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About the Economics Department
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Contents

Abstract

This study investigates how regional spillovers influence firms' climate investment decisions across EU regions using spatial econometric models. Using data from the European Investment Bank Investment Survey (EIBIS) 2023, we address two key questions: what triggers firms to adopt greener profiles, and how spillover effects impact investment decisions in neighbouring regions. Our study, reveals the existence of significant spatial dependence in firms' climate investment decisions across EU regions, underscoring at the same time the interconnected nature of adaptation and mitigation efforts. Further, risk perceptions, financial capabilities, external conditions like economic and institutional frameworks and EU funds, play a key role in shaping climate investment choices both locally and in neighbouring regions. The results underscore the critical need for spatial considerations in climate policy development, suggesting that policies tailored to regional dynamics can more effectively foster climate resilience and climate investments.

JEL Classification Numbers: C21, Q54, Q55, Q56, Q58, R11

Keywords: European Investment Bank Investment Survey, Green investment, Spatial regression analysis.

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1 Introduction

Climate change is a global challenge that requires urgent and coordinated action from all sectors of society. Among these, firms have a crucial role to play in addressing the climate emergency, as their choices affect not only their performance but also the well-being of the communities and ecosystems, they operate in. While recent updates of the National Energy and Climate Plans (NECPs) (European Commission, 2023) indicate progress towards the 2030 energy and climate targets among EU members, persistent ambition gaps and varying responses across Europe underscore the need for concerted efforts. Both adaptation and mitigation efforts are essential to meeting these targets, requiring alignment and commitment from every EU member and region.

To enhance the momentum of climate investments, it is crucial to extend our understanding beyond the firm-level factors that influence climate-related investments, as highlighted in previous research (Kalantzis and Dominguez, 2023). Understanding the broader context, including local and regional dynamics and the related spillover effects, is essential in shaping these investments. By acknowledging these regional interdependencies, policy makers can adopt more informed decisions, maximizing positive impacts at both local and wider scales. This comprehensive approach allows for a more nuanced understanding of the interconnected nature of climate investments and the various forces at play that can either facilitate or hinder progress in achieving climate targets.

In a broad sense, regional spillovers are the impacts that policies and strategies in one region have on neighbouring regions (Eurostat, 2023). In our work, we consider the effects that firms' actions have on other firms in neighbouring regions. Spillover effects can create positive or negative externalities, depending on whether they benefit or harm other firms (Eurostat, 2023). They can also generate network effects, where the value of an action increases with the number of adopters. For example, if more firms invest in renewable energy sources, they may create economies of scale and reduce the costs for others. Regional spillovers can also foster learning and innovation, as firms can share knowledge and best practices with each other. To this end, regional spillovers are important because they can amplify or hinder the diffusion of climate-friendly practices among firms (Carrico, 2021).

Our study reveals significant spatial dependence in climate investments across EU regions, underscoring the interconnectedness of firms' climate actions. Regions with similar levels of climate measure adoption tend to cluster geographically, highlighting the importance of considering regional dynamics in policy design. Key drivers of climate investments, such as firms' strategies, climate risk awareness, and energy costs, not only influence local decisions but also extend their impact to neighboring regions through spillover effects. These findings suggest that both firm-level actions and regional characteristics play crucial roles in shaping climate investments, with important implications for regional policy harmonization and the amplification of climate adaptation and mitigation efforts.

Climate investments by firms are increasingly recognized as a critical component in the global fight against climate change. However, these efforts often generate spillover effects that transcend regional boundaries, influencing markets beyond their immediate geographic scope (Awasthy et al., 2022). Understanding these spatial dependencies is essential for unraveling the complex mechanisms that drive climate-related investments and for designing policies that can effectively harness these spillovers to achieve broader environmental goals. Hence, our research is driven by two central questions: First, what triggers firms to adopt greener profiles, particularly in terms of adaptation and mitigation efforts? Second, how do firms' actions and characteristics, alongside specific regional attributes, influence climate investment decisions in neighboring regions?

Spatial clustering in the adoption of climate measures can arise from various factors, such as peer influence, industry-specific networks, or regional climate initiatives. These factors, by transcending regional boundaries, can create significant cross-regional spillover effects (Dharshing, 2017). From an empirical standpoint, capturing these complex spatial dependencies requires a methodological framework that goes beyond traditional estimation techniques like Ordinary Least Squares Regression (OLS). OLS models, while useful, may yield biased estimates due to their inability to account for spatial dynamics, thereby overlooking the interconnectedness of regional climate actions (Le Sage and Pace, 2009).

To address this gap, our study employs spatial econometric models that are specifically designed to account for the cross-regional spillovers and spatial dependencies inherent in climate investment decisions. We utilize the latest data from the European Investment Bank Investment Survey (EIBIS) 2023 to investigate how these regional spillovers influence firms' decisions to invest in climate adaptation and mitigation measures. Notably, to rigorously analyze the spatial dynamics of climate investment decisions, we applied spatial autocorrelation tests, including Moran's I and Local Moran's I, to assess whether our dependent variables exhibit spatial agglomeration characteristics. The significance of spatial autocorrelation guided our decision to employ spatial econometric models, ensuring that the cross-regional spillovers and spatial dependencies were appropriately captured. Specifically, we utilized both the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM), selected based on the results of Lagrange Multiplier (LM) tests, including the standard and robust versions of LM error and LM lag tests. These models were crucial in identifying whether spatial dependence is present in the dependent variable or in the error term, thereby allowing for a more accurate estimation of the drivers of firms' climate investments.

To our knowledge, this is one of the few studies in the EU to examine the drivers of both firms' adaptation and mitigation efforts using survey data within a spatial econometric framework. The existing literature has extensively analyzed the primary drivers of firms' climate investments, identifying factors such as climate risk perceptions, income, financial capabilities, and stakeholder pressure as significant influences (Kalantzis and Dominguez, 2023; Kalantzis et al., 2021; Bryan et al., 2009). Moreover, the role of external conditions, including economic and institutional frameworks, local governance quality, and technological diffusion, has been acknowledged as critical in shaping firms' investment decisions (Siedschlag and Yan, 2021). Recognizing the significance of spatial spillover effects, particularly in the context of clean technology diffusion and carbon emission dynamics, our study extends the scope of existing research by providing deeper insights into the spatial interdependence of firms' climate actions across EU regions.

The remainder of the paper is organized as follows. Section 2 presents the literature. Data and variables descriptions are presented in Section 3. Section 4 illustrates the econometric methodology and the models' specifications. Results are reported in Section 5 and discussed in Section 6. Finally, Section 7 provide policy implications and concludes.

2 Literature review

2.1 Drivers of firms' climate investments

The literature suggests that an increased awareness of climate change impacts is a key factor influencing adaptation and mitigation investments; firms that recognize the physical risks of climate change tend to be more proactive in seeking solutions to enhance resilience and reduce vulnerability (Kalantzis and Dominguez, 2023; Kalantzis et al., 2021; Hoffman et al., 2009; Bryan et al., 2009). However, as evidenced in the EIB Investment Report (2024), the awareness of other types of risks, i.e., transition risks associated to the cost of shifting to a low-carbon economy, are linked to firm's climate change actions. Another factor that is believed to influence climate investments is related to energy costs (Kalantzis and Dominguez, 2023; Stucki, 2019) highlights that firms with significant energy costs can achieve productivity improvements through green investments. This trend suggests that energy costs concerns are likely to drive firms towards adopting more sustainable strategies.

Income and financial capability significantly influence a firm's decision to invest in climate actions. While awareness of climate issues is crucial, the financial ability to afford climate-related investments is just as important. Studies, including those by Girma et al. (2008) and Bryan et al. (2009), have shown that firms with better access to finance are more motivated to innovate and invest in climate measures. Conversely, limited financial access can represent a major barrier to such investments, especially for adaptation (Kalantzis and Dominguez, 2023; IMF, 2021). Pressure from various stakeholders, including governments, citizens, and employees, plays a crucial role in driving firms towards greener investment strategies (Cadez et al., 2018). Regulatory bodies are particularly influential in driving corporate climate strategies as demonstrated by Damert et al. (2017) and Yunus (2017). Additionally, also the general public is becoming increasingly pivotal in advocating for climate change actions (Hjelmqvist, 2020), driving businesses to adopt more environmentally friendly practices in response to societal pressure.

The EIB Investment Report (2023) recognizes the key role of public funds in driving firms' climate investments, especially in vulnerable regions and sectors. In particular, EU funds significantly impact firms' adaptation investments, providing both financial support and a comprehensive framework to enhance adaptation strategies. Several studies in the literature also acknowledge the influence of external conditions, including economic and institutional frameworks, local governance quality, and technological diffusion, on shaping firms' investment decisions (see for example Yarrow and Chen, 2023; Siedschlag and Yan, 2021; Hrovatin et al., 2016; Cagno et al., 2013; Montalvo Corral 2003). This suggests that firms in more prosperous, stable, and innovative regions might be better positioned to undertake substantial climate-related investments. Moreover, the literature focusing on climate change studies has been increasingly recognizing the importance of analysing spatial spillover (or indirect) effects for designing effective climate change policies. Siedschlag and Yan (2021) for instance revealed that companies in the same industry or region significantly influence each other in terms of climate investment choices. This finding highlights the powerful role of spillover effects in shaping corporate environmental strategies and thus the need to delve deeper into these dynamics to formulate targeted policies and strategies that effectively promote and support climate investment decisions across various industries and regions.

2.2 Regional spillover effects in climate change studies

As climate change research evolves, there is a growing need to examine not only direct impacts but also spatial spillover effects to extensively capture the broader implications of climate change actions. Previous scholars in regional science posited that spatial dependence affects the economic behaviour of neighbouring regions (Elhorst, 2003). An emerging stream of literature investigates spillover effects in the adoption rates of clean technologies, particularly photovoltaic (PV) systems. One part of this research focuses on the role of geographical similarities (like global solar radiation) on PV diffusion, that can lead to the formation of “solar clusters” between neighbouring regions (Schaffer and Brun, 2015). Peer effects, also known as imitation behaviours, are often cited as determinants of investment in PV systems (Robinson and Ra, 2015; Bollinger and Gillingham, 2012). The existence of skilled labour clusters could also drive cross-regional spillovers in terms of knowledge diffusion (Schaffer and Brun, 2015), positively impacting PV adoption in neighbouring areas. The application of spatial econometric techniques in climate change literature is proving instrumental in more accurately identifying the magnitude of spillover effects. This methodological advancement allows for a deeper understanding of region-specific effects of climate change (Batabyal and Folmer, 2020). This literature, including works by Dharshing (2017) and Balta-Okzan (2015), observes a tendency for PV adoption rates to clustering and confirms the existence of spatial agglomeration.

Another body of literature focuses on spillover effects linked to the influential factors of energy efficiency, especially in the Chinese context. Du et al. (2016) and Ma et al. (2022), using spatial autoregressive techniques, observe evidence of spatial diffusion of energy efficiency across provinces, as energy efficiency improvements in each province tend to spill over to adjacent provinces. Similarly, Noonan et al. (2013), reveal analogous mechanics also in the residential sector in the US, highlighting the presence of "contagion" effects in the adoption of energy-efficient systems in neighbourhoods, indicating a pattern of spatial dependence. Direct and indirect effects do not always align, as illustrated by Wu et al. (2020) within the agricultural sector. While agricultural industrial agglomeration positively influences local energy efficiency directly, it paradoxically leads to negative spillovers. Key production factors like capital and technology tend to migrate to peripheral regions, thereby weakening the agricultural energy efficiency in core areas. These findings contribute to highlight the complex nature of spillover dynamics, that can diverge with respect to direct effects as showed by Pan et al. (2018); the authors studied the relationship between carbon emissions mitigation and energy efficiency and found that the direction of direct and indirect effects diverges. While the direct effect is positive, indicating that increased mitigation efforts within a region lead to improved energy utilization and innovation, the indirect effect is negative, suggesting that mitigation efforts may inadvertently lead to inefficient energy use in neighbouring areas. Similar patterns were found by Cheng et al (2023), who studied more broadly the drivers of green technologies innovations and found that while import trade and outward foreign direct investment within a region can act as catalysts for innovation in adjacent regions, the associated spillover effects tend to be negative.

A notable stream of literature focuses on carbon emissions, particularly in China, analysing spillover effects of different factors that may affect air pollution. Several authors found that carbon emissions in China present significant spatial agglomeration characteristics, highlighting the importance to capture the increasingly complex cross-regional spillover effects (Nan et al., 2022; Wang et al., 2021; Wang, 2020; Zeng et al., 2019; You and Lv, 2018; Cheng et al., 2013). Interestingly, Wang et al. (2021) observed that provinces with high (low) carbon emissions tend to be geographically close to other high-emission (low-emission) provinces. Numerous studies have highlighted a variety of spillover effects from different variables, underscoring the complex interplay of factors influencing emission levels across regions. Zeng et al. (20190 revealed that both emission reduction and renewable energy policies not only decrease local air pollutant emissions but also affect neighbouring provinces, suggesting a cross-regional impact of climate policies. Direct and indirect effects, as we have seen, can also diverge in terms of their direction. For instance, You and Lv (2018) found that economic globalization has a notably negative indirect effect on CO2 emissions, strong enough to offset its positive direct effect. This leads to an overall negative total effect, suggesting that countries surrounded by highly globalized nations experience improved environmental quality.

A growing number of scholars recognize the importance to spatial spillovers in the analysis of climate change impact on environmental, economic, and social dimensions. Batabyal and Folmer (2020) acknowledged that regional impacts of climate change vary and are often dissimilar across different areas. However, there are few studies focusing on regional or spatial dimensions of climate change compared to those concentrating on its global aspects. Schleypen et al. (2022) employed spatial econometric tools to assess climate change's impact on EU regions' sectoral labour productivity and revealed the existence of significant spillover effects. Similarly, Zeenat Fouzia et al. (2019) explored the varied impacts of different climate-related disasters on the US labor market, highlighting not only the heterogeneous effects of climate-related disasters but also their related temporal and spatial spillover effects. These studies highlight the complex and multifaceted impact of climate change on labor markets, emphasizing the necessity for comprehensive, region-specific approaches.

While the literature on climate change has explored spillover effects related to technology adoption, energy efficiency and carbon emissions, with a particular focus on China, there is a wide gap concerning the study of cross-regional dynamics in climate change investments, especially in the European context. In Europe, regional actions can have significant spillover effects and influence neighbouring regions, underscoring the key role of spatial interdependence in policy formulation (Schleypen et al., 2022). Therefore, investigating spillover effects related to the adoption of adaptation and mitigation strategies in the EU is crucial to reveal how strategies in one region influence neighbouring areas, guiding more effective climate actions. Addressing this gap can provide valuable insights into the interconnected nature of climate actions and the collective response required to tackle climate change effectively. Hence, in the present work we aim to address this gap, focusing on unveiling how regional and neighbours' choices and actions shape firms' decisions on climate investments.

3 Data and variables

3.1 Data

To evaluate the impact of firm-level characteristics and regional conditions on climate change investments, our analysis utilizes cross-sectional data for 215 EU regions. Firm-specific data were collected from the European Investment Bank Investment Survey (EIBIS) 2023 and collapsed to the regional (NUTS 2) level to align with our spatial econometrics approach. Additionally, we incorporated regional-level control variables, capturing the economic and institutional framework, as well as indicators of innovation and carbon emissions. The European Investment Bank Investment Survey stands as a unique source of information on investment activities and needs of firms within the European Union. Conducted annually since 2016, it encompasses a representative sample of over 12,000 firms from various sectors and sizes, ensuring its representativeness at the EU, country, sectoral, and firm size levels (Harasztosi et al., 2020). EIBIS primarily focuses on gathering data on firms' investment activities, financing requirements, and their responses to climate-related challenges. The latter includes inquiries into firms' perceptions of climate risks and opportunities, their strategies for climate change adaptation and mitigation, and their investments in green technologies and practices. The survey uses a stratified sampling methodology, drawing its sample from the Bureau van Dijk ORBIS database. Table A1 in Annex A describes the variables used and presents their main descriptive statistics.

3.2 Dependent variables

To investigate our research questions, we construct a set of variables representing green investment strategies of EU firms using EIBIS 2023 data: *adaptation intensity*, *mitigation intensity* and *degree of greenness*. At the regional level, our study differentiates between specific adaptation and mitigation efforts while also providing a comprehensive analysis of climate action measures through the "degree of greenness" variable. Specifically, we compute the three variables, assuming that all mitigation or adaptation measures are equally important, by first summing climate measures adopted for each firm, and then we aggregate these sums at the regional NUTS2 level. This aggregation is weighted based on the value-added reported by the firms, resulting in weighted average number of measures for each region. The choice of using value-added weights in aggregating firm-level data to the NUTS2 level allows us to highlight the role of economically significant firms in driving regional climate investments.[1] The variables are described in detail as follows:

i. *Adaptation intensity*: weighted (by value added) average number of adaptation measures adopted by firms per NUTS2 region:

$$Adaptation\ intensity_{NUTS2} = \frac{\sum_{i=1}^{n}(Adaptation\ Measures_i \times\ Value\ added_i)}{\sum_{i=1}^{n} Value\ added_i}$$

where:

- *Adaptation Measures$_i$* is the sum of adaptation measures (ranging from 0 to 3) adopted by firm *i;*
- *Value-added$_i$* is the value-added of firm *i;*
- *n* is the number of firms in the NUTS2 region.

The measures considered for adaptation include:

- Strategies for changing procedures and/or operations to increase organizational resilience;
- Technological, engineering, or nature-based solutions to avoid or reduce exposure to climate risks;
- Insurance products designed to offset climate-related losses, such as parametric insurance.

ii. *Mitigation intensity*: weighted (by value added) average number of mitigation measures adopted by firms per NUTS2 region.:

$$Mitigation\ intensity_{NUTS2} = \frac{\sum_{i=1}^{n}(Mitigation\ Measures_i \times\ Value\ added_i)}{\sum_{i=1}^{n} Value\ added_i}$$

where *Adaptation Measures$_i$* is the sum of adaptation measures (ranging from 0 to 5) adopted by firm *i.* These measures include:

- Adoption of new, less polluting business areas and technologies;
- Improvements in energy efficiency, including heating and cooling systems, and the implementation of energy-smart technologies or EMAS;
- Onsite or offsite renewable energy generation;
- Initiatives for waste minimization and recycling;
- Adoption of sustainable transport options, such as fuel-efficient and hybrid/electric vehicles, electric rolling stock.

iii. *Degree of Greenness*: weighted (by value added) average number of green actions (encompassing both adaptation and mitigation measures) adopted by firms within a region:

$$Degree\ of\ Greenneess_{NUTS2} = \frac{\sum_{i=1}^{n}(Total\ measures_i \times\ Value\ added_i)}{\sum_{i=1}^{n} Value\ added_i}$$

where *Total Measures$_i$* is the sum of adaptation and mitigation measures adopted by firm *I* (ranging from 0 to 8). The degree of greenness variable offers a more comprehensive understanding of firms' overall engagement in climate action. In fact, while adaptation and mitigation address different aspects of climate response, the degree of greenness allows for an assessment of overall environmental commitment and actions by firms, encompassing both climate strategies.

Then, to facilitate the interpretability and comparability of our findings across regions, we normalized our aggregated indicators using the min-max method, followed by a logarithmic transformation. This approach allowed us to standardize the data across regions, converting them into proportions that range from 0 to 1 (where 1 represents the full adoption of all available measures), while also handling potential skewness in the distribution of the indicators. Figure A in Appendix A displays box plots for the three main outcome variables.

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[1] More information about the estimations of the weighting scheme can be found at [Normal dot (Rev02 January 2009) (eib.org)](eib.org).

3.3 Explanatory variables

In our analysis, the explanatory variables are collected from EIBIS 2023 and can be summarized into two main factors: i) the complementarity between mitigation and adaptation investments, and ii) firm characteristics and perceptions. Further, we also include a set of iii) regional level characteristics, whose data are retrieved from European Commission datasets.

Complementarity between Mitigation and Adaptation Investments

Capturing the complementarity between adaptation and mitigation in climate action is crucial because it allows for a comprehensive understanding of how these strategies can be synergically implemented to enhance climate resilience in firms. Adaptation strategies, aimed at reducing vulnerability to climate change impacts, can be more effective when combined with mitigation efforts and vice-versa, as also emerged in the literature recognizing the complementarity between the two strategies (see for example Srivastava et al., 2023; Landauer et al. 2019; Landauer et al., 2015; Dang et al., 2003). Hence, to explore the interplay between mitigation and adaptation, our approach involves using one of these measures as a predictor of the other in our analysis. Specifically, when examining adaptation intensity as dependent variable, we use the previous year's mitigation intensity as an explanatory variable, and vice versa. Using previous years data helps in mitigating potential endogeneity issues. It is important to note that both mitigation and adaptation intensities related to previous year are calculated as our main dependent variables, using weighted aggregation and log transformation.

Firm Characteristics and Perceptions

Our analysis also includes a set of variables representing the regional share of firms with specific characteristics and perceptions. These variables, originally dichotomous at the firm level, have been aggregated to the regional level using weights based on firms’ added value. They include the share of firms at the regional level: i) for whom the impact of climate change (e.g., extreme weather events or changes in weather patterns) is a major concern, ii) that view the transition to stricter climate standards and regulations as a significant risk, iii) for whom energy costs are a major obstacle to investment activities, iv) that consider access to finance a major barrier to their investment activities, v) using a formal strategic business monitoring system to compare current performance against strategic key performance indicators, vi) that set and monitor targets for their own GHG emissions.

These variables provide a nuanced view of the regional business environment, highlighting how various firm-level factors and perceptions contribute to climate investment strategies. Previous literature supports the selection of our explanatory variables, demonstrating a clear link between these factors and firms' climate investment decisions (see for example Kalantzis and Dominguez, 2023; Kalantzis et al., 2021; Stucki, 2019; Hoffman et al., 2009; Bryan et al., 2009).

Regional characteristics

In our analysis, we incorporate several regional-level variables to account for broader economic and environmental factors that could influence climate investments, as also demonstrated in the literature (Yarrow and Chen, 2023; Siedschlag and Yan, 2021; Hrovatin et al., 2016; Cagno et al., 2013; Montalvo Corral 2003). These characteristics, chosen for their relevance and robustness, include the following variables:

a) Basic Framework: this variable is a sub-index of the Regional Competitiveness Index (RCI) developed by the DG Regional and Urban Policies of the European Commission (2022). This NUTS2 level indicator encompasses five pillars: institutions, macroeconomic stability, infrastructures, health, and basic education. These factors are key drivers in all types of economies and provide a comprehensive view of the foundational aspects that support regional development and competitiveness.
b) Innovation: to capture regional innovation and knowledge creation within firms, we use data from The Regional Innovation Scoreboard 2023 (European Commission, 2023), specifically the indicator of R&D expenditures in the business sector, expressed as a percentage of GDP. R&D investment serves as a key indicator of a region's innovation potential, representing how firms are active in developing new knowledge and technologies.
c) EU funds: As we have seen before, the EIB's Investment Survey (2023) acknowledges the crucial role of public funding in propelling climate investments by firms. Hence, we included a set of variables capturing EU financing for adaptation and mitigation (or both) projects, related to the 2014-2020 European Structural and Investment Funds (ESIF) (European Commission, 2023). The variables are expressed in billions of euros (and

transformed in log to control for outliers) and provides insight into the level of EU support for climate-related projects in each region.

d) CO_2 Emissions: to capture regional environmental factors, we use data on total GHG emissions (in kton CO_2eq) at NUTS2 level from the Emissions Database for Global Atmospheric Research (EDGAR) (European Commission, Joint Research Centre, 2023). We express emissions as a percentage of regional GDP and transform them into log to control for outliers, obtaining a measure of the environmental footprint relative to economic size.

4 Methodology

This study follows a systematic approach to investigate the drivers of firms' climate investments across EU regions, incorporating spatial econometric techniques to account for the spatial dependencies inherent in the data. The methodological framework comprises several key steps. First, we begin by assessing whether our dependent variables exhibit spatial autocorrelation, which is the tendency for regions to display similar climate investment behaviours based on their geographical proximity. Detecting spatial autocorrelation is crucial because it indicates that traditional econometric models, such as Ordinary Least Squares (OLS), may yield biased or inefficient estimates if spatial dependencies are ignored. Therefore, identifying spatial autocorrelation informs the subsequent choice of appropriate spatial econometric models that can accurately capture these dependencies. After detecting spatial autocorrelation, we estimate baseline non-spatial models to understand the primary drivers of climate investments. These models provide a reference point, helping us to compare the results with those obtained from spatial econometric models. Guided by the results of the spatial autocorrelation tests, we employ Spatial Autoregressive Models (SAR) and Spatial Error Models (SEM) to address the issues raised by spatial dependencies.

4.1 Spatial autocorrelation test

We applied a spatial autocorrelation analysis to assess whether our dependent variables present spatial agglomeration characteristics. Detecting spatial autocorrelation is crucial, as it necessitates the selection of an appropriate spatial econometric model to explain the relationships between various factors and the intensity of climate change measures adoption. First, Moran's I test (Moran, 1948) was applied to investigate potential spatial autocorrelation. Specifically, Moran's I is a global indicator of spatial dependence and can be calculated as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{1}$$

where, n is the number of spatial units; y_i and y_j represent climate measures (adaptation or mitigation) adoption intensity of region *i* and *j*; $\bar{y}$ is the mean value of *y* of all regions; w_{ij} denotes the element of the *i*th row and the *j*th column of the spatial weight matrix the spatial weighting matrix. The global Moran's I index value ranges from 1 to -1. A value greater than 0 suggests positive spatial autocorrelation, indicating a tendency for similar values to cluster together, while a negative value suggests a spatial pattern of dispersion or divergence across a geographical area.

We also considered local Moran's I index to measure whether the high and low values for local areas tend to agglomerate in space and identify local patterns of spatial autocorrelation:

$$I_i = \frac{n(y_i-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y}) \tag{2}$$

A positive value of the index indicates that climate measures adoption intensity has a positive spatial autocorrelation and presents spatial agglomeration; on the other hand, a negative correlation suggests the presence of a spatial pattern where values at a given location are significantly different from their immediate neighbours (Anselin, 1995).

Further, to detect spatial autocorrelation and determine the appropriate spatial econometric model, we employ Lagrange Multiplier (LM) tests (Anselin et al., 1996), including the standard LM error (LM-ERR) and LM lag (LM-LAG) tests, along with their robust variants. Specifically, these tests help identify whether spatial dependence is present in the dependent variable (LM-LAG) or in the error term (LM-ERR). The robust versions of these tests provide additional accuracy, particularly in the presence of multiple spatial effects or when the standard tests provide ambiguous results. Specifically, to select the appropriate model in our analysis we implement by Lagrange Multiplier (LM) tests (Anselin et al., 1996). The SAR model is chosen when the LM-LAG test is significant, indicating spatial dependence in the dependent variable. In contrast, the SEM model is selected when the LM-ERR test identifies spatial dependence in the error term, addressing spatially correlated unobserved factors without directly modelling regional spillover effects). The choice between SAR and SEM models shapes the interpretation of spatial effects in our analysis (Anselin et al., 1998); SAR model emphasizes direct spillover effects between regions, making it ideal for studying how climate investment decisions in one region influence neighboring regions. In contrast, SEM model focuses on capturing unobserved spatial processes that might be driving correlated errors across regions.

4.2 Spatial econometric models

Firstly, we construct non-spatial cross-section models to analyse the drivers of firms' climate investments, as follows:

$$\ln greenness_i = \alpha_0 + \alpha_1 \ln adapt(t-1)_i + \alpha_2 \ln mitig(t-1)_i + \alpha_3 C_i + \alpha_4 X_i + \varepsilon_i \quad (3)$$

$$\ln mitig_i = \beta_0 + \beta_1 \ln adapt(t-1)_i + \beta_2 C_i + \beta_3 X_i + \varepsilon_i \quad (4)$$

$$\ln adapt_i = \theta_0 + \theta_1 \ln mitig(t-1)_i + \theta_3 C_i + \theta_4 X_i + \varepsilon_i \quad (5)$$

where *i* represent the region; α denotes the intercept term; $\ln adapt_i$ and $\ln mitig_i$ represent the outcome variables of region *i* and $\ln adapt_i(t-1)$ and $\ln mitig_i(t-1)$ the explanatory variables at time t-1 of region *i*; C_i is a vector of explanatory variables representing firms' perceptions and characteristics; X_i is a vector including the regional characteristics and ε_i is the error term.

The employment of spatial econometric models in our study is justified by the presence of spatial autocorrelation, which suggests that climate investment decisions by firms in one region are influenced by those in neighbouring regions. However, the application of spatial econometric techniques to survey data introduces specific challenges due to inherent limitations; these include potential biases that may arise from the so-called "size effect" and the omission of spatially correlated units (Lardeux and Merly-Alpa, 2018). Despite these challenges, our methodology is designed to counteract these limitations by utilizing a robust and representative sample size. This approach ensures that our models capture the intricate spatial dynamics at play, providing meaningful insights into the regional interdependencies that shape firms' climate investment behaviours across the Europe.

Anselin et al. (2008) propose two approaches for addressing spatial autocorrelation: firstly, by incorporating spatial dependence by adding a spatially lagged term of the dependent variable, as in the Spatial Autoregressive Model (SAR); secondly, by integrating a spatially correlated component into the error term, typical of the Spatial Error Model (SEM). Hence, upon establishing the presence of spatial autocorrelation, we proceed with the implementation of SAR and SEM models. Then, the appropriate model is selected according to the results of the LM tests.

Specifically, the SAR model assumes that the value of the dependent variable in one region affects the dependent variable in a proximate region and thus captures the spatial dependency in the dependent variable itself. The SAR model can be specified as follows:

$$\ln greenness_i = \alpha_0 + \rho \sum_{j=1}^{n} w_{ij} \ln greenness_i + \alpha_1 \ln adapt(t-1)_i + \alpha_2 \ln mitig(t-1)_i + \alpha_3 C_i + \alpha_4 X_i + u_i + \varepsilon_i$$

(6)

$$\ln adapt_i = \beta_0 + \rho \sum_{j=1}^{n} w_{ij} \ln adapt_i + \beta_1 \ln mitig(t-1)_i + \beta_2 C_i + \beta_3 X_i + u_i + \varepsilon_i$$

(7)

$$\ln mitig_i = \theta_0 + \rho \sum_{j=1}^{n} w_{ij} \ln mitig_i + \theta_1 \ln adapt(t-1)_i + \theta_2 C_i + \theta_3 X_i + u_i + \varepsilon_i$$

(8)

where *ρ* represents the spatial autoregressive coefficient (a positive and statistically significant value of ρ implies that the levels of mitigation or adaptation measures adoption tend to spill over and have a positive effect on climates investments in neighbouring regions); w_{ij} is the spatial weight matrix; within the right-end side of the equation, $\ln greenness_i$, $\ln adapt_i$ and $\ln mitig_i$ represent the spatial lag terms, denoting the interaction effect of the related dependent variable in a given region with the same dependent variable in neighbouring regions; μ_i represents a spatial specific effect; all the other parameters are described above.

In contrast, the SEM is given by:

$$\ln greenness_i = \alpha_0 + \alpha_1 \ln adapt_i(t-1) + \alpha_2 \ln mitig_i(t-1) + \alpha_3 C_i + \alpha_4 X_i + u_i + \varphi_i$$

(9)

$$\ln adapt_i = \beta_0 + \beta_1 \ln mitig_i\,(t-1) + \beta_2 C_i + \beta_3 X_i + u_i + \varphi_i$$

(10)

$$\ln mitig_i = \theta_0 + \theta_1 \ln adapt_i\,(t-1) + \theta_2 C_i + \theta_3 X_i + u_i + \varphi_i$$

(11)

$$\varphi_i = \lambda \sum_{j=1}^{n} w_{ij} \varphi_i + \varepsilon_i$$

(12)

where φ_i represents the error component that includes the spatial autocorrelation effect with λ being the coefficient of spatial autocorrelation in the error term.

The construction of the spatial weighting matrix is a pivotal aspect of these models. For our analysis, based on Dharshing (2017), we utilize a row-standardized contiguity spatial weighting matrix. This matrix is based on geographical contiguity, where weights are assigned to neighbouring regions based on their shared borders or distances. In a row-standardized weights matrix (*W*), the elements of *W* are adjusted so that the sum of the weights in each row equals unity. Row standardization ensures that the influence of each spatial unit is proportionally distributed across its neighbours. Formally, let $W = [w_{ij}]$ be an *n x n* spatial weights matrix, where w_{ij} represents the weight from spatial unit *i* to spatial unit *j.* The row-standardization process transforms *W* into *W** (a row-standardized matrix), where each element w_{ij} is given by:

$$w^*{}_{ij} = \frac{w_{ij}}{\sum_{k=1}^{n} w_{ik}}$$

(13)

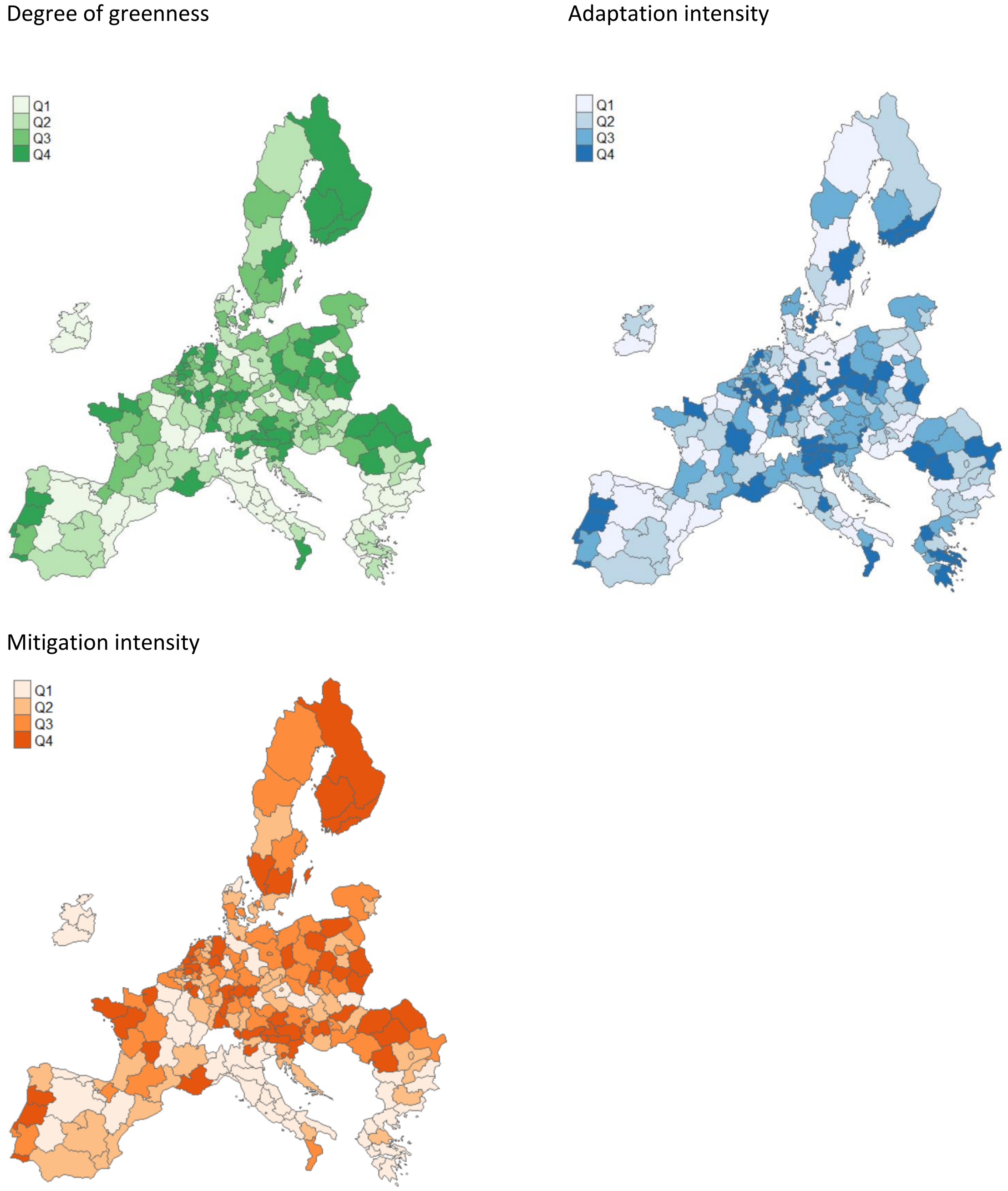
where $\sum_{k=1}^{n} w_{ik}$ is the sum of the weights in the *i*th row of the original weight matrix W.

5 Results

5.1 Spatial correlation analysis

Figure 1 visually depicts the regional distribution of climate measures adoption intensity, also considering individual measures (adaptation and mitigation) revealing distinct clusters of regions that are more or less active in addressing climate change. The existence of these clusters suggests that regions geographically proximate to each other tend to exhibit similar patterns in the intensity of climate change measure adoption. In other words, when a region exhibits a higher or lower level of climate change measures adoption, neighbouring regions' firms are more likely to make similar decisions. This underscores the potential presence of spatial dependence in the data.

Figure 1. Firms' degree of greenness, adaptation intensity and mitigation intensity, by NUTS 2 region and quartile



Source: authors' elaboration based on EIBIS (2023).

Spatial autocorrelation in the dependent variables has been first tested performing Morans' by using formula (1). The results are represented in Table 2. The test statistics for all variables are significant at 1%, suggesting the presence of spatial autocorrelation and thus the inappropriateness of OLS regressions. In such cases, the OLS model, which assumes independence among observations, may lead to biased and inconsistent estimates (Anselin and Bera, 1998). Therefore, employing spatial regression techniques is more appropriate in this context as they explicitly account for spatial dependencies, providing a more accurate representation of the determinants of firms' climate investment intensity.

Table 1. Moran's I results

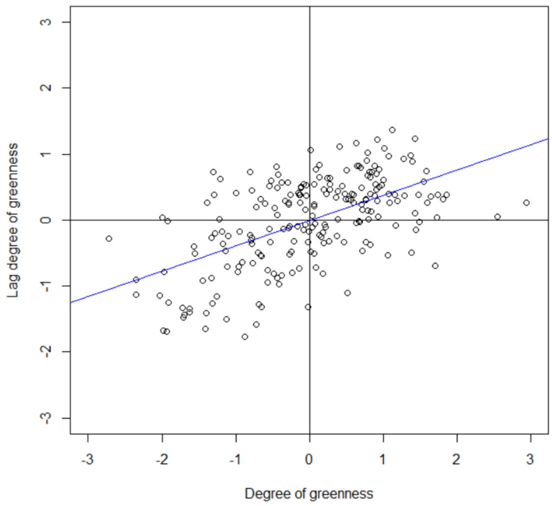
	Moran's I	Z(I)	P-value
Degree of greenness	0.383	7.947	0.000
Adaptation intensity	0.253	5.295	0.000
Mitigation intensity	0.430	8.904	0.000

The next step is to explore the local spatial correlations. We separately use the Moran scatterplots and the Local Indication of Spatial Association (LISA) figure to examine the existence of local spatial correlation of adoption intensity. Figure 2 reports the Moran scatterplots, where the blue line is the regression line of global Moran's I test, and its slope represents the test statistic. Every dot in the graph represents the regional adoption intensity of climate change measures. The vertical axis represents the spatially lagged variable and the horizontal axis the original variable. In a Moran scatterplot, observations can indeed be spread across all four quadrants, Specifically, quadrant 1 (high-high, i.e., high values regions surrounded by other areas with high values) and 3 (low-low) represent the positive spatial autocorrelation of the observed values, while quadrants 2 (high-low) and 4 (low-high) represent the negative spatial autocorrelation (i.e., spatial outliers). For both variables, most regions are in quadrants 1 and 3, with only a few in quadrants 2 and 4. This indicates a tendency for neighbouring areas to engage in similar levels of climate investment (positive spatial autocorrelation) and thus create clusters. However, especially for adaptation, we also have evidence of dissimilar values at neighbouring locations (negative spatial autocorrelation). This heterogeneity may suggest that the processes influencing the spatial distribution of the variables are not uniform across the study area. Different regions might be affected by different factors, or the same factor might have varying impacts in different locations.

Figure 2. Moran scatterplots

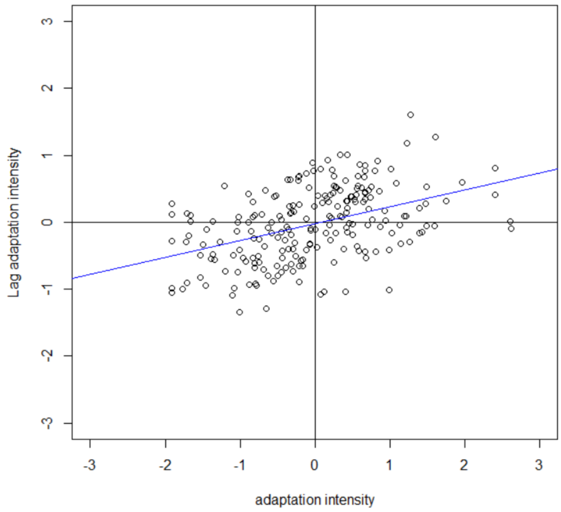
Degree of greenness

Moran's I = 0.383



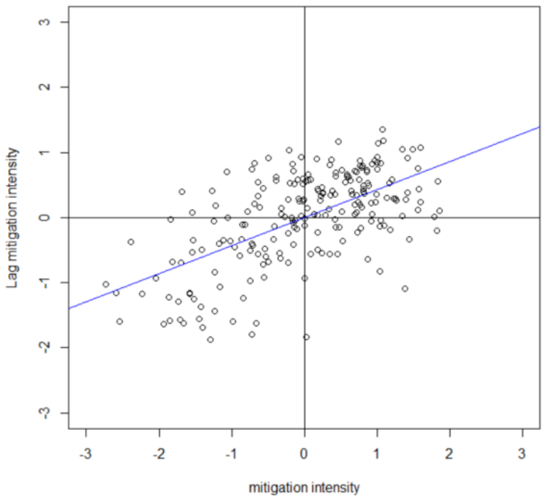
Adaptation intensity

Moran's I = 0.253



Mitigation intensity

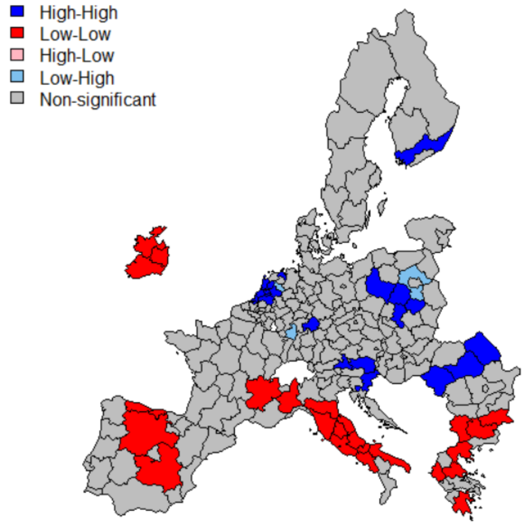
Moran's I = 0.430



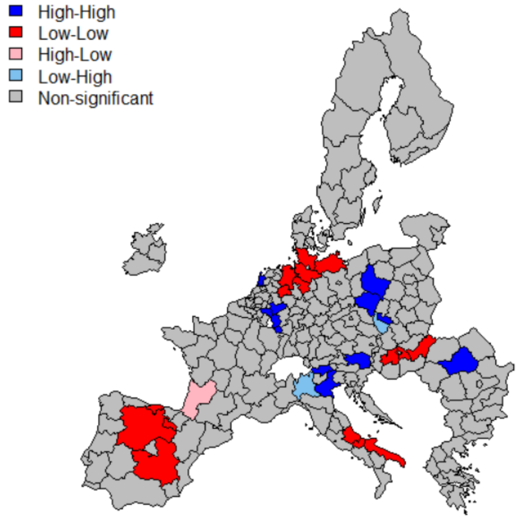
The local Moran index of our dependent variables is calculated using formula (2) and illustrated using LISA (Local Indicators of Spatial Association) maps (Figure 3). The LISA maps reveal distinct patterns of local spatial autocorrelation across the European regions under study. Notably, the map illustrates several clusters where regional climate investments are significantly above (HH) or below the average (LL), providing a nuanced understanding of the spatial dynamics at play. Specifically, for both adaptation and mitigation, HH clusters are mainly concentrated in Northern, Central and Eastern Europe. These areas are likely to be at the forefront of climate mitigation actions, possibly due to strong environmental policies, availability of green technologies, or higher public awareness and corporate responsibility towards climate change. The concentration of these clusters suggests a regional commitment that could be driven by shared economic or legislative frameworks. Interestingly, LL clusters are predominant and spread in different areas of the continent, especially in Southern European countries like Italy, Spain, and Greece (for mitigation only). This pattern may reflect areas where mitigation efforts are less pronounced, which could be attributable to economic constraints, differing policy priorities, or other regional challenges. Especially for mitigation, the map also reveals the existence of few outliers, especially LH clusters, denoting regions where mitigation efforts are lower than their peers.

Figure 3. LISA cluster maps

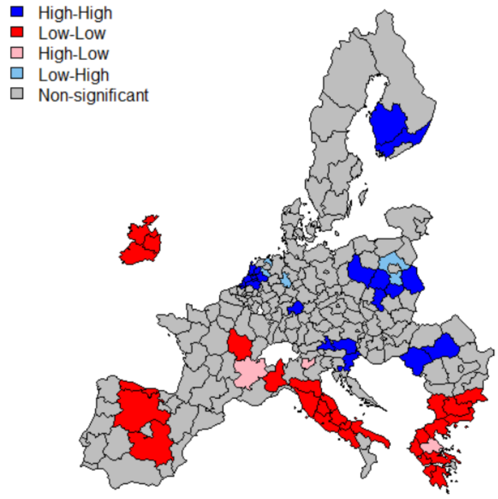
Degree of greenness



Adaptation intensity



Mitigation intensity



Source: authors' elaboration based on EIBIS (2023).

5.2 Determinants of firms' climate investments

Firstly, we constructed non-spatial OLS models and employed Lagrange Multiplier (LM) tests to determine whether a Spatial Autoregressive Model (SAR) or a Spatial Error Model (SEM) is more appropriate to describe the data compared to a model without spatial interaction effects (You and Lv, 2018). Both the LM test and its robust variants are significant, confirming the presence of spatial dependence and indicating the need for a spatial econometric model (Zeng et al., 2019). The detailed results of these tests are reported in Table A2 of Annex A. For adaptation, both the LM-error and LM-lag test were also significant, suggesting spatial autocorrelation in the dependent variable itself. Given the dual significance of both tests, our decision to choose the SAR model is guided by the study's primary objective: to capture and analyze the spatial dynamics and spillover effects of climate investments across regions. The SAR model is particularly suited for this purpose, as it directly models the influence of neighboring regions, thereby providing deeper insights into how investments propagate across space. While SEM accounts for spatial dependencies in the error terms, it does not capture these spillover effects, which are central to our research focus. This limitation makes the SEM model less suitable for our analysis, where understanding the interconnectedness and regional spillover effects is paramount (Vega and Elhorst, 2013). Therefore, the SAR model was selected for the empirical analysis.

Table 2 reports the regression results of SAR models for the three outcome variables. OLS and SEM regression results are reported in Table A3 and Table A4 in Appendix A. The indicators ρ and λ measure the total strength of spatial dependence between neighbouring regions for SEM and SAR, respectively (Dharshing, 2017).

Concerning the degree of greenness, SAR is the more appropriate model for our study. The coefficient λ is 0.370 and significant at 1% level, indicating that the intensity of climate investment has a positive spatial agglomeration effect. The results of the regression indicate that both previous year adaptation and mitigation intensity influence the current overall investments in climate measures, with adaptation showing a slightly stronger coefficient. Furthermore, a higher perception of climate transition risks and energy costs as an obstacle to investments a significant and positive relationship with the dependent variable, representing a potential enabler for climate-related investments. The existence of strategic and monitoring schemes positively affect climate actions and both coefficients are positive and strongly significant. Conversely, financial constraints confirm to be a barrier for climate investments. Notably, regional characteristics play a key role in determining firms' choices; the significant and positive value of the coefficient of the basic framework variable suggests the crucial role of local conditions for climate investments. EU funds for both adaptation and low-carbon projects show a strong positive association with the dependent variable, confirming the pivotal role of financial support from public funds. Lastly, CO2 emissions reveal a statistically significant and positive impact on the degree of greenness in the EU.

In our study, the SAR model proves to be the optimal choice for both investigating the drivers of adaptation and mitigation investments. The significant λ coefficients for adaptation (0.447) and mitigation (0.445) at the 1% level indicate a positive spatial agglomeration effect for both types of investments, in line with Moran's results. Interestingly, the mitigation regression reveals a significant positive association between adaptation investments and mitigation choices. However, the adaptation model does not indicate a similar complementarity between these two types of investments (the related coefficient is not significant). Findings show that for both adaptation and mitigation, firms' characteristics such as risk perception, financial constraints, and monitoring systems significantly impact investment intensity. Specifically, awareness of physical risks boosts adaptation investments, while higher perception of climate transition risks enhances mitigation efforts, underscoring the crucial role of risk awareness in climate action. Financial constraints negatively impact both adaptation and mitigation investments, highlighting economic barriers in climate change response. The presence of strategic monitoring and emission targets positively influences investment in both areas. Moreover, regional characteristics including basic framework and innovation, along with EU funds, show a strong positive association with mitigation investment investments, in contrast, for adaptation investments only EU adaptation funds play a role albeit with a less robust level of significance.

Table 2. SAR regression results

	Degree of greenness	Adaptation intensity	Mitigation intensity
ρ	0.370*** (0.067)	0.447*** (0.078)	0.445*** (0.062)
Adaptation intensity (t-1) (in logs)	0.156*** (0.052)		0.232*** (0.056)
Mitigation intensity (t-1) (logs)	0.137*** (0.044)	0.015 (0.056)	
Physical risk	-0.008 (0.027)	0.115*** (0.038)	
Transition risk	0.058*** (0.021)		0.103*** (0.026)
Energy costs	0.053*** (0.019)	0.015 (0.027)	0.064*** (0.023)
Financial constraints	-0.049* (0.029)	-0.080* (0.042)	-0.061* (0.035)
Strategic monitoring	0.067*** (0.020)	0.065** (0.029)	0.076*** (0.025)
Climate targets	0.079*** (0.021)	0.070** (0.030)	0.087*** (0.026)
Basic framework	0.029 (0.023)	0.019 (0.031)	0.082*** (0.028)
Innovation	0.026 (0.021)	0.019 (0.032)	0.044* (0.027)
EU adaptation funds (in logs)		0.028* (0.016)	
EU low-carbon funds (in logs)			0.052*** (0.010)
EU adaptation and low-carbon funds (in logs)	0.026*** (0.007)		
CO2 (in logs)	0.042** (0.020)	0.046 (0.028)	0.037 (0.025)
Intercept	-0.025 (0.026)	-0.041 (0.034)	-0.028 (0.031)
N	215	215	215
R^2	0.516	0.113	0.491

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

5.3 Decomposition of effects

The coefficients estimated by the SAR model alone cannot fully capture the spillover effects of the independent variables on the intensity of climate investments. To address this, we also estimate decomposed effects, which are presented in Tables 3-5 for the degree of greenness, adaptation, and mitigation dependent variables. Direct effects represent the immediate impact of an explanatory variable on the dependent variable within the same region. For example, an increase in climate risk awareness in one region directly boosts the intensity of climate investments within that region. Indirect effects, on the other hand, reflect the spillover impact that changes in an explanatory variable in one region have on the dependent variable in neighbouring regions (LeSage and Pace, 2009). These effects are particularly important as they reveal how regional dynamics and firm-level actions can influence peers in neighbouring areas. For instance, if a region enhances its adaptation strategies, neighbouring regions might also intensify their climate investments due to peer influence, shared environmental challenges, or competition. Total effects combine both direct and indirect impacts, offering a comprehensive view of how an explanatory variable influences climate investments across the entire network of regions.

Overall results show that while direct effects are stronger, also the indirect effects are substantial, especially for firms’ characteristics. Further, most variables that were significant in the previous model exhibit spillover effects, indicating that changes in an explanatory variable within one region, holding all other variables constant, can significantly impact the climate investment intensity of neighbouring regions.

The analysis for the degree of greenness shows that the direct, indirect, and total effects of firms’ characteristics are highly significant, except for financial constraints whose impacts seems to be confined to local settings without notable spillovers. Notably, the perception of transition risks, the burden of energy costs and financial constraints, and having in place both strategic and emissions monitoring systems lead to an increase in climate investments both locally and in adjacent regions, with other conditions being constant. Notably, EU funds for adaptation and low-carbon investments show both direct and indirect positive effects. Hence, all these factors collectively influence not only local climate activities but also potentially enable neighbouring regions to elevate their climate strategies.

The decomposition analysis for both adaptation and mitigation investments reveal significant direct, indirect, and total effects of various firm and regional characteristics, with some notable differences. For adaptation, physical risks, financial constraints, strategic monitoring, and climate targets exhibit significant indirect effects, suggesting that these factors enhance adaptation investments locally and in neighbouring regions. However, it's important to note that spillover effects for adaptation are generally weaker compared to those observed for mitigation. Additionally, the coefficient for EU adaptation funds coefficient shows a significant impact only in its direct effect, indicating a localized influence without considerable spillovers.

For mitigation, similar patterns emerge with transition risks, energy costs, and strategic measures showing significant effects in all categories, increasing mitigation efforts locally and in adjacent regions. In contrast, financial constraints again display only direct effects, reinforcing the idea that financial challenges predominantly affect local investments. Notably, adaptation investments positively influence mitigation efforts, both within the same region and in adjacent areas. Regional characteristics, except for CO_2 emissions, demonstrate both direct and indirect positive influences on mitigation activities; basic framework conditions, innovation, and EU funds for low-carbon investments collectively strengthen local mitigation efforts and encourage neighbouring regions to enhance their mitigation strategies, underscoring the interconnected nature of regional climate actions.

Table 3. Direct, indirect, and total effects for the degree of greenness

	Direct effect	Indirect effect	Total effect
Adaptation intensity (t-1) (in logs)	0.162***	0.086**	0.248***
	(0.054)	(0.038)	(0.087)
Mitigation intensity (t-1) (in logs)	0.143***	0.075***	0.218***
	(0.045)	(0.028)	(0.069)
Physical risk	-0.009	-0.005	-0.013
	(0.028)	(0.015)	(0.043)
Transition risk	0.061***	0.032**	0.093***
	(0.022)	(0.015)	(0.036)
Energy costs	0.055***	0.029**	0.083***
	(0.019)	(0.013)	(0.031)
Financial constraints	-0.051*	-0.027	-0.078*
	(0.030)	(0.017)	(0.046)
Strategic monitoring	0.069***	0.037**	0.106***
	(0.021)	(0.015)	(0.034)
Climate targets	0.082***	0.043***	0.125***
	(0.022)	(0.016)	(0.035)
Basic framework	0.030	0.016	0.045
	(0.024)	(0.013)	(0.036)
Innovation	0.027	0.014	0.041
	(0.022)	(0.012)	(0.034)
EU adaptation and low-carbon funds (in logs)	0.027***	0.014***	0.041***
	(0.008)	(0.005)	(0.011)
CO2 (in logs)	0.044**	0.023*	0.067**
	(0.021)	(0.012)	(0.032)

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Table 4. Direct, indirect, and total effects for adaptation intensity

	Direct effect	Indirect effect	Total effect
Mitigation intensity (t-1) (in logs)	0.016	0.011	0.026
	(0.059)	(0.042)	(0.101)
Physical risk	0.121***	0.086**	0.207***
	(0.040)	(0.038)	(0.074)
Energy costs	0.016	0.011	0.027
	(0.029)	(0.021)	(0.050)
Financial constraints	-0.085*	-0.060*	-0.145*
	(0.044)	(0.036)	(0.078)
Strategic monitoring	0.069**	0.049*	0.118**
	(0.031)	(0.026)	(0.055)
Climate targets	0.074**	0.052*	0.126**
	(0.032)	(0.029)	(0.059)
Basic framework	0.020	0.014	0.034
	(0.033)	(0.024)	(0.057)
Innovation	0.021	0.015	0.035
	(0.033)	(0.023)	(0.057)
EU adaptation funds (in logs)	0.030*	0.021	0.051*
	(0.017)	(0.013)	(0.029)
CO2 (in logs)	0.049	0.034	0.083
	(0.030)	(0.023)	(0.052)

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Table 5. Direct, indirect, and total effects for mitigation intensity

	Direct effect	Indirect effect	Total effect
Adaptation intensity (t-1) (in logs)	0.246***	0.172***	0.418***
	(0.059)	(0.057)	(0.107)
Transition risk	0.109***	0.076***	0.186***
	(0.028)	(0.027)	(0.052)
Energy costs	0.067***	0.047**	0.115***
	(0.025)	(0.021)	(0.044)
Financial constraints	-0.064*	-0.045	-0.110*
	(0.037)	(0.028)	(0.063)
Strategic monitoring	0.081***	0.057**	0.137***
	(0.027)	(0.024)	(0.048)
Climate targets	0.092***	0.065***	0.157***
	(0.028)	(0.024)	(0.048)
Basic framework	0.087***	0.061***	0.147***
	(0.029)	(0.022)	(0.048)
Innovation	0.047*	0.033	0.080*
	(0.028)	(0.021)	(0.048)
EU low-carbon funds (in logs)	0.055***	0.039***	0.094***
	(0.011)	(0.010)	(0.018)
CO2 (in logs)	0.039	0.028	0.067
	(0.027)	(0.020)	(0.046)

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

6 Discussion

The spatial analysis reveals the presence of spatial dependence in climate investments across EU regions at the NUTS2 level, highlighting the interconnectedness of firms' climate measure choices in neighbouring areas. Notably, regions with higher (lower) levels of climate measure adoption tend to be geographically proximate. This underscores the importance of considering regional nuances when formulating and implementing climate policies. These insights lay a critical groundwork for deeper exploration into the drivers of regional climate initiatives and the opportunities for policy harmonization to amplify climate adaptation and mitigation strategies.

Specifically, firms’ own strategies affect peers’ decision to invest in climate measures, including both adaptation and mitigation. For example, setting and monitoring targets for GHG emissions influences not only local investment decision, but also amplifies collective environmental efforts across regions. This is particularly true in interconnected regional markets where firms are keenly observant of their peers' strategies. Similarly, climate risk awareness significantly influences firms' climate investment decisions, in line with previous findings

(Hoffman et al., 2009; Bryan et al., 2009; EIB 2023). Awareness not only drives local action but also spills over to neighbouring regions, underscoring how shared environmental challenges can lead to collaborative efforts and interconnected investment strategies across regions. In our analysis, the role of energy costs emerges as a key factor driving firms' climate investment decisions, especially in the context of mitigation and overall green initiatives. Regions where firms face higher energy costs not only show a higher adoption intensity of climate measures but also exhibit spillover effects on neighbouring regions; this can be attributed to demonstration effects (e.g., observing the impacts achieved in abating energy costs, firms in adjacent areas may be encouraged to replicate a similar strategy) or the development of new, more energy-efficient technologies that spill over to neighbouring regions. Conversely, financial constraints negatively influence investment decisions, as also confirmed by Girma et al., 2008 and Bryan et al., 2009, highlighting economic disparities in addressing climate change. Further, financial barriers can have cross-regional implications on firms' engagement in adaptation actions. When firms face financial constraints, their peers in adjacent regions might perceive similar investments as risky or unfeasible, leading to a cautious approach towards climate initiatives. This phenomenon underscores the interconnected nature of regional economies and the importance of addressing financial barriers comprehensively to foster a collective move towards enhanced climate resilience.

Regional-level characteristics also play a key role in shaping climate investments, especially mitigation, with indirect impacts to neighbouring areas. Improved conditions in a region, such as a robust economic and institutional framework, not only foster a supportive environment for local mitigation initiatives but can also lead to positive spillover effects in adjacent regions. This influence can be exerted through peer effects (Manski, 1993), sharing of resources (including skills and knowledge) and best practices, and market dynamics (for example, if a region invests heavily in low-carbon technologies, it may create a market for these technologies that extends beyond its borders). Innovation, while significant only for mitigation investments, still indicates positive direct and indirect impact. Innovation is expected to play a crucial role in driving climate investments by introducing new technologies and processes that make climate actions more effective (Apostu et al., 2023). Notably, the role of EU funds is key in promoting both adaptation and mitigation investments, underlining the importance of policy-driven financial support. For mitigation this trend also extends beyond the immediate regional recipients, encouraging neighbouring regions to keep pace and align with emerging climate standards. When considering the regional degree of greenness, CO_2 emissions emerge as a significant factor with positive spillover effects. This suggests that regions with higher CO_2 emissions may be more inclined to adopt climate measures, possibly as a response to greater environmental pressures or regulatory measures aimed at reducing emissions (Seroka-Stolka, 2023), also influencing adjacent areas.

Importantly, results revealed an interesting interplay between adaptation and mitigation actions when promoting climate action among firms. This is in line with both our expectations and the existing literature (Srivastava et al., 2022; Landauer et al. 2015; Dang et al., 2013). Notably, firms having adaptation strategies in place are more likely to implement mitigation measures, but not vice versa. This can underscore that firms focusing on adaptation measures might encounter increased obstacles, especially of a financial nature (IMF, 2021), that can exacerbate when trying to invest in mitigation strategies. The complementarity between adaptation and mitigation also extends to neighbouring regions through spillover effects, amplifying collective response to climate change. This underscores the importance to encourage synergies and co-benefits between adaptation and mitigation measures, addressing at the same time trade-offs and conflicts that may arise between them (Landauer et al., 2019).

7 Conclusions and policy implications

Our study shows that firms' climate investment decisions across Europe depend on regional dynamics. This means that we need to understand how climate actions are connected among firms and how space matters for policy making. We find that regions differ in their climate engagement, so a one-size-fits-all approach may not work. Instead, we need to design strategies that suit the specific features and needs of each region to boost the impact of climate investments.

Building on the spatial econometric approach, our analysis reveals significant spatial dependence in firms' climate investment decisions across EU regions, underscoring at the same time the interconnected nature of adaptation and mitigation efforts. Results underscore the existence of regional clusters in climate action and highlights the importance of tailored policy interventions that leverage regional spillover effects, boosting collective climate resilience. Moreover, our study reveals that both firm-level attributes, such as risk perception, and broader regional factors, including EU funds, play pivotal roles in shaping climate investment choices. These insights not only highlight the direct impact of firms' strategies and regional characteristics on climate action but also demonstrate their influence on the climate investment decisions of neighbouring firms, suggesting a complex web of interdependencies that must be navigated to foster more effective and comprehensive climate policies.

To speed up the adoption of climate-friendly practices we suggest focusing on regions with low engagement or high spillover potential, and by using existing regional clusters of active firms as examples and sources of learning. We also need to think about how adaptation and mitigation actions work together to avoid conflicts and improve outcomes. To help us develop policies that can identify what works and what needs to be improved in adaptation or mitigation efforts, we measure the overall level of climate engagement, using the "greenness" degree. We can use insights from both firm-level and regional factors to create more effective strategies and policies to accelerate climate investments in a sustainable and fair way.

Based on our findings, we propose policies that are specific to each region, that target regions with low engagement and use regions with high engagement as models for sustainable practices. We also propose financial instruments that support firms that are most affected by climate change and that encourage them to adopt both adaptation and mitigation strategies. We also propose to give more resources and support to regions that are behind in climate action, to help them catch up and move towards sustainable practices.

Further, we emphasize the importance of using EU funds for climate investments across regions in the best way possible, making sure they support direct climate action initiatives and promote regional cooperation and knowledge sharing. We also propose to create mechanisms that help regions share best practices and learn from each other, to increase the adoption of effective measures and create a culture of learning and adaptation.

While our analysis did not specifically examine spillover effects within and across different cohesion regions, the observed spatial dependencies and regional dynamics have important implications for cohesion policy. Our findings indicate that climate investment decisions are influenced by both firm-level attributes and broader regional factors, which suggests that regions with similar economic and social characteristics might benefit from tailored policies that consider these shared contexts. To foster regional convergence, cohesion policies should recognize the potential for spillovers between regions.

To understand better how firm and regional factors affect neighbouring areas and to design more targeted policies, we need more research on the dynamics and channels of spatial spillovers. This includes looking at how adaptation and mitigation efforts can work together and how EU funds can help different regions adopt sustainable practices. Moreover, future research could further explore these dynamics by analyzing how the geographical distribution of regions within cohesion categories influences the strength and direction of spillover effects. This would help refine policies aimed at fostering regional convergence and ensuring that all regions can benefit from advancements in climate action. This research will help us make more effective climate policies and use EU funds in the best way possible to support wider and more efficient climate actions.

References

Anselin, L., (1995). Local indicators of spatial association-LISA. Geogr. Anal. 27 (2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. Regional science and urban economics, 26(1), 77-104.

Anselin, L., and Bera, A. K. (1998). Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In: Handbook of applied economic statistics, 237(5).

Anselin, L., Gallo, J., Jayet, H. (2008). Spatial panel econometrics. In The econometrics of panel data: Fundamentals and recent developments in theory and practice (pp. 625-660). Berlin, Heidelberg: Springer Berlin Heidelberg.

Awasthy, P., Gouda, S., Ghosh, D., and Swami, S. (2022). Analyzing product greening spillovers in multi-product markets. Transportation Research Part E: Logistics and Transportation Review, 158, 102586.

Batabyal, A. A., and Folmer, H. (2020). Spatial economic aspects of climate change. Spatial Economic Analysis, 15(3), 209-218.

Bollinger, B., and Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. Marketing Science, 31(6), 900-912.

Bryan, E., Deressa, T. T., Gbetibouo, G. A., and Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. Environmental science and policy, 12(4), 413-426.

Cadez, S., Czerny, A., and Letmathe, P. (2019). Stakeholder pressures and corporate climate change mitigation strategies. Business Strategy and the Environment, 28(1), 1-14.

Cagno, E., Worrell, E., Trianni, A., and Pugliese, G. (2013). A novel approach for barriers to industrial energy efficiency. Renewable and Sustainable Energy Reviews, 19, 290-308.

Carrico, A. R. (2021). Climate change, behavior, and the possibility of spillover effects: Recent advances and future directions. Current Opinion in Behavioral Sciences, 42, 76-82.

Cheng, P., Wang, X., Choi, B., and Huan, X. (2023). Green finance, international technology spillover and green technology innovation: a new perspective of regional innovation capability. Sustainability, 15(2), 1112.

Cheng, Y., Wang, Z., Zhang, S., Ye, X., and Jiang, H. (2013). Spatial econometric analysis of carbon emission intensity and its driving factors from energy consumption in China. Dili Xuebao/Acta Geographica Sinica, 68(10), 1418-1431.

Corral, C. M. (2003). Sustainable production and consumption systems—cooperation for change: assessing and simulating the willingness of the firm to adopt/develop cleaner technologies. The case of the In-Bond industry in northern Mexico. Journal of cleaner production, 11(4), 411-426.

Damert, M., Paul, A., and Baumgartner, R. J. (2017). Exploring the determinants and long-term performance outcomes of corporate carbon strategies. Journal of Cleaner Production, 160, 123-138.

Dang, H. H., Michaelowa, A., and Tuan, D. D. (2003). Synergy of adaptation and mitigation strategies in the context of sustainable development: the case of Vietnam. Climate policy, 3(sup1), S81-S96.

Dharshing, S. (2017). Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. Energy research and social science, 23, 113-124.

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. International regional science review, 26(3), 244-268.

European Commission. (2023). National Energy and Climate Plans. Retrieved from: National energy and climate plans (europa.eu). Last access: January 12th, 2024.

European Commission. (2023). ESIF 2014-2020 Finances Planned Details. Available from: https://cohesiondata.ec.europa.eu/2014-2020/ESIF-2014-2020-FINANCES-PLANNED-DETAILS/e4v6-qrrq/about_data. Last access: December 10th, 2023.

European Commission. (2023). Regional innovation scoreboard. Available from: Regional innovation scoreboard - European Commission (europa.eu). Last access: December 10th, 2023.

European Commission, Joint Research Centre. (2023). EDGAR_GHG_NUTS2_v2.0. GHG Emissions at sub-national level. Available from: http://data.europa.eu/89h/d67eeda8-c03e-4421-95d0-0adc460b9658. Last access: December 10th, 2023.

European Commission, DG Regional and Urban Policies. (2022). EU Regional Competitiveness Index 2.0 - 2022 edition. Available from: https://ec.europa.eu/regional_policy/assets/regional-competitiveness/index.html#/. Last access: December 10th, 2023.

European Investment Bank (EIB). 2024. EIB Investment Report 2023/2024. Chapter 5: Investing in green transformation. Luxembourg: European Investment Bank. Available from: Investment Report 2023/2024: Transforming for competitiveness: Chapter 5 (eib.org). Last access: February 10th, 2024.

European Investment Bank (EIB). 2023. EIB Investment Report 2022/2023. Chapter 6: Green transition and the energy crisis. Luxembourg: European Investment Bank. Available from: Investment Report 2022/2023: Resilience and renewal in Europe – Chapter 6 (eib.org). Last access: November 20th, 2023.

Eurostat. (2023). Sustainable development in the European Union. Monitoring report on progress towards the SDGs in an EU context. 2023 Edition. Luxembourg: Publications Office of the European Union.

Girma, S., Gong, Y., and Görg, H. (2008). Foreign direct investment, access to finance, and innovation activity in Chinese enterprises. The World Bank Economic Review, 22(2), 367-382.

Harasztosi, P., Delanote, J., Brutscher, P. B., and Coali, A. (2020). EIB Working Paper 2020/08-EIB Group Survey on Investment and Investment Finance: A technical note on data quality (Volume 2020/8). European Investment Bank.

Hjelmqvist, M. 2020. Corporate Climate Initiatives: An Inside-out Approach to Stakeholder Engagement. Master thesis, Uppsala University.

Hoffmann V. H., Sprengel, D.C. Ziegler, A., Kolb, M., Abegg, B. (2009). Determinants of corporate adaptation to climate change in winter tourism: An econometric analysis. Global Environmental Change 19, 256-264.

Hrovatin, N., Dolšak, N., and Zorić, J. (2016). Factors impacting investments in energy efficiency and clean technologies: empirical evidence from Slovenian manufacturing firms. Journal of cleaner production, 127, 475-486.

Lardeux, R., and Merly-Alpa, T. (2018). Spatial econometrics on survey data. In: INSEE and Eurostat (2018). Handbook of Spatial Analysis Theory and Application with R. Insee Méthodes N°131 - October 2018.

Kalantzis, F., and Dominguez, S. (2023). Determinants of EU Firms' Green Investment Strategies: A Survey-Based Analysis. Available at SSRN 4401441.

Kalantzis, F., Revoltella, D. and Savsek S. (2021). A new investment climate to unlock climate investment opportunities: Evidence from the EIB surveys. Bancni Vestnik, JEL G24 Q01, 14-21.

Landauer, M., Juhola, S., and Klein, J. (2019). The role of scale in integrating climate change adaptation and mitigation in cities. Journal of Environmental Planning and Management, 62(5), 741-765.

Landauer, M., Juhola, S., and Söderholm, M. (2015). Inter-relationships between adaptation and mitigation: a systematic literature review. Climatic change, 131, 505-517.

LeSage, J., and Pace, R. K. (2009). Introduction to spatial econometrics. Chapman and Hall/CRC.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. The review of economic studies, 60(3), 531-542.

Moran, P.A.P., (1948). The interpretation of statistical maps. J. R. Stat. Soc. Ser. B 10 (2), 243–251. Retrieved from. https://www.jstor.org/stable/2983777?seq=1#metadata_info_tab_contents.

Robinson, S. A., and Rai, V. (2015). Determinants of spatial-temporal patterns of energy technology adoption: An agent-based modelling approach. Applied Energy, 151, 273-284.

Schaffer, A. J., and Brun, S. (2015). Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. Energy Research and Social Science, 10, 220-227.

Seroka-Stolka, O. (2023). Enhancing environmental sustainability: Stakeholder pressure and corporate CO2-related performance—An examination of the mediating and moderating effects of corporate decarbonization strategies. Sustainability, 15(19), 14257.

Siedschlag, I., and Yan, W. (2021). Firm's green investments: What factors matter?. Journal of Cleaner Production 310.

Srivastava, A., Maity, R., and Desai, V. R. (2023). Assessing global-scale synergy between adaptation, mitigation, and sustainable development for projected climate change. In Ecological Footprints of Climate Change: Adaptive Approaches and Sustainability (pp. 31-61). Cham: Springer International Publishing.

Stucki, T. (2019). Which firms benefit from investments in green energy technologies?–The effect of energy costs. Research Policy, 48(3), 546-555.

Vega, S. H., and Elhorst, J. P. (2013, August). On spatial econometric models, spillover effects, and W. In 53rd ERSA Congress, Palermo, Italy (pp. 1-28).

Yarrow, R., and Chen, G. (2023). Climate Investment in China and the United States: Political, Monetary and Technological Drivers. East Asian Policy, 15(04), 38-60.

You, W., and Lv, Z. (2018). Spillover effects of economic globalization on CO2 emissions: a spatial panel approach. Energy economics, 73, 248-257.

Yunus, S. (2017). Drivers of corporate carbon management strategy (CMS) adoption and its impact on firm performance: Australian evidence. Unpublished PhD Thesis, Swinburne University of Technology, Australia.

Zeenat Fouzia, S., Mu, J., and Chen, Y. (2020). Local labour market impacts of climate-related disasters: a demand-and-supply analysis. Spatial Economic Analysis, 15(3), 336-352.

Zeng, J., Liu, T., Feiock, R., and Li, F. (2019). The impacts of China's provincial energy policies on major air pollutants: A spatial econometric analysis. Energy Policy, 132, 392-403.

ANNEX A

Figure A1. Distribution plots of the outcome variables

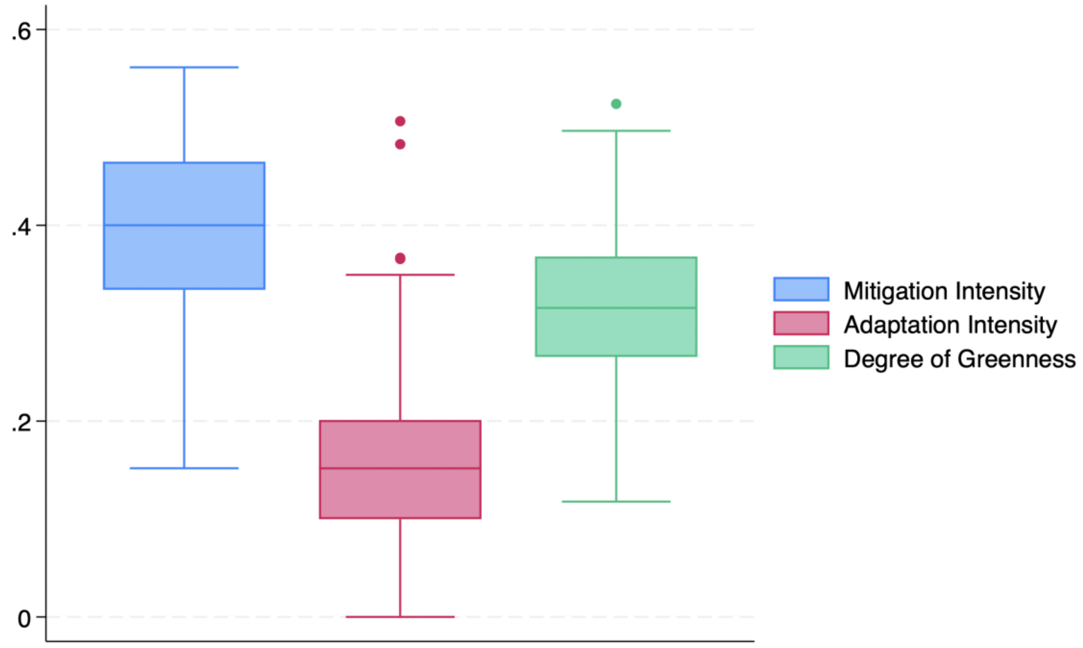


Table A1. Descriptive statistics

Variable	Obs.	Mean	SD	Min	Max	5th perc.	95th perc.
Degree of greenness (in logs)	215	0.31	0.07	0.12	0.52	0.19	0.42
Adaptation intensity (in logs)	215	0.15	0.08	0.00	0.51	0.02	0.33
Mitigation intensity (in logs)	215	0.40	0.09	0.15	0.56	0.23	0.52
Adaptation intensity (t-1) (in logs)	215	0.13	0.08	0.00	0.39	0.02	0.28
Mitigation intensity (t-1) (in logs)	215	0.38	0.10	0.06	0.60	0.21	0.53
Physical risk	215	0.19	0.14	0.00	0.78	0.00	0.47
Transition risk	215	0.26	0.16	0.00	0.83	0.00	0.55
Energy costs	215	0.34	0.19	0.00	0.88	0.06	0.64
Financial constraints	215	0.15	0.13	0.00	0.78	0.00	0.38
Strategic monitoring	215	0.46	0.18	0.00	0.90	0.09	0.76
Climate targets	215	0.40	0.18	0.00	0.84	0.08	0.70
Basic framework	215	0.56	0.25	0.00	1.00	0.09	0.93
Innovation	215	0.56	0.21	0.05	1.00	0.25	0.92
EU adaptation funds (in logs)	215	0.47	0.37	0.00	1.36	0.00	0.99
EU low-carbon funds (in logs)	215	0.49	0.59	0.00	3.44	0.01	1.77
EU adaptation and low-carbon funds (in logs)	215	0.77	0.65	0.00	3.48	0.02	1.93
CO2 (in logs)	215	0.31	0.22	0.03	1.44	0.09	0.76

Note: For variables transformed to logarithms, each value was incremented by 1 to avoid negative values.

Table A2. Testing results of LM and Robust LM-test

	Test	Statistics	P-value
Degree of greenness	LM-Lag test	26.850	0.000
	Robust LM-lag test	4.893	0.027
	LM-Error test	22.615	0.000
	Robust LM-Error test	0.658	0.417
Adaptation intensity	LM-Lag test	22.683	0.000
	Robust LM-Lag test	1.216	0.270
	LM-Error test	28.195	0.000
	Robust LM-Error test	6.727	0.009
Mitigation intensity	LM-Lag test	45.116	0.000
	Robust LM-lag test	14.603	0.000
	LM-Error test	30.649	0.000
	Robust LM-Error test	0.136	0.712

Table A3. OLS regression results

	Degree ofgreenness	Adaptation intensity	Mitigation intensity
Adaptation intensity (t-1) (in logs)	0.147**		0.267***
	(0.058)		(0.065)
Mitigation intensity (t-1) (in logs)	0.193***	0.029	
	(0.048)	(0.063)	
Physical risk	0.001	0.125***	
	(0.030)	(0.043)	
Transition risk	0.049**		0.098***
	(0.023)		(0.030)
Energy costs	0.049**	0.004	0.060**
	(0.021)	(0.031)	(0.027)
Financial constraints	-0.058*	-0.089*	-0.073*
	(0.032)	(0.047)	(0.040)
Strategic monitoring	0.063***	0.074**	0.072**
	(0.023)	(0.033)	(0.029)
Climate targets	0.087***	0.056	0.109***
	(0.023)	(0.034)	(0.030)
Basic framework	0.054**	0.018	0.147***
	(0.026)	(0.035)	(0.031)
Innovation	0.039	0.049	0.060*
	(0.024)	(0.035)	(0.031)
EU adaptation funds (in logs)		0.033*	
		(0.018)	
EU low-carbon funds (in logs)			0.077***
			(0.011)
EU adaptation and low-carbon funds (in logs)	0.036***		
	(0.008)		
CO2 (in logs)	0.051**	0.056*	0.048
	(0.023)	(0.032)	(0.029)
Intercept	0.040	0.004	0.081**
	(0.026)	(0.037)	(0.032)
N	215	215	215
R^2	0.514	0.156	0.456

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Table A4. SEM regression results

	Degree of greenness	Adaptation intensity	Mitigation intensity
λ	0.440***	0.487***	0.492***
	(0.079)	(0.075)	(0.074)
Adaptation intensity (t-1) (in logs)	0.135**		0.195***
	(0.053)		(0.060)
Mitigation intensity (t-1) (in logs)	0.164***	0.011	
	(0.050)	(0.066)	
Physical risk	-0.024	0.120***	
	(0.028)	(0.038)	
Transition risk	0.061***		0.111***
	(0.021)		(0.027)
Energy costs	0.044**	0.020	0.057**
	(0.020)	(0.029)	(0.026)
Financial constraints	-0.040	-0.084**	-0.043
	(0.029)	(0.042)	(0.036)
Strategic monitoring	0.082***	0.074**	0.096***
	(0.022)	(0.031)	(0.028)
Climate targets	0.072***	0.086***	0.073***
	(0.021)	(0.031)	(0.027)
Basic framework	0.053*	0.025	0.130***
	(0.031)	(0.043)	(0.041)
Innovation	0.014	0.002	0.042
	(0.024)	(0.034)	(0.030)
EU adaptation funds (in logs)		0.046**	
		(0.022)	
EU low-carbon funds (in logs)			0.060***
			(0.013)
EU adaptation and low-carbon funds (in logs)	0.036***		
	(0.009)		
CO2 (in logs)	0.029	0.031	0.032
	(0.021)	(0.030)	(0.027)
Intercept	0.073***	0.021	0.120***
	(0.028)	(0.039)	(0.035)
N	215	215	215
R^2	0.502	0.142	0.440

Note: Standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

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