Economics and Business Letters
15(3), 215-230, 2026

The creation of energy startups: the role of environmental knowledge spillovers

Aurelien Quignon[*]

ICN Business School, Université de Lorraine, CEREFIGE, Nancy, France

Received: 01 July 2025
Revised: 23 February 2026
Accepted: 18 March 2026

Abstract
This paper examines how environmental innovation influences startup creation in energy and non-energy sectors. Using a panel of 35 developed and developing countries from 1998 to 2019 and a two-way fixed effects model, I find that environmental knowledge significantly increases the creation of startups in energy sectors, while no effect is found for non-energy sectors. Further analysis reveals that environmental knowledge promotes startup creation across non-green, digital, and non-digital energy sectors, suggesting broad spillover effects. I also find that in less developed entrepreneurial ecosystems, environmental knowledge is critical for supporting the formation of startups in the clean energy sector. These results support policies aimed at fostering environmental innovation to stimulate entrepreneurship.

Keywords: environmental innovation, energy entrepreneurship, knowledge spillovers
JEL Classification Codes: O31, Q55, L26

1. Introduction

Climate change is a significant global challenge for future generations requiring a shift towards green growth (Aghion et al., 2016; De Haas et al., 2024). Central to this transition is the energy sector, which has received considerable attention from both researchers and policymakers (Sun et al., 2021). In this context, entrepreneurs serve as important agents of change, identifying and developing new market opportunities through radical innovations, particularly in energy sectors (Aghion & Howitt, 1992; Audretsch et al. 2006). The Knowledge Spillover Theory of Entrepreneurship (KSTE), conceptualized by Audretsch (1995), provides a framework for

[*] Corresponding author. E-mail: aurelien.quignon@icn-artem.com.

Citation: Quignon, A. (2026) The creation of energy startups: the role of environmental knowledge spillovers, *Economics and Business Letters*, 15(3), 215-230. DOI: 10.17811/ebl.15.3.2026.215-230.

ISSN: 2254-4380

understanding this phenomenon. According to KSTE, new ideas and knowledge created by incumbent firms, universities, and public research organizations but not commercialized constitute the main source of new opportunities for the development of new startups. Environmental technologies are particularly significant in this regard due to their higher generated spillovers compared to dirty technologies (Colombelli & Quatraro, 2019; Dechezlepretre et al., 2014). By offering a wide range of applications of environmental knowledge (EK), they are expected to have greater potential to create opportunities for new startups in the energy sector (Barbieri et al. 2023).

Recent evidence points to a positive impact of introducing environmental technologies on the creation of green startups (Cojoianu et al., 2020; Colombelli & Quatraro, 2019; Malen & Marcus, 2017). Despite the potential of EK spillovers, the existing literature has focused primarily on empirical evidence regarding green entrepreneurship. This focus potentially hides whether environmental spillovers encourage startup creation in the broader energy sector, without a formal green objective. In addition, most evidence has focused on developed countries. However, significant differences in economic, institutional environments, environmental policies, and innovation capacities across countries can limit entrepreneurial opportunities (Fu et al., 2011; Welter et al., 2019), and the generalization of findings. For instance, González-Pernía et al. (2015) argued that several assumptions of the KSTE may not hold in developing countries, reducing the opportunities for startup creation.

This paper aims to address these gaps by examining whether environmental knowledge fosters the creation of new startups. Rather than focusing on green entrepreneurship, this study assesses the long-term spillover effects on energy entrepreneurship. Specifically, this paper addresses the following research questions: (1) Does environmental knowledge creation spill over into the creation of startups in the energy and non-energy sectors? (2) How do spillovers vary at the energy sub-sectoral level? (3) How do impacts differ between developed and developing countries? Understanding these dynamics is essential for influencing entrepreneurial activity in the energy sector.

To answer these questions, this study explores the relationship between EK, proxied by environmental patent applications, and startup creation using a panel dataset of 35 developed and developing countries from 1997 to 2019. This study extends beyond existing research by considering several energy sub-sectors, including green, non-green, digital, and non-digital sectors, enabling comparative analysis that shed light on how EK influences startup creation.

Consistent with KSTE, I find that EK increases startup creation in the energy sectors, in contrast to the non-energy sectors. These results remain unchanged across robustness checks. Further, I find that the spillovers from EK extend to several sub-energy sectors, ranging from non-green to digital startups. These findings underscore the importance of fostering incentives in developing environmental innovation through policy to stimulate energy-related entrepreneurship. I finally find that spillovers on the creation of green startups are stronger in emerging and developing countries than in advanced countries.

2. Data and methodology

2.1. Data

The empirical analysis is based on an unbalanced panel of 35 countries from 1997 to 2019, with non-missing variables over the period. The sample includes Australia, Austria, Belgium, Brazil, Canada, Chile, China, the Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Japan, South Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Russia, the Slovak Republic, the Republic of Slovenia, South Africa, Sweden, Türkiye, the United Kingdom, and the United States. This sample allows for compiling a time series for the largest number of developed and developing countries to examine the relationship between EK and startup creation in energy and non-energy sectors.

Consistent with prior literature (Cojoianu et al., 2020; Colombelli & Quatraro, 2019), the dependent variable is the count of startup creations in country i in year t. Information is sourced from the International Energy Agency (IEA), which aggregates the number of startup creations by country, year, and sector, based on the commercial database Crunchbase. Crunchbase provides comprehensive coverage of startups regardless of funding status and is recognized as a primary source for high-technology startups, avoiding selection bias (Dalle et al., 2017).
Using IEA classification based on Crunchbase fields (n = 740) augmented with text recognition algorithms, I distinguish between energy-related startups (fossil fuels, nuclear, renewables, hydrogen, e-mobility, energy storage) and non-energy startups. To further explore spillover effects, I examine IEA-defined sub-sectors: green startups (sustainable objectives), brown startups (fossil and oil activities), digital startups (digitalization and internet), and non-digital startups. All dependent variables are log-transformed.

The development of EK is measured using patent applications from 1998 to 2019 in environmental-related technologies, as assigned by the country of residence of the inventors. This variable is derived from the Organisation for Economic Co-operation and Development (OECD). Environment-related technologies refer to technological innovation to minimize wastage, global warming, water use, air pollution, and the use of coal, oil, and electricity, and to preserve energy. These patents are identified using the OECD Environment-related Technologies (ENV-TECH) classification (Haščič & Migotto, 2015), based on the International Patent Classification (IPC) and Collaborative Patent Classification (CPC).[1] However, this measure has several limitations. Patenting rates differ across countries and sectors, and patent systems tend to favour codified, technology-based innovations over process or organizational improvements. For instance, Barbieri et al. (2023) suggest that the number of environmental and non-environmental innovations is correlated and occurs in the same regions. Moreover, not

[1] The environmental-related technologies encompass environmental management, water-related adaptation, biodiversity protection technologies, and climate change mitigation (energy, greenhouse gases, transport, and building).

all environmentally innovations are patented (Cojoianu et al., 2020). Despite these drawbacks, patents provide a standardized, internationally comparable measure of environmental technological knowledge.

Table 1. Summary statistics

Variable	Definition (Source)	Obs.	Mean	SD	Min	Max
log(Energy startups)	Number of energy startup creation per country and year (IEA)	767	2.849	1.516	0	7.094
log(Non-energy startups)	Number of non-energy startup creation per country and year (IEA)	792	6.126	1.515	2.079	10.599
log(Green startups)	Number of green startup creations per country and year (IEA)	724	2.215	1.436	0	6.404
log(Non-green startups)	Number of brown startup creation per country and year (IEA)	728	2.293	1.498	0	6.469
log(Digital startups)	Number of digital-energy startup creation per country and year (IEA)	677	1.740	1.352	0	5.903
log(Non-digital startups)	Number of non-digital-energy startup creation per country and year (IEA)	746	2.605	1.504	0	6.838
log(Environmental knowledge) t-1	Number of environmental patent applications in year t-1 (OECD)	788	3.958	2.095	0.154	9.010
log(GDP per capita) t-1	GDP per capita in year t-1 (WDI)	792	9.931	0.982	6.431	11.630
log(Academic papers) t-1	Number of scientific papers in year t-1 (WDI)	769	9.420	1.601	4.002	13.185
EPS t-1	Environmental policy stringency indicator (0-6) in year t-1 (OECD)	792	1.949	1.112	0	4.222
Trade Openness Low Carbon t-1	Sum of exports and imports of low carbon goods and services measured as a share of gross domestic product in year t-1 (WDI)	787	0.022	0.019	0.002	0.106
log(CO2) t-1	Total CO2 emissions aggregated across sectors per country in year t-1 (WDI)	792	5.094	1.628	1.378	9.320

Several characteristics that are likely to confound the creation of startups in energy and other sectors according to extant literature are included. These control variables are derived from the OECD and World Development Indicators (WDI). Consistent with the literature (Akhtaruzzaman et al., 2025; Cojoianu et al., 2020), I control for the economic development using the logarithm of GDP per capita to control for the fact that countries with higher economic development are more likely to promote environmental technologies and the startup creation. Another important characteristic influencing startup creation, especially in energy-related sectors, is the number of academic papers. A higher amount of academic knowledge can facilitate access to external knowledge critical for identifying and inventing in radical and relatively young technologies, like environmental ones (Cainelli et al., 2012). Hence, the logarithm of the number of academic papers is included. Stricter environmental policies implemented by countries might incentivize the development of technologies with a focus on the reduction of energy produced by firms, universities, and new startups. For instance, Cojoianu et al. (2020) found at a more stringent environmental policy regime negatively impacts the creation of new ventures, in particular in fossil related technologies. Therefore, I proxy the environmental instruments' stringency by including the economy-wide environmental policy stringency (EPS) indicator, ranging from 0 to 6. Exposure to international trade in environmentally friendly products can influence domestic entrepreneurship, especially in energy-related sectors (Susantiningrum & Rapih, 2025). Thus, the sum of exports and imports of low-carbon goods and services measured as a share of gross domestic product is included. Finally, climate change proxied by the level of CO2 emissions might incentive future entrepreneurs to develop new startups in the energy sector (Lin & Zhu, 2019). Therefore, I include the level of emissions using the logarithm of CO2 emissions.

Table 1 provides data description, sources, and summary statistics. Table 5 provides the correlation matrix, and Appendix Figure 1 shows the evolution of startup creation by sectors over time, with most sectors experiencing increased creation.

2.2. Methodology

To examine the impact of EK on the entry of energy startups, I estimate the following two-way fixed effects specification:

$$y_{it} = \beta_1 \log(Environmental\ Knowledge)_{it-1} + \beta_2 X_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it} \quad (1)$$

where y_{it} denotes one the dependent variables in country i and year t; $\log(Environmental\ Knowledge)_{it-1}$ is the logarithm of country's environmental-related technologies in year *t-1*; X_{it-1} is the set of control variables (GDP per capita, Academic papers, EPS, Trade openness in low carbon, and CO_2 emissions) lagged one year to alleviate concerns about reverse causality. α_i and α_t are the country and year fixed effects to control for common and time-invariant unobserved shocks across countries. ε_{it} is the error term that accounts for heteroskedasticity.

To test for potential non-linearities between environmental technologies and the level of country development, I extend the baseline specification with an interaction term:

$$y_{it} = \beta_1 \log(Environmental\ Knowledge)_{it-1} \times Emerging_i + \beta_2 X_{it-1} + \alpha_i + \alpha_t + \varepsilon_{it} \quad (2)$$

where $Emerging_i$ is a dummy variable equals to one for emerging and developing countries and zero for advanced countries.[2]

3. Results

3.1. Baseline results

Table 2 reports the regression results. Whether controlling for country characteristics or not, EK has a positive and significant effect on new energy startups (columns 1-2). These findings suggest that an increase in EK is likely to foster the creation of energy startups. In contrast, the relationship between EK and the creation of non-energy startups is statistically insignificant (columns 3-4 of Table 2). Overall, these results suggest that the stock of patent technologies related to the environment has two main opposing effects on the number of startup creations. Specifically, entrepreneurs may be more able to exploit knowledge spillovers for creating new startups within a related technology than in unrelated technologies. This is consistent with Colombelli & Quatraro (2019), who found that the development of new environmental ideas leads to an increase in new energy-related startups in Italian regions, and Cojoianu et al. (2020), who found that regional EK positively impacts the entry of new startups in different energy sectors.

Regarding controls, countries with larger academic knowledge bases tend to have fewer energy sector startups, indicating that knowledge spillovers stimulating energy startups are restricted to applied innovations. Countries with greater trade openness in low-carbon products and services tend to have lower energy startup creation. Higher CO2 emissions are positively associated with new startups in both energy and non-energy sectors.

3.2. Heterogeneity by sub-sectors and country development

After examining the relationship between EK and the creation of energy and non-energy startups, I investigate the effect across energy-sub sectors to understand whether EK spillovers apply only to energy startups with a green objective or to other startups in brown, digital, and non-digital sectors. Table 3 presents results. EK has a positive and significant effect on the creation of green (column 1), brown (column 2), and digital and non-digital startups (columns 3-4). Interestingly, the EK coefficients are larger for brown, digital, and non-digital startups compared to green startup creation, confirming the relevance of knowledge spillovers outside the sector of origin in fostering the creation of new startups. This underscores how investments in EK generate complex technological opportunities across sectors (Acs et al., 2009). This is consistent with previous studies within the Italian context that highlight knowledge spillovers as a driver of sustainable entrepreneurship (Colombelli & Quatraro, 2019; Corradini, 2019).

---

[2] The World Economic Outlook classifies countries into two main categories: advanced and emerging and developing countries. See supplementary material Appendix A2 for the detailed list of countries.

Table 2. Effect of environmental knowledge on energy and non-energy startup creation

Dep. Var.	**log(Green startups) (1)**	**log(Non-green startups) (2)**	**log(Digital startups) (3)**	**log(Non-digital startups) (4)**
log(Environmental knowledge) $_{t-1}$	0.223***	0.173***	0.074***	-0.002
	(0.040)	(0.044)	(0.021)	(0.021)
log(GDP Capita) $_{t-1}$		-0.143		0.012
		(0.234)		(0.139)
log(Academic papers) $_{t-1}$		-0.200**		0.068*
		(0.088)		(0.036)
EPS $_{t-1}$		0.035		0.045**
		(0.047)		(0.020)
Low Carbon Trade Openness $_{t-1}$		-9.945***		-3.663***
		(2.837)		(1.053)
$CO_{2\ t-1}$		0.559***		0.516***
		(0.184)		(0.091)
Country FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	763	737	788	761
R^2	0.915	0.923	0.979	0.983
VIF	1	8.8	1	9.05

Notes: This table reports estimates from Eq. (1). The dependent variables are "Energy startups" in columns 1-2, which denotes the number of energy startup creation per country and year, and "Non-energy startups" in columns 3-4, which denotes the number of non-energy startup creation per country and year. These dependent variables are log-transformed. All independent and control variables are one-year lagged. The sample period is 1998-2019. All regressions include fixed effects as specified. Robust standard errors are included in parentheses, where ***, **, and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively.

Finally, I investigate whether EK spillovers differ between advanced and emerging countries. Table 4 presents the results for EK interacted with an emerging country's dummy (Eq. 2). EK shows no significant effects on startup creation in energy, digital, non-digital, and non-energy sectors across the two groups of countries. However, the interacted term is positive and significant for green startups, suggesting that spillovers on the creation of green startups are stronger in emerging and developing countries than in advanced countries (column 3). However, the relationship reverses for non-green startups (column 4), with that spillover effects increasing brown startups in advanced countries but not in emerging and developing countries. These results align with González-Pernía et al. (2015), suggesting that the different contexts in emerging countries generate a limited connection between knowledge spillovers and startup creation, except in the green sectors.

Table 3. Effect of environmental knowledge on energy green, non-green, digital, and non-digital startup creation

Dep. Var.	**log(Green startups)** **(1)**	**log(Non-green startups)** **(2)**	**log(Digital startups)** **(3)**	**log(Non-digital startups)** **(4)**
log(Environmental knowledge) $_{t-1}$	0.097*	0.218***	0.167***	0.164***
	(0.053)	(0.045)	(0.057)	(0.046)
log(GDP Capita) $_{t-1}$	-0.460	-0.206	0.144	-0.413
	(0.293)	(0.248)	(0.287)	(0.251)
log(Academic papers) $_{t-1}$	-0.115	-0.273***	-0.222**	-0.124
	(0.102)	(0.088)	(0.112)	(0.084)
EPS $_{t-1}$	0.060	0.041	0.030	0.047
	(0.054)	(0.050)	(0.059)	(0.050)
Low Carbon Trade Openness $_{t-1}$	-7.649***	-8.641***	-6.523**	-9.509***
	(2.927)	(2.994)	(2.810)	(2.975)
$CO_{2\ t-1}$	0.877***	0.368*	0.340	0.554***
	(0.226)	(0.213)	(0.239)	(0.201)
Country FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	697	700	655	719
R^2	0.889	0.914	0.873	0.919
VIF	8.87	8.62	9.52	8.63

Notes: This table reports estimates from Eq. (1). The dependent variables are "Green startups", "Non-green startups", "Digital startups", and "Non-digital startups", which denote the number of startup creation per country and year in each sub-energy sector, respectively. These dependent variables are log-transformed. All independent and control variables are one-year lagged. The sample period is 1998-2019. All regressions include fixed effects as specified. Robust standard errors are included in parentheses, where ***, **, and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively.

3.3. Robustness checks

Results remain robust when using alternative model specifications, including a one-year lag of the dependent variables, a two-year lag of the control variables, and using the share of environmental patents over the total patent applications instead of the stock of environmental patents. In another set of robustness checks, I use other estimators, namely the Feasible Generalized Least Squares estimator to account for heteroscedasticity, and Driscoll & Kraay (1998)'s estimator to correct for cross-sectional dependence. The appendix provides robustness checks.

OLS estimation of Eq. 1 is likely to be biased because the EK may be influenced by other country characteristics that independently affect startup creations. To reduce endogeneity concerns, I instrument for country-level EK using the country's number of environmental patent applications in the first sampling year, multiplied by yearly total patents filed internationally, excluding that country's patents (leave-out). For each country, predicted EK depends on that country's initial environmental patenting and the number of such patents in other countries. The identification assumption is that startup creation in energy and non-energy sectors would have changed similarly in countries differentially exposed to environmental patenting activity. Table 11 reports the IV estimates. First-stage effects and Cragg-Donald F-statistics (51.5 to 56.2) exceed the rule of thumb value of 10 (Stock and Yogo, 2005). Second-stage estimates indicate that EK positively and significantly affects energy startup creation, including brown and digital sectors, and non-energy startups (ranging from 0.358 to 0.591). Effects on green and non-digital startup creation are nonsignificant. These results indicate main findings are robust to omitted variable bias.[3]

Table 4. Heterogeneous effect across economic development of environmental knowledge on energy green, non-green, digital, and non-digital startup creation

Dep. Var.	**log(Energy startups)**	**log(Non-energy startups)**	**log(Green startups)**	**log(Non-green startups startups)**	**log(Digital startups)**	**log(Non-digital startups)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
log(Environmental knowledge) $_{t-1}$	0.199***	-0.018	0.022	0.305***	0.191***	0.171***
	(0.056)	(0.027)	(0.067)	(0.065)	(0.072)	(0.059)
log(Environmental knowledge) $_{t-1}$ × Emerging $_i$	-0.047	0.029	0.134**	-0.148**	-0.041	-0.013
	(0.052)	(0.026)	(0.063)	(0.061)	(0.072)	(0.054)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	737	761	697	700	655	719
R^2	0.923	0.983	0.890	0.915	0.873	0.919
VIF	9.36	9.59	9.41	9.06	10.5	9.12

Notes: This table reports estimates from Eq. (2). All columns report the interactions of environmental knowledge with a dummy variable equal to one for emerging countries, and zero otherwise. All independent and control variables are one-year lagged as in Table 2. The sample period is 1998-2019. All regressions include fixed effects as specified. Robust standard errors are included in parentheses, where ***, **, and * indicate significance at the 1%, 5%, and 10% statistical levels, respectively.

4. Concluding remarks

This paper has investigated the relationship between the stock of environmental knowledge

[3] In unreported results, I instrument environmental knowledge with the country's five-year-lagged EK, assuming that reverse causality concerns do not exist for more than five years. This approach of using lagged instruments relies on the argument of rational expectations in economics (Sargent, 1987). The results are qualitatively similar.

and the creation of startups in several energy and non-energy sectors. By building on the Knowledge Spillover Theory of Entrepreneurship, the findings provide evidence that new knowledge in environmental technologies significantly enhances the creation of startups in energy sectors but does not favor the creation of startups in other sectors. These findings emphasize the importance of technology opportunities in increasing entrepreneurship. Furthermore, the findings highlight the importance of EK spillovers in stimulating entrepreneurship across other energy sectors, including those not directly focused on clean technologies. Finally, I find support that EK is an important opportunity for the creation of green startups in emerging and developing countries rather than in advanced countries.

For policymakers, these findings underscore the importance of designing effective policies that address climate change by fostering environmental innovation, given the opportunities that an expanding stock of new knowledge creates for the generation of energy startups. In this regard, addressing market failures through R&D subsidies or targeted tax incentives may generate substantial knowledge spillovers from low-carbon technologies. Yet such policies should also be tailored to the national or regional entrepreneurship ecosystem, as entrepreneurship is context-specific (Welter et al., 2019), and spillovers may be particularly effective in fostering green startup formation in contexts where the existing knowledge stock remains limited. For entrepreneurs, identifying and taking advantage of environmental technological opportunities may be consequential not only for green sectors but for new venture creation more broadly, given the wider scope of application that environmental technologies afford (Dechezlepretre et al., 2014)

This paper is not without limitations, presenting opportunities for further research. First, the study focuses on 35 developed and developing countries between 1997 and 2019, due to data availability. Future studies could broaden the time frame and country coverage, especially for developing countries, to reassess the relationship using more recent data. Second, while patents provide a useful measure of innovation, they capture only successful inventions. Thus, EK spillovers are not limited to patented innovations. Future research could also explore other forms of innovation, such as green R&D or academic publication related to EK, rather than limiting patents. Finally, another concerns the entrepreneurship data used that only capture startup creation. Relying on other indicators of startups, such as financing of VC-backed or IPO, would allow for a deeper understanding of the EK spillovers on subsequent success of energy startups.

References

Acs, Z.J., Braunerhjelm, P., Audretsch, D.B. and Carlsson, B. (2009) The knowledge spillover theory of entrepreneurship, *Small Business Economics*, 32(1), 15–30.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R. and Van Reenen, J. (2016) Carbon taxes, path dependency, and directed technical change: evidence from the auto industry, *Journal of Political Economy*, 124(1), 1–51.

Aghion, P., Howitt, P. (1992) A model of growth through creative destruction, *Econometrica*,

60(2), 323–351.
Akhtaruzzaman, M., Banerjee, A.K. and Boubaker, S. (2025) Government intervention and green innovation in renewable energy, *Energy Economics*, 108185.
Audretsch, D.B. (1995) *Innovation and industry evolution*, MIT press.
Audretsch, D.B., Keilbach, M.C. and Lehmann, E.E. (2006) *Entrepreneurship and economic growth*, Oxford University Press.
Barbieri, N., Marzucchi, A. and Rizzo, U. (2023) Green technologies, interdependencies, and policy, *Journal of Environmental Economics and Management*, 118, 102791.
Cainelli, G., Mazzanti, M. and Montresor, S. (2012) Environmental innovations, local networks and internationalization, *Industry & Innovation*, 19(8), 697–734.
Cojoianu, T.F., Clark, G.L., Hoepner, A.G.F., Veneri, P. and Wójcik, D. (2020) Entrepreneurs for a low carbon world: how environmental knowledge and policy shape the creation and financing of green start-ups, *Research Policy*, 49(6), 103988.
Colombelli, A. and Quatraro, F. (2019) Green start-ups and local knowledge spillovers from clean and dirty technologies, *Small Business Economics*, 52(4), 773–792.
Corradini, C. (2019) Location determinants of green technological entry: evidence from European regions, *Small Business Economics*, 52(4), 845–858.
Dalle, J.M., den Besten, M., Menon, C. (2017) *Using Crunchbase for economic and managerial research*, OECD Science, Technology and Industry Working Papers.
Dechezleprêtre, A., Märtin, R.P. and Mohnen, M. (2014) *Knowledge spillovers from clean and dirty technologies* (pp. 2042-2695), London, UK: Centre for Economic Performance.
De Haas, R., Martin, R., Muûls, M. and Schweiger, H. (2024) Managerial and financial barriers to the green transition, *Management Science*, mnsc.2023.00772.
Driscoll, J.C. and Kraay, A.C. (1998) Consistent covariance matrix estimation with spatially dependent panel data, *Review of Economics and Statistics*, 80(4), 549–560.
Fu, X., Pietrobelli, C. and Soete, L. (2011) The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up, *World Development*, 39(7), 1204-1212.
González-Pernía, J.L., Jung, A. and Peña-Legazkue, I. (2015) Innovation-driven entrepreneurship in developing economies, *Entrepreneurship and Regional Development*, 27(9–10), 555–573.
Haščič, I. and Migotto, M. (2015) *Measuring environmental innovation using patent data*, OECD Environment Working Papers No. 89.
Lin, B. and Zhu, J. (2019) Impact of energy saving and emission reduction policy on urban sustainable development: empirical evidence from China, *Applied Energy*, 239, 12-22.
Malen, J. and Marcus, A.A. (2017) Promoting clean energy technology entrepreneurship: the role of external context, *Energy Policy*, 102, 7–15.
Sargent, T.J. (1987) *Rational expectations*, in The New Palgrave Dictionary of Economics, 1-7, Palgrave Macmillan, London.
Stock, J. and Yogo, M. (2005) Asymptotic distributions of instrumental variables statistics with many instruments, *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*, 6, 109-120.
Sun, H., Edziah, B.K., Kporsu, A.K., Sarkodie, S.A. and Taghizadeh-Hesary, F. (2021) Energy

efficiency: the role of technological innovation and knowledge spillover, *Technological Forecasting and Social Change*, 167, 120659.

Susantiningrum, R.S. (2025) Driving green innovation: the impact of trade in low-carbon technology products on green entrepreneurship, *Applied Economics Letters*, 1-5.

Welter, F., Baker, T. and Wirsching, K. (2019) Three waves and counting: the rising tide of contextualization in entrepreneurship research, *Small Business Economics*, 52(2), 319-330.

Appendix

Figure 1. Dynamic of startup creation by sectors

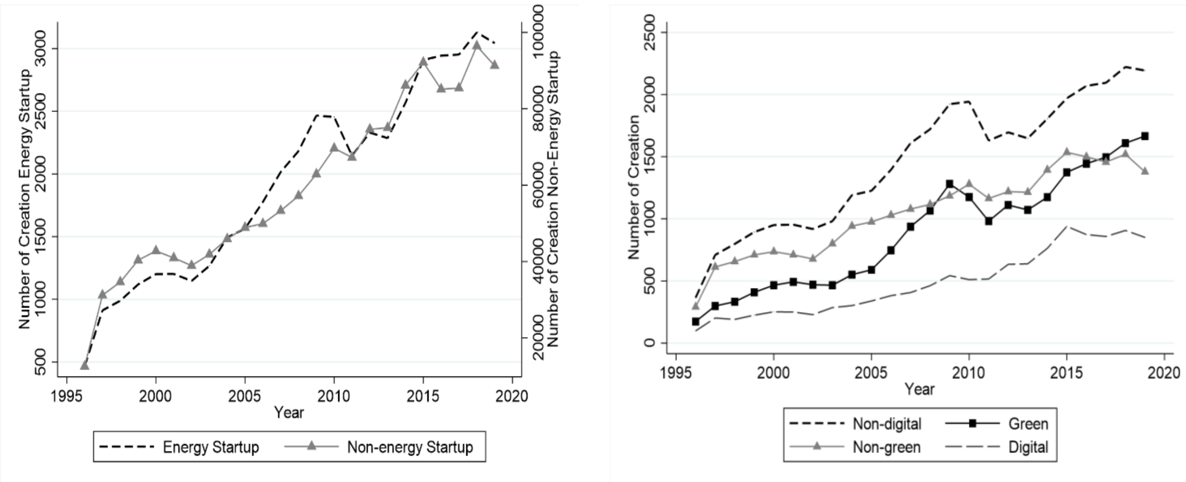

Table 5. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) log(Energy startups)	1											
(2) log(Non-energy startups)	0.946***	1										
(3) log(Green startups)	0.958***	0.907***	1									
(4) log(Brown startups)	0.966***	0.916***	0.860***	1								
(5) log(Digital startups)	0.930***	0.884***	0.894***	0.894***	1							
(6) log(Non-digital startups)	0.987***	0.931***	0.947***	0.953***	0.867***	1						
(7)log(Environmental knowledge) $_{t-1}$	0.616***	0.638***	0.587***	0.601***	0.635***	0.584***	1					
(8) log(GDP per capita) $_{t-1}$	0.0748	0.0123	0.125**	0.0326	0.142***	0.0467	0.277***	1				
(9) log(Academic papers) $_{t-1}$	0.813***	0.855***	0.762***	0.802***	0.777***	0.793***	0.834***	0.0316	1			
(10) EPS $_{t-1}$	0.0952*	0.0634	0.188***	0.0139	0.218***	0.0459	0.394***	0.500***	0.161***	1		
(11) Trade Openness Low Carbon $_{t-1}$	-0.243***	-0.246***	-0.188***	-0.266***	-0.128**	-0.285***	0.107**	0.112**	-0.116**	0.508***	1	
(12) log(CO_2) $_{t-1}$	0.684***	0.750***	0.593***	0.712***	0.605***	0.689***	0.629***	-0.361***	0.823***	-0.221***	-0.261***	1

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7. Alternative specifications using one-year lag of the dependent variable and share of environmental patents over the total patent applications instead of the stock of environmental patents

Dep. Var.	**(1) log(Energy Startup)**	**(2) log(Non-energy Startup)**	**(3) log(Energy Startup)**	**(4) log(Non-energy Startup)**
log(Environmental Knowledge) $_{t-1}$	0.146***	-0.020		
	(0.050)	(0.013)		
log(GDP Capita) $_{t-1}$	-0.106	-0.035	0.231	0.036
	(0.305)	(0.130)	(0.471)	(0.381)
log(Academic Paper) $_{t-1}$	-0.182*	0.013	-0.382**	-0.053
	(0.099)	(0.020)	(0.164)	(0.083)
EPS $_{t-1}$	0.045	0.002	-0.013	0.022
	(0.057)	(0.014)	(0.091)	(0.039)
Trade Openness Low Carbon $_{t-1}$	-6.959**	-0.555	-14.545***	-5.263**
	(2.931)	(0.886)	(3.375)	(2.011)
log(CO2) $_{t-1}$	0.461*	0.232***	0.777*	0.625***
	(0.254)	(0.073)	(0.403)	(0.204)
log(Energy Startup) $_{t-1}$	0.196***			
	(0.058)			
log(Non-energy Startup) $_{t-1}$		0.682***		
		(0.059)		
Percent Environmental Knowledge *t-1*			0.049**	0.042***
			(0.022)	(0.012)
Obs	713	757	598	622
R^2	0.449	0.875	0.414	0.783

Table 8. Advanced, emerging and developing countries

Advanced coun tries (n = 24)	Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, F inland, Germany, Greece, Iceland, Ireland, Japan, South Korea, Luxembour g, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia , Sweden, United Kingdom, US
Emerging and developing cou ntries (n = 11)	Brazil, Chile, China, Hungary, India, Indonesia, Mexico, Poland, Russia, S outh Africa, Türkiye

Table 9. FGLS and Driscoll and Kraay specifications

	FGLS		**Driscoll and Kraay**	
	(1)	**(2)**	**(3)**	**(4)**
	log(Energy Startup)	**log(Non-energy Startup)**	**log(Energy Startup)**	**log(Non-energy Startup)**
log(Environmental Knowledge) $_{t-1}$	0.114***	-0.001	0.154***	0.000
	(0.026)	(0.013)	(0.036)	(0.018)
log(GDP Capita) $_{t-1}$	0.117	0.281***	-0.195	0.018
	(0.156)	(0.080)	(0.199)	(0.235)
log(Academic Paper) $_{t-1}$	-0.183***	0.057**	-0.206***	0.065*
	(0.051)	(0.027)	(0.046)	(0.035)
EPS $_{t-1}$	0.013	0.005	0.033	0.044
	(0.022)	(0.012)	(0.031)	(0.029)
Trade Openness Low Carbon $_{t-1}$	-9.295***	-2.347***	-8.550***	-3.670**
	(1.681)	(0.672)	(1.782)	(1.398)
log(CO_2) $_{t-1}$	0.450***	0.263***	0.555***	0.510***
	(0.109)	(0.052)	(0.192)	(0.139)
Country FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	737	761	737	761

Notes: Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table 10. Two-year lags of the independent and control variables

	(1)	(2)
	log(Energy Startup)	log(Non-energy Startup)
log(Environmental Knowledge) $_{t-2}$	0.191***	0.014
	(0.062)	(0.027)
log(GDP Capita) $_{t-2}$	-0.193	0.071
	(0.385)	(0.302)
log(Academic Paper) $_{t-2}$	-0.285**	0.065
	(0.131)	(0.068)
EPS $_{t-2}$	0.065	0.040
	(0.065)	(0.039)
Trade Openness Low Carbon $_{t-2}$	-9.128**	-3.386
	(3.431)	(2.349)
log(CO_2) $_{t-2}$	0.703**	0.509**
	(0.288)	(0.188)
Country FEs	Yes	Yes
Year FEs	Yes	Yes
Observations	701	722
R^2	0.407	0.764

Notes: Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table 11. IV specifications

Dep. Var.	log(Energy startups) (1)	log(Non-energy startups) (2)	log(Green startups) (3)	log(Non-green startups) (4)	log(Digital startups) (5)	log(Non-digital startups) (6)
log(Environmental knowledge) $_{t-1}$	0.432**	0.358***	0.102	0.561**	0.591**	0.244
	(0.165)	(0.117)	(0.113)	(0.255)	(0.268)	(0.162)
log(GDP Capita) $_{t-1}$	-0.142	0.085	-0.372	-0.209	0.238	-0.424
	(0.288)	(0.277)	(0.340)	(0.366)	(0.360)	(0.283)
log(Academic papers) $_{t-1}$	-0.290*	-0.016	-0.169	-0.394**	-0.420**	-0.187
	(0.157)	(0.104)	(0.163)	(0.180)	(0.184)	(0.139)
EPS $_{t-1}$	0.049	0.061	0.058	0.046	0.049	0.050
	(0.056)	(0.052)	(0.051)	(0.070)	(0.075)	(0.059)
Low Carbon Trade Openness $_{t-1}$	-7.788***	-2.767	-7.496**	-4.740**	-5.533	-7.411***
	(2.362)	(2.267)	(3.000)	(2.234)	(3.699)	(2.182)
CO_2 $_{t-1}$	0.362	0.239	0.833**	0.166	0.059	0.522*
	(0.297)	(0.236)	(0.314)	(0.311)	(0.404)	(0.291)
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	733	757	694	696	651	715
First-stage Coefficient	-4.026	-4.062	-4.004	-3.929	-4.067	-4.004
Instrument *F*-statistic	52.725	52.634	52.954	51.547	56.175	51.840

Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.