Global Carbon Pricing and Industrial Decarbonization Innovation*

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Abstract

This paper elucidates trends in industrial decarbonization innovation from 1990 to 2022 and evaluates the causal effects of carbon pricing instruments on such innovation. Employing a hybrid classification framework that integrates large language models (LLMs) and natural language processing (NLP), we map global clean-technology patents into 604 decarbonisation technologies in the International Energy Agency (IEA) Clean Energy Technology Guide. Leveraging global variation in carbon pricing policies, our empirical findings indicate that carbon pricing—particularly through Emissions Trading Schemes (ETS)—plays a critical role in promoting decarbonization innovation, whereas carbon taxes exhibit limited effects. Innovation induced by ETS is concentrated at the prototype, demonstration, and commercialization stages. Furthermore, the effects of ETS on innovation are evident across a wide range of technology themes — including bioenergy, critical minerals, energy storage, electrochemistry, hydrogen, materials, and renewables — as well as across application sectors (buildings, energy transformation, industry, and transport) and patent assignee types (firms, universities, and individuals).
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1 Introduction

The invention and dissemination of clean technologies are critical for achieving global decarbonization and realizing net-zero objectives (Dugoua and Moscona, 2025; Gillingham et al., 2025). According to the latest International Energy Agency (IEA) projections, attaining net-zero emissions by 2050 and restricting the rise in global mean temperature to 1.5°C necessitates a substantial reduction of 34 GtCO2 across all sectors via energy transformation and carbon removal. This mitigation target encompasses sector-specific decarbonization pathways, including reductions of 12.7 GtCO2 from industry, 9.8 GtCO2 from power generation, and 7.9 GtCO2 from transportation (IEA, 2023). Despite notable advancements in technologies such as solar panels and electric vehicles (EVs), significant uncertainty persists regarding the extent to which the current supply of clean technologies can adequately support decarbonization pathways that meet sectoral demand, whether they are prepared for large-scale deployment or remain at the prototype stage, and how climate policy interplays with the invention and diffusion of these technologies.

In this paper, we map clean-technology patents to industrial decarbonization technologies drawn from the IEA Clean Energy Technology Guide to document innovation in technologies that contribute to sector-specific decarbonization pathways. We employ a hybrid semantic-classification framework that integrates Large Language Models (LLMs) and Natural Language Processing (NLP) to classify patents into 604 decarbonization technologies in the global energy system that span ten major themes: bioenergy, CCUS, critical minerals, digitalisation, electrification, electrochemistry, energy storage, hydrogen, materials, and renewables. It also enables us to analyse how innovation is distributedted across different stages of technological development based on technology readiness levels (TRLs). Drawing on 5.1 million granted patents from 1990 to 2022, we identify 1.5 million patents linked to the 604 technologies defined in the IEA Clean Energy Technology Guide.

Leveraging this global patent dataset linked to industrial decarbonization technologies, we further estimate the causal effects of carbon pricing policies on industrial decarbonization innovation. Specifically, we compare and contrast the impacts of carbon taxes and ETS in fostering innovation worldwide. Utilizing a staggered difference-in-differences (DID) approach, we examine patenting activity across countries with and without carbon pricing policies. We further

investigate the role of carbon price levels in spurring innovation under both carbon tax and ETS regimes. Finally, we conduct analyses of heterogeneity in induced innovation across technology readiness levels (TRLs), spanning the stages from concept and prototype to demonstration and commercialization, and further disaggregate the results by technology themes, application sectors, and patent assignee types.

Our descriptive analysis on patents demonstrates a marked acceleration in global industrial decarbonization innovation since the mid-2000s, characterized by growth across major technology themes and application sectors. Innovation has increasingly concentrated on more mature technologies, those with higher TRLs, reflecting a broader shift toward deployment and scaling. The geographic landscape has also undergone substantial transformation, evolving from dominance by advanced economies in the 1990s and early 2000s to a context in which China emerged as the largest contributor during the 2010s. Simultaneously, cross-border patenting patterns reveal persistent asymmetries in international technology diffusion, with advanced economies serving as net exporters of decarbonization technologies and emerging economies remaining major recipients.

Our regression findings indicate that the innovation effects of carbon pricing depend on policy design. In particular, adoption of ETS leads to a significant increase in decarbonization patenting, whereas adoption of a carbon tax has a weaker, less statistically significant impact. Further examination of price heterogeneity reveals that higher-priced ETS regimes are associated with stronger increases in innovation, while the effects of carbon taxes remain muted across different price levels. Dynamic event-study estimates underscore divergent trajectories: the effects of ETS accumulate gradually and become clearly positive in the medium term, whereas the influence of carbon taxes remains weaker and less stable over time. Finally, the technology heterogeneity analysis demonstrates that the positive effects of ETS are especially pronounced in decarbonization patenting across the prototype, demonstration, and commercialization stages, with these effects intensifying as technologies mature. These impacts extend across a broad spectrum of technology themes, application sectors, and assignee types.

This paper contributes to the growing literature on tracking the evolution of environmental or climate innovation using worldwide patent data, such as environmental innovation (Haščič and Migotto, 2015), climate change mitigation technologies (Probst et al., 2021), tracking artificial intelligence with climate invention (Verendel, 2023), methane abatement invention (Jiang et al.,

2024), battery and fuel cell (Dugoua and Dumas, 2024), and carbon capture, utilization, and storage (Cui, Popp, and Wang, 2025). We contribute to a better understanding of the evolution of 604 emerging industrial decarbonization technologies in the global energy system from 1990 to 2022. This is also among first papers to link patents with TRLs, which depicts the stages of technological development.

This paper also contributes to the literature estimating the causal impacts of climate policies, such as carbon taxes and ETS, on innovation and energy-induced technological change (Haščič and Migotto, 2015; Dechezleprêtre and Sato, 2017; Popp, 2019). While previous research has thoroughly documented the effects of energy prices on innovation (Popp, 2002; Dugoua and Gerarden, 2025), recent studies emphasize that ETS, as a prominent climate policy implemented in multiple jurisdictions, has had a pronounced impact in stimulating low-carbon innovation in the European Union (Calel and Dechezleprêtre, 2016), the United Kingdom (Calel, 2022), and China (Cui, Zhang, and Zheng, 2018). Furthermore, there is suggestive evidence that carbon taxes have driven innovation in the Swedish transport sector (aus dem Moore, Brehm, and Gruhl, 2025), while fuel taxes and standards have played a pivotal role in incentivizing the development of EV and hydrogen fuel cell technologies (Rozendaal and Vollebergh, 2025). A key distinction of this study is its comparative analysis of carbon taxes and ETS implemented across jurisdictions over the past three decades. Leveraging global patent panel data, we differentiate the induced-innovation effects of carbon taxes and ETS and quantify the heterogeneous impacts of carbon pricing across a broad array of industrial decarbonization technological pathways.

This paper adds to the methodological literature on identifying emerging technologies from patent data. Early studies utilized broad taxonomies, such as the OECD ENV-TECH, CPC Y02, and WIPO IPC Green Inventory, to link patents to general environmental or climate-related innovations (Dechezleprêtre, Glachant, and Ménière, 2011; Haščič and Migotto, 2015; Cui, Zhang, and Zheng, 2018). To track specific emerging technologies, such as batteries or fuel cells, some research combined keywords with IPC/CPC taxonomies (Dugoua and Dumas, 2024). To capture the substantive novelty of complex innovations, recent work has shifted toward "text-as-data" approaches, leveraging NLP and machine learning algorithms (Arts, Melluso, and Veugelers, 2025; Bergeaud, Jaffe, and Papanikolaou, 2025; Dugoua, 2025).[1] This methodological landscape has

[1]The methodological evolution began with simple keyword matching and Boolean queries, which—while transpar-

rapidly developed from transformer-based models that capture deep semantic context (Lee and Hsiang, 2020) to modern LLMs. The latter—especially the 'LLM-as-a-judge' framework—enables consistent semantic evaluation, particularly when ensemble methods are employed (Zheng et al., 2023; Gu et al., 2024; Bedemariam et al., 2025; Xia et al., 2025; Yuan et al., 2025). Against this backdrop, our study makes a contribution by integrating advanced LLM pipelines to generate high-resolution indicators for environmental and climate innovation. We build on this methodological shift implementing a hierarchical multi-model pipeline to classify global patents into granular IEA technology categories.

The remainder of the paper is organized as follows. Section 2 introduces our dataset and categorization process. Section 3 introduces the empirical strategy. Section 4 illustrates data patterns and empirical findings. Section 5 concludes.

2 Data

2.1 Data Sources

Global Patent. We obtain patent data from the Lens and Google Patent Project, both of which provide open access to over 132 million patent publications associated with 52 million granted patents across more than 100 patent offices worldwide. To identify patents relevant to climate change mitigation and adaptation, we focus on approximately 5.1 million granted patents tagged with Y02 under the EPO CPC Taxonomy. These climate-related patents pertain to about 2.8 million unique families across 79 jurisdictions from 1990 to 2022. In addition, we have a comprehensive set of patent details, including the priority number, IPC, CPC, publication number, publication date, assignee, inventor, citations, title, and abstract. A patent family is defined as a set of patents sharing the same priority number.

IEA Clean Energy Technology Guide. The IEA Clean Energy Technology Guide database contains detailed information on more than 600 individual technologies across ten cross-cutting themes, all related to the energy system as a whole and contributing to the net-zero goal. There are

ent—were brittle and prone to false negatives. Building on these early techniques, later studies adopted supervised machine learning (e.g., Support Vector Machines) and unsupervised topic modeling (e.g., LDA) to statistically analyze corpus content. Most recently, the introduction of deep learning and transformer-based models (e.g., BERT) has further advanced the field, enabling researchers to capture semantic context beyond mere word co-occurrence. Despite these advances, the application of sophisticated NLP techniques to granular policy analysis remains limited.

10 cross-cutting themes: CCUS, renewables, materials, digitalization, energy storage, bioenergy, electrification, hydrogen, electrochemistry, and critical minerals. Notably, a single technology can span multiple themes. Additionally, for each technology, the database provides a brief technical description, identifies its application sector, and specifies its technology maturity index (i.e., TRL) as of 2024, based on its actual deployment status. There are six main application sectors (covering energy transformation, building, industry, transport, CO_2 management, and mining) and 28 detailed subsectors. More importantly, each technology is classified by its stage of development using TRLs ranging from 1 to 11, covering concept (TRL 1-3), prototype (TRL 4-6), demonstration (TRL 7-9), and commercialization (TRL 9-11).

In the Appendix, Figure A1 shows the inter-theme nature of more than 600 technologies in the IEA Clean Energy Technology Guide. The three largest themes are Materials, Hydrogen, and Renewables, each comprising more than 100 specific technologies. Within the Materials theme, technologies could span multiple themes, including CCUS, Critical Minerals, Renewables, Energy Storage, and Hydrogen. It provides some flexibility for linking technologies with patents. Figure A2 further displays the distribution of these technologies across application sectors and TRLs. It tracks the technology flow from TRL maturity stages (ranging from concept to commercialization deployment) on the left, through core themes such as hydrogen and electrification in the middle, to deployment in sectors such as energy transformation, industry, transport, and buildings on the right. The diagram shows how decarbonization technologies at different maturity levels support the net-zero goals of major global industries.

Carbon Pricing Tools. We use carbon-pricing data from the World Carbon Pricing Database (Dolphin and Xiahou, 2022), which tracks national and subnational carbon taxes and ETS policies, including annual rates and permit prices. To capture the carbon-pricing environment in our sample, we create unified indicators from global data. We include four policy types: national carbon taxes, national ETS, subnational carbon taxes, and subnational ETS. A country is classified as implementing carbon pricing if either national or subnational jurisdictions have such policies in effect. This approach more accurately reflects the effective coverage of policies and avoids understating carbon-pricing incentives. We construct two sets of carbon-pricing policy variables, distinguishing between carbon taxes and ETSs. This separation allows us to evaluate differences in policy design and incentives across the two instruments. To capture policy heterogeneity within

each type, we also collect statutory carbon tax rates (in USD per ton) and average inflation-adjusted permit prices for ETSs. All prices are converted to constant-year U.S. dollars for comparability. Since carbon taxes and ETSs differ in compliance flexibility, regulatory obligations, and price formation, estimating their separate effects clarifies how each tool influences clean-technology innovation.

Country Covariates. Country-level characteristics are sourced from the World Bank, including emission intensity, GDP per capita, total residential patent applications, and the renewable electricity ratio. Specifically, GDP per capita (constant USD) reflects economic development. The renewable electricity ratio quantifies dependence on renewable energy, whereas emission intensity reflects environmental efficiency. Total residential patent applications serve as a proxy for overall innovation capability.

2.2 Mapping Patents to IEA Clean Energy Technology

To systematically classify patents into 604 individual technologies in the IEA Clean Energy Technology Guide, we develop a multi-stage pipeline that integrates LLMs, classical machine learning, NLP algorithms, and expert manual validation. In the Appendix, Figure A3 illustrates the flowchart for each major step. After the mapping process, clean-technology patents are referred to patents successfully mapped to individual technologies in the IEA Clean Energy Technology Guide, which are innovations that underpin industrial decarbonization.

Sample Pre-processing. We start with 2.8 million unique patent families, representing 5.1 million granted patents carrying the Y02 label across 79 jurisdictions between 1990 and 2022. For each invention, we first standardize assignee names across multiple languages and use the English name to represent the assignee.[2] We then select one representative patent from the family with an English title and abstract. If a family has no English-language text components, we use the Google

[2]We standardize patent assignee names for consistency across jurisdictions and languages. Our rule-based unification process uses the longest English name for single applicants, as these often include full institutional identifiers such as "Co., Ltd." or "Research Institute." This method preserves semantic precision and improves cross-record matching. We then create a bilingual mapping that links English names to non-English variants in Chinese, Japanese, Korean, and Russian. Using this mapping, we replace all shorter English and verified non-English names with their unified English forms, ensuring consistent applicant representation across jurisdictions. For patents with records listing multiple applicants, we again select the longest English name in the family and use it to standardize all applicant variants for that family. This step harmonizes single- and multi-applicant patents, ensuring that all applicants for the same invention are labeled consistently. These standardizations enable robust measurement of technological concentration, cross-border collaboration, and the diffusion of innovation.

Translate API to translate non-English text into English. We concatenate each patent family's title and abstract, standardize the text to lowercase, normalize punctuation, and clean whitespace. Next, we add an IPC/CPC filter to better align patents with each of the ten IEA cross-cutting themes. These filters are constructed using the IPC Green Inventory maintained by WIPO, along with detailed Y02 labels in the EPO's taxonomy. For technologies in the "Materials" and "Critical Minerals" categories, due to vague technological descriptions and a lack of clear mapping from technologies to IPC/CPC filters, we exclude these two themes from the sample.[3] For each of the remaining eight themes, we use the integrated LLM and NLP framework to map patents to the specific technologies based on the similarity between the IEA-provided technology descriptions and the textual information in patents' titles and abstracts.

LLM-Based Semantic Classification. Given the complexity of the taxonomy and the large number of patent examples, a single, all-in-one prompt often fails to reliably classify 2.8 million patents across 604 technologies, leading to wasted computational resources and excessive assignments to the "Other" category. To address this, we implement a hierarchical batch strategy in which technologies are first grouped into the remaining eight themes. Each theme is then divided into several smaller and manageable sets of 10-20 technologies that are closely related to one another. A validated prompt frames the model as a patent classification specialist. To proceed with classification, several representative few-shot patent examples are pre-selected to ensure fine-grained discrimination among closely related technologies. The prompt further guides the model through a structured semantic assessment of each invention. For each patent, the model identifies the core technical contribution and interprets the underlying innovation. It then selects the most appropriate technology domain within the IEA taxonomy, relying solely on the title and abstract. The model also assigns a confidence level reflecting textual clarity.

To ensure robustness and consistency, inference is performed at a low temperature, and cases assigned ambiguous labels — especially "Other" — are flagged to reduce randomness and improve reproducibility. This practice is supported by recent findings showing that calibration and controlled sampling improve cross-run agreement in LLM outputs (Xia et al., 2025). This procedure ensures that semantic assignments produced in this stage are stable, interpretable, and

[3]While the IEA taxonomy is comprehensive, we exclude "Materials" and "Critical Minerals" from this direct LLM-based classification process. This exclusion is due to the lack of clearly defined technological boundaries and specific IPC/CPC classification codes for these categories, which makes direct semantic processing less reliable.

aligned with expert expectations. To assess semantic consistency across architectures, the same prompt is applied to DeepSeek, ChatGPT, and Gemini. Pairwise agreement rates—including the "Other" class—are computed for identical patent samples. Average cross-model agreement between DeepSeek–Gemini and DeepSeek–ChatGPT is approximately 70–75%. These results are comparable to agreement levels reported in the recent "LLM-as-a-Judge" literature (Gu et al., 2024; Zheng et al., 2023). Empirical validation within our pipeline further confirms this stability: in 10-iteration consistency tests using DeepSeek, the probability of obtaining identical classification results across all 10 runs reached 90%, with 97.6% of cases achieving a majority consensus of 6 or more identical assignments.

NLP Classification. As a benchmark, a supervised TF–IDF + XGBoost classifier is trained on a manually validated subset of patents processed by the LLM. Texts are vectorized using unigrams and bigrams, with a vocabulary size capped at 10,000 and a minimum document frequency of 1. The XGBoost model employs a multi-class mode with well-trained hyperparameters.[4] On a 50/50 train–test split, the model achieves 94.4% accuracy, closely matching that of the LLM-based classifier and confirming the robustness of the semantic prompt approach (Lee and Hsiang, 2020).

Expert Spot-Check Validation. To further validate the pipeline's accuracy, random samples of classified patents are manually reviewed by domain experts based solely on titles and abstracts. Approximately 85% of model-assigned categories align with expert judgments. Misclassifications primarily occur at the boundaries of hybrid technologies, such as electrochemical storage overlapping with renewable energy systems (Sbardella et al., 2018).

2.3 Descriptive Statistics

Finally, approximately 0.469 million patent families associated with 1.13 million patents granted have been classified into 364 technologies across eight major themes. Although two themes (i.e., "Materials" and "Critical minerals") were excluded from direct LLM classification due to vague boundaries, they appear in the final dataset because of the inter-theme nature of technologies set by the IEA.

Figure A4 in the Appendix presents the distribution of patent families across various themes.

[4]These parameters are `learning_rate = 0.134`, `max_depth = 6`, `n_estimators = 200`, `colsample_bytree = 0.9`, and `subsample = 1.0`.

The horizontal bar chart in the bottom-left corner shows the total number of patents for each theme. The dot matrix at the bottom delineates specific cross-theme combinations, with linkages between solid circles and vertical lines illustrating interconnections among themes. On the right side of the dot matrix, the number of technologies for each theme is reported in purple, while at the bottom, the number of technologies spanning multiple themes is shown in orange, as specified by the dot-and-vertical visual combination. Finally, the top vertical bar chart displays the number of patent families associated with these inter-theme combinations. Collectively, these components depict the extent of technological coupling in the energy sector, encompassing 400 individual technologies across 10 themes.

Several notable features emerge from this analysis. First, across all themes, hydrogen and renewables represent the most significant categories by technology count, comprising 115 and 95 technologies, respectively. In contrast, critical minerals constitute the smallest category, with only four technologies, most of which are identified through cross-theme areas such as electrochemistry and energy storage.[5] Second, the intersection of electrochemistry and energy storage encompasses five technologies, while the inter-theme combination of bioenergy and renewables includes a more diverse set of 32 technologies.[6] Third, in terms of patent counts, the largest inter-theme combination is the nexus of energy storage and electrochemistry, featuring around 171,000 patents across five individual technologies, whereas the smallest is among CCUS and digitalization, with only 159 patents in only one individual technology. These findings underscore the combinations and overlaps of technological themes in industrial decarbonization.

Table 1 presents descriptive statistics for the key variables used in the subsequent empirical analysis. Panel A reports statistics for patents across TRLs and thematic areas. On average, each country holds 76.38 clean-technology patents, with approximately 70.4% ($\approx$ 53.77/76.38) at the commercialization TRL stage, 15.1% at the demonstration stage, 10.8% at the prototype stage, and 3.7% at the concept stage. Regarding the distribution across themes, electrochemistry and energy storage are the most prominent, with mean values of 33.31 and 30.7 patent families per country, respectively, followed by materials, renewables, hydrogen, critical minerals, digitalization,

[5]These four technologies are Lithium-ion battery, Li-Air battery, Low silicon content graphite anode battery, and Li-S battery.

[6]For example, technologies including electrical storage for building systems integration, manganese-rich cathode battery, zinc-manganese oxide battery, cell-to-chassis battery technology, and cell-to-pack battery technology, are at the intersection of electrochemistry and energy storage themes.

electrification, bioenergy, and CCUS. Patents are further distinguished by application sector, with the top four being energy transformation, transport, buildings, and industry. Concerning assignee types, firms are the leading assignees and account for the majority of innovations, followed by individuals and universities, which have similar average numbers of granted patents. Panel B summarizes carbon pricing tools, indicating that only 6% of observations are from jurisdictions implementing a carbon tax, while 10.3% are subject to pressure from an ETS. Panel C provides summary statistics for key country-level attributes, including carbon emission intensity, GDP per capita, total patents, and the renewable electricity ratio.

[Insert Table 1 about here]

3 Empirical Method

This study examines the impact of carbon pricing on clean technology innovation using a panel of country-year observations, with clean technology patent family counts as the outcome variable. Given the count nature of the dependent variable, we estimate the policy effect using Poisson pseudo-maximum likelihood (PPML) regression (Chen and Roth, 2024). Since carbon pricing was introduced at different times across countries. In such staggered-adoption settings, the coefficient from a conventional two-way fixed effects (TWFE) DID regression can be biased when treatment effects are heterogeneous across cohorts or over time, because early-treated countries may serve as controls for later-treated countries (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020). Motivated by this concern, we build on the approach proposed by Wooldridge (2021, 2023), which extends the standard fixed-effects DID framework by allowing treatment effects to vary across adoption cohorts and years and then aggregating these cohort–year effects into an overall policy effect (Nagengast, Rios-Avila, and Yotov, 2026). An additional advantage of this approach is that it can be adapted to non-linear models, including the PPML estimator (Nagengast and Yotov, 2025). We use never-treated units in the control group to ensure that its composition does not change over time (Cassidy and Velayudhan, 2026). Thus, for a country c at year t, we estimate the

following Poisson regression model:

$$\text{CleanPatent}_{ct} = \exp\Big(\alpha_c + \lambda_t + \sum_{g=g_0}^{G}\sum_{t=g}^{T} \theta_{gt}\,\text{CarbonPricing}_{ct}\,\mathbf{1}(g,t) + \Gamma' X_{ct}\Big) + \varepsilon_{ct}, \tag{1}$$

In this specification, $\text{CarbonPricing}_{ct}$ is a binary indicator equal to one if country c is covered by a carbon pricing instrument in year t (a carbon tax or an ETS, respectively), and zero otherwise. The term $\mathbf{1}(g,t)$ is a cohort–year cell indicator, defined as $\mathbf{1}(g,t) \equiv \mathbf{1}\{G_c = g\}\mathbf{1}\{\text{Year} = t\}$. G_c denotes the first year when country c is subject to the policy (the adoption cohort). The coefficient θ_{gt} allows the policy effect to vary across cohort–year cells (g,t) for $t \geq g$. We obtain the overall effect of the carbon pricing policy by aggregating the estimated cohort–year effects θ_{gt} across treated cohort–year cells, weighted by the corresponding sample weights.

The outcome variable, denoted by CleanPatent_{ct}, measures the number of clean-technology patent families. When an invention is first filed, it is assigned a priority number. Subsequent patent applications for the same invention in other jurisdictions share this priority number and are therefore grouped into a single patent family. The patent family count captures the number of granted patent families that were initially assigned in country c at year t.

We also incorporate country-level control variables denoted by X_{ct}. Emission intensity is included to represent the demand side for decarbonization technologies aimed at reducing carbon emissions. GDP per capita serves as a proxy for a country's level of economic development. Total resident patent applications capture national innovation capacity, while the renewable electricity ratio controls for the status of the energy transition in the power sector. Finally, we include the fixed effect at the country and year levels, denoted by α_c and λ_t, respectively. The former absorbs time-invariant country-level characteristics that may shape innovation, while the latter controls for year-specific unobservables. ε_{ct} is the error term for the regression. Standard errors are clustered at the country level.

4 Results

4.1 Global Trends in Industrial Decarbonization Innovation

Global innovation in decarbonization has expanded significantly over the past three decades, accompanied by substantial shifts in technology themes, application sectors, maturity levels, and geographic distribution. Figure 1 depicts the global evolution of clean-technology innovation across major technology themes, as defined by the IEA Clean Energy Technology Guide, from 1990 to 2022. Patenting activity remained relatively modest throughout the 1990s and early 2000s, but accelerated after the mid-2000s. A more pronounced surge occurred after 2010, driven by rapid growth in energy storage technologies, renewable energy sectors, electrochemistry, and hydrogen-related innovations. Notably, this expansion has not been limited to a narrow set of technologies. While energy storage, renewables, and electrochemistry continue to dominate overall volumes, emerging domains such as digitalization and critical materials have exhibited sustained and increasingly steep growth trajectories during the 2010s. Despite a temporary contraction around 2020, patenting activity rebounded strongly thereafter, indicating a robust, resilient expansion in global decarbonization innovation.

[Insert Figure 1 about here]

Figure 2 illustrates global trends in clean-technology patenting by application sector, revealing a distinct pattern of sectoral expansion. Energy transformation is identified as the dominant sector, reflecting the global transition toward renewable energy sources. The transportation and building sectors also contribute substantially, underscoring the critical roles of low-emission vehicles and energy-efficient construction. In contrast, the industrial sector represents a smaller proportion of total clean-technology patenting activity.[7] Despite considerable differences in scale, all sectors exhibit significant growth, particularly after 2010. This acceleration indicates that the recent surge in clean-technology innovation constitutes a systemic transformation across the entire energy system.

[Insert Figure 2 about here]

[7] Patents mapped to CO_2 management and mining sectors remain very limited throughout the sample period. Consequently, even if these sectors were included, they would remain effectively invisible in the figure because they are underrepresented among the approximately 600 technologies in the IEA Clean Energy Technology Guide.

Figure 3 illustrates the evolution of clean-technology innovation across different maturity stages proxied by TRLs, emphasizing a marked shift toward more mature technologies over time. Concept-stage innovations (TRLs 1–3) exhibit only modest growth, whereas patents at the prototype (TRLs 4–6) and demonstration (TRLs 7–8) stages increase steadily throughout the period, reflecting sustained efforts to develop and demonstrate new technological solutions. The most rapid expansion is observed in commercialization-stage technologies (TRLs 9–11), indicating accelerated market adoption and large-scale deployment. This trend is particularly pronounced in batteries, electrochemical systems, and integrated energy-storage technologies, which are advancing rapidly from prototyping to market-ready applications. The overall increase across TRL stages, coupled with the growing prominence of commercialization-stage innovations, suggests that global decarbonization efforts have advanced toward deployment and scaling.

[Insert Figure 3 about here]

Figure 4 illustrates the evolving geographic distribution of clean-technology innovation, demonstrating a significant shift in global leadership over the past three decades. In the 1990s and early 2000s, innovation activity was predominantly led by advanced economies, with Japan emerging as the principal contributor, followed by the United States, South Korea, and Germany. However, from approximately 2010 onwards, the innovation landscape changed markedly as China experienced a dramatic acceleration in clean-technology patenting, quickly surpassing traditional leaders. By the late 2010s, China accounted for the largest share of global clean-technology patent families. Although advanced economies continue to play a vital role, China's rapid ascent underscores its dominance in decarbonization innovation.

[Insert Figure 4 about here]

Figure 5 displays the network of cross-border technology flows, revealing a persistent structural asymmetry in global clean-technology diffusion. Japan emerges as the predominant source of technology outflows, accounting for one-third (32.4%) of the total, thereby reinforcing its position as a primary net exporter alongside Germany, the United States, and South Korea. In contrast, China demonstrates a pronounced imbalance: while it functions as a critical destination market, absorbing 18.8% of global flows—comparable to the United States (29.1%)—it accounts for only

a minor fraction (5.9%) of outflows. Europe and the United States are also the key destinations for cross-border technology flows. This distribution highlights that although innovation activity remains concentrated in a select number of advanced economies, the global decarbonization trajectory is heavily contingent on the cross-border diffusion of these technologies into deployment markets. In the Appendix, Figure A5 further shows the overall technological flows, including both domestic and cross-border ones. Among all 0.466 million unique families, only 0.077 million have cross-border technology flows, whereas 72% of them have never filed as international patent families. China dominates these non-international patent families, followed by Japan, Korea, and the United States.

[Insert Figure 5 about here]

4.2 Baseline Effects of Carbon Pricing on Clean Technology Innovation

Table 2 presents PPML estimates of the impact of carbon-pricing adoption on clean-technology innovation. The estimated coefficient for the carbon tax, reported in Column (1), is positive but not statistically significant, suggesting no evidence that introducing a carbon tax substantially influences clean-technology patenting when controlling for country- and year-fixed effects and the full set of covariates. In contrast, the coefficient for the ETS, shown in Column (2), reveals a statistically significant increase in the number of clean-technology patent families following ETS adoption. Specifically, the results indicate that ETS implementation is associated with a 50.5% increase in clean-technology patent families.[8] The comparison of coefficients between the carbon tax and the ETS suggests that market-based mechanisms, specifically ETS, exert a stronger effect in stimulating clean-technology innovation than the carbon tax.

[Insert Table 2 about here]

We further examine the dynamic effects of each policy instrument, specifically the carbon tax and the ETS. Figure 6 depicts the dynamic impact of carbon pricing adoption on clean-technology patenting. The reported coefficients are measured relative to one year prior to carbon pricing

[8] The coefficients from this PPML regression can be interpreted as proportional effects, calculated as $(\exp^{0.409} - 1) \times 100\% \approx 50.5\%$.

adoption (the reference period), with 95% confidence intervals constructed using country-clustered standard errors and the same set of fixed effects and controls as in the baseline regression.

[Insert Figure 6 about here]

The upper subfigure presents the coefficients for the leads and lags associated with carbon tax adoption. There is no clear pre-trend preceding policy implementation. In the post-adoption period, the effect on clean-technology innovation remains relatively weak in the short term and exhibits fluctuations over time, with many coefficients not significantly different from zero. This pattern suggests limited changes in clean-technology patenting following the introduction of the carbon tax.

In contrast, the dynamic effects of ETS regimes exhibit a distinct trajectory, as illustrated in the lower subfigure. The estimated coefficients for the leads of ETS adoption are small in magnitude and not statistically distinguishable from zero, indicating no evidence of differential trends in clean-technology innovation prior to ETS adoption and supporting the presence of a parallel pre-trend. Following ETS adoption, estimates begin to increase within the first two years, then continue to rise, becoming clearly positive in the medium term. The effect intensifies over time, peaking approximately five to six years after ETS implementation. Although the estimates exhibit minor fluctuations in the long run, they remain positive throughout the post-adoption period, indicating a sustained expansion of clean-technology innovation under ETS regimes.

4.3 Robustness

We perform a series of robustness checks to evaluate the stability of our primary findings. Figure 7 presents results derived from alternative clean-technology patenting innovation outcomes and from models incorporating expanded sets of control variables. Across these various specifications, our principal conclusions remain consistent.

[Insert Figure 7 about here]

A primary concern is that the baseline count of clean-technology patent families may encompass lower-quality innovations with limited commercial value. To address this issue, we employ

three alternative measures of innovation. First, we consider the number of international clean-technology patent families, defined as those with filings in more than one jurisdiction. Since extending patent protection across multiple jurisdictions incurs substantial costs, international patent families are more likely to represent innovations with broader applicability and greater commercial value. Second, we utilize patent family size, measured as the total number of patent filings within a family, which reflects the breadth of jurisdictional coverage and, consequently, the geographic scope of protection sought. Third, we restrict the sample to clean-technology patent families classified as invention patents, which typically denote more substantive technological advances than utility model patents and are commonly regarded as higher-quality innovative outputs. Estimates of the impacts of carbon pricing on clean-technology patenting, using these alternative measures, are reported in the first three rows of Figure 7.

We further assess robustness by incorporating additional country characteristics that may confound the relationship between carbon pricing and clean-technology innovation. Specifically, we re-estimate the baseline model with controls for energy use (energy consumption scale), PM2.5 concentrations (local pollution levels), R&D expenditure (innovation inputs), and climate commitment (policy orientation toward climate mitigation). Estimates from this specification are presented in the final row of Figure 7, and remain consistent with our baseline results.

4.4 Heterogeneity

Heterogeneity by Policy Stringency. We further investigate heterogeneity in treatment effects by classifying countries with carbon pricing into two groups according to the mean carbon price. A variant of the baseline model is specified as follows.

$$\begin{aligned} \text{CleanPatent}_{ct} = \exp\Big(\alpha_c + \lambda_t + \sum_{g=g_0}^{G}\sum_{t=g}^{T} \theta_{gt}^{L}\,\text{CarbonPricing}_{ct}^{L}\,\mathbf{1}(g,t) \\ + \sum_{g=g_0}^{G}\sum_{t=g}^{T} \theta_{gt}^{H}\,\text{CarbonPricing}_{ct}^{H}\,\mathbf{1}(g,t) + \Gamma' X_{ct}\Big) + \varepsilon_{ct}, \end{aligned} \tag{2}$$

In this model, $\text{CarbonPricing}_{ct}^{L} = \text{CarbonPricing}_{ct} \cdot Low_c$ and $\text{CarbonPricing}_{ct}^{H} = \text{CarbonPricing}_{ct} \cdot High_c$, where Low_c and $High_c$ indicate whether country c belongs to the low- or high-price group, respectively. The coefficients θ_{gt}^{L} and θ_{gt}^{H} capture group-specific policy effects for each treated

cohort–year cell, which we aggregate using the corresponding sample weights to obtain overall effects for the low- and high-price groups. Table 3 presents the results. We also conduct the analyses separately for carbon taxes (tax rates) and ETS (permit prices), as shown in Columns (1) and (2), respectively. For the carbon tax, neither the low-price nor the high-price group yields a statistically significant estimate, indicating that variation in tax rates does not lead to substantially different levels of clean-technology innovation. In contrast, the effect of ETS is more pronounced: the high-price group shows a positive, statistically significant impact on clean-technology patenting, whereas the estimate for the low-price group is smaller and not statistically significant. Overall, these findings align with the induced-innovation hypothesis, which posits that higher carbon prices signal greater regulatory pressure and abatement costs, thereby strengthening incentives to invest in clean technologies. Such effects appear more salient under ETS regimes, whereas innovation in response to carbon taxes remains muted across different price levels.

[Insert Table 3 about here]

Effects by Theme. Figure 8 further explores heterogeneity across the technology themes defined by the IEA Clean Energy Technology Guide, including bioenergy, CCUS, critical minerals, digitalization, electrification, electrochemistry, energy storage, hydrogen, materials, and renewables. The results indicate that under carbon taxes, significant effects are observed only in a limited subset of themes, with mixed signs across areas. In contrast, ETS adoption yields positive and statistically significant effects across a wide range of technology themes, including several core domains related to industrial decarbonization and energy system transformation. For a small number of themes (such as CCUS and digitalization), the estimates are not statistically distinguishable from zero, suggesting that the innovation effects of ETS are not uniform across all technology domains.

[Insert Figure 8 about here]

Effects by Technology Maturity. Table 4 disaggregates the baseline policy effects by technology maturity, as measured by TRL, categorizing clean-technology patent families into concept (TRLs 1–3), prototype (TRLs 4–6), demonstration (TRLs 7–8), and commercialization (TRLs 9–11) stages. The findings reveal a clear distinction between the impacts of carbon taxes and ETS. For

carbon taxes, the estimated effects are not significantly different from zero across all TRL categories, indicating no robust evidence that adopting such taxes influences clean-technology patenting at any stage of technological maturity. In contrast, implementing ETS leads to significant increases in clean-technology patenting at the prototype, demonstration, and commercialization stages, with effects that intensify as technologies advance to higher levels of maturity. This pattern suggests that carbon-pricing policies — particularly ETSs — are more likely to stimulate innovation closer to market deployment, where commercial incentives and expected returns are more substantial and predictable.

[Insert Table 4 about here]

Effects by Application Sector. Figure 9 investigates heterogeneity across application sectors, distinguishing between buildings, energy transformation, industry, and transport. The estimated effects of carbon taxes are consistently small in magnitude and statistically indistinguishable from zero across all sectors, indicating that carbon tax adoption does not increase clean-technology patenting in any application sector. By contrast, ETS adoption is associated with positive and statistically significant increases in clean-technology patenting across all four sectors. These findings reinforce the baseline result that ETS is more effective than carbon taxes at stimulating clean-technology innovation, while also demonstrating that the innovations induced by ETS are not limited to specific end-use application domains.

[Insert Figure 9 about here]

Assignee Type. Table 5 further disaggregates the effects of carbon pricing policy by assignee type, distinguishing among firms, universities (including research institutions), and individual inventors. The results once again reveal a marked contrast between policy instruments. Carbon tax adoption is not associated with statistically significant changes in patenting for any assignee type, suggesting that tax regimes do not generate a detectable induced-innovation effect among firms, universities, or individual assignees. In contrast, ETS adoption results in positive and statistically significant increases in patenting across all three assignee categories. Notably, the estimated ETS effect is larger for patents assigned to universities and individual inventors than for those assigned

to firms. These findings indicate that the clean-technology patent innovation stimulated by ETS is not confined to firms but extends to a broader set of actors within the innovation ecosystem.

[Insert Table 5 about here]

5 Discussion and Policy Implications

This paper elucidates the global trajectory of industrial decarbonization innovation and provides causal evidence on the influence of distinct carbon pricing policies in shaping these technological pathways. Employing a novel "text-as-data" pipeline that integrates LLMs with expert validation, we construct a high-resolution dataset mapping global clean-technology patent families to specific IEA decarbonization technologies from 1990 to 2022.

Our descriptive analysis documents a profound transformation in the landscape of decarbonization innovation. We observe a systemic acceleration in patenting activity after 2010, driven by synchronized growth across the energy transformation, transport, and building sectors. Importantly, the granularity of our data reveals a decisive shift in technological maturity: innovation has advanced beyond the concept stage and now predominates in the prototype, demonstration, and commercialization phases. Geographically, although advanced economies remain principal exporters of clean technologies, emerging economies, most notably China, have surged to become the largest contributors to global clean-technology patenting by volume.

The core empirical contribution of this study is the identification of a clear divergence in the effectiveness of carbon pricing instruments. We find that ETS significantly outperforms carbon taxes in fostering decarbonization innovation. Adoption of an ETS is associated with an approximate 50.5% increase in clean-technology patent families. In contrast, carbon taxes exhibit no statistically significant impact on innovation outcomes, a finding that holds across varying tax rates. Moreover, higher carbon prices in ETS markets are positively correlated with increased patenting, suggesting that price signals operate effectively only within the institutional framework of an ETS.

Dynamic analysis further elucidates the mechanisms at play. We find that the innovation response to ETS is not immediate, but materializes over time. The effects are negligible in the initial years post-adoption, but increase gradually to become statistically significant in the medium term, peaking five to six years after implementation. This trajectory suggests that the flexibility

and long-term expectations inherent in ETS regimes effectively incentivize firms to adjust their R&D planning. In contrast, carbon taxes do not generate a consistent dynamic response during the post-adoption period.

Finally, our technology-specific heterogeneity analysis underscores that policy design determines the locus of innovation. Innovation induced by ETS is concentrated in technologies at the prototype, demonstration, and commercialization stages, thereby driving advancements at higher maturity levels. Furthermore, ETS adoption drives substantial progress across critical themes such as hydrogen, energy storage, and renewables, whereas carbon taxes have limited capacity to incentivize innovation in hard-to-abate sectors. These findings suggest that, to accelerate the clean-technology transition required for the net-zero roadmap, policy frameworks should prioritize the market-based flexibility and dynamic incentives characteristic of ETS regimes over taxation-based pricing mechanisms.

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Figures and Tables

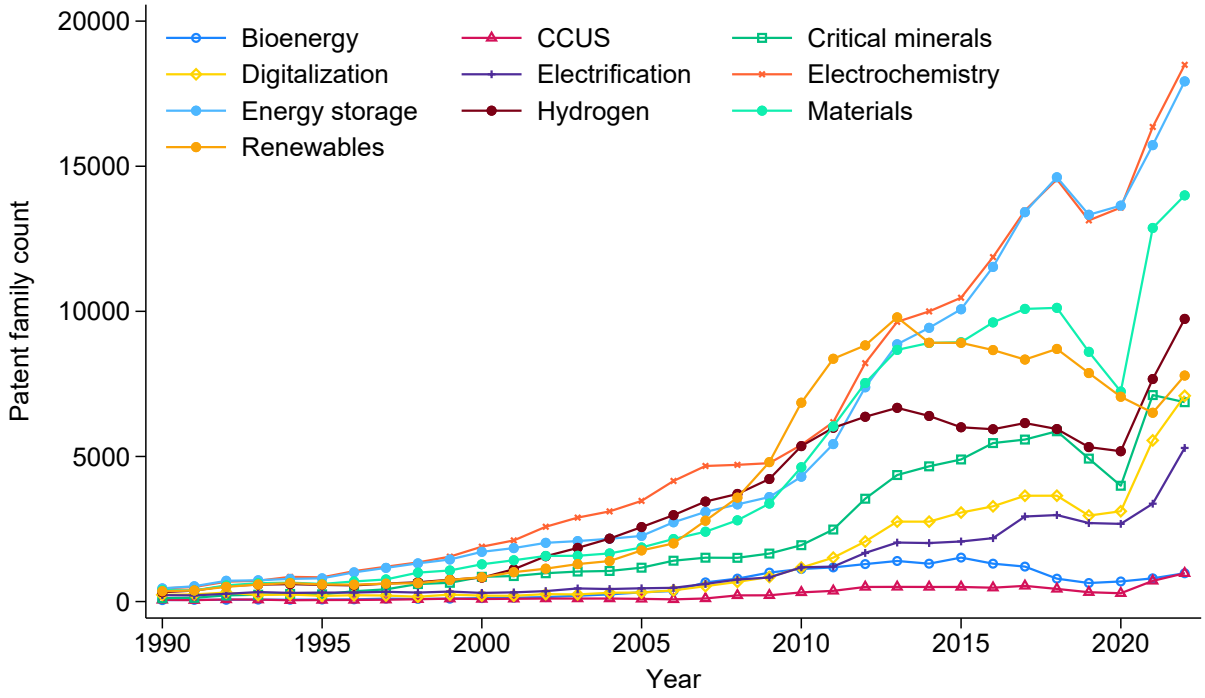


Figure 1: Global Trend of IEA Innovation by Technology Themes

Notes: The figure shows global trends in clean technology patent families across different technology themes, based on the IEA Clean Energy Technology Guide, from 1990 to 2022.

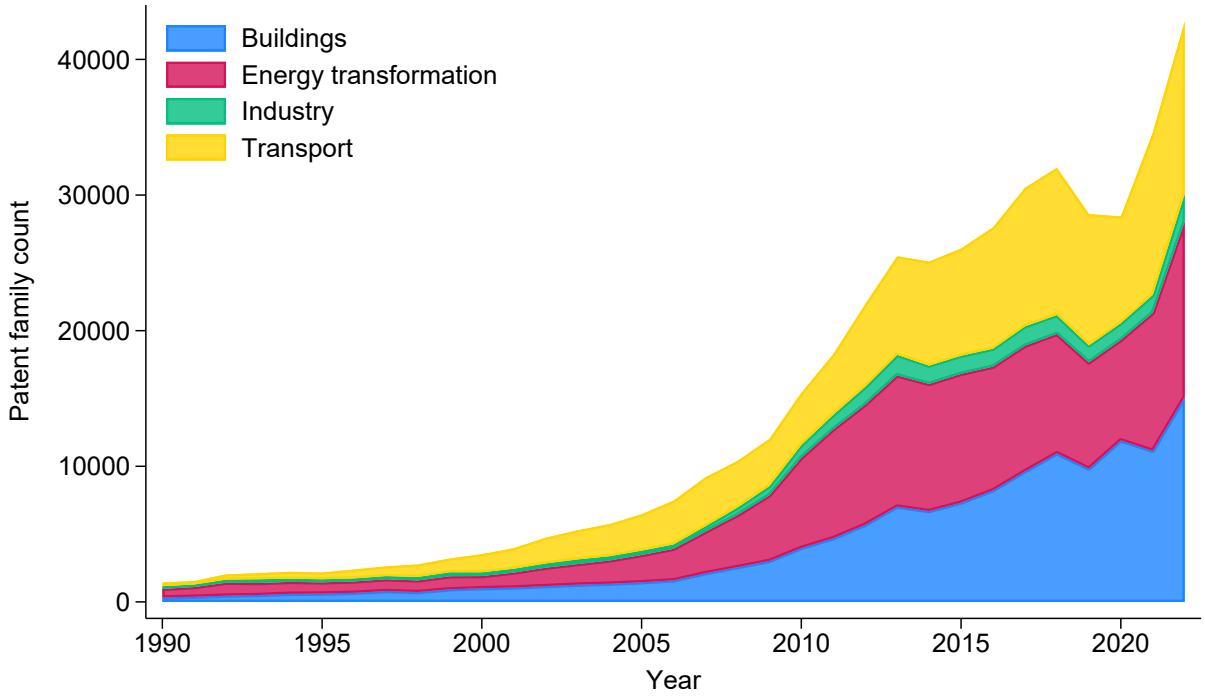


Figure 2: Global Trend of IEA Innovation by Application Sectors

Notes: The figure shows global trends in clean technology patent families across different application sectors, based on the IEA Clean Energy Technology Guide, from 1990 to 2022.

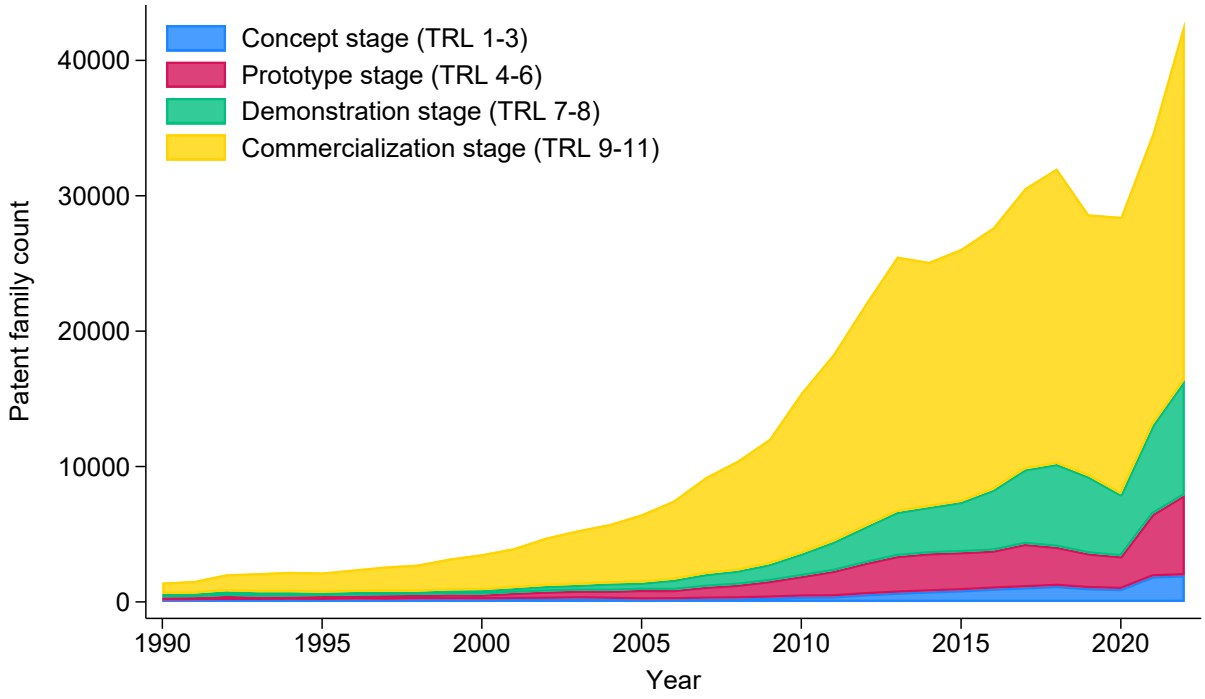


Figure 3: Global Trend of IEA Innovation by TRL

Notes: The figure shows global trends in clean technology patent families with different stages of TRL, based on the IEA Clean Energy Technology Guide, from 1990 to 2022. The TRL stages are defined as follows: Concept stage (TRL 1–3), Prototype stage (TRL 4–6), Demonstration stage (TRL 7–8), and Commercialization stage (TRL 9–11).

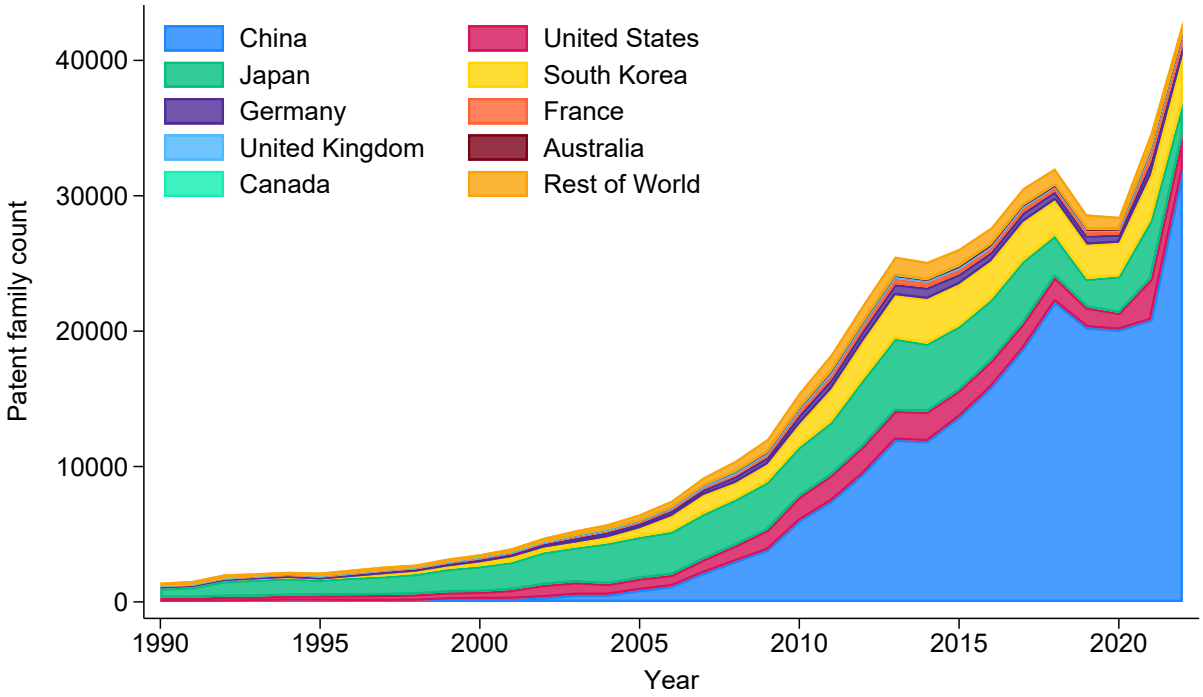


Figure 4: Global Trend of IEA Innovation by Countries

Notes: The figure shows global trends in clean technology patent families across different countries from 1990 to 2022.

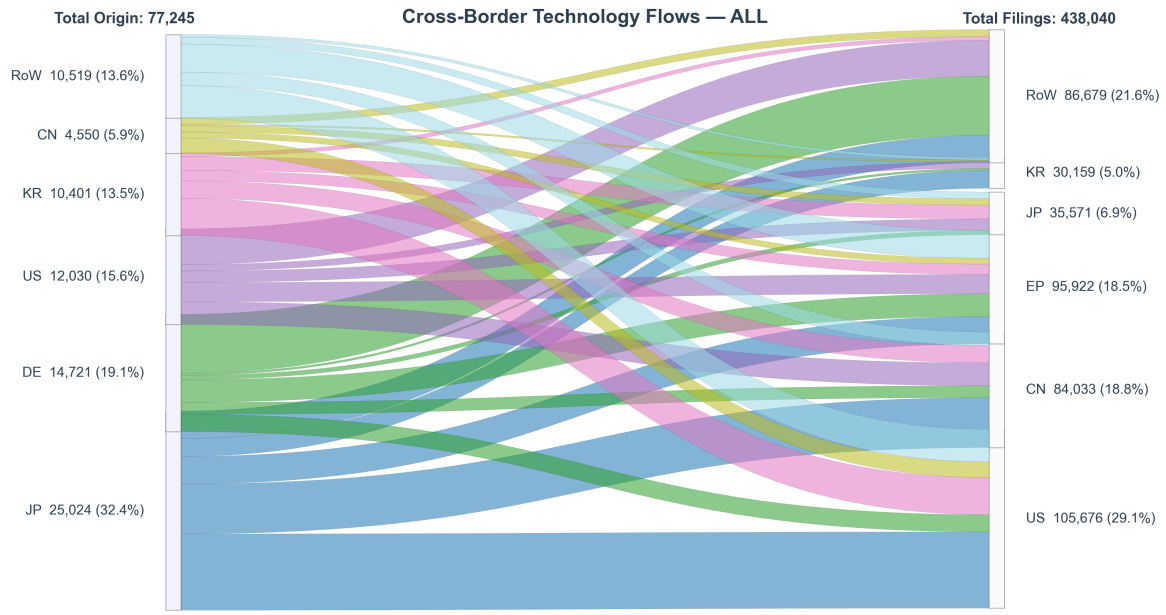


Figure 5: Cross-Border Technology Flows

Notes: This figure shows cross-border clean-technology patenting flows between countries. Bars on the left denote origin countries (where patent families originate), and bars on the right denote destination countries (other jurisdictions in which patent protection is sought; patents filed in European national offices and the EPO are grouped together for readability). Each ribbon represents the patent-family flows from origin to destination, with ribbon width proportional to the number of cross-border patent-family links. RoW aggregates all other countries not shown separately.

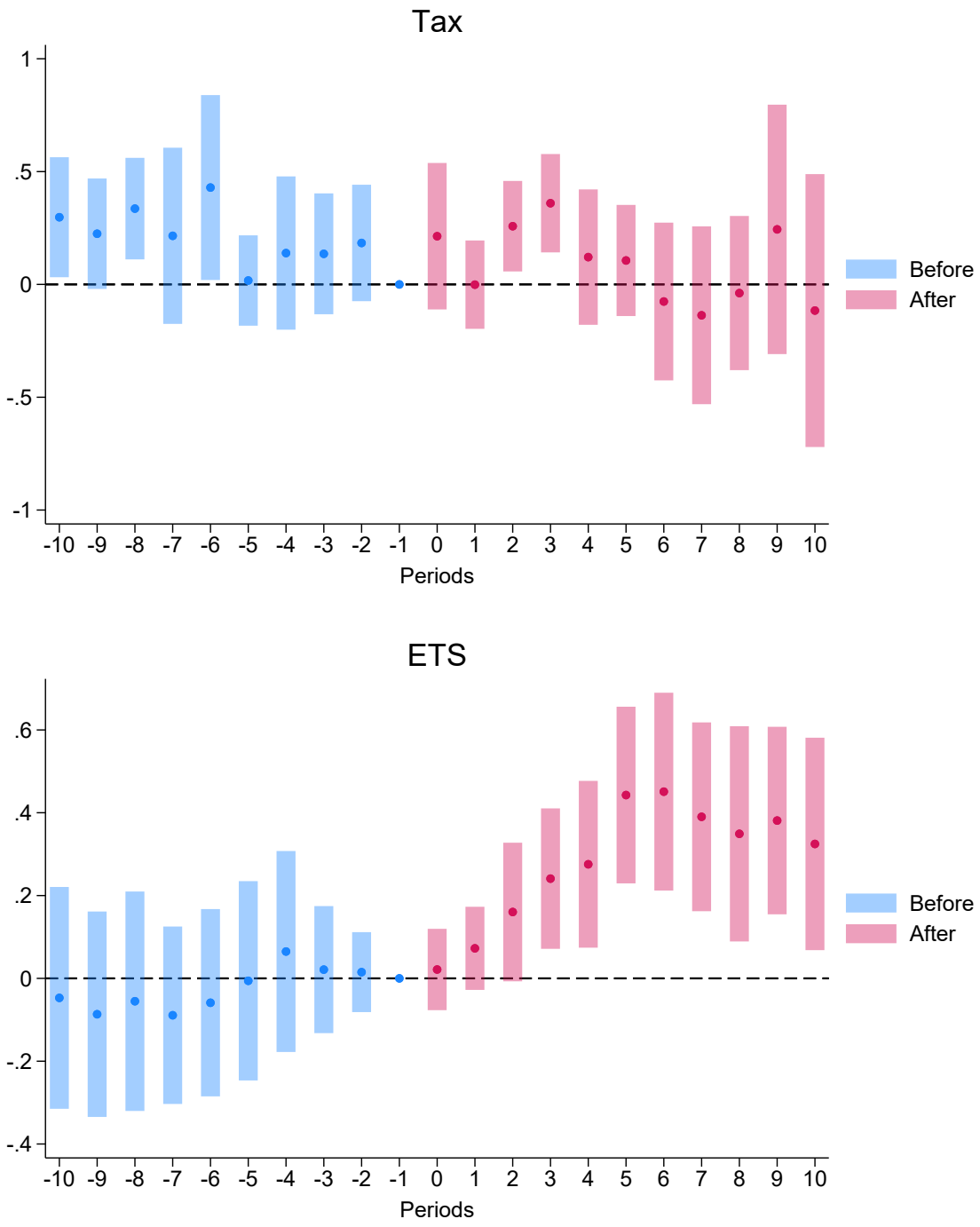


Figure 6: Event Study Estimates of Carbon Pricing Policy Effects

Notes: The two figures plot coefficients and their 95% confidence intervals from an event-study model that estimates the dynamic effect of carbon tax and ETS on clean technology patenting, respectively. The outcome variable is clean technology patent families. The regression controls for country- and year-fixed effects, along with control variables: emission intensity, GDP per capita, total patents, and renewable electricity ratio. One year before the carbon pricing policies is considered the reference period. The standard errors are clustered at the country level.

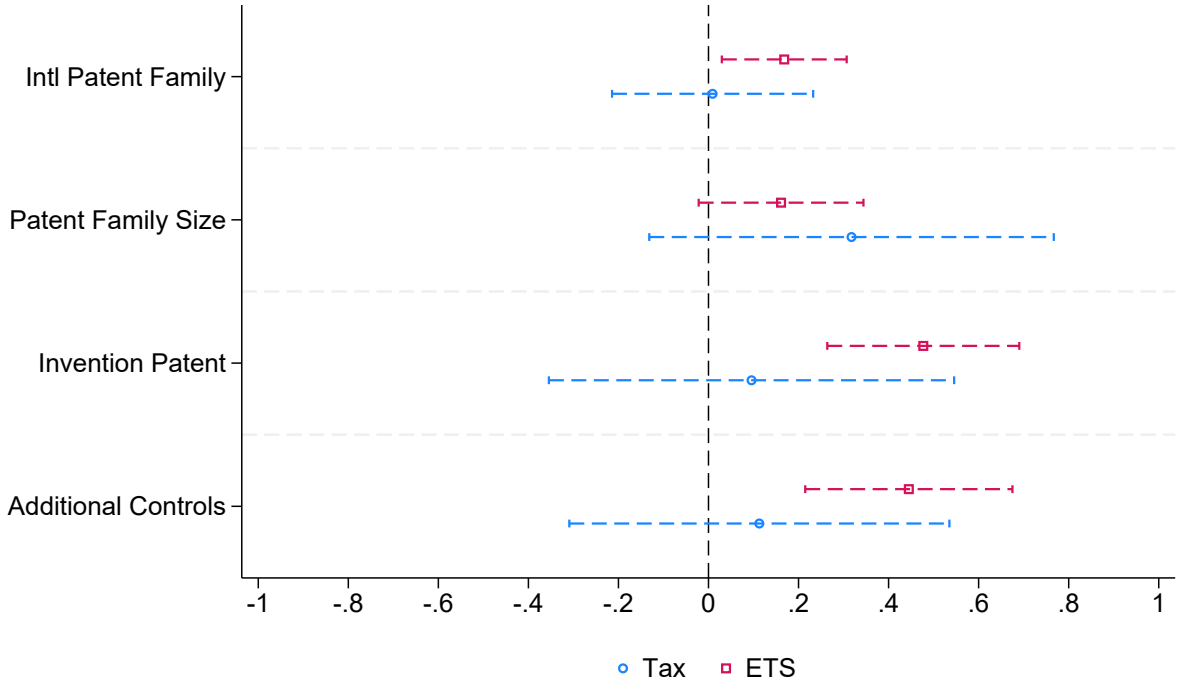


Figure 7: Robustness Checks

Notes: This figure plots coefficient estimates of carbon pricing policies and their corresponding 95% confidence intervals, from a series of regression models as robustness checks. The first row presents an alternative measure of clean technology patenting based on the number of international patent families. The second row uses an alternative measure of clean technology patenting based on the size of patent families. The third row focuses on clean technology patent families with inventions. The last row reports results with additional control variables, including energy use, PM2.5, R&D expenditure, and climate commitment. We separately estimate the impacts of the carbon tax and the ETS. All regression models control for country- and year-fixed effects.

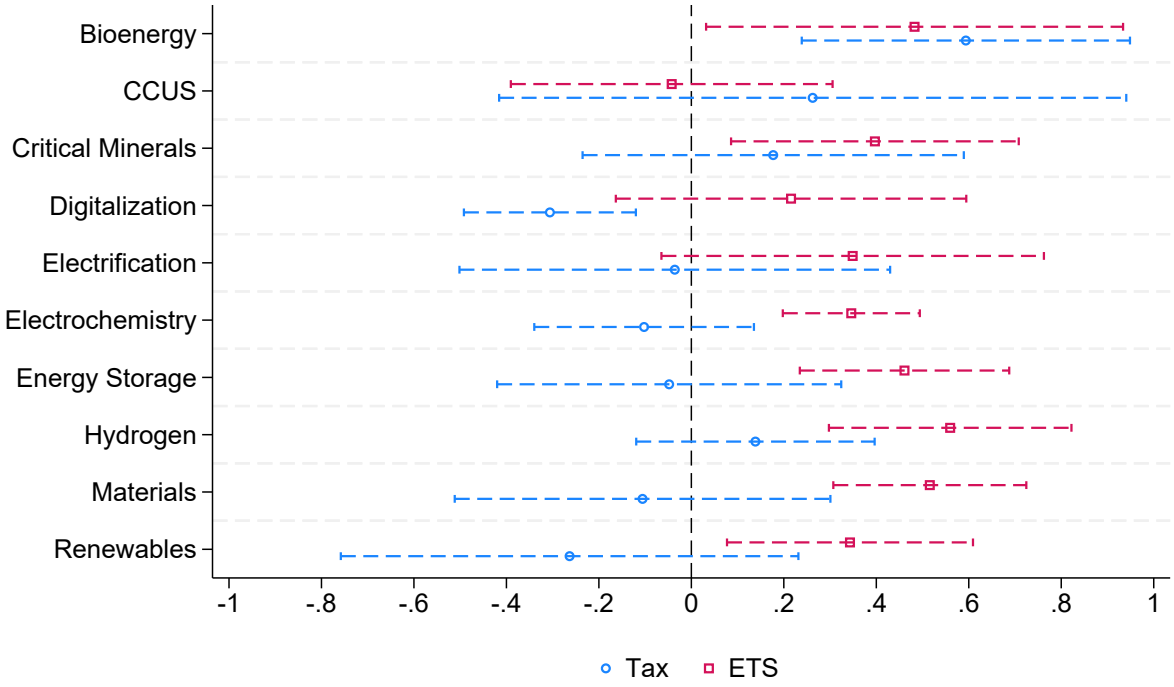


Figure 8: Impact of Carbon Pricing on Patent by IEA Clean Energy Tech Theme

Notes: This figure plots coefficient estimates of carbon pricing policies and their corresponding 95% confidence intervals. The outcome variables are clean technology patenting across different technology themes, classified according to the IEA Clean Energy Technology Guide (indicated on the vertical axis). We separately estimate the impacts of the carbon tax and the ETS. All regression models control for country- and year-fixed effects, along with the following control variables: emission intensity, GDP per capita, total patents, and renewable electricity ratio.

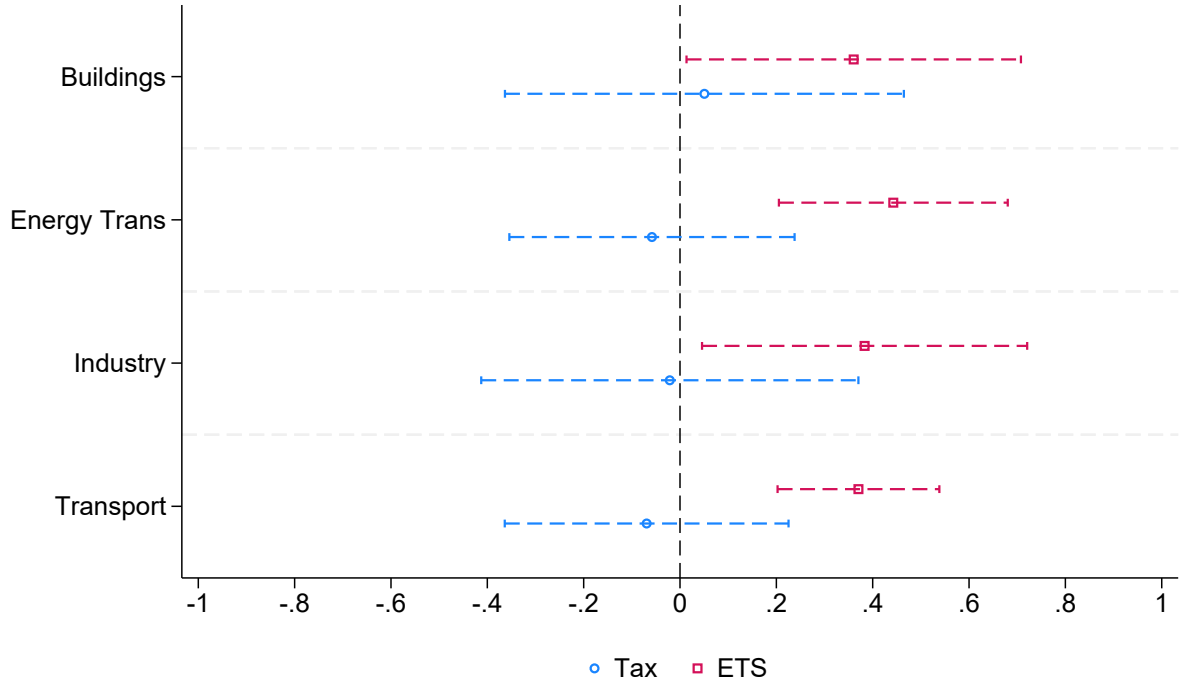


Figure 9: Impact of Carbon Pricing on Patent by IEA Clean Energy Tech Application Sector

Notes: This figure plots coefficient estimates of carbon pricing policies and their corresponding 95% confidence intervals. The outcome variables are clean technology patenting across different application sectors (buildings, energy transformation, industry, transport), classified according to the IEA Clean Energy Technology Guide (indicated on the vertical axis). We separately estimate the impacts of the carbon tax and the ETS. All regression models control for country- and year-fixed effects, along with the following control variables: emission intensity, GDP per capita, total patents, and renewable electricity ratio.

Table 1: Summary Statistics

Variables	N	Mean	S.D.	Min.	Max.
Panel A. Clean Technology Patent					
Clean tech	5791	76.38	883.9	0	31970
by TRL Stage					
Concept	5791	2.818	31.84	0	1439
Prototype	5791	8.219	98.03	0	4659
Demonstration	5791	11.57	151.0	0	6266
Commercialization	5791	53.77	615.0	0	19606
by Themes					
Bioenergy	5791	3.236	35.56	0	1045
CCUS	5791	1.415	13.26	0	603
Critical minerals	5791	13.20	159.3	0	5336
Digitalization	5791	8.338	118.4	0	5484
Electrification	5791	6.879	92.61	0	4289
Electrochemistry	5791	33.31	388.8	0	13500
Energy storage	5791	30.70	380.4	0	13190
Hydrogen	5791	19.04	186.8	0	7135
Materials	5791	24.48	281.2	0	10645
Renewables	5791	22.45	248.7	0	6235
by Application Sectors					
Buildings	5791	23.03	299.2	0	10884
Energy transformation	5791	25.15	277.6	0	10066
Industry	5791	4.018	41.41	0	1472
Transport	5791	24.10	278.6	0	9513
by Assignee Types					
Firm assignee	5791	60.11	727.0	0	27446
University assignee	5791	7.413	89.05	0	2848
Individual assignee	5791	8.821	79.80	0	1798
Panel B. Carbon Policy Indicators					
Carbon tax (dummy)	5791	0.061	0.240	0	1
Carbon ETS (dummy)	5791	0.103	0.304	0	1
Carbon tax rate (log)	5791	1.097	7.502	0	109.8
Carbon ETS price (log)	5791	0.846	4.037	0	59.33
Panel C. Other Country Attributes					
Emission intensity (log)	5791	0.390	0.280	0.002	1.945
GDP per capita (log)	5791	8.138	1.567	4.475	11.80
Total patent (log)	5791	2.890	3.371	0	14.17
Renewable electricity (ratio)	5791	0.253	0.333	0	1

Notes: Panel A reports the number of patent families for clean technologies mapped to the IEA Clean Energy Technology, for stages of technology readiness levels (concept, prototype, demonstration, and commercialization), for themes (Bioenergy, CCUS, critical minerals, digitalization, electrification, electrochemistry, energy storage, hydrogen, materials, and renewables), for application sectors (buildings, energy transformation, industry, and transport), and for assignee types (firm, university and research institutions, and individual). In Panel B, carbon tax policy and carbon ETS policy are binary indicators, while carbon tax rates and carbon ETS prices are in CPI-adjusted USD. In Panel C, emission intensity, GDP per capita, and total patents are in logarithmic form, while renewable electricity is the ratio of renewable electricity output to total electricity output.

Table 2: Impact of Carbon Pricing on Clean Tech Patent

Variables	Clean Tech Patent	
	(1)	(2)
Carbon Tax	0.118	
	(0.231)	
Carbon ETS		0.409***
		(0.115)
Observations	2,394	2,538
Country control	Y	Y
Country FE	Y	Y
Year FE	Y	Y

Notes: Dependent variable is the number of clean-technology patent families mapped to the IEA Clean Energy Technology. Carbon Tax is a binary indicator of whether a country implements a carbon tax. The Carbon ETS indicator is a binary indicator of whether a country has implemented a carbon ETS. Country-level controls include emission intensity, GDP per capita, total residential patents, and renewable electricity ratio. All columns include country and year fixed effects. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Heterogeneity of Carbon Pricing Level

Variables	Clean Tech Patent	
Policy Instrument	Tax	ETS
	(1)	(2)
Carbon Tax_Low	-0.069	
	(0.211)	
Carbon Tax_High	0.372	
	(0.356)	
Carbon ETS_Low		0.283**
		(0.131)
Carbon ETS_High		0.500***
		(0.128)
Observations	2,392	2,530
Country Control	Y	Y
Country FE	Y	Y
Year FE	Y	Y

Notes: Dependent variable is the number of clean-technology patent families mapped to the IEA Clean Energy Technology. Here, we split the treatment effects of carbon pricing policies by the mean carbon price level, using the carbon tax rate and the ETS carbon permit price, respectively. Country-level controls include emission intensity, GDP per capita, total patents, and renewable electricity ratio. All regressions include country and year fixed effects. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Impact of Carbon Pricing on Clean Tech Patent by TRL

Variables	Concept		Prototype		Demonstration		Commercialization	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Carbon Tax	-0.019		-0.247		0.072		0.213	
	(0.227)		(0.297)		(0.149)		(0.239)	
Carbon ETS		0.223		0.277*		0.325**		0.427***
		(0.173)		(0.145)		(0.147)		(0.117)
Observations	844	1,121	1,748	2,013	1,622	1,865	2,133	2,304
Country Control	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Dependent variable is the number of clean-technology patent families mapped to the IEA Clean Energy Technology by TRLs, classified by the technology stage of concept (TRL 1-3), prototype (TRL 4-6), demonstration (TRL 7-8), and commercialization (TRL 9-11). Carbon Tax is a binary indicator of whether a country implements a carbon tax. The Carbon ETS indicator is a binary indicator of whether a country has implemented a carbon ETS. Country-level controls include emission intensity, GDP per capita, total residential patents, and renewable electricity ratio. All regressions include country- and year-fixed effects. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Impact of Carbon Pricing on Clean Tech Patent by Patent Assignee Type

Variables	Firm		University		Individual	
	(1)	(2)	(3)	(4)	(5)	(6)
Carbon Tax	-0.025		-0.108		0.016	
	(0.132)		(0.122)		(0.222)	
Carbon ETS		0.327***		0.450***		0.647***
		(0.116)		(0.113)		(0.163)
Observations	2,270	2,433	1,461	1,726	1,625	1,867
Country Control	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Notes: Dependent variable is the number of clean-technology patent families mapped to the IEA Clean Energy Technology by assignee type, including firm in Columns (1)-(2), university and research institution in Columns (3)-(4), and individual in Columns (5)-(6). Carbon Tax is a binary indicator of whether a country implements a carbon tax. The Carbon ETS indicator is a binary indicator of whether a country has implemented a carbon ETS. Country-level controls include emission intensity, GDP per capita, total residential patents, and renewable electricity ratio. All regressions include country- and year-fixed effects. Standard errors clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

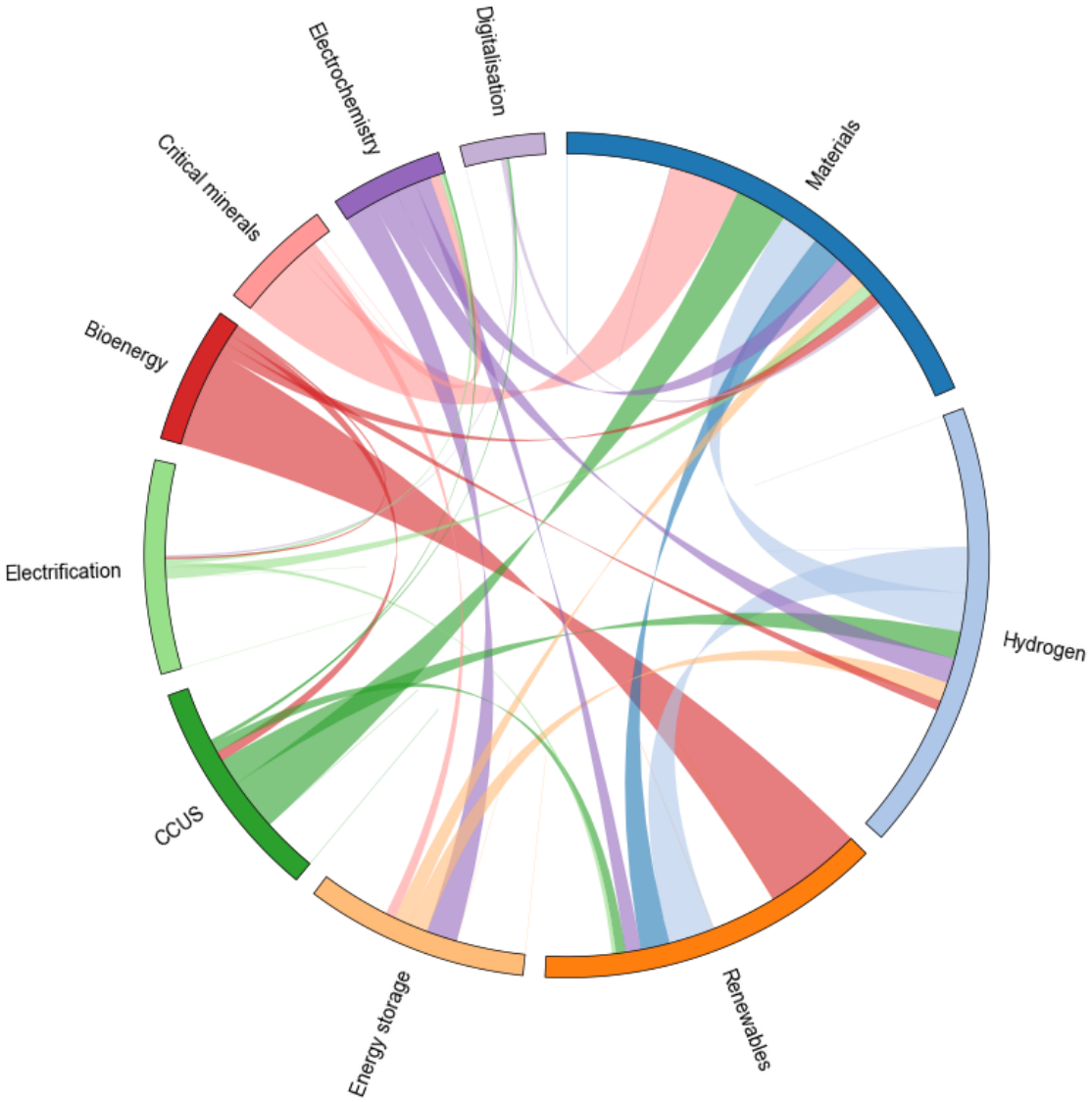


Figure A1: IEA Technology across Themes

Notes: The outer arcs represent the total patent volume for each theme, while the internal ribbons connect two themes that appear together in a single patent. The width of the ribbon at its base indicates the relative frequency of that specific cross-thematic intersection. A larger ribbon suggests a stronger technological coupling between the two connected sectors. The image does not include technology that is not part of the theme.

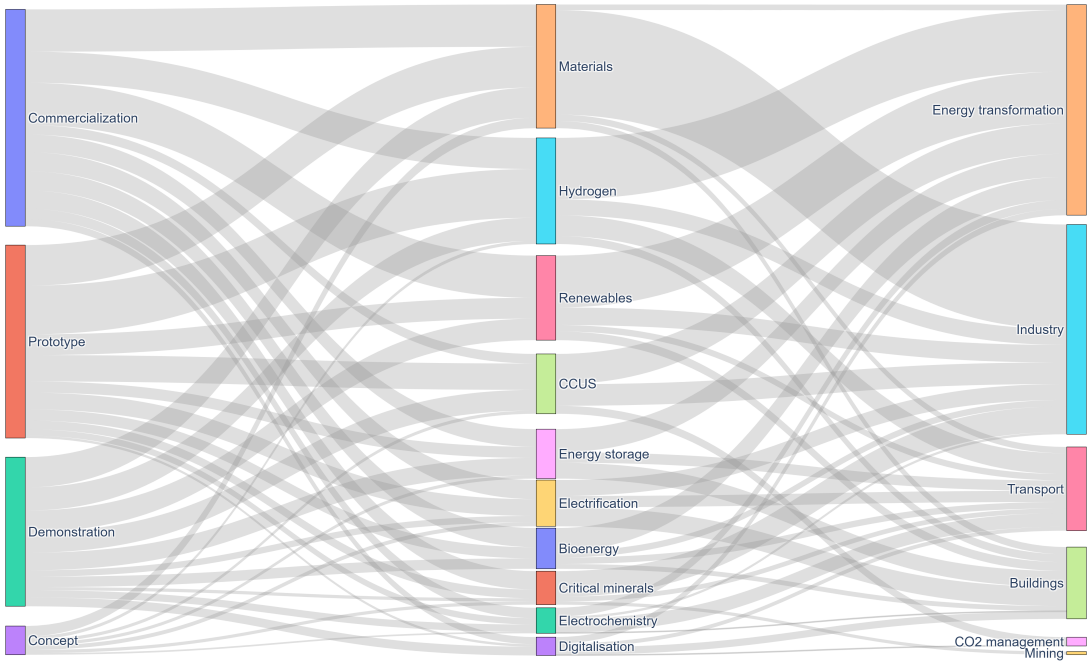


Figure A2: IEA Technology cross TRLs, Themes, and Applications Sectors

Notes: The nodes (vertical bars) represent categories, while the width of the flows is proportional to the volume of patent families. The diagram reads from left to right, tracing innovations from their development stage on the left, through specific technological themes in the center, to their final end-use application sectors on the right. TRL stages are classified by technology development stage as of 2024 and defined as follows: Concept (TRL 1–3), Prototype (TRL 4–6), Demonstration (TRL 7–8), and Commercialization (TRL 9–11). Themes are disaggregated into multiple flows where applicable.

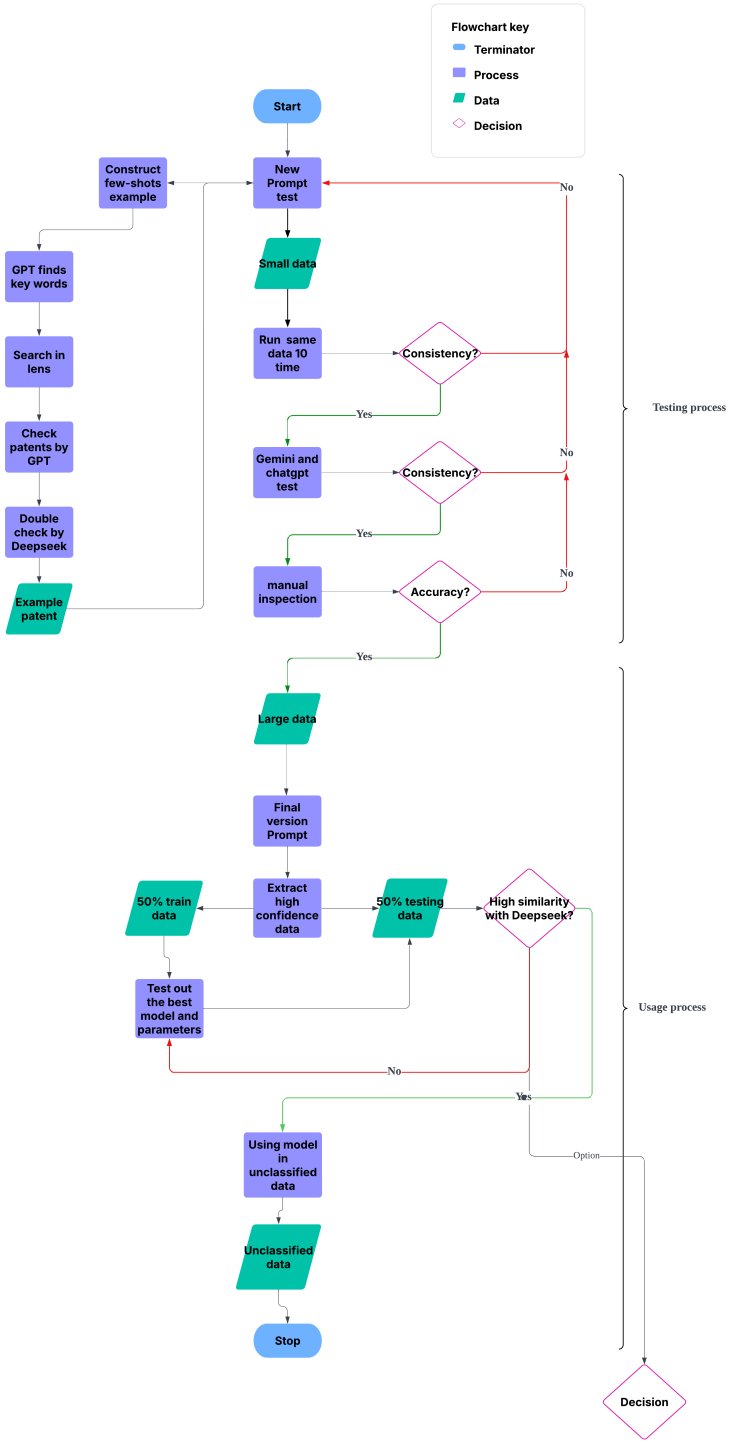


Figure A3: Multi-stage Pipeline for LLM-Based Patent Classification

Notes: Summary of the multi-stage pipeline including prompt testing, dual-LLM validation, and final scaling.

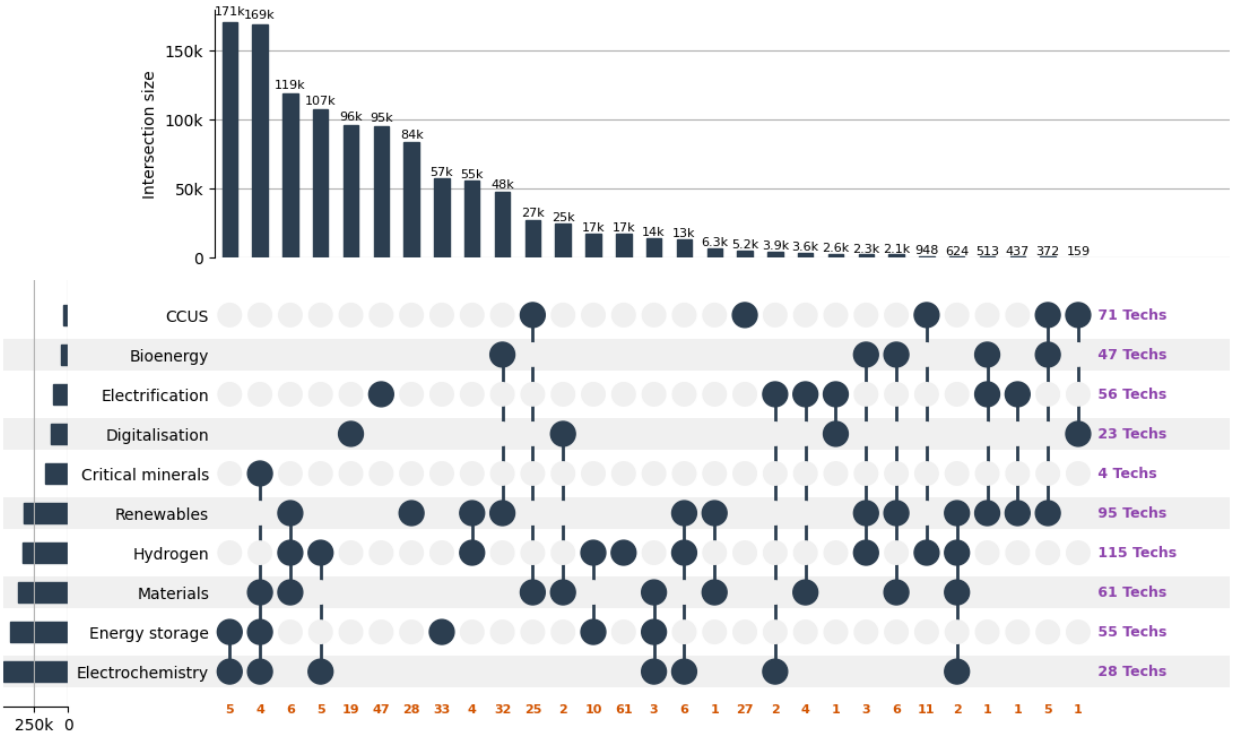


Figure A4: Patents Mapped with IEA Technological Theme

Notes: The horizontal bar chart (bottom left) indicates the total patent volume per theme. The dot matrix (bottom right) defines specific combinations, with connected solid circles representing patents spanning multiple themes. The vertical bar chart (top) quantifies the number of patent families (Intersection Size) for each corresponding combination. Right-side number labels in purple indicate the count of individual technologies ("Techs") defined by the IEA Clean Energy Technology Guide within each theme, while bottom number labels in orange specify the number of individual technologies involved in each combination of themes (for instance, as shown at the bottom of the first column, there are 5 individual technologies defined by the IEA Clean Energy Technology Guide that stretch over the themes of electrochemistry and energy storage).

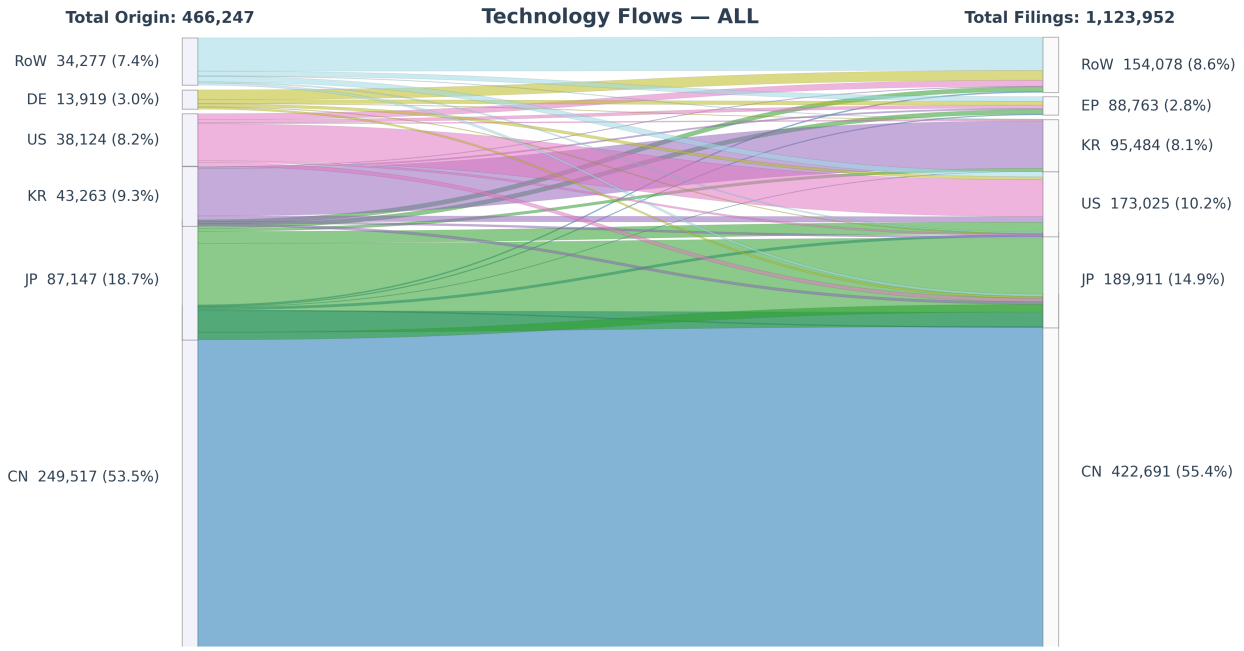


Figure A5: Overall Technology Flows

Notes: This figure shows global technology patenting flows between countries, encompassing both cross-border transfers and domestic applications. Bars on the left denote origin countries (where patent families originate), and bars on the right denote destination countries (jurisdictions in which patent protection is sought, including domestic offices; patents filed in European national offices and the EPO are grouped together for readability). Each ribbon represents the patent-family flows from origin to destination, with ribbon width proportional to the number of patent-family links. The broad horizontal bands indicate the substantial volume of domestic self-filings (e.g., CN-to-CN). RoW aggregates all other countries not shown separately.