is to manage increased carbon emissions and climate-related business risks. However, the question of whether exposure to climate risk is a driver of ICP adoption remains unaddressed at the empirical level. In this study, we examine whether firm-level exposure to climate change has an impact on firms' decision to put in place an ICP program. This paper uses two proxies for firm-level carbon exposure. First, similar to the literature (Jung et al., 2018; Seltzer et al., 2020),

we use GHG emissions at the firm level as a proxy for firm exposure to carbon risk and climate-related regulatory risks. Second, we take advantage of the newly developed measure of Sautner et al. (2020) as a proxy for firm-level exposure to climate change business effects.

Drawing on a sample of 3,170 firm–year observations covering 1,362 global companies reporting on their ICP programs to the CDP from 2016 to 2018, we find that firm-level exposure to climate-related risks plays a major role in ICP implementation. Specifically, we show that each unit increase in GHG and climate change exposure at firm level increases the odds of adopting an ICP program by 6.3% and 14.9%, respectively. Our results are robust to different model specifications, the use of an alternate dependent variable, propensity score matching (PSM), and year-by-year regressions.

We aim to contribute to the literature in several ways. First, this paper is, to our knowledge, the first to offer new insights into the nascent and scant research on the drivers of the implementation of ICP among other mitigation strategies. GHG emissions as well as a firm’s exposure to carbon risks have significant economic consequences for investors, as well as creditors (Choi & Luo, 2021; Jung et al., 2018; Matsumura et al., 2014; Seltzer et al., 2020). For instance, Matsumura et al. (2014) find that a firm’s value decreases, on average, by \$212 for every additional metric ton of carbon emissions. Therefore, it is important to understand the drivers of the voluntary adoption of mitigation strategies, such as ICP programs, in a context of rising pressures toward the transition to a net zero carbon economy and the potential introduction of a universal carbon price.

Second, our findings highlight the specific role of climate change exposure in adopting an ICP program. In a related study, Bento and Gianfrate (2020) explore the factors explaining carbon prices levels among firms that have implemented ICP programs. Their findings reveal that variation in internal carbon prices is mostly explained by national climate policy, a

country's level of economic development, industry, and corporate governance effectiveness. However, the authors do not consider firm-level carbon or climate risk exposure among the potential drivers of internal carbon prices. In addition, although they study ICP levels, they do not specifically address the determinants of ICP adoption. Our study builds upon and extends the findings of Bento and Gianfrate (2020) by exploring and investigating the rationale underlying the adoption of ICP at the corporate level.

We argue that the initial corporate decision to adopt an ICP program may respond to different motivations than the second-stage decision on the level/magnitude at which firms set a price on carbon when they decide to implement such a program. Our findings show that firm-level exposure to carbon risks is one of the leading drivers of ICP implementation while controlling for country-level factors such as a national carbon price policy and a nation's economic development. Moreover, we show that this effect on ICP adoption is significant when climate change exposure is linked to regulatory shocks and opportunities, but not in the case of physical shocks related to climate change. Besides, we find that the presence of effective boards acts as a moderating variable in the relation.

The remainder of this paper is organized as follows. The next section summarizes the literature and develops our hypothesis. We describe our data and methodology in Section 3. Section 4 presents the empirical results and robustness checks, and Section 5 concludes the paper.

2. Literature review

2.1 ICP as a mitigation tool

In the past 10 years, companies have considered long-term environmental risks an integral part of their sustainability performance. Financial institutions, as creditors to companies from all

sectors and sizes, have started considering environmental risk assessment in their lending decisions. In addition, lenders sometimes concentrate investments in companies and projects with good environmental performance (Orsato et al., 2015). Increased awareness of these issues and increased pressure from stakeholders and capital providers increasingly lead companies to factor climate change exposure into their operations. Hoffmann and Busch (2008) contend that GHG emissions reduction can serve as an opportunity for firms to reduce financial risks and their natural and financial consequences. For example, companies could face unexpected regulatory, product and process-based caps and taxes. Consequently, some companies recognize the need for action today against future exposure.

Climate strategy adoption is in line with the natural resource–based view (NRBV). As an extension of the resource-based view, the NRBV incorporates the environmental impact of firm resources and of the processes originating from these resources. According to the NRBV of the firm, strategic and competitive advantages can be achieved through firms’ capabilities in enabling environmentally responsible activity in recognition of natural and social environment challenges (Hart, 1995). NRBV seeks to examine how resources can result in competitive advantages, as well as positive outcomes for the natural environment. For example, the ability to continuously improve and refine production processes can result in reduced emissions, as well as lower costs (Hart, 1995), and strategic proactivity can result in first-mover advantages, as well as more proactive environmental management. As a recent example, Demirel and Kesidou (2019) show that firms using voluntary self-regulation are more likely to engage in eco-innovations. Additionally, Jiang et al. (2019) find that voluntary environmental regulation leads to increased research and development (R&D) investment for technological innovation.

Proactive environmental strategy is a systematic pattern of voluntary practices that go beyond regulatory requirements to reduce the environmental impact of a company (Aragón-Correa et al., 2008). According to Karstensen et al. (2018), carbon pricing is one of the most important voluntary tools to reduce GHG emissions and mitigate climate change effects. ICP is increasingly being used as a new tool for carbon management, investment analysis, as well as a means to analyze the climate change risk exposure of firms (Byrd et al., 2020).

Byrd et al. (2020) explore the impact of ICP adoption on CO₂ emissions reduction. Their study shows that firms implementing carbon-pricing mechanisms, which belong to high CO₂-emitting industries and are capital intensive, reduce emissions faster than non-carbon-pricing firms do, based on both revenue intensity and employee intensity measures. In addition, Bento and Gianfrate (2020) show that internal carbon price levels could be explained through national climate policy, a country's economic development level and industry, and corporate governance effectiveness (Bento & Gianfrate, 2020), but they do not precisely investigate the exposition of firms to climate change in regard to ICP adoption.

2.2. Climate change exposure and ICP adoption

The Intergovernmental Panel on Climate Change defines climate exposure as “the nature and degree to which a system is exposed to significant climate variations” (Monterroso & Conde, 2015, p. 273). It further states that climate change exposure increases in periods when there are changes in perceptions of climate change risks, market opportunities, and regulatory uncertainty. Cardona et al. (2012) explain that understanding the many-sided nature of vulnerability and exposure is a precondition for determining the climate change impact and implementing effective adaptation and risk management strategies.

Lazrus (2015) states that the decision making and planning of climate adaptation are closely linked to people's perception of climate risks. Similarly, Weinhofer and Busch (2013)

argue that the extent to which companies actually start managing climate risks depends on management's risk beliefs and interpretations. Escobar and Vredenburg (2011) study the climate strategies of four oil and gas corporations using both resource-based and institutional perspectives. They argue that sustainability development pressures, that is, climate change, biodiversity, renewable energy development, and social investment, vary across multinationals, and they propose that business-level strategies of reduced costs, green consumerism, reduced liability, and reduced risk exposure could resolve sustainable development issues.

Similarly, Amran et al. (2016) explore the effects of internal resources and geographical location on companies' climate strategy adoption. Using the same theoretical basis, Orsato et al. (2015) examine the drivers and motivation behind the adoption of voluntary climate initiatives among low-carbon intensity firms by focusing on the Brazilian banking industry. According to these studies, firm-level factors (managerial capabilities, resource slack etc.) as well as host-country-specific factors affect the incorporation of climate change strategies, in addition to pressures related to the home-country institutional framework that could force companies into the adoption of climate strategies. Bui and de Villiers (2017) conduct a study on five New Zealand electricity generators to examine their strategies in response to climate change. It appears that firms adopt proactive, creative, anticipatory or reactive strategies at different times, considering different climate-related risks.

As identified by Bui and de Villiers (2017), companies move toward the adoption of proactive and creative strategies to manage their carbon performance when climate change risk exposure and market opportunities increase. Drawing on a survey of managers of Italian manufacturing companies, Todaro et al. (2021) also identify climate change awareness and perceived exposure to climate risk as factors behind corporate responses to climate change.

Capitalizing on these studies concerning and considering ICP as a voluntary and proactive initiative to reduce carbon emissions, we postulate that climate change exposure could foster the adoption of ICP by firms.

3. Methodology

3.1 Data and variables

This study aims to investigate the precise effect of climate change exposure on a company's propensity to adopt ICP. We test whether firm-level climate change exposure plays a role in the strategic decision to adopt ICP. To answer this question, we collect data covering 1,362 firms reporting to the CDP in the years 2016–2018, resulting in 3,170 firm–year observations. The CDP gathers and requests information about climate change strategies, including internal carbon prices, from companies around the globe and presents these in its annual report. CDP data have been used in several previous climate change research works (Andrew & Cortese, 2011; Ben-Amar & McIlkenny, 2015; Stanny & Ely, 2008). For the purpose of our analysis, we create a binary variable (*ICPAdoption*) that takes the value of one for firms that have adopted ICP, and zero otherwise.

The independent variables include GHG emissions (*GHG*) and climate change exposure measures (*CC_Expo*). In this study, we use GHG emissions as a proxy for carbon exposure, as well as the climate change exposure measure identified by Sautner et al. (2020), to test whether firm-level climate change exposure affects the firm's ICP adoption decision. We use these two exposure measures because they exhibit cross-sectional and time-series variations and are better at capturing firm-level variations and are more specific than ratings. A report on carbon exposure by Deloitte (2018) defines the carbon footprint to quantify the exposure a stock or portfolio may have and a simple method is to analyze the carbon emissions of each company.

Litterman (2013), Pindyck (2013) and Weitzman (2009) argue that firms emitting carbon are exposed to carbon risk because of climate change's potential impacts. Hence, we use the GHG impact ratio (the company's total external environmental costs, direct and indirect, divided by the company's turnover/revenue) from Trucost as a proxy for firm-level carbon exposure.

Sautner et al. (2020) recently developed a measure to quantify firm-level climate change exposure from conversations in earnings conference calls. Transcripts of quarterly earnings conference calls were used to construct time-varying measures of firm-level exposure to climate change. They state that, while a firm's voluntarily disclosed carbon emissions are gaining some traction as an exposure measure, such data are claimed to only exist for a limited and selected sample. Therefore, the authors use quarterly earnings conference calls to develop a measure of firm-level exposure to climate change. According to Hollander et al. (2010), earnings calls are vital corporate events on stakeholders' agenda and allow them to know management views, as well as ask questions about significant current and future developments. Sautner et al. (2020) perceive the use of conference calls as a major benefit, because they are less susceptible to greenwashing by management, since stakeholders will act as a counterpoint by asking probing questions. They state that this is different compared with other documents such as annual reports, ESG reports, or press releases, which exclusively reflect the views of management and show that voluntary information exchanges between management and financial analysts during conference calls do not appear to be effected by variation across countries in terms of mandatory disclosure standards. Climate change exposure measures the relative frequency with which bigrams related to three main climate change components occur in conference calls: first, bigrams that capture opportunities related to climate change; second, bigrams that capture regulatory shocks related to climate change; and, last, bigrams that capture physical shocks related to climate change. We assume this measure covers potentially related

aspects of climate change exposure and is a good proxy for measuring exposure at the firm level².

Following Bento and Gianfrate (2020), we control for firm characteristics such as *Size* (natural logarithm of a firm's total assets), *Leverage* (debt-to-equity ratio), *ROA* (return on assets), and the percentages of independent board members (*Board Indp.*) and of women on the board (*Female*). We also control for country-level variables, including the national carbon price (*NCP*), a dummy variable that takes the value of one when the corporation is headquartered in a country with an active carbon pricing scheme, and zero otherwise, and the gross domestic product (*GDP*) per capita. Financial data are obtained from Datastream, governance data from Thomson Reuters ESG data, and national data from the World Bank. Our regression models also include *year* and *sector* fixed effects. Table 1 provides the variable definitions and sources.

[INSERT TABLE 1 ABOUT HERE]

3.2 Empirical model

To test the relation between firm-level carbon exposure and ICP adoption, we employ a logit model. Welch et al. (2000) use logit analysis to estimate the adoption and non-adoption of the voluntary climate change program in their study on the level of adoption and contribution of the program to the reduction of CO₂. de Abreu et al. (2021) also use a logit regression model to explore the factors affecting low-carbon decision making in the Canadian oil and gas sector. Many studies on farmers' adaptation strategies to climate change and their implications have

² The data underlying the climate-change exposure measure we use in our study is global and publicly available at: <https://osf.io/fd6jq/>.

used logit model (Fadina & Barjolle, 2018; Legesse et al., 2013; Trinh et al., 2018). The model we use is as follows:

$$\ln (ICP_{i,t} \text{ Adoption} | 1 - ICP_{i,t} \text{ Adoption}) = \beta_0 + \beta_1 CC_Expo + \beta_3 Size_{i,t} + \beta_4 Leverage_{i,t} + \beta_5 ROA_{i,t} + \beta_6 Board\ Indp_{i,t} + \beta_7 Female_{i,t} + \beta_8 GDP_{i,t} + \beta_9 NCP_{i,t} + \beta_{10} Sector_{i,t} + \beta_{11} Year_{i,t} \quad (1)$$

where $ICP_{i,t} \text{ Adoption}$ is the binary dependent variable taking the value of one if firm i has adopted an internal carbon price in year t , and zero otherwise. The variable *Climate change exposure*, our variable of interest, is measured through two proxies, GHG and CC_Expo . The variable $GHG_{i,t}$ is the GHG impact ratio for firm i in year t , and $CC_Expo_{i,t}$ is the firm-level climate change exposure of Sautner et al. (2020) for firm i in year t . For firm i in year t , the variable $Size_{i,t}$ is the natural logarithm of the total assets, $Leverage_{i,t}$ is the firm's total debt-to-equity ratio, $Board\ Indp_{i,t}$ is the percentage of independent board members as reported by the company, and $Female_{i,t}$ is the percentage of women on the board. *Sector* and *year* fixed effects are also included in the model.

4. Results

4.1 Descriptive statistics

Table 2 provides descriptive statistics of the variables. The GHG total impact ratio ranges from 0.08 to 64.86, with an average of 2.11. The mean CC_Expo is 1.464, with a minimum of zero and a maximum of 31.855. Over the period 2016–2018, the average firm $Size$ is \$38.3 billion ($e^{17.461}$), with mean $Leverage$ 28.75% and ROA , on average, equal to 6.46%. The average level of $Board\ Indp.$ is 67.4%, whereas the average percentage of $Female$ board members is 24.2%. The mean GDP for the countries is 10.70, and the average NCP (national carbon price) for the firm–year sample is 0.53.

[INSERT TABLE 2 ABOUT HERE]

4.2 Bivariate tests

To better understand *GHG* and *CC_Expo*, we first perform bivariate analysis comparing the means and medians at different levels of *GHG* and *CC_Expo*. The analysis (see Table 3) shows that the mean *GHG* value for ICP adopters is largely higher than for non-adopters (3.810 > 1.443). Moreover, non-adopters appear to emit lower *GHG* for all three quartiles than adopters. The value of *CC_Expo* for adopters is also higher than for their non-adopting counterparts. The two-sample t-tests (see Table 4) of cultural dimensions for ICP adoption show t-values of -14.065 and -13.875, respectively, indicating that the values for the two samples are significantly different (at the 1% level). A two-sample Wilcoxon rank-sum (Mann-Whitney) test (see Table 5) shows statistically significant differences in *GHG* and *CC_Expo* between ICP adopters and non-adopters (*Z-value* = -13.282, *p* = 0.000 for *GHG*; *Z-value* = -12.478, *p* = 0.000 for *CC_Expo*). The boxplot in Figure 1 depicts the *GHG* and *CC_Expo* measures for ICP adopters and non-adopters.

[INSERT FIGURE 1 ABOUT HERE]

[INSERT TABLE 3 ABOUT HERE]

[INSERT TABLE 4 ABOUT HERE]

[INSERT TABLE 5 ABOUT HERE]

Table 6 presents the Pearson correlations between the dependent, independent, and control variables. The correlation between *GHG* and *CC_Expo* is positive and statistically significant (0.408). This relatively high correlation is expected, given that these two variables capture firm exposure to carbon- and climate-related risks. Table 6 also shows that *GHG* and

CC_Expo are positively and significantly correlated with the likelihood of ICP adoption, with correlations coefficients of 0.242 and 0.239, respectively. These bivariate tests seem to provide preliminary support for our hypothesis. Further, with the exception of the previously mentioned correlation between *GHG* and *CC_Expo*, the correlation coefficients between independent and control variables are relatively low, which suggests that multicollinearity is not a serious threat to our multivariate analysis, which is confirmed by the average variance inflation factor of less than 2.50.

[INSERT TABLE 6 ABOUT HERE]

4.3 Baseline regression

Table 7 presents the model specifications. Models (1) and (2) focus on the role of firm-level carbon exposure (*GHG* emissions) and climate change exposure in firms' adoption of ICP. The dependent variable is *ICP Adoption*, a binary variable taking the value of one if the firm has adopted ICP, and zero otherwise. Both *GHG* and *CC_Expo* are positively associated with *ICP Adoption* and are highly statistically significant (at the 1% level). Table 7 presents the logit coefficients associated with *GHG* and *CC_Expo*, which are 0.061 and 0.139, respectively, with odds ratios 1.063 and 1.149, respectively. Therefore, for each unit increase in *GHG* and *CC_Expo*, the odds of adopting ICP increase by 6.1% and 14.9%, respectively. We therefore find that firm-level carbon and climate change exposure are significantly linked to a firm's decision to adopt ICP.

[INSERT TABLE 7 ABOUT HERE]

In terms of firm-level controls, *Size* is anticipated to have an effect on *ICP Adoption*, since larger firms are scrutinized more carefully (Bansal, 2005). Prior research has confirmed

a positive relation between company size and both voluntary carbon disclosure (Andrikopoulos & Kriklani, 2013; Brammer & Pavelin, 2006; Luo & Tang, 2014) and climate change mitigation strategy implementation (Damert et al., 2017; Weinhofer & Hoffmann, 2010). *Leverage* has no significant impact, whereas *Board Indp.* and the percentage of women on the board (*Female*) show positive and significant effects on *ICP Adoption*. Among the country-level control variables, the national carbon price (*NCP*) turns out to have a significantly positive effect on *ICP Adoption*. According to Matsumura et al. (2014); Reid and Toffel (2009), to lessen the risk of regulatory intervention in the prevalence of national carbon policy (e.g. carbon tax, quotas), companies tend to disclose information voluntarily. The positive coefficients of *Size*, *Board Indp.*, *Female*, and *NCP* are in line with the findings of Bento and Gianfrate (2020) concerning ICP levels. In all our models, we control for *Sector*³ and *Year fixed effects*. Overall, our results show that ICP adoption decision significantly depends upon firms' carbon footprint and climate change exposure, in line with our hypothesis.

4.4. Robustness tests

To test the robustness of our results, we use the shadow price as an alternate dependent variable. According to the 2017 CDP report (Bartlett et al., 2017), most companies utilize a shadow price by attaching a hypothetical cost of carbon to each ton of CO₂ emissions as a tool to reveal hidden risks and opportunities and to support strategic decision making related to future capital investments. In their study on the social costs of carbon and the shadow price of carbon in the United Kingdom, Price et al. (2007) suggest that the shadow price of carbon should be implemented as a starting point based on the social cost of carbon as a target for global action

³ Following (Bento & Gianfrate, 2020), we run our regression model controlling for the energy sector as a dummy variable, and the results are not affected.

considering carbon concentrations. With a policy and economic perspective, the shadow price of carbon is said to be a more flexible concept to ensure that government programs remain in line with governmental climate change goals. Boussemart et al. (2017) examine carbon shadow prices for 119 countries and find that global carbon shadow prices are increasing by around 2.24% annually. Most research on the shadow price of carbon is from the country's perspective and is used for government policy formulation. We therefore use the shadow price as an alternative dependent variable. Table 8 shows that the results are the same, since both *GHG* and *CC_Expo* show positive and significant relations with shadow price adoption. The variables of *Size* and *NCP* also have positive and significant effects on the adoption of ICP.

[INSERT TABLE 8 ABOUT HERE]

Table 9 shows the robustness of the results, using the propensity score matching (PSM) technique. PSM is a widely used method to estimate average treatment effects (Abadie & Imbens, 2016). It applies to all situations with a treatment, a group of treated individuals, and a group of untreated individuals (Caliendo & Kopeinig, 2008). Matching is carried out by pairing treatment and control units that are alike in terms of observable characteristics (Dehejia & Wahba, 2002). Cassiman and Golovko (2011) use a matching model framework to address endogeneity in a study on innovation and exports while Kanashiro (2020) uses PSM to examine whether environmental governance mechanisms contribute to lowering toxic emissions in high-polluting industries. In our study, observations are matched based on firm-level characteristics, that is, size, leverage, return on assets, board independence, and the percentage

of women on the board. We find that our results are unaffected: using PSM, we find *GHG* and *CC_Expo* are still positively associated with ICP adoption and highly statistically significant.⁴

[INSERT TABLE 9 ABOUT HERE]

Finally, in Table 10, we use cross-sectional data for each year (2016–2018) to ensure the robustness of our findings. The results for *GHG* and *CC_Expo* are consistent with the base model results. We find that *GHG* and *CC_Expo* are still positively and significantly associated with *ICP Adoption*. The variables *Size* and *NCP*, in the year-wise model, are also significantly associated with *ICP Adoption*.

[INSERT TABLE 10 ABOUT HERE]

4.5 Additional analyses

We further extend our analysis of the association between climate change exposure and ICP adoption by considering different dimensions of firm-level climate change exposure to physical risks, as well to transition risks (Task Force on Climate-Related Financial Disclosures, 2017). These transition risks result from increasing regulatory pressures toward a transition to a net zero carbon economy through the introduction of carbon taxes and emission trading schemes. Climate change also offers several opportunities to corporations with massive investments in green innovation and low-carbon technologies. Following Sautner et al. (2020), we consider the effects of these individual dimensions in relation to the opportunities as well as regulatory and physical risks associated with climate change. Table 11 presents the results of the effects

⁴ We also test the shadow price adoption variable with the PSM technique: the variables *GHG* and *CC_Expo* are positively associated with shadow price adoption and highly statistically significant.

of three individual climate change exposure measures (CC_Expo^{Opp} , CC_Expo^{Reg} , and CC_Expo^{Phy}) on *ICP Adoption*.

Our findings show that firm-level exposure to climate change opportunities, as well as to regulatory risks, is positively related to the propensity of ICP adoption. In contrast, firm-level exposure to physical impacts of climate change do not seem to affect the decision to adopt ICP. These results suggest that corporations respond to increasing regulatory pressure, in the form of either carbon taxes or cap and trade mechanisms, through the voluntary adoption of ICP programs to guide corporate investment assessments. This result is in line with the study of Suk (2018) that examines carbon management under the carbon pricing scheme in South Korea and shows that firms' carbon pricing is particularly related to government pressure.

[INSERT TABLE 11 ABOUT HERE]

We also examine whether the effect of climate change exposure on ICP adoption is greater in the presence of effective governance mechanisms. Given that climate change exposes corporations to material financial risks, we would expect effective governance devices to foster the implementation of proactive adaptation strategies, such as ICP programs, as part of their risk oversight and management roles. In contrast, with ineffective governance structures, corporations might not implement proactive adaptation strategies, even though they are exposed to significant climate-related risks. Prior governance studies (Ben-Amar & McIlkenny, 2015; de Villiers et al., 2011; Haque, 2017; Liao et al., 2015) have relied on board independence as a proxy for effective boards of directors. Independent boards are expected to perform effective monitoring over management, which, in turn, mitigates agency costs and enhances firm performance (de Villiers et al. 2011). In the specific context of climate change, several studies reveal a positive association between board independence and climate change

disclosures (Aggarwal & Dow, 2012; Ben-Amar & McIlkenny, 2015; Liao et al., 2015). Haque (2017) also reports that board independence is positively related to the implementation of carbon reduction initiatives such as participation in emission trading scheme initiatives or initiatives to reduce, recycle, substitute, or compensate for CO₂ equivalents in their manufacturing processes.

Consequently, we test whether board independence moderates the relation between climate change exposure and ICP adoption. We create a board independence dummy variable that takes the value of one if board independence is above the median level, and zero otherwise. We then include an interaction term between climate change exposure and the board independence dummy. Table 12 shows that board independence plays a significant role as a moderator between climate change exposure and ICP adoption. This finding highlights that an independent board and effective corporate governance increase the inclination toward ICP adoption when the corporation faces material climate change exposure.

[INSERT TABLE 12 ABOUT HERE]

Stakeholders are increasingly scrutinizing firms' environmental stewardship and applying growing pressure for the implementation of environmentally friendly business practices (Suk, 2018). Corporations must bear the costs associated with their emissions (Engels, 2009; Hopwood & Unerman, 2010), which can affect their relative competitiveness and potentially deprive them of their competitive advantage (Reinaud, 2005). Companies then move toward the adoption of proactive and creative strategies to manage their carbon performance when their climate change risk exposure and market opportunities increase (Bui & de Villiers, 2017). Firms facing greater risk from the consequences of climate change have strong incentives to develop strategies to address them (Hoffmann & Busch, 2008). The results of the effect of climate change exposure on ICP adoption are in line with studies on different

facets of climate change strategies. More specifically, besides the country-level factors identified by previous research concerning ICP levels (Bento & Gianfrate, 2020), we find clear evidence of a link between ICP adoption and a firm's exposure to carbon and climate change.

5. Conclusion and policy implications

This paper explores the determinants of ICP adoption among global companies reporting to the CDP. ICP implementation plays a key role in a company's proactive strategy to address the business effects of climate change (Bento & Gianfrate, 2020). Our paper aims to identify the factors driving the adoption of such programs to curb carbon emissions and hence mitigate climate-related business risks. More specifically, we investigate the impact of carbon and climate change exposure on firms' ICP adoption.

To the best of our knowledge, our study is the first to consider climate change exposure at the firm level as a driver of ICP adoption. Drawing on an international sample of 3,710 observations from CDP respondents over the period 2016–2018, our results show that firm-level carbon exposure as well as climate change exposure influence the propensity toward ICP adoption. This result is robust to two measures of climate change exposure (*GHG* and firm level *CC_Expo*), the use of the shadow price as an alternative explanatory variable, propensity score matching, and year-by-year regressions. Companies with higher emissions and greater climate change exposure have a larger probability of adopting ICP. Firm-level climate change exposure turns out to be a significant determinant of ICP adoption, in line with the work of Bui and de Villiers (2017), who suggest that corporate strategies change in response to increased climate change exposure. Companies with higher emissions and greater climate change exposure are more likely to actually put a price on carbon to guide their investments and strategies toward a net zero economy.

More specifically, we also find that some dimensions of exposure are more strongly linked to ICP adoption. Whereas climate change exposure linked to regulation and opportunities is particularly significant, exposure to physical shocks is not. In addition, we uncover the role of governance as a moderating variable. Climate change exposure combined with strong board independence seems to foster ICP adoption at the firm level.

This study provides several avenues for future research. ICP is an emerging practice and can still be explored. This paper highlights the role of carbon and climate change exposure in influencing ICP adoption and aims to shed light on the conditions of ICP implementation; it can thus be seen as a step toward better understanding this emerging tool. Future research could explore other motives, at both the firm and country levels, and the forms in which ICP is used. Further investigation on ICP levels can also be carried out, since vast heterogeneity is seen among the levels of internal carbon prices. The pros and cons associated with ICP adoption could be explored in depth, since ICP could be an opportunity to gain competitive advantage for some firms, but a mere cost for others.

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Figure 1 - ICP adopters vs. non-adopters carbon and climate-change exposure box plot

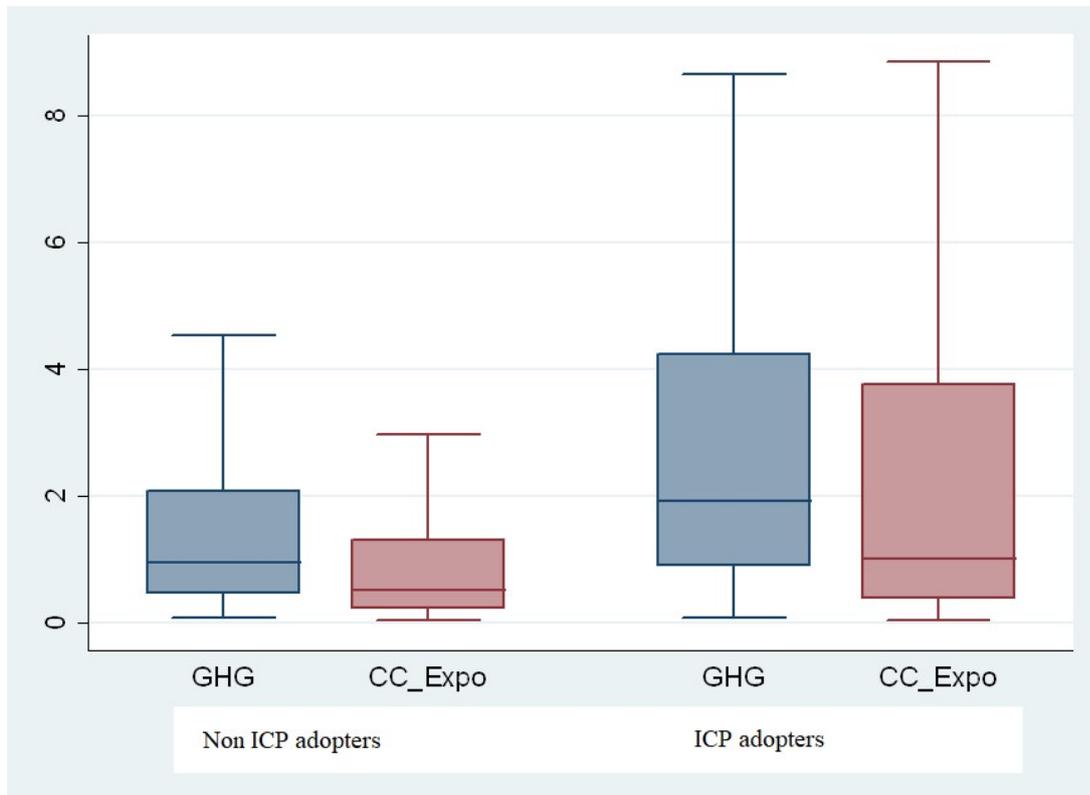


Table 1 - Variable description

Variable	Variable description	Source
ICP Adoption	Dummy variable taking 1 if ICP is adopted , 0 otherwise	CDP
GHG	GHG-Total Impact Ratio (%) Greenhouse Gas Emissions at firm level The total external environmental costs of the company (direct and indirect) divided by the company's turnover/revenue.	Trucost
CC_Expo	Climate Change Exposure at Firm Level	Data source: osf.io; Variable developed by Sautner et al., (2020)
CC_Expo ^{Opp}	Climate Change Exposure at Firm Level specifically opportunities related to climate change	Data source: osf.io; Variable developed by Sautner et al., (2020)
CC_Expo ^{Reg}	Climate Change Exposure at Firm Level specifically regulation shocks related to climate change	Data source: osf.io; Variable developed by Sautner et al., (2020)
CC_Expo ^{Phy}	Climate Change Exposure at Firm Level specifically physical shocks related to climate change	Data source: osf.io; Variable developed by Sautner et al., (2020)
Size	Log of total assets	Worldscope
Leverage	Total company debt/shareholder's equity	Worldscope
ROA	Return on Asset	Worldscope
Board Indp.	Percentage of independent board members as reported by the company	Asset4
Female	Percentage of female on the board	Asset4
GDP	Natural log of GDP per capita of the country of the firm	World Bank
NCP	National Carbon Price Dummy variable = 1 if the country where company is headquartered has a national carbon price in place, 0 otherwise)	World Bank
Year	ICP Adoption and other data taken for year 2016-2018	CDP
Sector	Firms sectors classification	CDP

Table 2 - Summary statistics

VARIABLE	Mean	Median	Minimum	Maximum	Std.Dev.	Observations
ICP Adoption	0.281	0	0	1	0.450	3,170
GHG	2.109	0.774	0.080	64.856	4.391	3,170
CC_Expo	1.464	.398	0	31.855	3.143	3,170
CC_Expo ^{Opp}	0.662	.104	0	18.080	1.745	3,170
CC_Expo ^{Reg}	0.084	0	0	6.093	0.322	3,170
CC_Expo ^{Phy}	0.0169	0	0	5.767	0.151	3,170
Size	17.461	16.963	13.329	24.579	2.423	3,170
Leverage	28.752	26.355	0.010	75.77	16.725	3,170
ROA	6.459	5.405	-13.02	28.17	6.168	3,170
Board Indp	67.492	73.33	0	100	23.71	3,170
Female	24.213	25	0	69.23	12.558	3,170
GDP	10.707	10.821	8.672	11.634	0.480	3,170
NCP	0.531	1	0	1	.499	3,170

Table 3 - Descriptive statistics

ICP Adoption	ICP non-adopters	ICP adopters
GHG		
Mean	1.443	3.810
25th percentile (1st quartile)	.304	.449
50th percentile (Median Q2)	.647	1.559
75th percentile (3rd quartile)	1.459	3.991
CC_Expo		
Mean	.992	2.665
25th percentile (1st quartile)	.131	.238
50th percentile (Median Q2)	.327	.664
75th percentile (3rd quartile)	.838	2.686

Table 4 - Year-wise industry sample description

Industry	Year			Total
	2016	2017	2018	
Consumer Discretionary	135	157	166	458
Consumer Staples	79	91	94	264
Energy	57	62	54	173
Financials	103	138	129	370
Health Care	68	85	82	235
Industrials	177	216	231	624
Materials	89	101	93	283
Real Estate	43	41	37	121
Technology	87	98	90	275
Telecommunications	51	53	56	160
Utilities	57	72	78	207
Total	946	1,114	1,110	3,170

Table 5 - Two sample t test and Wilcoxon rank-sum (Mann-Whitney)

		Freq.	Mean	Std. Err.	Std. Dev.	t-test
Two sample t test						
GHG						
ICP Non-Adopters	2,278	1.443	.058	2.788		
ICP Adopters	892	3.810	.224	6.685		
Diff		-2.367	.168			-14.065***
CC_Expo						
ICP Non-Adopters	2,278	.993	.048	2.289		
ICP Adopters	892	2.666	.149	4.442		
Diff		-1.673	.121			-13.875***
		Freq.	Rank-sum			
Wilcoxon rank-sum (Mann-Whitney)						
GHG						
ICP Non-Adopters	2,278	3303990				
ICP Adopters	892	1722045				
Z-value					-13.282***	
Probability					0.000	
CC_Expo						
ICP Non-Adopters	2,278	3322898.5				
ICP Adopters	892	1703136.5				
Z-value					-12.478***	
Probability					0.000	

Table 6 - Correlation Matrix

Variables	ICP Adopt	GHG	CC Expo	CC Expo ^{Opp}	CC Expo ^{Reg}	CC Expo ^{Phy}	Size	Leverage	ROA	Board Indp	Female	GDP	NCP
ICP Adoption	1.000												
GHG	0.242***	1.000											
CC_Expo	0.239***	0.408***	1.000										
CC_Expo ^{Opp}	0.198***	0.320***	0.902***	1.000									
CC_Expo ^{Reg}	0.193***	0.397***	0.569***	0.423***	1.000								
CC_Expo ^{Phy}	0.024	0.043**	0.075***	0.007	0.019	1.000							
Size	0.150***	0.001	0.030*	0.032*	0.020	0.014	1.000						
Leverage	-0.000	0.084***	0.062***	0.062***	0.028*	-0.016	-0.126***	1.000					
ROA	-0.118***	-0.074***	-0.100***	-0.084***	-0.062***	-0.001	-0.168***	0.057***	1.000				
Board Indp.	-0.011	0.056***	-0.001	0.008	0.027	-0.034*	-0.272***	0.073***	0.031*	1.000			
Female	0.034*	-0.038**	-0.032*	-0.023	0.007	0.002	-0.254***	-0.063***	0.008	0.255***	1.000		
GDP	-0.061***	-0.085***	-0.002	-0.016	0.028	-0.031*	-0.299***	0.021	0.002	0.370***	0.242***	1.000	
NCP	0.119***	-0.009	-0.021	-0.037**	0.025	0.001	0.098***	-0.157***	-0.057***	-0.276***	0.127***	-0.075***	1.000

*** p<0.01, ** p<0.05, * p<0.1

Table 7 - Logit regression of GHG and CC_Expo on ICP adoption

VARIABLES	Model 1	Model 1	Model 2	Model 2
	Logit coeff	Odds ratio	Logit coeff	Odds ratio
GHG	0.061*** (0.014)	1.063*** (0.015)		
CC_Expo			0.139*** (0.015)	1.149*** (0.018)
Size	0.171*** (0.022)	1.186*** (0.026)	0.172*** (0.021)	1.188*** (0.025)
Leverage	-0.001 (0.003)	0.999 (0.003)	0.003 (0.003)	1.003 (0.003)
ROA	-0.022*** (0.008)	0.979*** (0.008)	-0.028*** (0.008)	0.972*** (0.008)
Board Indp.	0.005** (0.002)	1.005** (0.002)	0.007*** (0.002)	1.007*** (0.002)
Female	0.012*** (0.004)	1.012*** (0.004)	0.014*** (0.004)	1.014*** (0.004)
GDP	-0.088 (0.099)	0.916 (0.091)	-0.206** (0.096)	0.814** (0.078)
NCP	0.572*** (0.097)	1.772*** (0.171)	0.501*** (0.094)	1.651*** (0.155)
Year fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Constant	-2.331** (1.187)	0.097** (0.115)	-3.123*** (1.141)	0.044*** (0.050)
Observations	3,170	3,170	3,170	3,170

Notes: This table provides the regression results estimated by using GHG and CC_Expo as a proxy for climate change exposure and its impact on ICP adoption. Controlling for the firm level and country level variables, year and sector fixed effects are added to the model. *** p<0.01, ** p<0.05, * p<0.1

Table 8 - Robustness test using shadow price adoption

VARIABLES	Model 1 Logit coeff	Model 1 Odds ratio	Model 2 Logit coeff	Model 2 Odds ratio
GHG	0.055*** (0.011)	1.056*** (0.011)		
CC_Expo			0.060*** (0.014)	1.062*** (0.015)
Size	0.119*** (0.024)	1.127*** (0.027)	0.119*** (0.024)	1.127*** (0.027)
Leverage	0.001 (0.003)	1.001 (0.003)	0.001 (0.003)	1.001 (0.003)
ROA	-0.037*** (0.009)	0.964*** (0.009)	-0.038*** (0.010)	0.963*** (0.009)
Board Indp.	0.001 (0.003)	1.001 (0.003)	0.003 (0.003)	1.003 (0.003)
Female	0.014*** (0.004)	1.014*** (0.005)	0.013*** (0.004)	1.013*** (0.005)
GDP	-0.280** (0.110)	0.756** (0.083)	-0.363*** (0.107)	0.695*** (0.075)
NCP	0.331*** (0.111)	1.392*** (0.155)	0.347*** (0.111)	1.414*** (0.157)
Year fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Constant	-1.209 (1.313)	0.298 (0.392)	-0.423 (1.288)	0.655 (0.844)
Observations	3,170	3,170	3,170	3,170

Notes: This table provides the regression results estimated by using GHG and CC_Expo as a proxy for climate change exposure and its impact on ICP adoption. This regression model uses shadow price, which is a form of internal carbon price used by vast majority of corporations. For example, the shadow price used by the major global oil and gas companies operating in regulated carbon markets ranged between \$27.92 and \$80 per metric ton Ahluwalia (2017). Controlling for the firm level and country level variables, year and sector fixed effects are added to the model. *** p<0.01, ** p<0.05, * p<0.1

Table 9 - Robustness tests using propensity score matching

VARIABLES	Model 1	Model 1	Model 2	Model 2
	Logit coeff	Odds ratio	Logit coeff	Odds ratio
GHG	0.061*** (0.018)	1.062*** (0.019)		
CC_Expo			0.121*** (0.019)	1.129*** (0.022)
Size	0.052** (0.024)	1.053** (0.026)	0.045* (0.024)	1.046* (0.025)
Leverage	-0.003 (0.003)	0.997 (0.003)	0.000 (0.003)	1.000 (0.003)
ROA	0.011 (0.010)	1.011 (0.010)	0.008 (0.010)	1.008 (0.010)
Board Indp.	0.005* (0.003)	1.005* (0.003)	0.006** (0.003)	1.006** (0.003)
Female	-0.003 (0.005)	0.997 (0.005)	-0.003 (0.004)	0.997 (0.004)
GDP	-0.030 (0.117)	0.971 (0.114)	-0.118 (0.114)	0.889 (0.101)
NCP	0.567*** (0.113)	1.763*** (0.200)	0.523*** (0.111)	1.688*** (0.187)
Year fixed effect	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes
Constant	0.091 (1.397)	1.095 (1.530)	-0.576 (1.345)	0.562 (0.756)
Observations	1,784	1,784	1,784	1,784

Notes: Regression results estimated by using GHG and CC_Expo as a proxy for climate change exposure and its impact on ICP adoption. This regression model uses propensity score matching technique using an equal sample size for ICP adopters and non-adopters. *** p<0.01, ** p<0.05, * p<0.1

Table 10 - Robustness tests using year-wise sample on ICP adoption

VARIABLES	Model 1	Model 1	Model 2	Model 2	Model 1	Model 1	Model 2	Model 2	Model 1	Model 1	Model 2	Model 2
	Logit coeff	Odds ratio	Logit coeff	Odds ratio	Logit coeff	Odds ratio	Logit coeff	Odds ratio	Logit coeff	Odds ratio	Logit coeff	Odds ratio
	2016				2017				2018			
GHG	0.092*** (0.029)	1.096*** (0.031)			0.102*** (0.023)	1.108*** (0.025)			0.101*** (0.022)	1.106*** (0.025)		
CC_Expo			0.182*** (0.031)	1.200*** (0.038)			0.125*** (0.024)	1.133*** (0.028)			123.7*** (24.76)	5.105e+53*** (1.264e+55)
Size	0.208*** (0.043)	1.231*** (0.053)	0.206*** (0.042)	1.228*** (0.052)	0.132*** (0.036)	1.141*** (0.042)	0.133*** (0.036)	1.142*** (0.042)	0.196*** (0.034)	1.216*** (0.041)	0.194*** (0.034)	1.214*** (0.041)
Leverage	-0.013** (0.006)	0.987** (0.006)	-0.007 (0.006)	0.993 (0.006)	0.006 (0.005)	1.006 (0.005)	0.006 (0.005)	1.006 (0.005)	0.006 (0.004)	1.006 (0.004)	0.008* (0.004)	1.008* (0.005)
ROA	-0.005 (0.016)	0.995 (0.016)	-0.024 (0.016)	0.977 (0.015)	-0.044*** (0.014)	0.957*** (0.013)	-0.047*** (0.014)	0.954*** (0.013)	-0.032** (0.013)	0.968** (0.013)	-0.028** (0.013)	0.973** (0.013)
Board Indp.	0.004 (0.004)	1.004 (0.005)	0.007 (0.004)	1.007 (0.004)	0.007* (0.004)	1.007* (0.004)	0.009** (0.004)	1.009** (0.004)	0.003 (0.003)	1.003 (0.003)	0.004 (0.003)	1.004 (0.003)
Female	0.013 (0.008)	1.013 (0.008)	0.014* (0.008)	1.014* (0.008)	0.013** (0.006)	1.013** (0.007)	0.013** (0.006)	1.013** (0.007)	0.016*** (0.006)	1.016*** (0.006)	0.015** (0.006)	1.015** (0.006)
GDP	-0.031 (0.232)	0.970 (0.225)	-0.239 (0.224)	0.788 (0.176)	-0.181 (0.163)	0.834 (0.136)	-0.306* (0.157)	0.737* (0.116)	-0.031 (0.151)	0.969 (0.146)	-0.099 (0.148)	0.906 (0.134)
NCP	0.656*** (0.194)	1.928*** (0.374)	0.588*** (0.187)	1.801*** (0.337)	0.542*** (0.161)	1.719*** (0.277)	0.561*** (0.161)	1.752*** (0.282)	0.401*** (0.151)	1.494*** (0.226)	0.399*** (0.151)	1.490*** (0.225)
Sector fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.124 (2.636)	0.044 (0.116)	-3.198 (2.540)	0.041 (0.104)	-2.373 (1.942)	0.093 (0.181)	-1.274 (1.881)	0.280 (0.526)	-4.848*** (1.814)	0.008*** (0.014)	-4.295** (1.786)	0.014** (0.024)
Observations	946	946	946	946	1,114	1,114	1,114	1,114	1,110	1,110	1,110	1,110

Notes: Regression results estimated by using GHG and CC_Expo as a proxy for climate change exposure and its impact on ICP adoption. This regression model uses cross section data for year 2016, 2017 and 2018. *** p<0.01, ** p<0.05, * p<0.1

Table 11 - Logit regression using CC_Expo dimensions (Opp, Reg, Phy) on ICP adoption

VARIABLES	Model 1	Model 1	Model 2	Model 2	Model 3	Model 3	Model 4	Model 4
	Logit coeff	Odds ratio						
CC_Expo	0.139*** (0.015)	1.149*** (0.018)						
CC_Expo ^{Opp}			0.200*** (0.027)	1.222*** (0.033)				
CC_Expo ^{Reg}					1.289*** (0.189)	3.631*** (0.687)		
CC_Expo ^{Phy}							0.267 (0.250)	1.306 (0.326)
Size	0.172*** (0.021)	1.188*** (0.025)	0.176*** (0.021)	1.193*** (0.025)	0.179*** (0.021)	1.197*** (0.025)	0.191*** (0.021)	1.210*** (0.025)
Leverage	0.003 (0.003)	1.003 (0.003)	0.003 (0.003)	1.003 (0.003)	0.004 (0.003)	1.004 (0.003)	0.004 (0.003)	1.004 (0.003)
ROA	-0.028*** (0.008)	0.972*** (0.008)	-0.030*** (0.008)	0.970*** (0.008)	-0.032*** (0.008)	0.968*** (0.008)	-0.035*** (0.008)	0.965*** (0.007)
Board Indp.	0.007*** (0.002)	1.007*** (0.002)	0.006*** (0.002)	1.006*** (0.002)	0.006*** (0.002)	1.006*** (0.002)	0.006*** (0.002)	1.007*** (0.002)
Female	0.014*** (0.004)	1.014*** (0.004)	0.014*** (0.004)	1.014*** (0.004)	0.013*** (0.004)	1.013*** (0.004)	0.014*** (0.004)	1.014*** (0.004)
GDP	-0.206** (0.096)	0.814** (0.078)	-0.180* (0.096)	0.835* (0.080)	-0.219** (0.095)	0.803** (0.077)	-0.187** (0.095)	0.829** (0.079)
NCP	0.501*** (0.094)	1.651*** (0.155)	0.495*** (0.093)	1.640*** (0.153)	0.459*** (0.093)	1.582*** (0.147)	0.450*** (0.092)	1.568*** (0.144)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.123*** (1.141)	0.044*** (0.050)	-3.283*** (1.140)	0.038*** (0.043)	-2.750** (1.135)	0.064** (0.073)	-3.144*** (1.130)	0.043*** (0.049)
Observations	3,170	3,170	3,170	3,170	3,170	3,170	3,170	3,170

Notes: This table provides the regression results estimated by using GHG and CC_Expo including exposure dimensions (Opportunity, regulatory, physical) as a proxy for climate change exposure and its impact on ICP adoption. Controlling for the firm level and country level variables, year and sector fixed effects are added to the model. *** p<0.01, ** p<0.05, * p<0.1

Table 12 - Logit regression using Board Independence dummy as interaction term

VARIABLES	Model 1	Model 1	Model 2	Model 2
	Logit coeff	Odds ratio	Logit coeff	Odds ratio
GHG	0.046*** (0.017)	1.047*** (0.018)		
Board Indp dummy *GHG	0.110*** (0.025)	1.116*** (0.0282)		
CC Expo			0.062*** (0.019)	1.064*** (0.021)
Board Indp dummy *CCExpo			0.113*** (0.029)	1.119*** (0.032)
Board Indp dummy	0.008 (0.115)	1.008 (0.116)	0.142 (0.112)	1.152 (0.129)
Size	0.153*** (0.021)	1.165*** (0.024)	0.153*** (0.021)	1.165*** (0.024)
Leverage	0.001 (0.003)	0.999 (0.003)	-9.56e-05 (0.003)	1.000 (0.003)
ROA	-0.024*** (0.008)	0.976*** (0.008)	-0.024*** (0.008)	0.977*** (0.008)
Female	0.014*** (0.004)	1.014*** (0.004)	0.014*** (0.004)	1.014*** (0.004)
GDP	-0.139* (0.101)	0.870 (0.088)	-0.204** (0.099)	0.815** (0.081)
NCP	0.533*** (0.098)	1.704*** (0.166)	0.550*** (0.097)	1.733*** (0.168)
Year fixed effect	Yes		Yes	
Sector fixed effect	Yes		Yes	
Constant	-2.363** (1.196)	0.094** (0.113)	-1.828* (1.173)	0.161 (0.188)
Observations	3,170	3,170	3,170	3,170

Notes: This table provides the regression results estimated by using GHG and CC_Expo as a proxy for climate change exposure and its impact on ICP adoption using board independence as a mediating variable. Controlling for the firm level and country level variables, year and sector fixed effects are added to the model. *** p<0.01, ** p<0.05, * p<0.1