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Recombining Knowledge for Climate Innovation: Evidence From US Energy Incumbents

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ABSTRACT

As the climate crisis intensifies, energy incumbents must strategically transform their fossil-fueled legacies to remain competitive and sustainable. Yet, little is known about how internal knowledge architectures and external industry positions jointly shape their capacity for climate innovation. Building on the knowledge recombination literature, this study introduces knowledge coupling—the integration of diverse knowledge elements—as a structural mechanism enabling technological adaptation. We theorize an inverted U-shaped relationship between coupling and climate technology development, where moderate coupling balances coherence and flexibility. Extending this logic, we argue that firms positioned at the technological periphery—facing fewer institutional constraints—derive greater sustainability benefits from coupling by pursuing unconventional innovation paths. Using panel data on US energy incumbents from 1981 to 2022, our analysis supports these propositions. The findings reveal how internal knowledge design and external positioning jointly drive environmental innovation in the transition toward sustainable energy systems.

1 | Introduction

Climate change has become one of the most critical global challenges, prompting intensified efforts to develop technological solutions that mitigate emissions (IPCC 2023) and accelerate the transition to sustainable energy systems (Matos et al. 2022). Climate technologies, also termed green or clean technologies, including renewable energy generation, carbon capture and storage, low-emission transportation, and energy-efficient industrial processes, have gained increasing attention from both policymakers and corporate managers (Colombelli et al. 2020). This growing attention reflects the strategic and policy salience of green technologies across firms and markets (Barbieri et al. 2023). While governments and public institutions establish environmental policies and regulatory frameworks, private sector firms, especially those embedded in carbon-intensive industries, remain central to the development and implementation of these technologies (IEA 2024).

Developing climate technologies is inherently complex. Unlike conventional innovations rooted in established domains, they require integration across diverse and often unfamiliar fields, including chemistry, materials science, and environmental engineering (Ardito et al. 2016). Such cross-domain integration is especially salient in green innovation contexts (Barbieri et al. 2023). This integrative challenge requires incumbent firms to reconfigure legacy knowledge systems to enable novel recombination that supports low-carbon transitions (Nemet 2012). Evidence from European firms similarly highlights the role of reconfiguring knowledge linkages for green innovation (Ghisetti et al. 2015). This presents a formidable strategic challenge to energy incumbents, which are traditionally rooted in fossil-fueled expertise and entrenched organizational routines (Henderson and Sen 2021). Although many have invested in green innovation, their innovation performance remains uneven, raising the question of why some incumbents are more successful than others (Matos et al. 2022).

Research on green innovation has identified several drivers, including regulatory pressure (Rennings and Rammer 2011), public and private partnerships (Hou et al. 2023), stakeholder influences (Murillo-Luna et al. 2008), R&D team diversity (Marino and Quatraro 2023), and supply chain engagement (Chaudhuri et al. 2023). Much of the literature emphasizes external pressures or organizational drivers, while giving limited attention to the internal structures of knowledge that shape how incumbents mobilize capabilities for climate innovation. Because energy incumbents rely heavily on legacy knowledge rooted in fossil fuels, understanding how they reconfigure internal knowledge linkages to pursue new trajectories is critical yet underexplored.

We address this gap by examining climate innovation through the lens of knowledge recombination. The recombination perspective emphasizes how firms innovate by connecting distinct knowledge elements into coherent systems (Xiao et al. 2022). Building on this literature, we focus on *knowledge coupling*, defined as the extent to which knowledge elements within a firm are interconnected and repeatedly recombined (Yayavaram and Ahuja 2008). In our context, a firm's degree of knowledge coupling captures the integration of knowledge from different internal sources. Prior research suggests that moderate coupling fosters innovation by balancing integration with flexibility, while too little or too much integration undermines search effectiveness (Huang et al. 2022). Yet few studies assess whether these dynamics apply to climate technologies, which require particularly complex recombinations across distant domains.

We further extend this argument by situating internal structures in their external technological environment. Drawing on the literature on technological landscapes (Stuart and Podolny 1996; Aharonson and Schilling 2016), we argue that a firm's external positioning relative to its industry peers conditions the effects of internal coupling. Firms at the industry core face strong institutional and cognitive pressures that reinforce path dependence, while those at the periphery enjoy greater latitude to explore unconventional combinations (Barbieri et al. 2023). Although scholars have noted the importance of positioning, few studies examine how it interacts with internal architectures to influence climate innovation—an important omission in understanding the adaptive capacity of incumbents.

To investigate these dynamics, we analyze panel data on US energy incumbents. These firms have been at the forefront of the energy transition, facing increasing social and regulatory pressures to reduce carbon emissions. Using their patenting activities and corporate information from 1981 to 2022, we examine how an incumbent's knowledge coupling is associated with climate technology development and how this effect is moderated by the firm's position relative to industry peers.

Our findings suggest that moderate levels of internal knowledge coupling maximize climate innovation, whereas both low and excessive coupling diminish inventive output. Moreover, this curvilinear effect is strongest among firms occupying peripheral positions in the technological landscape. By integrating the literatures on knowledge recombination (Xiao et al. 2022; Yayavaram and Ahuja 2008) and technological landscapes (Aharonson and Schilling 2016; Stuart and Podolny 1996), we confirm that an energy incumbent's internal knowledge linkages are critical for success in climate innovation, and that its external position can amplify the benefits of these internal linkages. In sum, these findings highlight the nonlinear dynamics of knowledge coupling and reveal the moderating role of external positioning in creating climate innovation. Our study offers actionable insights for firms seeking to reconfigure their knowledge networks and leverage existing capabilities to accelerate low-carbon transitions.

2 | Theory and Hypotheses

2.1 | Climate Innovation as a Knowledge Recombination Process

The knowledge recombination perspective emphasizes that innovation often arises from recombining existing knowledge components in novel ways (Fleming 2001). Distinct knowledge elements, each associated with core scientific or technological principles, can be integrated to generate new meanings and functions that underlie inventive output (Xiao et al. 2022). From this perspective, climate innovation is best understood as the process of knowledge recombination. Rather than arising solely from the acquisition of new knowledge, climate technologies emerge when firms creatively combine existing knowledge elements in novel ways (Carnabuci and Operti 2013). This view also highlights that recombining unfamiliar components increases uncertainty yet can yield disproportionately high impact once architectural fit is achieved (Rosenkopf and Nerkar 2001).

Climate technologies are a particularly demanding case of recombination. Unlike more conventional innovations rooted in stable domains, climate-oriented inventions depend on bridging distant and heterogeneous knowledge bases, including chemistry, materials science, environmental engineering, and emerging clean energy fields (Ardito et al. 2016; Barbieri et al. 2023). The multidisciplinary nature of such innovations further reinforces their recombinant character and requires the ability to integrate disparate knowledge bases into coherent solutions that support transitions away from fossil-fueled systems (Nemet 2012; Ghisetti et al. 2015).

Empirical evidence underscores this recombinant nature of climate innovation. Green inventions typically display greater technological diversity, stronger boundary-spanning intensity, and higher novelty than those in traditional domains (Ning and Guo 2022). They often combine established knowledge with emerging, less codified areas, highlighting interdependencies between conventional and green innovation paths (Barbieri et al. 2023). In this sense, climate innovation is not simply about adding new knowledge but about reconfiguring and orchestrating diverse inputs to produce environmentally beneficial outcomes.

Developing such technologies requires firms to manage complex interdependencies, align general-purpose and domain-specific capabilities, and identify viable combinations that do not naturally co-occur in conventional R&D (Carnabuci and Operti 2013; Nakamura et al. 2015). Success depends on dynamic capabilities to repurpose and recombine existing knowledge bases, as well as organizational capacity to coordinate across heterogeneous inputs (Orsatti et al. 2020). For energy incumbents in particular, the challenge is acute: They must adapt legacy systems rooted in fossil-fueled technologies while mobilizing recombination processes to generate low-carbon innovations (Henderson and Sen 2021; Sahoo et al. 2023). This motivates our focus on the internal architecture that enables or constrains effective recombination.

In this study, we view climate innovation as a knowledge recombination process. It reflects how firms configure, repurpose, and integrate diverse knowledge bases to create technological solutions that advance sustainability. This conceptualization provides the foundation for our theoretical framework of how internal knowledge structures and external industry positioning jointly shape the development of climate technologies.

2.2 | Knowledge Coupling as a Structural Mechanism for Climate Innovation

From a knowledge recombination perspective, innovation depends not only on the diversity of available knowledge but also on the architecture that links these elements into a coherent system (Xiao et al. 2022). Simply possessing a wide range of technological inputs does not guarantee successful innovation. The critical issue is whether firms can connect and integrate these elements in ways that enable productive recombination. Prior research shows that firms able to manage cross-cluster linkages and integrate diverse technological components generate more impactful environmental inventions (Orsatti et al. 2020; Marino and Quatraro 2023). Knowledge diversity can produce overload and incoherence if not supported by effective knowledge structures (Kneeland et al. 2020). Foundational work on complex systems further shows that neither fully modular nor fully integrated structures are uniformly superior; performance depends on how interdependencies are patterned (Baldwin and Clark 2000; Ethiraj and Levinthal 2004).

This perspective has led scholars to conceptualize the firm's knowledge base as a structured network of interdependent elements that are repeatedly used in inventive activity (Schilling and Green 2011; Kneeland et al. 2020). The configuration of this network determines the scope of experimentation and the opportunities available for recombination. Different architectures yield different trade-offs. Highly modular structures support specialization but constrain integrative search (Sanchez and Mahoney 1996; Henderson and Clark 1990). In contrast, highly integrated structures enable cross-domain interaction but risk overload and rigidity (Keijl et al. 2016; Antonelli et al. 2022). A nearly decomposable architecture, balancing local density with selective cross-cluster ties, has been identified as particularly conducive to innovation (Simon 1962), and these nearly decomposable knowledge bases generate more useful and adaptable inventions (Yayavaram and Ahuja 2008). Further empirical evidence confirms that such balanced architectures are especially useful in complex domains, including environmental technologies, where recombination across distant fields is often required (Guan and Liu 2016; Orsatti et al. 2020).

Building on this stream of work, researchers have introduced the concept of knowledge coupling to describe the extent to which knowledge elements within a firm are interconnected and repeatedly recombined (Yayavaram and Ahuja 2008). Knowledge coupling represents a structural mechanism that determines whether firms can mobilize knowledge elements for novel uses or become constrained by interdependencies (Huang et al. 2022). At low levels of coupling, knowledge remains fragmented, where firms may possess valuable components but lack the integrative links to exploit complementarities (Yayavaram and Ahuja 2008). By contrast, moderate levels of coupling provide cross-domain linkages that activate complementarities and broaden the search space (Huang et al. 2022). This structural configuration allows firms to balance local specialization with boundary-spanning integration, a balance particularly aligned with the complex demands of climate innovation (Barbieri et al. 2023). At the other extreme, high levels of coupling create excessive interdependencies that limit flexibility (Kneeland et al. 2020). Dense entanglement across the knowledge base raises coordination costs and narrows the scope for experimentation. As a result, firms become locked into familiar, path-dependent trajectories rather than exploring novel solutions (Zan et al. 2024). This inertia is particularly problematic for energy incumbents, which must adapt legacy fossil-fueled-based knowledge systems to low-carbon imperatives (Battke et al. 2016).

Taken together, these insights suggest a nonlinear relationship between knowledge coupling and innovation outcomes. Weak coupling fragments knowledge, leaving synergies underexploited, while excessive coupling generates rigidity and inertia. Moderate coupling provides the structural balance that enables firms to integrate diverse knowledge domains, sustain recombinant search, and generate novel solutions. We argue that this mechanism is especially relevant to energy incumbents. While these firms possess extensive technological legacies and deep reservoirs of expertise, they are also embedded in entrenched routines that can limit adaptation (Henderson and Sen 2021). Maintaining knowledge linkages at moderate levels of coupling offers a pathway for incumbents to mobilize their capabilities and meet the integrative demands of climate innovation. We hence hypothesize as follows:

H1. *There is an inverted U-shaped relationship between knowledge coupling and climate technology development, such that moderate coupling maximizes innovation outcomes.*

2.3 | External Technological Positioning as a Boundary Condition

While internal architectures determine how firms mobilize and recombine their knowledge, innovation outcomes are also shaped by the broader technological environment in which firms operate. A firm's external positioning vis-à-vis its industry peers influences its exposure to institutional pressures, its access to diverse ideas, and its latitude for experimentation (Stuart and Podolny 1996; Aharonson and Schilling 2016). From a knowledge recombination perspective, this positioning defines the search space in which internal coupling operates. It determines whether recombination reinforces established trajectories or opens opportunities for novelty (Xiao et al. 2022).

We conceptualize external positioning as technological similarity, defined as the degree to which a firm's knowledge base overlaps with those of its industry peers (Aharonson and Schilling 2016). High similarity places firms near the technological core of the industry, where dominant designs, legacy competencies, and institutional norms are concentrated (Stuart and Podolny 1996; Qu et al. 2025). Low similarity, in contrast, places firms at the periphery, where they are more exposed to alternative technological domains and divergent paths of development (Nylund et al. 2022; Sahoo et al. 2023). Consistent with this core–periphery view, central positions face stronger legitimacy expectations that penalize deviation from accepted templates (Zuckerman 1999; Hsu 2006), whereas peripheral positions often provide the creative latitude where novel combinations are more likely to emerge (Cattani and Ferriani 2008; Uzzi and Spiro 2005).

When similarity is high, the benefits of internal coupling are constrained. In such contexts, coupling tends to reinforce conventional routines rather than enabling departure from them. Because many firms draw on overlapping domains, recombination risks redundancy, producing familiar solutions that conform to dominant expectations. Moreover, high similarity amplifies isomorphic pressures: centrally positioned firms face institutional and cognitive constraints that narrow the scope of experimentation (Zan et al. 2024; Battke et al. 2016). These firms also experience technological gravity—the pull of established suppliers, competitive dynamics, and entrenched design trajectories—that makes deviation from the fossil-fueled paradigm costly. As a result, even optimal internal architectures may fail to generate transformative climate innovations when firms are embedded in the technological core.

By contrast, when similarity is low, incumbents face weaker institutional pressures and enjoy greater latitude for experimentation. Peripheral firms are less constrained by dominant configurations and thus encounter fewer barriers when reconfiguring knowledge toward climate imperatives (Marino and Quatraro 2023; Barbieri et al. 2023). Under these conditions, moderate coupling becomes especially valuable: it enables firms to connect specialized clusters in ways that activate complementarities without being constrained by legacy norms. Peripheral positioning also broadens the effective search space, allowing firms to draw from unconventional knowledge domains, experiment with unorthodox combinations, and generate outcomes that depart from established trajectories. This structural freedom increases the likelihood that recombination produces impactful climate technologies rather than incremental extensions of fossil-based competencies.

Taken together, these insights highlight that recombination is not only an internal process but also one embedded in the technological landscape of the industry (Aharonson and Schilling 2016; Sahoo et al. 2023). Internal architectures interact with external environments: in central positions, coupling reinforces conformity and path dependence; in peripheral positions, coupling supports structural flexibility and experimentation.

This boundary condition is particularly salient for energy incumbents, whose main technological domains are historically rooted in fossil-fueled systems. Their industrial surroundings shape the opportunities and constraints for climate-oriented innovation. Thus, we argue that an incumbent's position in the technological landscape conditions the effect of internal coupling. At the industry core, even optimal levels of coupling are unlikely to yield transformative climate innovation. At the periphery, however, optimal coupling can translate into fruitful recombinations that accelerate the transition toward sustainability.

H2. *The inverted U-shaped relationship between knowledge coupling and climate technology development is more pronounced when the firm has lower technological similarity with its industry peers.*

3 | Data and Method

3.1 | Research Context and Sample

This study focuses on energy incumbent firms operating in the US oil and gas industry, a sector facing intensifying pressure to decarbonize amid the global climate crisis. Fossil fuels continue to dominate the US energy landscape, accounting for over 60% of total energy production in recent years (IEA 2024). At the same time, international climate agreements such as the Paris Accord have prompted national governments to adopt more aggressive climate targets, including the US goal of achieving net-zero greenhouse gas emissions by 2050 (Dimitrov 2016). In line with these goals, recent federal legislation and regulatory policies have increased investment in clean energy research and technology development (O'Rear et al. 2025).

Within this context, energy incumbents play a critical role in bridging the transition from legacy fossil-fueled technologies to low-carbon and renewable alternatives. Despite a notable rise in clean energy patents and investments over the past two decades (IEA 2017; Probst et al. 2021; Popp et al. 2024), energy incumbents still face structural and cognitive challenges when attempting to align their existing knowledge systems with new demands for environmental innovation (Henderson and Sen 2021). Their innovation outcomes vary widely, making them a valuable setting for examining how different knowledge configurations affect the development of climate technologies.

To construct the empirical sample, we begin by identifying all firms listed under the energy sector (GICS code 1010) in the Compustat database, which includes energy equipment and services (101010) and oil, gas, and consumable fuels (101020). We then narrow the sample to technology-intensive incumbents using two criteria: (1) The firm must report research and development (R&D) expenditures in its annual 10-K filings, and (2) the firm must have been granted at least 100 US patents during the study period. These criteria ensure the inclusion of firms with significant innovation activity and established knowledge portfolios. Our final sample consists of 32 energy incumbent firms spanning subfields such as oil and gas exploration and production, refining and marketing, oilfield services, and integrated operations. These firms collectively account for 82,247 patents granted by the US Patent and Trademark Office (USPTO) between 1976 and 2022. We organize the data at the firm–year level from 1981 to 2022, yielding 721 nonmissing observations.

Patent data were retrieved from the USPTO bulk patent database, which includes detailed information on Cooperative Patent Classification (CPC) codes, filing and grant dates, forward citations, and assignee names. Firm-level accounting data were obtained from Compustat and SEC filings. These sources allow us to construct comprehensive, firm-level indicators of internal knowledge structure, external technological similarity, and climate innovation outcomes. This design directly aligns with our theoretical focus on how internal architecture (*knowledge coupling*) interacts with external positioning (*technological similarity*) to shape climate-oriented invention among incumbents.

3.2 | Variables

3.2.1 | Dependent Variable: Climate Technology Development

We measure firms' engagement in climate technology development based on their patenting activities in climate-related domains. Specifically, we rely on the Y02 category of the CPC system. The Y02 scheme, developed by the US Patent and Trademark Office and the European Patent Office, was specifically designed to capture technologies that contribute to climate change mitigation and adaptation (Angelucci et al. 2018). Aligned with international climate policy frameworks, such as the Kyoto Protocol and the Paris Agreement, it includes subclasses covering renewable energy generation and distribution, carbon capture and storage, low-emission transportation systems, energy-efficient industrial processes, and waste management solutions (Angelucci et al. 2018). This classification has been widely adopted in studies of climate innovation (Colombelli et al. 2020; Barbieri et al. 2023). A full breakdown of Y02 subclasses, along with the distribution of patents across sample firms, is provided in Table 1.

TABLE 1 | Description of Y02 subclass codes in the cooperative patent classification (CPC).

CPC subclass code	Description	Count of patents[a]
Y02A	Technologies for adaptation to climate change	343
Y02B	Climate change mitigation technologies related to buildings, e.g., housing, house appliances, or related end user applications	131
Y02C	Capture, storage, sequestration, or disposal of greenhouse gases (GHG)	635
Y02D	Climate change mitigation technologies in information and communication technologies (ICT), i.e., information and communication technologies aiming at the reduction of their own energy use	18
Y02E	Reduction of GHG emissions, related to energy generation, transmission, or distribution	1598
Y02P	Climate change mitigation technologies in the production or processing of goods	4752
Y02T	Climate change mitigation technologies related to transportation	367
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management	361

Note: Note that the patent class membership is not mutually exclusive, i.e., a patent can belong to more than one subclass.
[a]Denotes the count of patents granted to sample firms for each Y02 code from 1976 to 2022.

Our measure is the annual count of Y02-classified patents filed and granted to each firm. This measure captures the volume of climate-related inventive activity. The validity of the construct is strong as Y02 patents explicitly cover climate technologies and are internationally recognized. Patent counts are widely accepted in the innovation literature as important measures of inventive activity (Ghisetti et al. 2015; Orsatti et al. 2020; Barbieri et al. 2023).

3.2.2 | Explanatory Variable: Knowledge Coupling

To examine the role of internal knowledge structures in shaping firms' climate technology development, we operationalize a measure of knowledge coupling. This measure captures the extent to which a firm repeatedly recombines distinct technological domains in its inventive activity, reflecting an internal orientation toward integration versus fragmentation. Our operationalization follows established approaches in the literature on knowledge coupling (Yayavaram and Ahuja 2008; Yayavaram and Chen 2015; Huang et al. 2022).

We begin by constructing a representation of each firm's knowledge base using patent classification data. For each firm–year observation, we collect all patents granted to the firm in the prior 5 years, creating a 5-year moving window that captures cumulative knowledge activity. Each patent is assigned to one or more CPC subclasses, which serve as the building blocks of our measure. To stabilize the domain space while preserving coverage, we focus on the 30 most frequently used four-digit CPC subclasses across the sample, covering over 80% of patent activity.

Using this restricted domain set, we then identify all possible pairs of subclasses and calculate the frequency with which each pair is jointly assigned to the same patent within a given firm and time window. The repeated co-occurrence of two subclasses on the same patent indicates that the firm is actively recombining knowledge across those domains. For each subclass pair *j* and *k*, we compute a Jaccard coefficient for firm *i* in year *t*, defined as

$$L_{i,jk,t_w} = \frac{n_{jk}}{n_j + n_k - n_{jk}} \quad (1)$$

where n_{jk} is the number of patents assigned to both subclasses j and k, and n_j and n_k are the number of patents assigned to each subclass individually. All counts are calculated over the 5-year window ending in year t. This Jaccard coefficient normalizes joint use over the total presence of each domain, following standard practice in similarity measurement (Everitt et al. 2011; Yayavaram and Ahuja 2008). This measure reflects the firm's repeated recombination efforts and provides insight into how tightly its knowledge domains are interconnected.

For each firm–year, we compute the Jaccard coefficient for all possible pairs of the 30 selected subclasses, yielding a symmetric matrix of pairwise coupling strengths. To construct a firm-level measure, we sum all pairwise coefficients in this matrix, producing an aggregate measure of the average intensity of interconnection within the firm's knowledge base. Higher values indicate greater integration and tighter coupling of domains, whereas lower values reflect fragmentation or modularity.

This operationalization has been widely employed to capture the structural dynamics of knowledge systems (Yayavaram and Ahuja 2008) in which repeated coclassification directly reflects firms' recombinant efforts. The construct validity is established through consistent use of this measure in strategy and innovation research to capture interdependencies in knowledge bases (Huang et al. 2022). To enhance the measurement reliability, we use a 5-year moving window and focus on the dominant CPC subclasses, which reduces noise and enhances comparability across firms and time.

3.2.3 | Moderating Variable: Technological Similarity

To examine how technological landscapes shape the effect of this internal structure, we construct a measure of technological similarity between each firm and its industry peers. This measure captures a firm's position in the industry's technological landscape by assessing the extent to which it shares knowledge domains with those of other firms. Our approach follows the method developed by Aharonson and Schilling (2016).

Each firm is represented by a binary vector indicating the presence or absence of activity in each of the 30 selected CPC subclasses. For each subclass, a value of 1 is assigned if the firm has at least one patent in that domain during the relevant 5-year moving window, and 0 otherwise. This representation reflects the breadth of technological domains in which the firm is active during a given period.

Using these binary vectors, we calculate pairwise similarities between all firms for each year in the sample. The similarity between firm *i* and firm *k* in year *t*, denoted as C_{ijt_w}, is defined as

$$C_{ijt_w} = \frac{|\, S_{it_w} \cap S_{jt_w} \,|}{|\, S_{it_w} \,|} \quad (2)$$

where S_{it_w} and S_{jt_w} denote the sets of CPC subclasses used by firms *i* and *j*, respectively, during the 5-year window ending in year *t*. The resulting value ranges from 0 to 1, with higher values indicating that a larger share of firm *i*'s technological activity overlaps with that of firm *j*. To derive a firm-level measure, we calculate the average similarity between each focal firm and all other firms in the sample. This yields a continuous measure of external positioning, where higher values represent greater alignment with industry peers (technological core) and lower values represent greater distinctiveness (technological periphery).

This operationalization is consistent with prior research that uses overlap in technological domains to represent firms' proximity in knowledge space (Aharonson and Schilling 2016). The measure directly reflects whether firms develop knowledge in the same technological areas. It provides construct validity by capturing institutional and cognitive pressures associated with core versus peripheral positions in the industry landscape. Firms near the core are more likely to face isomorphic constraints that reinforce conventional trajectories, while firms at the periphery enjoy greater latitude to pursue unconventional recombinations.

3.3 | Control Variables

We include a set of control variables to account for firm-level characteristics that may influence climate technology development. Firm size is measured as the natural logarithm of total assets, and firm age is calculated as the number of years since founding. To capture a firm's investment in innovation activities, we control for R&D intensity, measured as R&D expenditure divided by total sales. To reduce simultaneity, all explanatory variables, including controls, are lagged by 1 year. We further control for sub-industry heterogeneity within the energy sector using indicator variables for four categories: oil and gas equipment and services, integrated oil and gas, oil and gas exploration and production, and oil and gas refining and marketing. Year dummy variables are included in all model specifications to account for broader temporal changes related to policy, market conditions, and macroeconomic shocks.

3.4 | Model Specification

To examine the relationship between a firm's knowledge coupling and its climate technology development, we employ negative binomial regression with firm fixed effects. This model is well suited to our data for both theoretical and statistical reasons. Our dependent variable—the annual count of climate-related patents filed by each firm—is a nonnegative, highly skewed count variable, consistent with the distributional properties of patent data in prior innovation research (Kovács et al. 2021; Savage et al. 2020). Unlike Poisson regression, which assumes equality of the mean and variance, the negative binomial model accounts for overdispersion. The fixed-effects specification further controls for time-invariant firm-specific heterogeneity, such as organizational routines, legacy competencies, or structural factors that might otherwise confound estimates. Together, these features make the negative binomial regression with fixed effects the most appropriate baseline model for our research question.

We tested key statistical assumptions for the negative binomial regression. We tested overdispersion through likelihood ratio tests comparing Poisson and negative binomial specifications, which strongly rejected the null hypothesis that the dispersion parameter equals zero ($\chi^{-2}(1) = 961.56$, $p < 0.001$), confirming substantial overdispersion and justifying the use of the negative binomial specification over Poisson. Multicollinearity was assessed through variance inflation factors (VIF), with a mean VIF of 4.27 across all variables, and no values exceeded conventional thresholds of 10 (Kutner 2005). Additionally, likelihood ratio tests confirmed that each set of additional parameters in our nested models contributed significant explanatory power: The quadratic coupling terms (Model 2) improved fit over the baseline (Model 1) with $\chi^2 = 16.80$ ($p < 0.001$), and the interaction terms (Model 3) further improved fit with $\chi^2 = 7.47$ ($p = 0.024$), as reported in Table 4 in the results section.

Because our variables are constructed from archival data sources (patents and corporate databases), common method bias is less likely to be a concern compared to perceptual survey data (Podsakoff et al. 2003). Nonetheless, we conducted additional diagnostic checks. Specifically, we compared models using alternative operationalizations of key constructs (e.g., extending knowledge base definitions beyond the 30 most frequent CPC subclasses). The consistency of results across these specifications suggests that common method variance does not drive our findings. To further ensure reliability, we conducted robustness checks using negative binomial regression with random effects and Poisson pseudo-maximum likelihood (PPML) estimation Silva and Tenreyro 2006.

4 | Results

Tables 2 and 3 present the descriptive statistics and correlation matrix for the variables used in the analysis. The average number of climate technology patents per firm–year is relatively low, reflecting the nascent and complex nature of green innovation within the energy sector. Knowledge coupling and technological similarity exhibit moderate variation across firms, providing a suitable empirical setting to test the theoretical expectations. While certain explanatory variables are moderately correlated, none exceed conventional thresholds that would indicate problematic multicollinearity. VIF scores remain below 5 across models, indicating that multicollinearity is unlikely to bias coefficient estimates.

4.1 | Main Analyses

Table 4 presents the results from negative binomial analyses examining the relationship between a firm's knowledge coupling and its climate technology development. Model 1 includes only the control variables to establish a baseline estimate. In this model, both total assets (ln) and firm age exhibit positive and statistically significant associations with climate technology development ($\beta = 0.045$, $p < 0.01$; $\beta = 0.007$, $p < 0.05$, respectively). Additionally, the coefficient on technological similarity is negative and statistically significant ($\beta = -5.221$, $p < 0.001$), indicating that greater similarity between the focal firm and its industry peers is associated with fewer climate patents generated by the focal firm.

TABLE 2 | Descriptive statistics.

Variables	Obs	Mean	SD
(1) Climate tech development	721	7.68	14.51
(2) Climate tech impact	721	145.09	694.28
(3) Knowledge coupling	721	2.69	2.19
(4) Technological similarity	721	0.29	0.08
(5) Total asset (ln)	721	7.81	3.70
(6) Firm age	721	61.99	36.33
(7) ROA	721	0.04	0.05
(8) R&D intensity	721	0.01	0.01
Industry classification			
Oil and gas equipment and services	721	0.55	0.50
Integrated Oil and gas	721	0.29	0.45
Oil and gas exploration and production	721	0.13	0.34
Oil and gas refining and marketing	721	0.04	0.20

To test the first hypothesis that knowledge coupling exhibits an inverted U-shaped relationship with climate technology development, Model 2 introduces both the linear and quadratic terms for knowledge coupling. The coefficient of the linear term is positive and significant ($\beta = 0.232$, $p < 0.001$), suggesting that increases in knowledge coupling are initially associated with higher levels of climate patenting. The coefficient for the quadratic term is negative and significant ($\beta = -0.018$, $p < 0.01$), supporting the proposed curvilinear relationship in which excessive knowledge coupling eventually dampens climate technology development.

To visualize this nonlinear pattern, Figure 1 plots the predicted relationship between knowledge coupling and climate patent count based on Model 2. The x-axis represents the level of knowledge coupling, while the y-axis displays the predicted number of climate patents, with 95% confidence intervals. As knowledge coupling increases, climate patenting initially rises; beyond a moderate threshold, the positive effect diminishes, the curve flattens and then declines, consistent with the hypothesized inverted U-shaped relationship. These results provide empirical support for Hypothesis 1.

TABLE 3 | Bivariate correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Climate tech development							
(2) Climate technology impact	0.41						
(3) Knowledge coupling	0.56	0.11					
(4) Technological similarity	−0.19	−0.13	−0.05				
(5) Total asset (ln)	0.17	−0.04	0.26	0.07			
(6) Firm age	0.47	0.14	0.52	−0.10	0.18		
(7) ROA	0.18	0.05	0.11	−0.17	0.07	0.11	
(8) R&D intensity	−0.15	0.00	−0.29	−0.32	−0.20	−0.14	−0.07

Note: The number of firm–year observations is 721. Correlation coefficients greater than 0.0087 or less than −0.0087 are significant at the 5% level. Variance inflation factors were computed for all explanatory and control variables to assess multicollinearity. The mean VIF is 4.27, which is below conventional concern thresholds of 10 for serious collinearity and the more conservative benchmark of 5 (Kutner 2005), indicating that multicollinearity is unlikely to threaten the validity of the estimates.

Model 3 of Table 4 incorporates the interaction terms between knowledge coupling and technological similarity. The interaction between the linear coupling term and similarity is negative and statistically significant ($\beta = -2.024$, $p < 0.05$), whereas the interaction between the quadratic coupling term and similarity is positive and marginally significant ($\beta = 0.215$, $p < 0.10$). To fully interpret these interaction effects, Figure 2 presents a graphical depiction of the relationship between knowledge coupling and climate technology development at two levels of technological similarity: one standard deviation below the mean (low similarity) and one standard deviation above the mean (high similarity). Under low similarity, the positive association between knowledge coupling and climate patenting is more pronounced. Specifically, climate patent output increases with knowledge coupling, peaking at the middle level, and subsequently showing a decline, consistent with the hypothesized diminishing returns. In contrast, for firms characterized by high technological similarity, the effect of knowledge coupling is substantially weaker. Across all levels of knowledge coupling, the predicted number of climate patents remains relatively low, indicating that high technological similarity constrains the benefits derived from internal knowledge recombination.

Overall, these results demonstrate that technological similarity moderates the relationship between knowledge coupling and climate technology development in a manner consistent with Hypothesis 2.

4.2 | Additional Analyses

We provide additional analyses by capturing varying degrees of influence on subsequent technological advancements. To capture the influence of each climate patent, we employ forward citations—the number of times a focal patent has been cited by subsequent patents—as a measure of patent impact. Forward citations are a well-established indicator of technological influence because patents cited more frequently serve as important foundations for subsequent innovations (Aristodemou and Tietze 2018). This citation-based approach provides a complementary lens on inventive significance and allows us to test whether our theoretical relationships hold for the quality as well as the quantity of climate inventions.

Table 5 shows the results from additional analyses using this impact-based measure as an alternative dependent variable. The results replicate our main findings: knowledge coupling exhibits an inverted U-shaped relationship with impact, and this curvilinear pattern is significantly more pronounced when technological similarity is low. Figures 3 and 4 graphically depict these main and interaction effects. These additional analyses complement our main findings.

To further substantiate the stability of our findings, we estimate two alternative model specifications. First, we re-estimate our core specifications using negative binomial regression with firm-level random effects (using the *xtnbreg*, *re* command in Stata 18), which relaxes the assumption of strict exogeneity of unobserved heterogeneity. Second, we implement PPML estimation with standard errors clustered at the firm level (using *ppml* in Stata 18 with *cluster* option), a specification known for its robustness to distributional misspecification and zero-inflation. Across both alternative approaches, as reported in Tables 6 and 7, coefficient signs, magnitudes, and levels of statistical significance are virtually unchanged, demonstrating that our findings are not an artifact of a particular estimation strategy but instead reflect robust relationships between internal knowledge coupling, external positioning, and climate-technology innovation.

5 | Discussion and Conclusion

This study has examined how the internal architecture of knowledge within incumbent firms, in the form of knowledge coupling, and their external technological positioning relative to their industry peers jointly shape the development of climate technologies. Our empirical findings confirm the theorized inverted U-shaped relationship between internal knowledge coupling and climate patent output. Furthermore, this relationship is moderated by a firm's position in the technological landscape of the industry, such that the innovation-enhancing effects of coupling are more pronounced for firms

TABLE 4 | Negative binomial regression of a firm's climate patent count.

	M1	M2	M3
Firm fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Industry classification[a]			
Oil and gas equipment and services	−1.226** (0.456)	−0.890* (0.451)	−0.943* (0.447)
Integrated oil and gas	−0.581	−0.534	−0.556
	(0.467)	(0.452)	(0.451)
Oil and gas exploration and production	−1.157* (0.466)	−0.960* (0.459)	−0.895+ (0.458)
Total asset (ln)	0.045**	0.051***	0.045**
	(0.015)	(0.015)	(0.014)
Firm age	0.007*	0.006*	0.005+
	(0.003)	(0.003)	(0.003)
ROA	−0.080	0.021	0.260
	(0.818)	(0.813)	(0.828)
R&D intensity	7.929	15.722*	16.271*
	(7.182)	(7.723)	(7.882)
Technological similarity	−5.221***	−4.588***	−2.463*
	(0.773)	(0.824)	(1.143)
Knowledge coupling		0.232***	0.773**
		(0.058)	(0.237)
Knowledge coupling squared		−0.018**	−0.075*
		(0.006)	(0.034)
Knowledge coupling * technological similarity			−2.024* (0.805)
Knowledge coupling squared* technological similarity			0.215+ (0.113)
Constant	2.593***	1.592**	1.135+
	(0.555)	(0.606)	(0.633)
Observations	721	721	721
Log likelihood	−1423.959	−1415.560	−1411.825
AIC	2947.919	2935.121	2931.650
Chi-square	422.019	432.290	440.200
Degree of freedom	49	51	53

[a]The omitted category for industry is "oil and gas refining and marketing."
+0.10.
*0.05.
**0.01.
***0.001.
Note: Model fit: Relative to the specification with similarity only (M1), the model with the quadratic in coupling (M2) achieved a higher log likelihood (−1415.56 vs. −1423.96) and a lower AIC (2935.12 vs. 2947.92). A likelihood ratio test confirms that M2 significantly improves fit over M1 ($\chi^2 = 16.80$, $p < 0.001$). Adding the interaction between coupling and similarity (M3) further improved fit (log likelihood = −1411.83; AIC = 2931.65), and the likelihood ratio test again supports the added terms ($\chi^2 = 7.47$, $p = 0.024$). Taken together, the AIC and likelihood ratio results indicate that including both the quadratic in coupling and its interaction with similarity provides additional explanatory power, consistent with the theorized moderation.
Note: Overdispersion: As a diagnostic for dispersion, a negative binomial model was estimated and the likelihood ratio test of the null hypothesis that the dispersion parameter equals zero strongly rejected the Poisson specification (LR test of $\alpha = 0$: $\chi^{-2}(1) = 961.56$, $p < 0.001$). This indicates substantial overdispersion relative to Poisson and supports the use of estimators that are robust to variance exceeding the mean.

TABLE 5 | Additional analyses: negative binomial regression of a firm's climate patent impact.

	M1	M2	M3
Firm fixed effects	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Industry classification[a]			
Oil and gas equipment and services	−3.243*** (0.381)	−2.498*** (0.390)	−2.766*** (0.416)
Integrated oil and gas	−2.024***	−1.651***	−1.848***
	(0.379)	(0.369)	(0.391)
Oil and gas exploration and production	−2.342*** (0.385)	−1.951*** (0.379)	−2.181*** (0.402)
Total asset (ln)	0.074***	0.071***	0.064***
	(0.016)	(0.015)	(0.015)
Firm age	0.008***	0.005*	0.004+
	(0.002)	(0.002)	(0.002)
ROA	−0.295	0.180	0.724
	(1.085)	(1.106)	(1.135)
R&D intensity	24.689***	25.540**	25.426**
	(7.181)	(7.764)	(7.777)
Technological similarity	−5.403*** (0.777)	−5.153*** (0.852)	−1.906 (1.184)
Knowledge coupling		0.457***	1.431***
		(0.075)	(0.302)
Knowledge coupling squared		−0.042*** (0.009)	−0.153** (0.052)
Knowledge coupling * technological similarity			−3.692*** (1.043)
Knowledge coupling squared * technological similarity			0.413* (0.178)
Constant	1.690**	0.528	0.043
	(0.518)	(0.547)	(0.604)
Observations	721	721	721
Chi-square	310.339	341.781	378.001
Degree of freedom	49	51	53

[a]The omitted category for industry is "oil and gas refining and marketing."
+0.10.
*0.05.
**0.01.
***0.001.

that are less similar to others in the industry. These results provide new insights into how energy incumbents can reconfigure their legacy knowledge structures to meet the demands of climate innovation.

The findings suggest that firms benefit from a moderate level of coupling across knowledge domains. This allows for the activation of complementarities without becoming trapped by excessive interdependencies. This supports the recombination view of innovation, in which inventive success depends not only on the content of knowledge but also on the architectures that govern how knowledge elements are linked and mobilized (Fleming 2001; Yayavaram and Ahuja 2008; Xiao et al. 2022).

Furthermore, firms positioned further from the technological center of their industry—those whose knowledge portfolios differ more substantially from peers—are more capable of leveraging internal coupling for impactful climate innovations. This pattern aligns directly with our second hypothesis and the core–periphery logic, whereby technological distance appears to reduce institutional inertia and expand the search space for novel recombinations (Cattani and Ferriani 2008; Qu et al. 2025).

These dynamics are particularly significant in the context of climate technologies, as prior research shows that combining heterogeneous knowledge domains and bridging conventional

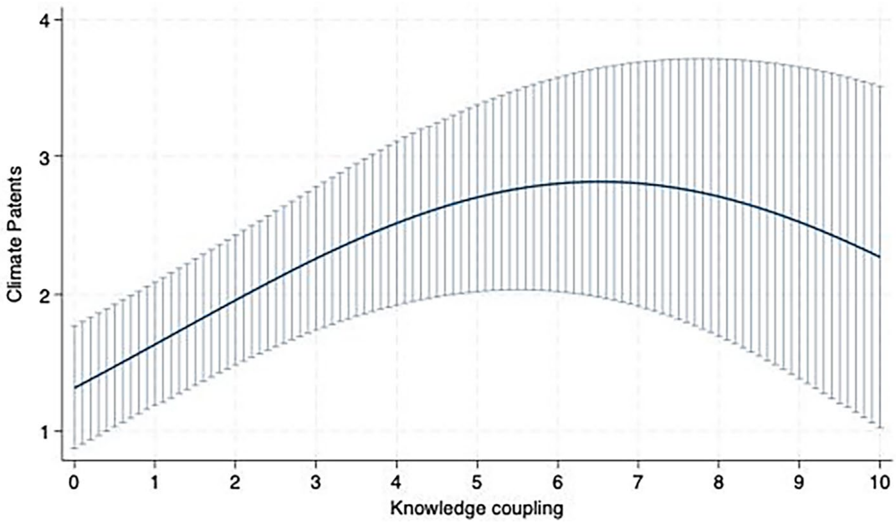

FIGURE 1 | Relationship between a firm's knowledge coupling and its climate patent count.ote: The graphs are based on the results of negative binomial regression in Model 2 of Table 4 and show predictive margins with a 95% confidence level.

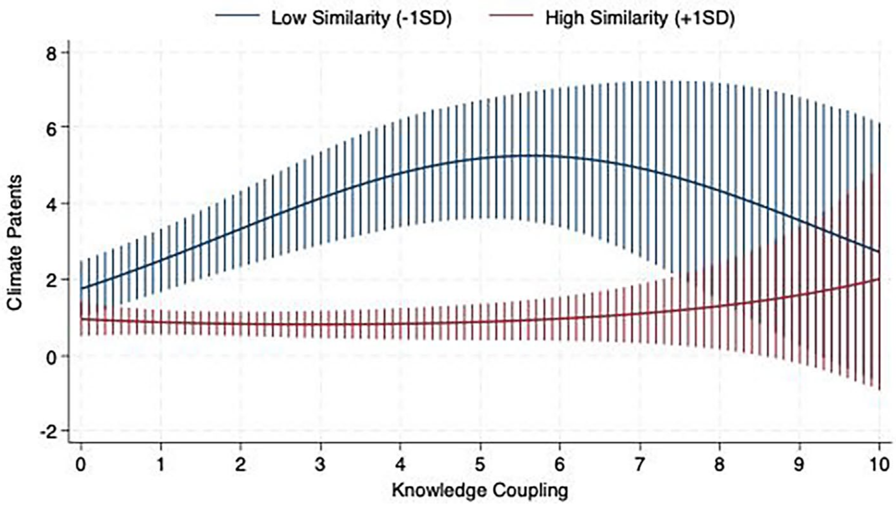

FIGURE 2 | Relationship between a firm's knowledge coupling and its climate patent count moderated by a firm's technological similarity. The graphs are based on the results of negative binomial regression in Model 3 of Table 4 and show predictive margins with a 95% confidence level.

with emerging fields (Ardito et al. 2016; Barbieri et al. 2023) is essential to green innovation. Our results align with the view that structural flexibility, both within and across firms, is essential to enable the blending of mature technical capabilities with exploratory insights required for green innovation (Ghisetti et al. 2015; Orsatti et al. 2020).

5.1 | Theoretical Contribution

This study contributes to the innovation literature in three ways. First, it extends recombination theory by shifting attention from the breadth or novelty of knowledge components to the architectures through which they are interconnected. While prior research emphasizes knowledge depth, breadth, or novelty as drivers of innovation (Schilling and Green 2011; Kaplan and Vakili 2015; Vakili and Kaplan 2021), our findings highlight coupling as an architectural mechanism that can both enable and constrain recombinant search. By theorizing and showing an inverted U-shaped effect of coupling on climate patenting, we specify when integration helps versus hinders complex innovation, enriching understanding of recombinant innovation and architectural search (Fleming 2001; Carnabuci and Operti 2013; Kneeland et al. 2020).

Second, the study advances knowledge of boundary conditions in innovation. Most work treats internal structures as self-contained determinants, but we show that external positioning—in particular, technological similarity to peers—conditions whether coupling supports or hinders innovation. This cross-level effect links internal architecture to external location and clarifies why the same coupling can yield different outcomes across firms, resonating with ecosystem perspectives that emphasize embeddedness (Stuart and Podolny 1996; Aharonson and Schilling 2016; Sahoo et al. 2023). The finding that high similarity reduces the benefits of coupling highlights the risks of technological isomorphism and path dependence in clustered ecosystems (Zuckerman 1999; Hsu 2006; Zan et al. 2024).

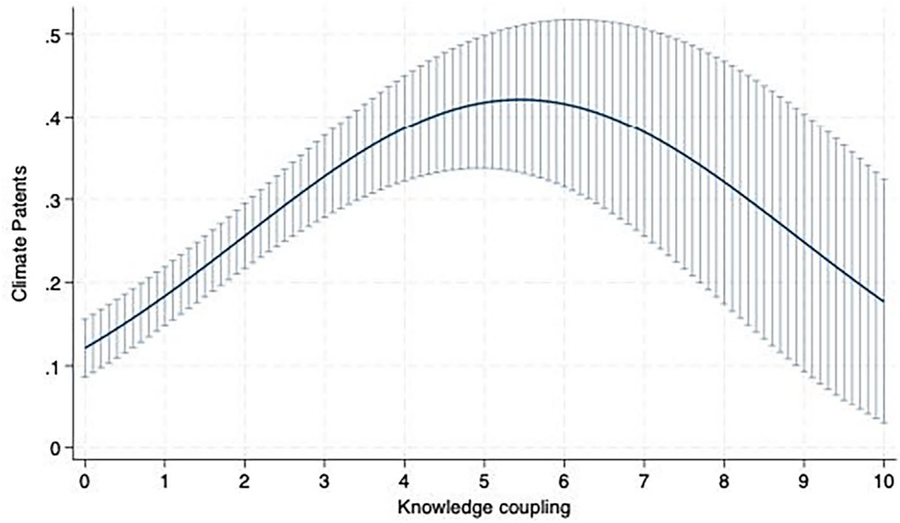

FIGURE 3 | Relationship between a firm's knowledge coupling and its climate patent impact. The graphs are based on the results of negative binomial regression in Model 2 of Table 5 and show predictive margins with a 95% confidence level.

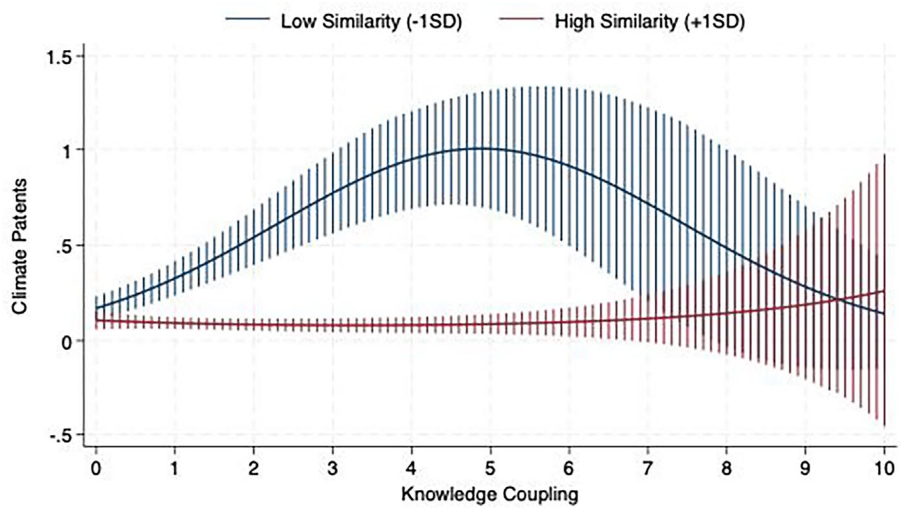

FIGURE 4 | Relationship between a firm's knowledge coupling and its climate patent impact moderated by technological similarity. The graphs are based on the results of negative binomial regression in Model 3 of Table 5 and show predictive margins with a 95% confidence level.

Finally, this study contributes to research on climate innovation by offering a knowledge-structural explanation for why some incumbents generate more impactful environmental technologies than others. Prior work has focused primarily on regulatory, stakeholder, or resource-based explanations (Hu and Liu 2019; Murillo-Luna et al. 2008; Awan et al. 2019). By pointing to the interaction between internal architectures and external positioning, we identify a tractable organizational lever—configuring moderate coupling while considering technological distinctiveness—that explains variation in incumbents' climate inventions, responding to calls for mechanism-focused accounts (Ardito et al. 2016; De Bem Machado et al. 2022).

5.2 | Managerial and Policy Implications

The results offer several implications for managers and policymakers seeking to accelerate innovation in climate technologies. Managers of energy firms should be attentive not only to depth, breadth, or novelty of knowledge inputs but also to the architecture of how internal knowledge domains are linked. Excessive separation across domains can limit opportunities for recombination, while overly dense coupling may create rigidity. A nearly decomposable knowledge base, where clusters of knowledge are internally coherent but linked through selective interconnections, appears most conducive to innovation in complex technological areas. Practically, this implies prioritizing integrative projects that connect a limited set of distant clusters rather than indiscriminate, organization-wide coupling.

Moreover, the strategic location of a firm in the broader technological space influences how effectively internal resources can be mobilized. Firms that align too closely with peers may find their coupling activities reinforcing existing paths. Those that diverge, however, may have more leeway to experiment with

TABLE 6 | Additional analyses: negative binomial regression of a firm's climate patent count with random effects.

	M1	M2	M3
Industry classification[a]			
Oil and gas equipment and services	−1.725*** (0.410)	−1.369*** (0.401)	−1.477*** (0.396)
Integrated oil and gas	−0.810+	−0.734+	−0.790*
	(0.426)	(0.405)	(0.400)
Oil and gas exploration and production	−1.368** (0.421)	−1.131** (0.407)	−1.091** (0.403)
Total asset (ln)	0.046***	0.051***	0.045***
	(0.014)	(0.014)	(0.013)
Firm age	0.008**	0.007*	0.006*
	(0.003)	(0.003)	(0.003)
ROA	−0.056	0.012	0.301
	(0.809)	(0.801)	(0.818)
R&D intensity	9.889	17.595*	18.733*
	(7.036)	(7.492)	(7.655)
Technological similarity	−5.625*** (0.768)	−5.024*** (0.818)	−2.684* (1.146)
Knowledge coupling		0.251***	0.855***
		(0.056)	(0.235)
Knowledge Coupling squared		−0.019*** (0.005)	−0.083* (0.034)
Knowledge coupling * technological similarity			−2.241** (0.795)
Knowledge coupling squared * technological similarity			0.240* (0.111)
Constant	2.909***	1.887***	1.380*
	(0.520)	(0.563)	(0.594)
Observations	721	721	721
Chi-square	462.190	472.866	480.543
Degree of freedom	49	51	53

[a]The omitted category for industry is "oil and gas refining and marketing."
+0.10.
*0.05.
**0.01.
***0.001.
Note: All specifications include year-fixed effects.

unconventional combinations. Managers should therefore pair architectural adjustments with portfolio choices that maintain some technological distinctiveness, suggesting that innovation strategies consider both internal capabilities and relative technological positioning when seeking to shift toward green innovation.

For policymakers, the findings underscore the importance of supporting not just green R&D but also the organizational conditions under which green innovation becomes feasible. Incentives that promote knowledge diversity, experimentation, and architectural reconfiguration within firms could yield higher returns than those focused solely on expanding knowledge content. Policy tools that encourage selective cross-domain collaboration (e.g., mission-oriented consortia that link complementary domains) may help firms reach the "moderate coupling" region more reliably. Promoting internal restructuring through grants, technical assistance, or flexible reporting standards may serve as a strategic lever for accelerating climate technology transitions.

5.3 | Limitations and Future Research

This study also has several limitations that provide opportunities for future inquiry. First, our empirical setting is limited to US-based energy incumbents. While these firms are well suited for examining the challenges of climate-oriented recombination, future research could extend our findings to firms in other countries or sectors where regulatory pressures and technological trajectories differ. Studies focusing on renewable energy startups, utilities, or clean-tech ventures may

TABLE 7 | Additional analyses: Poisson pseudo-maximum likelihood model of a firm's climate patent count.

	M1	M2	M3
Industry classification[a]			
Oil and gas equipment and services	−2.608*** (0.162)	−1.951*** (0.169)	−2.063*** (0.171)
Integrated oil and gas	−1.470***	−1.282***	−1.218***
	(0.173)	(0.171)	(0.165)
Oil and gas exploration and production	−1.087*** (0.139)	−0.845*** (0.141)	−0.879*** (0.136)
Total asset (ln)	0.055***	0.052***	0.051***
	(0.011)	(0.011)	(0.011)
Firm age	0.016***	0.012***	0.010***
	(0.002)	(0.002)	(0.002)
ROA	0.388	0.337	0.835
	(1.049)	(1.072)	(1.139)
R&D intensity	15.448**	19.131**	24.294***
	(5.987)	(5.929)	(6.208)
Technological similarity	−11.012*** (0.812)	−9.642*** (0.871)	−4.595*** (1.092)
Knowledge coupling		0.397***	1.453***
		(0.048)	(0.247)
Knowledge coupling squared		−0.023*** (0.005)	−0.147*** (0.036)
Knowledge coupling * Technological Similarity			−3.958*** (0.856)
Knowledge coupling squared * Technological similarity			0.451*** (0.119)
Constant	4.837***	3.410***	2.193***
	(0.402)	(0.434)	(0.465)
Observations	721	721	721
Log likelihood	−2354.7572	−2179.6137	−2128.2645
Parameters	50	52	54

[a]The omitted category for industry is "oil and gas refining and marketing."
+0.10
*0.05
**0.01
***0.001.
Note: All specifications include year fixed effects.

help to clarify whether the observed effects are unique to fossil-fueled incumbents or more generalizable across organizational types.

Second, our operationalization of knowledge coupling relies on patent coclassification data. While widely used in prior literature (Yayavaram and Ahuja 2008; Huang et al. 2022), this approach may not capture informal knowledge flows, organizational learning routines, or unpatented innovations. Incorporating survey data, interview-based assessments, or internal R&D documentation could deepen our understanding of how knowledge structuring occurs in practice and how it relates to broader innovation processes (Knoppen et al. 2022). Future mixed-method designs that triangulate patent-based measures with within-firm process data would be especially valuable.

Third, although we use lagged independent variables and firm fixed effects to mitigate reverse causality, endogeneity concerns cannot be entirely ruled out. It is possible that firms with greater innovative capacity also invest more strategically in recombination, which could bias the estimates. Future research could explore instrumental variable approaches or exploit quasi-experimental variation in technology policy or organizational restructuring to strengthen causal claims.

Lastly, future research could examine how firms dynamically adjust their knowledge coupling over time in response to external shocks or internal learning. While our research assumes knowledge coupling as given at a particular point in time, architectural search is a dynamic process, often iterative, path-dependent, and shaped by prior failures (Fleming and Sorenson 2004; Kapoor and Adner 2012). Addressing how firms reconfigure their knowledge networks in evolving technological landscapes could offer richer insights into the dynamics of knowledge coupling.

Taken together, these findings underscore the importance of viewing innovation capacity not only as a function of knowledge accumulation but also as a product of how knowledge is internally structured and externally situated. In climate technology development, where firms must reconcile legacy systems with new demands, both architectural balance and external differentiation play decisive roles. Understanding how firms reconfigure and reposition their knowledge provides critical insight into how incumbents can engage in transformative innovation during sustainability transitions.

Authors Contributions

Kyung-Baek Min conceptualized the research idea, developed the theoretical framework, collected and curated the data, conducted the empirical analysis, and led the writing of the manuscript. Kyzai Baikishieva conducted the literature review, collected and curated the data, conducted the empirical analysis, and contributed to the interpretation of the results. Young-Choon Kim conceptualized the research idea, developed the theoretical framework, contributed to the study design, provided critical revisions, and refined the manuscript. All authors reviewed and approved the final version of the manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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