










“Patent-based technological signals and green and digital energy start-up development: Global evidence and insights for Kazakhstan, Armenia, and Ukraine”

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PATENT-BASED TECHNOLOGICAL SIGNALS AND GREEN AND DIGITAL ENERGY START-UP DEVELOPMENT: GLOBAL EVIDENCE AND INSIGHTS FOR KAZAKHSTAN, ARMENIA, AND UKRAINE

Abstract

Innovative marketing increasingly requires reliable market intelligence signals that reduce uncertainty, support product positioning, and guide venture financing in technology-intensive green and digital markets. This study aims to assess how patent-based technological signals shape innovative market development by predicting the formation and venture financing of green and digital energy start-ups, while also examining whether entrepreneurial market entry and funding stimulate subsequent patenting activity. The empirical analysis is based on a balanced panel of 146 countries for 2000–2023, combining IEA energy start-up and funding indicators with OECD patent data. The empirical strategy follows a sequential design: descriptive statistics and log1p transformations are used to characterize the data; Dumitrescu–Hurlin panel Granger causality tests provide the main evidence on predictive causality; and PVAR, multiple-testing corrections, PPML and TWFE models are used as complementary robustness and dynamic checks. The results show highly concentrated innovative market development: average green and digital energy start-up activity is around 7 per country-year, while the median is 0 for both indicators. The Dumitrescu–Hurlin tests reveal 69 significant relationships out of 120, with stronger evidence for patents predicting start-up formation and funding than for the reverse direction. These findings remain robust after Benjamini–Hochberg correction and after excluding numerically extreme statistics. TWFE results support the positive association between climate adaptation and ICT-mitigation patents, digital energy start-up formation and early-stage digital funding, while PVAR models provide only complementary dynamic evidence and are interpreted cautiously due to stability limitations in the main GMM specification. Country fixed effects indicate that Ukraine has a more favorable estimated structural position for digital energy start-up formation than Kazakhstan and Armenia.

Keywords

innovations, patent-based signals, green energy start-ups, digital energy start-ups, venture financing, intellectual property, innovative market

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INTRODUCTION

Marketing is increasingly moving beyond promotion and sales towards a strategic mechanism for creating, communicating, and commercializing value in innovation-driven markets. The American Marketing Association (n.d.) defines marketing as a set of activities, institutions, and processes through which value is created, communicated, delivered, and exchanged for customers, partners, and society, linking marketing to technology diffusion and demand formation. This is particularly relevant for green and digital energy start-ups, whose success depends on technological novelty, credibility signaling, uncer-

tainty reduction, and effective market positioning. The study, therefore, aligns with innovative marketing directions related to new product commercialization, innovation management, intellectual property, data-driven market analysis, financial-market signaling, and the marketing of innovative goods and services. Innovation also includes developmental, financial, and commercial activities, while marketing analytics supports customer understanding, decision-making, and innovation-related value creation (OECD/Eurostat, 2018; Wedel & Kannan, 2016). In technology-intensive energy markets, young firms often lack stable revenues and verified demand, making external signals important for investors, partners, and early adopters. Although patents do not directly measure marketing practices, they provide observable information about technological activity and commercial opportunities. Thus, patent indicators are interpreted as market-relevant technological signals associated with start-up formation and venture financing, consistent with signaling theory, intellectual property perspectives, and evidence on patents, trademarks, and start-up finance (Conti et al., 2013; WIPO, 2015; EPO & EUIPO, 2023).

Current marketing and management agendas increasingly connect sustainability, digital transformation, AI, market intelligence, and cross-sector cooperation with innovation commercialization (Ganushchak et al., 2025; Bashynska, 2026). The European Marketing Agenda 2026 highlights AI adoption, customer experience, and omnichannel excellence as key competitiveness drivers, confirming the growing role of intelligence, responsiveness, and data-based decision-making in marketing (EMC, 2026). For green and digital energy firms, credible patent-based technological signals can reduce uncertainty and support market entry, positioning, financing, and commercialization decisions (Klymenchukova & Riashchenko, 2023).

The energy transition makes this research timely, especially for post-Soviet economies such as Kazakhstan, Armenia, and Ukraine, where green and digital technology commercialization remains uneven (Redko et al., 2023). Start-ups are recognized as drivers of breakthrough innovation, economic dynamism, and green and digital transitions, but their success depends on funding, policy support, and strong innovation ecosystems (OECD, n.d.-b). The growing relevance of energy start-up formation and venture financing is also reflected in IEA lifecycle tracking and evidence that clean energy start-ups often commercialize novel technologies before achieving profitability, making technological credibility and investor signaling crucial (IEA, n.d.; IEA, 2022). Since the energy transition requires stronger policy support, large-scale investment, and faster project development, patents may translate into start-up creation and financing only when supported by market readiness, venture capital, commercialization channels, and innovation-oriented marketing mechanisms (IRENA, 2024). For Kazakhstan, Armenia, and Ukraine, these issues are especially relevant because patents alone may not automatically translate into start-up creation or financing unless they are supported by market readiness, venture capital infrastructure, commercialization channels, and innovation-oriented marketing mechanisms. Accordingly, this study examines whether patent-based technological information is dynamically associated with green and digital energy start-up formation and venture financing, rather than directly testing firm-level marketing practices.

1. LITERATURE REVIEW

Innovative marketing increasingly explains market development as the interaction of technological knowledge, data, customer value, financial signals and commercialization capabilities. Recent research shows a shift from traditional promotion towards market intelligence, digital transformation, customer-oriented innovation and evidence-based decision-making (Xolmurotov et al., 2025).

Digital marketing also increasingly relies on cloud-based knowledge-management platforms, which improve information sharing and support the transformation of knowledge into market-relevant innovation (Al-Hamamy et al., 2025; Potwora et al., 2024). Market success, therefore, depends not only on knowledge availability but also on innovation capability, product positioning and business-model adaptation (Abou-Moghli, 2025). This is especially important for technology-push in-

novations, where pricing, market acceptance, and value communication must align with technological novelty and customer readiness (Chukhray et al., 2025). In sustainable entrepreneurship, green branding and environmental management help translate environmental value into customer trust and competitive differentiation, while AI-powered storytelling and sensemaking support the communication of complex technologies as credible and investable market opportunities (Starchenko et al., 2021; Behar Villegas et al., 2024).

Within the innovative-marketing landscape, patents can function not only as legal protection but also as credible signals of technological potential, invention quality and market opportunity. Patents reduce information asymmetry between entrepreneurs and investors, which is especially important for young firms with limited market history, weak revenues or high technological uncertainty (Conti et al., 2013; Zolkover & Ovcharenko, 2024). At the same time, uncertainty in intellectual property rights can delay commercialization, weaken the market for ideas, and limit access to external capital, underscoring that the reliability of patent protection affects both market entry and financing conditions (Gans et al., 2008; Heger & Hussinger, 2016). Evidence from software and technology start-ups confirms that patents can support venture-capital attraction, while trademarks may complement patents by strengthening market identity and commercial visibility (Mann & Sager, 2007; Zhou et al., 2016). Patent landscapes also help identify technological opportunities, competitive positions and innovation niches, while open science and open access policies may stimulate patent activity and support broader innovation dynamics (Smyer, 2009; Fatkul et al., 2025; Sitnicki et al., 2025).

The technology commercialization and entrepreneurial finance literature shows that innovative market development depends on the interaction among invention, start-up formation, investor confidence, and market validation. Commercialization requires technological readiness, market knowledge, organizational capabilities, access to financing, and ecosystem support (Megits et al., 2022). At the same time, university start-ups and academic entrepreneurship demonstrate how research knowledge can be trans-

formed into market-oriented ventures through intellectual property, partnerships, and knowledge-transfer mechanisms (Kirchberger & Pohl, 2016; Swamidass, 2012; Sitenko et al., 2024). Scientific funding and output are connected, but their conversion into market outcomes depends on institutional conditions that support productivity, applied knowledge and innovation performance (Abdikadirova et al., 2024). Venture financing is crucial for labelled and technology-oriented start-ups because it enables experimentation, scaling and market entry under uncertainty, especially in renewable energy, where regulation, infrastructure, technological maturity and long payback periods increase investment risks (Benlefkı et al., 2024; Dobrovolska et al., 2024). Start-up innovation is also influenced by investment cycles, public research grants and technological labels, confirming that investors use credible external signals and market narratives when direct performance information is limited (Nanda & Rhodes-Kropf, 2013; Islam et al., 2018; Sudarmaji, 2026).

Start-up success is embedded in entrepreneurial ecosystems where universities, institutions, spatial proximity, leadership and human capital shape the transformation of technological signals into market outcomes. University and academic ecosystems support start-up success through mentorship, entrepreneurial culture, infrastructure, networks, research collaboration and technology-transfer mechanisms (Jurgelevičius & Raišienė, 2025; Lenart & Sułkowski, 2025; Kuzior et al., 2024). Digitalization further strengthens entrepreneurial ecosystems by improving connectivity, knowledge exchange, platform-based cooperation and innovation diffusion (Mursalov et al., 2023; Bielialov & Gechbaia, 2023). Individual entrepreneurial readiness also matters, since self-efficacy, attitudes and intentions influence start-up success alongside ecosystem conditions (Yassin et al., 2024). Spatial proximity, clustering and macro-economic conditions affect opportunity recognition, enterprise births, access to knowledge spillovers, specialized labor and financial advantages for technology firms (Zahidi et al., 2025; Wosiek, 2025; Prokopenko et al., 2026). Human-capital intellectualization, business leadership and managerial capabilities are therefore essential for innovative transformation, because patents alone are insufficient unless supported by skills, credibil-

ity, strategic flexibility and organisational capacity (Kuzior et al., 2022a; Saba et al., 2025; Slavik & Bednarova, 2024).

The green and digital energy context adds complexity because market development depends on sustainability pressure, policy frameworks, institutional quality, circular-economy challenges and technological readiness (Prokopenko et al., 2023). Green intellectual capital, green accounting, and green innovation influence firm value, while the renewable-energy transition depends on economic drivers, environmental priorities, investment incentives, and policy support (Astuti & Ahmar, 2025; Vasa et al., 2024). Institutional quality improves regulatory predictability and investor confidence, and government AI readiness strengthens renewable electricity development through digital governance and data-based decision-making (Mukhtarov et al., 2023; Lyeonov et al., 2025). Technological development, eco-efficiency, and big data policies support productivity, corporate green innovation, and market intelligence capacity in sustainability-oriented sectors (Morales-Piñero et al., 2024; Zhu et al., 2026). At the same time, circular-economy transition and eco-innovation adoption require institutional readiness, industrial modernization, economic security, open-innovation mechanisms, business leadership and firm-level capabilities (Churikanova & Tykhoplav, 2025; Kuzior et al., 2022b; Živković & Štrbac, 2025).

The energy start-up literature shows that renewable-energy entrepreneurship faces regulatory and technological barriers but also benefits from decentralization, renewability, digitalization, and AI-enabled innovation (Ksonzhyk et al., 2021; Bashynska et al., 2024). Regulatory barriers can restrict market entry, slow scaling, and increase investor uncertainty, which makes credible technological and policy signals especially important for renewable-energy start-ups (Myroshnychenko et al., 2024). At the same time, decentralized energy systems and renewable energy create new opportunities for distributed generation, renewable technologies, and systemic energy transformation (Belgibayeva et al., 2025). Evidence from other innovation-intensive sectors shows that AI and advanced technologies attract investor and researcher attention when they demonstrate cred-

ible value creation, commercial potential and responsible governance (Springs, 2025; Kritikos et al., 2025). However, digital transformation supports innovation only when knowledge flows are effectively managed, since knowledge hiding can weaken innovation climate even under AI adoption (Jiraphanumes, 2026; Spivakovskyy et al., 2025). Therefore, green and digital energy start-up development requires not only patents, but also technological credibility, open knowledge flows, investor trust, institutional support and effective market communication.

Previous research supports interpreting patents as both technological and market signals, but it remains fragmented across innovative marketing, intellectual property, entrepreneurial finance, renewable energy transition and ecosystem studies. Existing work explains how patents support financing, how start-ups commercialize technologies, how ecosystems shape success, and how green innovation depends on policy conditions, but pays less attention to the two-way dynamics among patents, start-up formation, and venture financing in green and digital energy markets. This gap justifies examining whether patent-based signals predict innovative market development and whether market entry and funding later stimulate patenting. Such analysis contributes to innovative marketing by linking intellectual property, market intelligence, investor behavior, and venture-financed start-up development within a single empirical framework.

This study aims to assess how patent-based technological signals shape innovative market development by predicting the formation and venture financing of green and digital energy start-ups, while also examining whether entrepreneurial market entry and funding stimulate subsequent patenting activity.

2. METHODOLOGY

This study examines whether patenting activity in energy-related technologies precedes the emergence and financing of energy start-ups, and whether start-up formation and funding, in turn, stimulate subsequent patenting activity. From an innovative marketing perspective, patents are

treated not only as indicators of technological knowledge but also as market signals that may reduce uncertainty, reveal new commercial opportunities, and support the positioning of innovative energy solutions. Energy start-ups and their funding are interpreted as entrepreneurial and investor responses to these technological signals.

The empirical dataset was compiled from two international data sources. Information on energy start-up activity and financing was collected from the International Energy Agency Energy Start-up Data Explorer, including six indicators: Energy and green start-ups (Number), Energy and digital start-ups (Number), Early-stage funding of energy and green start-ups (USD), Later-stage funding of energy and green start-ups (USD), Later-stage funding of energy and digital start-ups (USD), and Early-stage funding of energy and digital start-ups (USD) (IEA, n.d.). Patent indicators were obtained from the OECD Data Explorer and cover five technology domains: Environmental management, Climate change adaptation technologies, Climate change mitigation in information and communication technologies (ICT), Climate change mitigation technologies related to energy generation, transmission or distribution, and Sustainable ocean economy (OECD, n.d.-a). The final balanced panel covers 146 countries over the period 2000–2023. The full list of countries included in the sample is presented in Appendix D: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026). The dependent variables describe the development and financing of energy start-up ecosystems. They include the number of energy and green start-ups, the number of energy and digital start-ups, early-stage funding for energy and green start-ups, and later-stage funding for energy and green start-ups. The explanatory patent variables cover five technological domains: environmental management; climate change adaptation technologies; climate change mitigation in information and communication technologies; climate change mitigation technologies related to energy generation, transmission, or distribution; and sustainable ocean economy patents. The descriptive analysis in the current results confirms that the dataset is highly zero-heavy and right-skewed, especially for start-up and funding variables, which justifies the use of transformations and robustness checks suitable for sparse innovation data.

The empirical strategy follows a sequential logic rather than a set of unrelated econometric tests. First, descriptive statistics and log1p transformations are used to characterize the zero-heavy and skewed structure of the data. Second, the Dumitrescu–Hurlin panel Granger causality test is used as the core method because the main research question concerns whether patents predict later start-up formation and funding, and whether the reverse direction also exists. Third, PVAR models and bootstrapped generalised impulse response functions are used only as complementary dynamic tools to explore adjustment mechanisms in selected innovation blocks. Fourth, Benjamini–Hochberg and Bonferroni corrections assess whether the causality results remain robust under multiple testing. Fifth, PPML and TWFE models are used as supplementary robustness checks, while country fixed effects are extracted only to describe cross-country heterogeneity, with particular attention to Kazakhstan, Armenia and Ukraine. Thus, each method has a distinct function in the empirical design: diagnosis, causality testing, dynamic exploration, robustness assessment or heterogeneity interpretation.

The study does not directly measure firm-level marketing mechanisms such as branding, promotion, pricing, customer acquisition, digital communication or customer adoption. The marketing dimension is therefore conceptualized more narrowly as the role of patent-based technological information in reducing market uncertainty, supporting commercialization decisions and informing investor and entrepreneurial responses in green and digital energy markets.

To reduce the influence of extreme values and to preserve zero observations, all patent, start-up and funding variables used in the dynamic models were transformed using the natural logarithm of one plus the original value:

$$x_{it}^* = \ln(1 + x_{it}), \quad (1)$$

where x_{it} denotes the original value of the indicator for the country i in year t . This transformation is appropriate because many countries record no start-up activity or no funding in several years, while a small number of countries display very large values. The use of log1p, therefore, allows the

analysis to retain the full panel structure while reducing the effect of extreme observations.

The first stage of the empirical analysis consists of descriptive statistics. Means, medians, standard deviations, minimum and maximum values, skewness and kurtosis are calculated for all patent, start-up and funding variables. This stage is used to identify the distributional properties of the data and to justify the subsequent use of panel causality methods and robustness checks. Particular attention is paid to the difference between mean and median values, since this difference indicates the extent to which start-up activity and venture funding are concentrated in a limited number of countries and years.

The second stage applies the Dumitrescu–Hurlin panel Granger causality test. This method is suitable because the study investigates predictive temporal relationships in panel data rather than simple contemporaneous correlations. The test allows the causal relationship to differ across countries. It is therefore appropriate for an international sample characterized by substantial heterogeneity in innovation systems, patenting activity and start-up ecosystems. The null hypothesis is that one variable does not Granger-cause another variable for all countries in the panel. Rejection of the null indicates that past values of one variable improve the prediction of another variable.

The Dumitrescu–Hurlin tests are estimated in both directions. First, patent indicators are tested as potential causes of energy start-up formation and start-up funding. Second, start-up and funding indicators are tested as potential causes of patenting activity. This bidirectional design reflects the theoretical assumption that innovation ecosystems may operate through feedback loops: patents can create technological and market opportunities for entrepreneurs, while start-ups and funding can stimulate further applied research and intellectual-property development. The test is performed for one-year and two-year lag structures to capture both short-term and delayed effects.

Because the variables are sparse and many country-level series contain long periods of zero values, not all countries can be used in every pairwise causality test. Countries with insufficient within-

country variation or aliased coefficients are excluded from the relevant pairwise model. As a result, the number of countries and observations differs across tests. This procedure is necessary to ensure that each estimated causality relationship is based on meaningful within-country dynamic variation. Full information on the number of countries and observations used in each test is provided in the appendix. For transparency and reproducibility, all supplementary materials are deposited in the Zenodo repository (Tasbolatova, 2026). The repository includes Appendix A – Descriptive statistics of the main variables; Appendix B – Dumitrescu–Hurlin panel Granger causality results; Appendix C – Robustness checks and corrected results; Appendix D – Full list of countries included in the sample; and Appendix E – Country fixed effects and cross-country heterogeneity results.

The third stage uses panel vector autoregression as a complementary dynamic analysis. The purpose of PVAR is not to replace the Dumitrescu–Hurlin test, but to examine how patents, start-ups and funding interact dynamically within selected innovation blocks. In the main specification, the green energy innovation block includes energy-related climate-mitigation patents, green energy start-ups, and early-stage green energy funding. PVAR treats all variables in the system as endogenous, which is important because the relationship between technological knowledge, entrepreneurial entry and financing may be mutually reinforcing rather than one-directional.

The baseline PVAR model can be written as follows:

$$Y_{it} = A_1 Y_{i,t-1} + \mu_i + \varepsilon_{it}, \quad (2)$$

where Y_{it} is a vector of endogenous variables for the country i in year t , A_1 is the matrix of lagged dynamic coefficients, μ_i captures country-specific effects, and ε_{it} is the error term. The model is estimated using a one-step GMM with forward-orthogonal deviations and collapsed instruments. Fixed-effects OLS PVAR estimates are also reported as a supplementary comparison. Since PVAR models require stability for reliable impulse-response interpretation, eigenvalue stability tests are applied. Impulse response functions are interpreted only for specifications that satisfy the

stability condition. The results file shows that the initial three-variable GMM PVAR does not satisfy the stability condition, so it should be treated as exploratory rather than as the final source of dynamic causal inference.

For stable PVAR specifications, bootstrapped generalized impulse response functions are estimated. These functions show how a shock to one variable affects the future path of the other variables over a six-year horizon. In this study, particular attention is paid to two types of shocks: patent shocks and funding shocks. Patent shocks indicate whether technological knowledge generates a subsequent entrepreneurial or financial response. Funding shocks indicate whether investor activity contributes to further patenting and technological development. A year-demeaned PVAR specification is additionally used to remove common global shocks and general time trends in green innovation, allowing the analysis to focus on country-specific deviations from the annual cross-country average.

The fourth stage consists of robustness checks. First, because many Dumitrescu–Hurlin tests are estimated, p-values are adjusted using the Benjamini–Hochberg false discovery rate procedure. This correction reduces the risk of overstating significance due to multiple testing. A Bonferroni correction is also reported as a stricter benchmark. Second, numerically extreme Dumitrescu–Hurlin statistics are separated into an Appendix: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026) and excluded from the preferred BH-clean robust-

ness set. This is important because very large test statistics may reflect numerical instability caused by sparse series, near-perfect prediction or limited within-country variation.

Additional robustness checks are estimated using dynamic fixed-effects models. For start-up count outcomes, Poisson fixed-effects/PPML models are used because the dependent variables are non-negative counts with many zero observations. For funding outcomes, two-way fixed-effects OLS models are estimated using log1p-transformed funding variables and robust standard errors. Reverse-direction fixed-effects models are also estimated to test whether lagged start-up and funding indicators predict subsequent patenting activity. These models are used as supportive robustness checks, while the Dumitrescu–Hurlin test remains the main method for assessing predictive causality.

To assess cross-country heterogeneity, country fixed effects were additionally extracted from selected TWFE specifications. These effects capture persistent country-specific baseline differences in digital energy start-up formation and early-stage digital funding, after controlling for lagged outcomes, lagged patenting activity, and common-year shocks. The centered fixed effects were converted into relative baseline deviations using $100 \cdot [\exp(\text{centred fixed effect}) - 1]$, which allows comparison of countries' structural positions in the digital energy start-up ecosystem. Particular attention was paid to Kazakhstan, Armenia and Ukraine because these countries represent post-

Table 1. Methodological sequence and role of empirical methods

Stage	Method	Purpose in the study	Status in interpretation
1	Descriptive statistics and log1p transformation	Diagnose skewness, zero-heavy variables and cross-country heterogeneity	Data preparation and justification
2	Dumitrescu–Hurlin panel Granger causality test	Test whether patents predict start-up/funding outcomes and whether reverse causality exists	Main causality evidence
3	Benjamini–Hochberg and Bonferroni corrections	Control for multiple testing across many pairwise causality tests	Robustness of main causality results
4	PVAR and bootstrapped GIRFs	Explore dynamic interactions and shock responses in selected innovation blocks	Complementary dynamic evidence only
5	PPML fixed effects and TWFE regressions	Check whether selected patent–start-up/funding relationships remain under alternative estimators	Supplementary robustness checks
6	Country fixed effects from TWFE models	Identify persistent country-level baseline differences, with emphasis on Kazakhstan, Armenia and Ukraine	Heterogeneity analysis, not causal inference

Soviet innovation systems with different levels of market readiness and start-up financing capacity.

Table 1 summarizes the stepwise methodological logic of the study by clarifying the purpose of each empirical method and distinguishing the main causality test from complementary dynamic analysis, robustness checks and cross-country heterogeneity assessment.

All computations are conducted in R Studio. The main empirical procedures include descriptive statistics, log1p transformations, Dumitrescu–Hurlin panel Granger causality testing, PVAR estimation, eigenvalue stability diagnostics, bootstrapped generalized impulse response functions, Benjamini–Hochberg and Bonferroni corrections, PPML fixed-effects models, and two-way fixed-effects regressions. The methodological sequence is designed to provide both statistical evidence of predictive causality and an applied interpretation relevant to innovative marketing: whether technological knowledge signals embodied in patents are followed by entrepreneurial market entry and financing, and whether these market responses feed back into later technological development.

3. RESULTS

3.1. Descriptive statistics

The descriptive statistics, presented in Appendix: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), indicate that the study is based on a balanced country-year panel covering 146 countries over the period 2000–2023, with 3,504 observations per variable. The average number of energy and green start-ups is 7.26, while the average number of energy and digital start-ups is 7.03. However, the median value for both indicators is zero, indicating that in most country-year observations, no recorded energy start-up activity is observed. This suggests that energy start-up formation is highly concentrated in a relatively small group of countries and periods. The very large difference between the mean and median, together with high standard deviations, confirms strong heterogeneity across countries in the development of green and digital energy start-up ecosystems.

A similar pattern is observed for start-up financing. The mean values of funding indicators are relatively high, ranging from approximately USD 11.60 million for early-stage funding of energy and digital start-ups to USD 30.81 million for later-stage funding of energy and green start-ups. Nevertheless, the median value is zero for all four funding variables. This indicates that financing is not evenly distributed across the panel but is concentrated in a limited number of observations, most likely corresponding to more developed venture capital markets and more advanced innovation ecosystems. The high maximum values, especially for later-stage funding of energy and green start-ups, which reach approximately USD 15.49 billion, further confirm the presence of extreme observations and strong right-skewness in the financial variables.

The patent indicators also demonstrate substantial cross-country and temporal asymmetry. The highest average value is observed for patents related to climate change mitigation technologies in energy generation, transmission or distribution, with a mean of 150.29 patents, followed by environmental management patents, with a mean of 136.02 patents. By contrast, sustainable ocean economy patents have the lowest average value, at 14.21 patents. The median values are very low across all patent categories, ranging from 0 to 1, suggesting that patenting activity in energy and environmental technologies is also concentrated in a limited number of technologically advanced countries. The high skewness and kurtosis values across both start-up and patent indicators indicate non-normal distributions, many zero observations and extreme values. Therefore, subsequent econometric analysis should use methods suitable for skewed panel data, such as log1p transformations, Poisson fixed-effects models, PPML estimators, or panel Granger causality tests with appropriate robustness checks.

3.2. Main panel causality evidence: Dumitrescu–Hurlin tests

The Dumitrescu–Hurlin panel Granger causality results provide substantial evidence that patenting activity and the development of energy start-ups are dynamically interconnected rather than isolated processes. The test was applied to 120 pairwise relationships, covering both possible causal

directions between five patent indicators and six start-up/funding indicators under two lag structures. 69 relationships are statistically significant at the 5% level. These significant results are reported in Table B1 (in Appendix B: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026)), while the complete set of estimated tests, including non-significant relationships and pair-specific sample sizes, is presented in Table B2 (in Appendix B: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026)).

The results show that the dominant direction of causality runs from patenting activity to energy start-up formation and financing. In total, 43 out of 60 patent-to-start-up/funding relationships are statistically significant. This indicates that accumulated technological knowledge, measured through patents in environmental management, climate change adaptation, ICT-related climate mitigation, energy-related climate mitigation, and sustainable ocean economy technologies, often precedes the emergence and financial development of energy start-ups. This finding is consistent with the view that patents act as technological signals and knowledge assets that reduce uncertainty, reveal commercial opportunities and provide a foundation for entrepreneurial experimentation in green and digital energy markets. In this sense, patenting activity may contribute to the formation of technological niches from which new energy start-ups emerge and attract investment.

At the same time, the evidence also demonstrates that the relationship is not purely one-directional. The reverse direction is statistically significant in 26 out of 60 tests, meaning that start-up activity and start-up financing also Granger-cause patent indicators in a considerable number of cases. This suggests that entrepreneurial ecosystems may themselves stimulate further technological knowledge production. As energy start-ups enter markets, test new business models, attract venture capital and commercialize emerging technologies, they can create demand for additional inventions, applied research and intellectual property protection. This feedback effect is particularly important because it implies that start-ups are not only passive users of existing patented technologies but may also become active contributors to subsequent innovation dynamics.

The results, therefore, point to a cumulative innovation mechanism in which patents and start-ups mutually reinforce each other over time. Patents can provide the technological base for entrepreneurial entry, while start-up formation and funding can accelerate the practical application, refinement and further development of patented knowledge. Such a mechanism is especially relevant in energy transition sectors, where innovation depends on the interaction between scientific discovery, applied technological development, market experimentation and financial support. The observed bidirectional causality supports the interpretation that energy start-up ecosystems function as dynamic innovation systems rather than as linear pipelines from invention to commercialization.

The lag structure provides further insight into the timing of these relationships. The one-year lag produces more statistically significant causal relationships than the two-year lag, especially in the direction from patents to start-up and funding outcomes. This suggests that the predictive relationship between technological knowledge and start-up development may materialize relatively quickly, particularly for start-up formation and early-stage financing. Early-stage investors may respond more rapidly to patent signals because patents can signal the emergence of new technological opportunities, potential market niches, or promising areas of applied research. By contrast, later-stage funding shows fewer significant relationships, which is reasonable because later-stage investment usually depends not only on technological potential but also on business performance, scalability, market validation, revenue prospects and investor confidence.

An additional methodological consideration is that the number of countries used in each test varies across pairs of variables. This variation results from excluding countries with insufficient within-country variation or aliased coefficients from the country-specific regressions. Given the high number of zero observations in both start-up and funding variables, this filtering procedure is necessary for obtaining reliable Dumitrescu–Hurlin test statistics. Therefore, the results should be interpreted as pair-specific evidence of panel Granger causality based on the countries for which meaningful dynamic variation exists. This should be clearly

stated in the methodology, and the full information on the number of observations and countries included in each test should be retained in Appendix B: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026).

3.3. Complementary dynamic evidence: PVAR and impulse responses

As a complementary dynamic check, PVAR models (Table 2) were estimated to explore whether the main Dumitrescu–Hurlin findings are consistent with dynamic feedback within selected innovation blocks. PVAR results are not treated as the main source of causal inference. They are used only to explore dynamic adjustment patterns,

and impulse responses are interpreted only for stable specifications. In the one-step GMM PVAR model, all three variables show statistically significant own-lag effects. The strongest persistence is observed for energy-related climate-mitigation patents, with a lagged coefficient of 0.8159 and significance at the 0.1% level. This indicates that countries with higher patenting activity in the previous year tend to maintain that level in the following year. Green start-up formation and early-stage green start-up funding also show significant persistence, with coefficients of 0.4997 and 0.5342, respectively. This confirms that technological knowledge creation, entrepreneurial entry and early-stage financing are not isolated annual events but follow cumulative dynamic paths.

Table 2. Dynamic panel VAR results for the green energy innovation block

Explanatory variable	Patents in energy-related climate mitigation	Green energy start-ups	Early-stage green energy funding
Panel A. One-step GMM PVAR, forward orthogonal deviations			
Lagged patents in energy-related climate mitigation	0.8159*** (0.0804)	0.9657*** (0.1515)	3.0719** (1.1173)
Lagged green energy start-ups	0.1900*** (0.0393)	0.4997*** (0.0925)	0.2495 (0.6136)
Lagged early-stage green energy funding	−0.0052 (0.0033)	−0.0273*** (0.0061)	0.5342*** (0.0520)
Observations	1,650	1,650	1,650
Countries	75	75	75
Instruments	18	18	18
Hansen test	$\chi^2(9) = 5011.31$		$p < 0.0001$
Panel B. Fixed-effects OLS PVAR, demeaned transformation			
Lagged patents in energy-related climate mitigation	0.6477*** (0.0181)	0.1891*** (0.0206)	1.3349*** (0.2136)
Lagged green energy start-ups	0.1120*** (0.0219)	0.3156*** (0.0249)	1.2960*** (0.2590)
Lagged early-stage green energy funding	−0.0009 (0.0018)	−0.0032 (0.0021)	0.4805*** (0.0215)
Observations	1,800	1,800	1,800
Countries	75	75	75
Panel C. GMM diagnostic tests			
Hansen test of overidentifying restrictions	$\chi^2(9) = 5011.31$		$p < 0.0001$
Number of instruments	18		
Andrews–Lu MMSC BIC	4900.179		
Andrews–Lu MMSC AIC	4981.307		
Andrews–Lu MMSC HQIC	4948.224		
Stability condition	Not satisfied	Maximum eigenvalue modulus = 1.0514	

Note: Standard errors are reported in parentheses. All variables are transformed using log1p. The GMM model is estimated using forward orthogonal deviations and collapsed GMM-type instruments based on lags 2–3 of the dependent variables. The FEOLS model is estimated using demeaned fixed effects. ***, ** and * denote significance at the 0.1%, 1% and 5% levels, respectively. The Hansen test and stability results indicate that the one-step GMM PVAR should be interpreted cautiously and should not be used for impulse-response analysis unless a stable alternative specification is available.

The cross-variable coefficients provide evidence of a reinforcing relationship between technological knowledge and entrepreneurial activity. Lagged energy-related patents have a positive and significant effect on both green start-ups and early-stage green funding. In the GMM model, the coefficient for lagged patents on green start-ups is 0.9657, while the coefficient for lagged patents on early-stage green funding is 3.0719. This supports the interpretation that patenting activity may act as a technological signal and opportunity for green energy entrepreneurship and investment. At the same time, lagged green start-ups positively and significantly predict subsequent patenting activity, with a coefficient of 0.1900, which suggests a reverse feedback mechanism: start-up formation may also stimulate further technological development and patenting. This is consistent with the broader idea that green innovation systems are not linear but operate through cumulative interactions among knowledge creation, entrepreneurial experimentation, and finance.

The FEOLS PVAR estimates generally confirm the direction of the main relationships. Lagged energy-related patents remain positively associated with green start-up formation and early-stage green funding, while lagged green start-ups also positively predict future patenting and funding. In particular, the FEOLS coefficient from lagged green start-ups to early-stage green funding is 1.2960 and highly significant, suggesting that observable start-up formation may be an important signal for subsequent investor activity. However, early-stage green funding does not consistently stimulate either patenting or start-up formation in the next period. In the GMM model, lagged early-stage green funding has a significantly negative association with green start-ups, while in the FEOLS model, this relationship becomes statistically insignificant. Therefore, the evidence for finance as a direct driver of subsequent start-up formation is weaker than the evidence for patents and start-up activity as mutually reinforcing factors.

However, the diagnostic tests require caution in interpreting the GMM PVAR model as a final dynamic specification. The Hansen test strongly rejects the validity of the overidentifying restrictions, with $\chi^2(9) = 5011.31$ and $p < 0.0001$. In addition, the software warns that the Hansen test is not

fully meaningful for the first-step GMM estimator. However, the rejection still signals that the instrument structure may be problematic. More importantly, the stability test shows that one eigenvalue has a modulus greater than 1, namely 1.0514. This means that the estimated PVAR does not satisfy the stability condition. As a result, impulse response functions from this model should not be interpreted as reliable. The coefficient estimates may still be discussed as exploratory dynamic evidence, especially because the FEOLS model supports similar directions of association. Still, the current GMM PVAR specification should not be used as the main source of causal inference without further re-estimation or robustness checks.

Figure 1 presents the bootstrapped generalized impulse response functions for the stable two-variable PVAR model linking energy-related climate-mitigation patents to early-stage green energy funding. The results show that a shock to early-stage green funding has the strongest immediate own effect. The response of early-stage funding to its own shock is positive and relatively large in the first period, but it gradually declines over the six-period horizon. This indicates that early-stage green funding is dynamically persistent in the short run, although the effect weakens over time. In other words, a temporary increase in early-stage funding tends to sustain higher funding levels for several subsequent years, but this persistence is not permanent.

The response of early-stage green funding to a shock in energy-related patents is very small and remains close to zero throughout the forecast horizon. This suggests that, once the system's dynamic structure is taken into account, patent shocks do not generate a strong immediate impulse response in early-stage funding. This does not necessarily contradict the positive coefficient found in the PVAR estimates, but it shows that the dynamic response path is weak and short-lived. Therefore, patenting activity may help explain funding in the regression system, but the simulated shock effect is not large in the bootstrapped impulse-response framework.

The lower-left panel shows a positive response of energy-related patents to a shock in early-stage green funding. The central impulse-response line

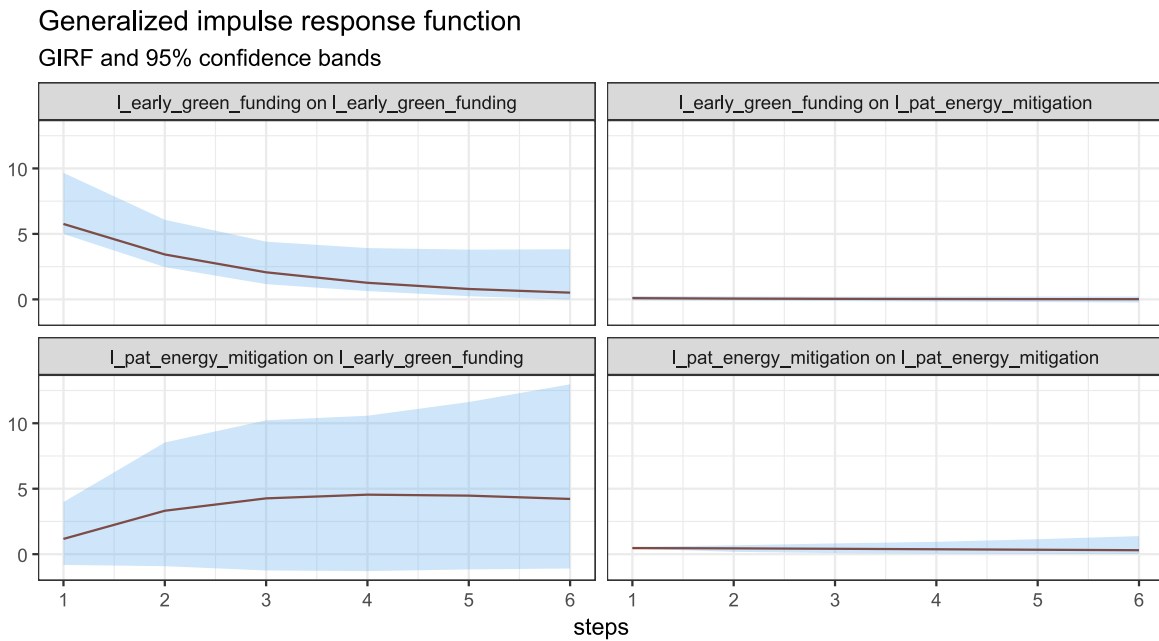


Figure 1. Bootstrapped generalized impulse response functions for the patent–funding PVAR model

increases during the first few periods and remains positive up to the sixth period. This may indicate that early-stage green funding can support subsequent patenting activity by financing experimentation, technological development, and research oriented toward commercialization. However, the confidence interval is wide and appears to include zero, especially across the later periods. Therefore, this result should be interpreted as suggestive evidence of a possible funding-to-patenting feedback mechanism rather than as strong statistical confirmation.

Finally, the response of energy-related patents to their own shock is positive but small and relatively flat. This suggests that patenting shocks in this specification do not produce a large cumulative response in future patenting activity. Figure 1 indicates that the patent–funding system is dynamically stable and characterized mainly by short-term persistence in early-stage funding, a weak funding response to patent shocks, and a possible, though statistically uncertain, positive response of patenting activity to early-stage funding shocks. These results should be interpreted as complementary dynamic evidence to the Dumitrescu–Hurlin panel Granger causality results rather than as the main basis for causal inference.

Figure 2 presents the bootstrapped generalized impulse response functions for the year-de-

meaned green innovation PVAR model, which includes energy-related climate-mitigation patents, green energy start-ups, and early-stage green energy funding. Since the variables are year-demeaned, the results should be interpreted as responses of country-level deviations from the annual cross-country average rather than as changes in raw levels. This specification is useful because it removes common global shocks and general time trends in green innovation, allowing the analysis to focus on relative country-specific dynamics. The impulse responses generally converge to zero within the six-period horizon, consistent with the previously confirmed stability condition for this model.

The strongest and most persistent response is observed for early-stage green funding after its own shock. A positive funding shock initially produces a clear positive response, but this effect gradually declines over time. This indicates that countries experiencing above-average early-stage green funding tend to remain above the annual cross-country average for a short period. However, the effect weakens and is not permanent. Their own responses to patents and green start-ups are more moderate, suggesting that deviations in patenting activity and start-up formation are less persistent once common year effects are removed.

Generalized impulse response function

GIRF and 95% confidence bands

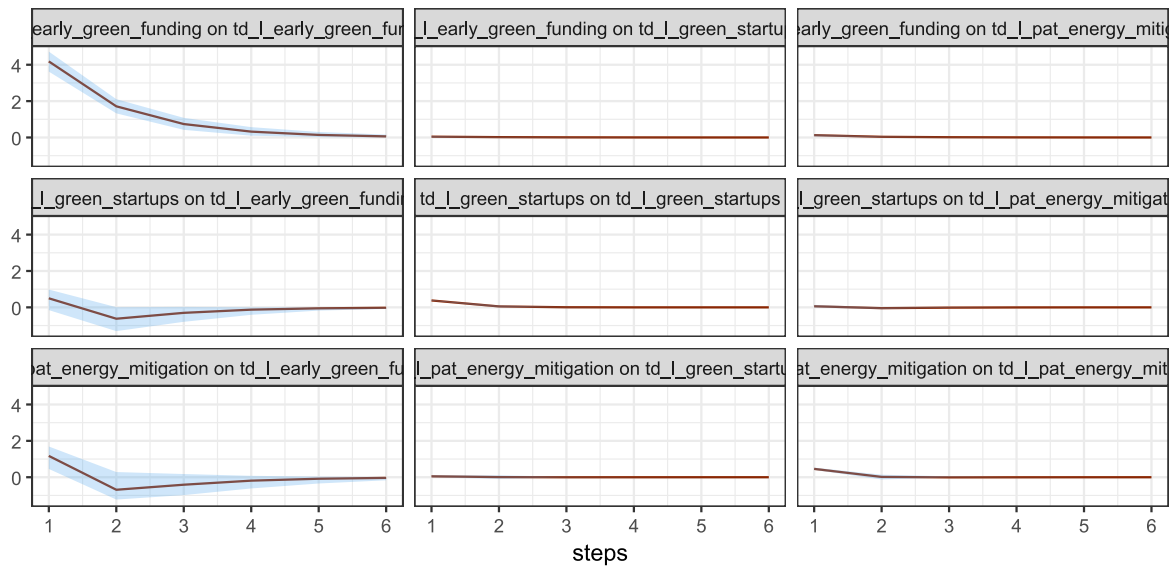


Figure 2. Bootstrapped generalised impulse response functions for the year-demeaned green innovation PVAR model

Cross-variable responses are weaker and shorter-lived. Shocks to energy-related patents do not appear to generate a strong or persistent positive response in green start-ups or funding. Similarly, shocks to green start-up formation have limited dynamic effects on later patenting and funding deviations. The response of patenting activity to funding shocks is more pronounced in the short run, suggesting that above-average early-stage funding can temporarily support subsequent technological development and patenting. However, the bootstrapped confidence bands are

relatively wide and often include zero, so these effects should be interpreted cautiously.

Figure 2 suggests that after controlling for common year-specific trends, the green innovation system is dynamically stable and characterized mainly by short-term adjustment rather than permanent shock effects. The results support the idea that common global dynamics in green technologies, venture financing, and energy transition policies may drive part of the strong relationship observed in the level models. Therefore, the year-

Table 3. Robustness of Dumitrescu–Hurlin panel Granger causality results to multiple testing

Correction / sensitivity rule	Significant tests	Patents → start-ups/funding	Start-ups/funding → patents	Lag 1	Lag 2	Interpretation
Unadjusted $p < 0.05$	69	43	26	38	31	Baseline significance before correction for multiple testing.
Benjamini–Hochberg FDR, global $p < 0.05$	61	39	22	34	27	Most causal relationships remain significant after global FDR correction.
Benjamini–Hochberg FDR, global $p < 0.05$, excluding extreme statistics	55	37	18	29	26	The conservative preferred robustness set; numerically extreme tests excluded.
Bonferroni correction, global $p < 0.05$	32	24	8	21	11	Very conservative correction; confirms the strongest relationships.
Benjamini–Hochberg FDR within direction, $p < 0.05$	60	39	21	34	26	Correction applied separately within each causal direction.

demeaned PVAR provides a more conservative interpretation: country-specific deviations in patents, start-ups and early-stage funding matter, but their effects tend to dissipate over time.

3.4. Robustness of causality results

The robustness analysis provides additional support for the reliability of the Dumitrescu–Hurlin panel Granger causality findings and shows that the main conclusions are not merely an artefact of unadjusted p-values. As reported in Table 3, 69 out of 119 usable pairwise relationships are statistically significant at the conventional unadjusted 5% level. After applying the global Benjamini–Hochberg correction for multiple testing, 61 relationships remain statistically significant. This is important because the study estimates a large number of pairwise causal relationships, and without p-value adjustment, there is a risk of overstating statistical significance. The persistence of most significant relationships after correction indicates that the evidence of dynamic relationship between patenting activity, energy start-up formation, and start-up financing is robust to multiple comparisons.

The sensitivity check based on numerically extreme Dumitrescu–Hurlin statistics further strengthens this conclusion. As shown in Table C1 Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), six results produced exceptionally large Z -statistics, which may reflect numerical instability caused by sparse data, near-perfect prediction, or limited within-country variation in some variable pairs. These observations are retained in the Appendix: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026) for transparency, but they are not treated as the strongest basis for interpretation. After excluding these extreme-statistic cases, Table 3 shows that 55 relationships remain significant after Benjamini–Hochberg correction. Thus, although the number of significant relationships decreases, the substantive conclusion remains unchanged: the relationship between patents, start-up activity and funding is not driven by a small number of numerically unusual results.

The corrected Dumitrescu–Hurlin evidence remains stronger in the direction from patents to start-up and funding outcomes than in the re-

verse direction. This supports the interpretation that patented technological knowledge often precedes the development of energy start-ups and their financing. Patents may therefore operate as technological signals, knowledge assets and opportunity indicators that help reduce uncertainty for entrepreneurs and investors. At the same time, the reverse relationship persists in several cases, indicating that start-up ecosystems and financing activity can also stimulate subsequent technological development. The full corrected results reported in Table C2 Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026) and the cleaned significant results in Table C3 in Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026) therefore confirm that the patent–start-up relationship is best understood as dynamic and partly bidirectional, rather than as a purely linear sequence from invention to commercialization.

3.5. Heterogeneity: selected TWFE models and country fixed effects

The PPML and TWFE models are not intended to replace the panel Granger causality framework. They are used as supplementary robustness checks to examine whether selected predictive relationships remain visible under alternative fixed-effects estimators. The PPML fixed-effects robustness models for start-up count outcomes provide a more conservative picture. As summarized in Table 4 and reported in detail in Table C4 of Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), some patent variables show statistically significant raw p-values in models explaining the number of green or digital energy start-ups. However, none of these relationships remains significant after Benjamini–Hochberg correction. This means that, under the stricter PPML specification with country- and year-fixed effects, there is no robust evidence that lagged patenting activity directly increases the number of green or digital energy start-ups. This does not contradict the Dumitrescu–Hurlin results, because the Granger test captures predictive temporal dependence. In contrast, the PPML models estimate conditional count effects under a more demanding fixed-effects structure. Rather, the PPML results suggest that patent-based predictive effects are not always strong enough to

Table 4. Summary of dynamic fixed-effects and PPML robustness checks

Robustness model	Direction tested	Outcomes	Number of tests	Raw p < 0.05	BH p < 0.05	BH p < 0.10	Main interpretation
PPML fixed effects	Patents → start-up counts	Green and digital energy start-ups count	20	2	0	0	No patent effect remains significant after BH correction; count-outcome evidence is not robust in PPML.
TWFE OLS with Driscoll–Kraay SE	Patents → funding	Early- and later-stage green/digital funding, log1p USD	40	12	10	12	Several statistical relationships remain after BH correction, but estimates are numerically close to zero and should be treated as weak economic evidence.
TWFE OLS with Driscoll–Kraay SE	Start-ups/funding → patents	Five patent indicators, log1p	60	24	16	24	Reverse-direction evidence remains more visible than PPML results, but estimated magnitudes are very small.

translate into statistically robust count-model effects when unobserved country heterogeneity and common-year shocks are controlled for.

The TWFE funding models provide stronger supportive evidence than the PPML count models. As shown in Table 4 and Table C5 of Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), several patent–funding relationships remain statistically significant after Benjamini–Hochberg correction, particularly for climate adaptation, ICT-related mitigation, energy-related mitigation and sustainable-ocean patent categories. This indicates that patenting activity may be more closely linked to the financing dimension of energy start-up ecosystems than to the simple count of newly recorded start-ups. This interpretation is consistent with the idea that investors may respond to technological signals and intellectual property activity when allocating early- and later-stage funding. However, many coefficients are numerically small, so these results should be interpreted primarily as evidence of statistically detectable dynamic association rather than as evidence of large economic effects.

The reverse-direction FEOLS models also support the existence of feedback effects, although again with some caution. The results reported in Tables C6 and C7 of Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), show that selected start-up and funding

variables significantly predict later patenting activity after Benjamini–Hochberg correction. This suggests that energy start-ups and their financing may contribute to subsequent knowledge creation by supporting experimentation, applied research, commercialization processes, and intellectual property development. Nevertheless, the reverse effects are less systematic than the patent-to-start-up/funding direction, and many estimated coefficients are close to zero. Therefore, these models should be treated as complementary robustness checks rather than as the primary source of causal interpretation.

The robustness analysis confirms the study’s main empirical conclusion. The strongest and most consistent evidence remains the Dumitrescu–Hurlin panel Granger causality results, especially after multiple-testing correction and the exclusion of numerically extreme statistics. The additional PPML and FEOLS models refine this conclusion by showing that the patent–start-up relationship is more robust for financing outcomes than for start-up count outcomes. That reverse feedback from start-ups and funding to patenting exists, but is less uniform. Taken together, Tables 2–3 and Appendix C1–C7 of Appendix C: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026), support the interpretation that energy start-up ecosystems develop through cumulative interactions among technological knowledge, entrepreneurial activity, and financial support.

Country fixed effects are not interpreted as causal estimates. They are extracted from selected TWFE models to describe persistent country-specific baseline differences in the conversion of patent signals into digital energy start-up formation and funding. The two TWFE models (Table 5) provide complementary evidence that patenting activity is positively associated with the development of the digital energy start-up ecosystem. In Model 1, where the dependent variable is the number of digital energy start-ups, the lagged dependent variable is positive and statistically significant, indicating moderate persistence in start-up formation. The coefficient for lagged climate change adaptation patents is also positive and significant, suggesting that countries with stronger patenting activity in climate adaptation technologies tend to record higher digital energy start-up activity in the following year. This supports the interpretation that climate adaptation patents can serve as technological and market signals to identify commercially relevant opportunities for digital energy entrepreneurship.

Table 5. TWFE robustness models for digital energy start-up formation and early-stage digital energy start-up funding

Variable	Model 1: Digital energy start-ups	Model 2: Early-stage digital energy funding
Lagged dependent variable	0.193*** (0.050)	0.378*** (0.069)
Lagged climate change adaptation patents	0.079** (0.025)	
Lagged ICT-related climate mitigation patents		1.667*** (0.325)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	3,358	3,358
Countries	146	146
Years	23	23
Standard errors	Driscoll–Kraay, L = 2	Driscoll–Kraay, L = 2
RMSE	0.381	3.466
Adjusted R ²	0.857	0.638
Within R ²	0.045	0.190

Note: Standard errors are reported in parentheses. Model 1 uses the log_{1p}-transformed number of digital energy start-ups as the dependent variable. Model 2 uses the log_{1p}-transformed early-stage funding of energy and digital start-ups as the dependent variable. Patent and funding variables are transformed using log_{1p}. ***, ** and * denote significance at the 0.1%, 1% and 5% levels, respectively.

Model 2 shows an even stronger relationship between patenting and financing. The dependent variable is early-stage funding for digital energy start-ups, and both the lagged dependent variable and the lagged ICT-related climate-mitigation patents are positive and highly significant. The coefficient for ICT-related mitigation patents is substantially larger than in Model 1, indicating that patenting activity in ICT-based climate mitigation technologies is more strongly associated with subsequent investor response than with start-up counts alone. This suggests that patents may be particularly important for attracting early-stage capital, as they reduce technological uncertainty and signal the commercial potential of digital energy solutions. Overall, the two models show that patents matter both for the emergence of digital energy start-ups and, more strongly, for their early-stage financing.

The two TWFE models confirm that patenting activity is positively associated with the digital energy start-up ecosystem. In Model 1, lagged climate change adaptation patents significantly predict the number of digital energy start-ups, while the lagged dependent variable indicates moderate persistence in start-up formation. In Model 2, lagged ICT-related climate-mitigation patents have a much stronger positive association with early-stage digital funding, suggesting that ICT-oriented mitigation patents may serve as particularly important technological and market signals for investors. Overall, the results indicate that patents matter not only for the emergence of digital energy start-ups but also, and more strongly, for attracting early-stage investment.

The country-fixed effects (Table E1 Appendix E: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026)) reveal strong cross-country heterogeneity in the structural conditions for the formation of digital energy start-ups. The largest positive effects are observed for the United States, the United Kingdom, Canada, India, Germany, and China, indicating stronger baseline ecosystems after controlling for lagged start-up activity, patenting, and year effects. Among the post-Soviet countries of interest, Ukraine has a positive, centered fixed effect, suggesting an above-average structural position for the formation of digital energy start-ups. By contrast, Kazakhstan and

Armenia have negative centered effects, indicating below-average baseline conditions in this model. This does not mean that patenting is irrelevant in these countries; rather, it shows that the transformation of technological signals into digital energy start-up activity depends on broader market, innovation, financing and entrepreneurial conditions. This result is important because it highlights that patents can serve as market signals, but their commercialization varies substantially across national ecosystems.

The country-fixed effects for the TWFE model of early-stage digital energy start-up funding (Table E2, Appendix E: Dataset for this research, deposited in Zenodo (Tasbolatova, 2026)) reveal substantial cross-country heterogeneity in the ability to convert ICT-related climate-mitigation patents into investor-backed digital energy ventures. The strongest positive structural effects are observed for Portugal, Belgium, Chile, Lithuania, Brazil, Spain, and the United Kingdom, indicating that these countries have above-average baseline conditions for attracting early-stage digital energy funding, even after controlling for lagged funding, patenting activity, and common-year shocks. Among the post-Soviet countries of interest, Ukraine occupies a relatively moderate position: its centered country fixed effect is slightly negative (-0.144), corresponding to an estimated relative baseline deviation of about -13.4% , which suggests that Ukraine is below the sample average but not among the weakest countries. Kazakhstan has a lower position, with a centered fixed effect of -0.437 and a relative deviation of about -35.4% , indicating weaker structural conditions for early-stage digital energy funding. Armenia performs even less favorably, with a centered fixed effect of -0.713 and a relative deviation of about -51.0% . These results suggest that, for Kazakhstan and especially Armenia, the presence of patenting activity alone may be insufficient to attract early-stage digital energy investment without stronger market infrastructure, venture capital channels, commercialization capacity, and innovation-support mechanisms. For Ukraine, the result is more promising but still indicates a need to strengthen the investment and marketing environment that transforms technological signals into start-up financing.

4. DISCUSSION

The results confirm that patent-based technological signals are important for the development of innovative markets, particularly in green and digital energy start-up ecosystems. The stronger causal relationship between patents and start-up formation and venture financing shows that patents can serve not only as legal or technical outputs but also as market intelligence signals that reduce uncertainty, reveal technological niches, and support entrepreneurial positioning. This is consistent with entrepreneurial finance signaling theory, which holds that patents increase young firms' credibility and help investors assess the quality of inventions under uncertainty (Conti et al., 2013). It also supports the evidence that uncertain intellectual property rights can delay commercialization and restrict external capital, while reliable patent protection strengthens technology exchange (Gans et al., 2008; Heger & Hussinger, 2016). The closer relationship between patents and financing than between patents and start-ups also aligns with studies showing that patents support venture capital attraction, although their value depends on sectoral context, portfolio quality, and commercial relevance (Mann & Sager, 2007; Zhou et al., 2016).

The results also show that the relationship between patents, start-ups and funding is not one-directional. Reverse causality from start-up formation and venture financing to later patenting suggests that entrepreneurial market entry can stimulate further technological development, applied research, and intellectual property activity. This aligns with technology commercialization literature, which views innovation as a multidimensional process involving technological readiness, market knowledge, organizational capabilities, financing and ecosystem support (Kirchberger & Pohl, 2016). It also supports the evidence that university start-ups, academic entrepreneurship, and R&D commercialization depend on knowledge transfer, partnerships, and market orientation (Swamidass, 2012; Sitenko et al., 2024). Venture financing is especially important because it enables experimentation, scaling, and market validation under uncertainty, particularly in renewable energy sectors with regulatory, infrastructural, and technological risks (Benlefi

et al., 2024; Dobrovolska et al., 2024). This is consistent with studies showing that investors rely on external signals, technological labels and market narratives when direct performance information is limited (Islam et al., 2018; Sudarmaji, 2026).

The robustness results suggest a more cautious interpretation of the patent–start-up relationship. The lack of robust PPML evidence for start-up counts after Benjamini–Hochberg correction indicates that patents alone do not automatically generate new green or digital energy start-ups, even after controlling for country and year heterogeneity. This is consistent with the ecosystem literature, which shows that start-up success also depends on universities, institutions, leadership, human capital, spatial proximity, digitalization, and managerial capabilities (Kuzior et al., 2024; Mursalov et al., 2023; Zahidi et al., 2025). It also aligns with studies on the renewable energy transition, which show that green market development depends on institutional quality, policy support, investment incentives, digital governance, and firm-level eco-innovation capabilities (Mukhtarov et al., 2023; Lyeonov et al., 2025; Živković & Štrbac, 2025). From an innovative marketing perspective, patents are therefore important but insufficient signals: they can reduce uncertainty and attract investors, but their commercial impact depends on ecosystem conditions, financing channels, customer trust, regulatory predictability, and the convincing communication of technological value.

The country fixed-effect results add an ecosystem-level explanation to the main patent–start-up findings. Ukraine’s above-average structural position in digital energy start-up formation, compared with weaker positions for Kazakhstan and Armenia, suggests that similar patent-based technological signals may generate different entrepreneurial outcomes across national innovation systems. This is consistent with the literature showing that technology commercialisation depends not only on invention, but also on market knowledge, organisational capabilities, financing, technology transfer and ecosystem support (Kirchberger & Pohl, 2016; Megits et al., 2022; Sitenko et al., 2024). However, Ukraine remains below the sample average in early-stage digital funding, with a centred fixed effect of -0.144 , while Kazakhstan

and Armenia show even weaker funding positions, with centred fixed effects of -0.437 and -0.713 , respectively. These values correspond to relative baseline deviations of approximately -13.4% for Ukraine, -35.4% for Kazakhstan and -51.0% for Armenia. This finding supports previous evidence that patents may reduce information asymmetry and serve as credible signals for investors, but their financing effect depends on commercial relevance, venture-capital conditions and complementary market signals (Conti et al., 2013; Mann & Sager, 2007; Zhou et al., 2016). It also corresponds to research showing that start-up success is shaped by university–industry cooperation, digitalisation, human capital, spatial proximity and entrepreneurial readiness (Kuzior et al., 2024; Mursalov et al., 2023; Zahidi et al., 2025; Yassin et al., 2024). Therefore, in Kazakhstan, Armenia and Ukraine, patenting activity alone is unlikely to generate sufficient digital energy start-up financing unless it is supported by stronger venture-capital infrastructure, commercialisation channels, market-entry mechanisms and investor-oriented innovation marketing.

This study has several limitations that indicate directions for future research. First, the country-level panel data allow for the identification of broad dynamic relationships between patenting, start-up formation, and venture financing, but do not capture firm-level marketing strategies, investor decisions, customer adoption, or differences across individual start-ups. Second, patent indicators reflect technological activity but not patent quality, commercial value, licensing intensity, or the strength of intellectual property protection. Third, Dumitrescu–Hurlin tests show predictive causality, but not direct causal mechanisms, especially given the skewed and uneven distribution of start-up and funding data. A limitation of the study is that it does not directly observe firm-level marketing mechanisms, such as branding, pricing, digital communication, customer acquisition or market-orientation strategies. Therefore, the marketing interpretation should be understood as a commercialization and market-intelligence perspective rather than as direct evidence of marketing practice. Future research should combine patent and start-up data with firm-level marketing in-

dicators to test how patent-based credibility is converted into customer demand, investor communication and market positioning. Future research could combine international panel analysis with firm-level data, patent-quality measures, venture-capital deal information, customer adoption indicators and case studies of

green and digital energy start-ups. It should also examine how marketing capabilities, branding, digital channels, customer experience, policy support and institutional quality moderate the transformation of patent-based signals into market entry, investor confidence and sustainable commercial growth.

CONCLUSION

This study examined whether patent-based technological signals are associated with the formation and venture financing of green and digital energy start-ups, and whether start-up activity and funding subsequently predict patenting. Patents were treated as observable technological information that may reduce market uncertainty and support commercialization decisions, rather than as direct measures of firm-level marketing practices.

The empirical analysis used a balanced panel of 146 countries for 2000–2023, combining IEA energy start-up and funding indicators with OECD patent data. The methodological framework included log1p transformations, descriptive statistics, Dumitrescu–Hurlin panel Granger causality tests, multiple-testing corrections, PVAR models, PPML fixed effects and TWFE regressions. The results show that green and digital energy start-up activity is highly concentrated across countries and years, with positive mean values but zero medians for both start-up indicators.

The strongest evidence comes from the Dumitrescu–Hurlin tests, which show that patenting activity more frequently predicts start-up formation and financing than the reverse direction. This supports the interpretation that patents may function as market-relevant technological signals associated with later entrepreneurial and investment activity. Reverse relationships from start-ups and funding to patents also indicate feedback effects, although they are less systematic. Robustness checks confirm that the main relationships remain significant after multiple-testing correction, with stronger evidence for financing outcomes than for start-up counts. PVAR results provide only cautious complementary evidence because the main GMM PVAR specification does not satisfy the stability condition.

The country-fixed-effect analysis shows that national structural conditions matter for converting patent-based technological information into the development of digital energy start-ups. Ukraine has a more favorable estimated structural position for the formation of digital energy start-ups than Kazakhstan and Armenia, but all three countries face limitations in attracting early-stage digital energy funding. This confirms that the patent–start-up–investment relationship is not automatic and depends on market readiness, financing infrastructure and commercialization capacity.

From a policy and managerial perspective, patent systems, start-up ecosystems, and venture financing instruments should be developed in tandem. Public support should combine intellectual property protection, technology transfer, investor matchmaking, early-stage financing and market-readiness assistance. For Kazakhstan, Armenia and Ukraine, policy efforts should focus not only on increasing patenting activity but also on improving the conversion of technological knowledge into investable start-up projects. Ukraine should strengthen early-stage investment channels and international venture partnerships; Kazakhstan should develop specialized green and digital energy accelerators and university–industry relationships; and Armenia should prioritize seed-financing mechanisms, commercialization infrastructure and international visibility for technology-based ventures.

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