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The Effect of Academic Freedom on Green Patenting by Different Participants of the National Innovation System Moderated by Corruption

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Abstract
At the backdrop of encroachments on democratic values, including academic freedom, global environmental challenges, and a growing patent output, this paper investigates the effect of academic freedom on green patenting. We zoom into the green patent filings generated by different participants of the national innovation system: universities, government funded research institutes, individual inventors and companies. By incorporating corruption as a moderator, we explore whether corruption amplifies or dampens the positive impact of academic freedom on green invention. Our results reveal that academic freedom generally increases the number of green patent applications, but the effect is different for different types of applicants. Individuals, universities and research institutions overall seem to benefit from greater academic freedom especially in the models containing the interaction between academic freedom and corruption. Our main conclusion is that academic freedom is conducive to green patenting especially accompanied by low levels of corruption. However, companies respond to a complex set of incentives and engage in diverse innovation strategies. We offer our explanations and shed light on the complexity of factors involved and their interactions.

Keywords Green patent · Green invention · Academic freedom · Corruption

Introduction

At the backdrop of encroachments on democratic values, including academic freedom, global environmental challenges, and a growing patent output, this paper investigates the effect of academic freedom on green patenting. Academic freedom responsible for institutional arrangements enabling free and open scientific endeavours, as well as freedom of instruction, is one of the inalienable characteristics of

Extended author information available on the last page of the article democratic societies. Since free self-expression is a key prerequisite of entrepreneurial behaviour (Florida, 2014), academic freedom and innovation are directly linked (Audretsch et al., 2024). However, the link between the two phenomena requires further empirical investigation (Audretsch et al., 2024) with a particular emphasis on green or environmental patenting as a type of inventive output. Because of the pressing concerns about the negative consequences of industrialization, green innovation comes into the foreground of scholarly attention, as well as the attention of policy makers and the public at large.

The key question is whether societies that enjoy higher levels of academic freedom also channel their research activities into tackling environmental challenges. To understand the effect of academic freedom on different participants of the national system of innovation, this paper focuses on the link between academic freedom and international green patent output by different types of applicants: companies, individuals, universities and research institutes. By incorporating the Corruption Perceptions Index (CPI) as a moderating variable, we explore whether corruption amplifies or dampens the positive impact of academic freedom on green innovation. While academic freedom fosters an open and competitive knowledge ecosystem, corruption can distort incentives and hinder merit-based resource allocation.

"Green innovation" or innovation aimed at reducing the environmental harm of human activities and efficient use of natural resources has been advocated by intergovernmental organizations such as the United Nations on the global scale or the European Union – regionally. Recent EU regulations like the Corporate Sustainability Reporting Directive (CSRD) that entered into force in 2023 require companies to disclose their practices vis-a-vis the environment, their governance principles and social obligations. Green technology is becoming one of the instruments of fulfilling these legal requirements. Simultaneously, the EU launched the European Green Deal in 2020, a set of policies encouraging green innovation and featuring funding schemes aimed at reaching climate neutrality in the EU by 2050. Horizon Europe is the EU's large-scale research and innovation program (2021–2027) that funds industry-academia partnerships in green innovation. This "carrots and sticks" approach is practiced to different degrees in other countries as well.

Green innovation implies reducing pollution and other negative impacts of economic activity on nature, as well as mitigating climate change. But green patent output has declined in the last decade, which raises concerns whether the present level of innovation is sufficient to meet the net-zero challenge (Cervantes, et al., 2023). The academic freedom is also in decline (Audretsch et al., 2024). In the past decade, academic freedoms declined in Eastern Europe Central Asia, South America, Latin America and in the Asia–Pacific region with Afghanistan and Hong Kong leading the race to the bottom. China and India have witnessed substantial declines in academic freedom affecting about three billion people (Papada et al., 2023). Academic freedom is also declining in liberal democracies like the US and UK (Papada et al., 2023).

At the backdrop of declining academic freedom, growing global environmental concerns and the surge of patenting worldwide (Hartung, 2025), understanding the effect of academic freedom on green patent output by different participants of the national innovation system is important. This paper addresses the relationships between "green patent output" and Academic Freedom Index (AFI), a measure of quality and independence of academic scholarship and instruction. Of course, patent output is only one element of the innovation value chain. And not all inventions end up as patent applications. We use the so-called “international” or Patent Cooperation Treaty (PCT) filings as a source of patent data. PCT applications are filed in multiple countries simultaneously, which implies a higher level of commitment by an applicant. And they promise a higher impact globally than domestically oriented applications. In the following section we discuss the link between academic freedom and innovation, the moderating effect of corruption and then present our methodological approach, results and draw conclusions.

Literature Review

Academic Freedom and Innovation

Technological globalization, including the recent developments in the field of information technology, put the role of institutions in innovation into the spotlight. As economic history demonstrates, institutions have played a key role in technical change (King et al., 1994). Democratic institutions, which imply low levels of corruption and a system of rewards based on merit rather than nepotism, are believed to have a positive effect on innovation generated by domestic companies and other entities (Mungiu-Pippidi, 2015). A few scholars explored the link between institutions and cross-national discrepancies in national rates of innovation (Huang & Xu, 1999; van Waarden, 2001; Tebaldi & Elmslie, 2013; Taylor, 2009; Cvetanovic & Sredojevic, 2012; Gao et al., 2017; Ervits & Zmuda, 2018). Knutsen (2015) explains that the characteristics of democracies like freedom of speech, press, assembly and travel create a more conducive environment for the spread of ideas, engender creativity, exchange of information and open discussion. Academic freedom is another inalienable part of democratic values. Autocracies, on the contrary, stifle alternative points of view and, thus, by association, they also should stifle innovation.

Vrielink et al. (2011) contend that academic freedom is a fundamental individual right[1] that refers to a “system of complementary rights of teachers and students, mainly as free enquirers. It includes at least the following and interrelated aspects: (i) the freedom to study, (ii) the freedom to teach, (iii) the freedom of research and information, (iv) the freedom of expression and publication (including the right to err), and (v) the right to undertake professional activities outside of academic employment” (p. 123).

The provisions pertaining to academic freedom are part of national constitutions and international law, for example, the European Convention on Human Rights (1950) of the Council of Europe and the UN International Covenant on Civil and Political Rights (1966) and International Covenant on Economic, Social and Cultural Rights (1966). Article 13 of the Charter of Fundamental Rights of the European

[1] Apart from academic freedom as an individual right, there is also an institutional right aspect, as well as the obligations of public authorities to respect academic freedom (Audretsch et al., 2024).

Union states that “arts and scientific research must be free from constraint” (European Union, 2007).

Academic freedom is the basis for knowledge production, especially innovation, which leads to the development and patenting of technologies for environmental sustainability (Aghion et al., 2008). Open disclosure and freedom of critique are the cornerstones of science. Knowledge can only result from open and transparent information exchange mechanisms (Larsson et al., 1998), which exist in free academia. Related research on social freedom emphasizes the role of social tolerance (Lehmann & Seitz, 2017) in fostering knowledge flows and creativity. Lehmann and Seitz (2017) use an index that reflects the level of hospitality toward homosexuals as a measure of social tolerance. They find a positive relationship between social freedom and innovation capacity. However, there is still little research on the role of academic freedom in innovation (Audretsch et al., 2024). This paper empirically investigates this relation.

Academic Freedom, Corruption and Innovation

The free exchange of ideas, the openness to criticism and the independence of academic institutions are essential elements of scientific development that foster innovation. At the same time, corruption modifies this effect by limiting or distorting the mechanisms of scientific activity (Knutsen, 2013; Shleifer & Vishny, 1993). In countries with high levels of corruption, these mechanisms are weakened by political pressure, censorship and inefficient allocation of resources, which limits the possibility of independent research and affects the quality of scientific activity (Murphy et al., 1991).

Corruption also affects the commercialisation of knowledge and technology. In systems with high levels of corruption, decisions on research funding may be based on personal connections rather than its scientific value (Mironov & Zhuravskaya, 2016). As a result, countries with high levels of corruption may have lower innovation performance, including in the areas of environmental research, as academic freedom and scientific integrity are threatened (Bhattacharyya & Jha, 2013).

Thus, academic freedom, which is a prerequisite for the early stages of scientific research, is closely linked to the level of corruption in a country. Universities play an important role in the creation and dissemination of knowledge, and undermining their autonomy through corruption negatively affects a country’s ability to generate high-quality inventions (Mungiu-Pippidi, 2015). Environmental innovation is especially vulnerable to corruption, as it is the type of technology that draws special attention from the government as part of promoting sustainable development. Therefore, in this paper we explore the moderating effects of the Corruption Perceptions Index (CPI) on the relationship between academic freedom and green patent output.

Green Innovation by Different Participants of the National Innovation System

The threat of climate change requires collaborative efforts from various stakeholders (Wang et al., 2025). Universities and academic research play a critical role in the green transformation of the economy. Universities have been called to “serve as "living labs" developing, testing, and upscaling innovative energy and climate technologies" (Mesot, 2023). And they are responding to the call by partnering with the industry and generating highly socially and environmentally impactful inventions (Ervits, 2024).

Universities, where academic freedom allows scientists to pursue their interests, mainly engage in early-stage research (Aghion et al., 2008). Thus, especially the early-stage research process is directly linked to academic freedom, the ability to exercise inquisitiveness, unconstrained exploration and freedom of critique. Academic research shares several features that differentiate it from research pursued in the private sector. The features include the tenure process that is part of the academic reward system and guarantor of academic freedom, peer review procedures in publications or in allocation of prizes. These features can properly be implemented to generate and diffuse knowledge only if there is a sufficient degree of academic freedom (Audretsch et al., 2024). The importance of academic research for innovative output has been stressed by various scholars (Furman et al., 2002; Lee, 2000; Motohashi, 2008). Universities conduct basic research, explore and generate new knowledge, while the industry is better at appropriating, applying and commercializing technology to gain competitive advantage (Bruneel, et al., 2010; Hall et al., 2003; Tian et al., 2022).

For companies, green innovation serves as a source of competitiveness and a way to improve the market position, attract customers and cut costs by using resources more efficiently (Chavira et al., 2023; Cobbinah et al., 2025; Takalo et al., 2021). Green innovation also enhances corporate value (Saeed et al., 2025**).** And, of course, green innovation is good for society at large. The process of R&D conducted in the private sector results in invention, the initial stage of the innovation process involving exploration and conceptualization of novel products and solutions. Invention can result in patenting. Then, companies apply the technical solutions described in a patent application, translate into products, services or processes and commercialize. Thus, green innovation can be exercised through the collective efforts of universities, government funded research institutes, individual inventors who might or might not be business proprietors and companies. These are different participants of the national system of innovation that generate and diffuse new technologies and solutions as a network (Freeman, 1987; Lundvall, 1992). And academic freedom creates a conducive environment for all these invention-producing entities.

Hypotheses and Conceptual Framework

The recent study by Audretsch et al., (2024) focusing on the relationship between academic freedom and innovation output – the topic that had not been addressed for decades – use the V-Dem Index of Academic Freedom (AFI) and patent data as a measure of innovation output. They conclude that there is a positive relationship between the two variables: as academic freedom increases; the patent output also increases. We have a narrower focus on green patent output and the AFI. We also look at the effect of AFI interacting with the Corruption Perception Index (CPI).

H: There is a positive relationship between the Index of Academic Freedom (AFI) and green patent output.
Ha: There is a positive relationship between AFI and green patent output using the interaction of AFI with the Corruption Perceptions Index (CPI) as a control variable.
H1: There is a positive relationship between AFI and green patent output by companies.
H1a: There is a positive relationship between AFI and green patent output by companies using the interaction of AFI with CPI as a control variable.
H2: There is a positive relationship between AFI and green patent output by individuals.
H2a: There is a positive relationship between AFI and green patent output by individuals using the interaction of AFI with CPI as a control variable.
H3: There is a positive relationship between AFI and green patent output by universities.
H3a: There is a positive relationship between AFI and green patent output by universities using the interaction of AFI with CPI as a control variable.
H4: There is a positive relationship between AFI and green patent output by public research organizations.
H4a: There is a positive relationship between AFI and green patent output by public research organizations using the interaction of AFI with CPI as a control variable.

We assume that academic freedom has a similar effect on the four different participants of the national system of innovation. Patenting is associated with the first stage of the innovation process—invention. Invention, which involves creating a new product or process that may or may not have economic value (King et al., 1994, p 140), has been frequently treated as a proxy for technological change and operationalized as patent statistics. And it is strongly associated with freedom to pursue and exchange creative ideas, experiment and explore. These are the important components of academic freedom.

Methods and Data

Variables

Measure of Internationally Oriented Green Invention

Economists, operating at the macro level, treat patent data as an indicator of technical change or inventive output (Comanor & Scherer, 1969; Griliches, 1990). *According to the World Intellectual Property Organization (WIPO), a patent is "a set of exclusive rights granted by law to applicants for inventions that are new, non-obvious and commercially applicable. It is valid for a limited period of time (generally 20 years), during which patent holders can commercially exploit their inventions on an exclusive basis. In return, applicants are obliged to disclose their inventions to the public in a manner that enables others, skilled in the art, to replicate the invention" (*WIPO, 2019*).* A patent indicates a promise of innovation or commercial application of technology, not its material realization yet (plus, patent applications differ considerably in quality and commercial potential). Thus, Griliches (1990) notes that a patent should satisfy the requirements of novelty and applicability and can be utilized as a measure of invention implying a commercialization intention.

We use the unique dataset of “international” or Patent Cooperation Treaty (PCT) patent filings compiled by Ervits et al. (2024). The PCT filings are referred to as “international” because they can be filed in multiple countries simultaneously with a single application. The dataset contains International Patent Classification (IPC) “green patent” filings based on the World Intellectual Property Organization (WIPO) PatentScope patent data for the years 2014–2021 (PatentScope, 2023). As per this dataset, 78 countries filed “green” PCT applications in the period between 2014 and 2021. The patent applications are classified as “green applications” followings the Environmentally Sound Technologies (ESTs) IPC technology codes as per United Nations Framework Convention on Climate Change (UNFCCC) (WIPO, 2023). The PatentScope database provides access to the list of patent applications filed in a particular year. These lists contain the first IPC code as the most relevant to the invention described in the patent application. Thus, patent applications have been categorized as “green” after matching the first IPC code with the “green” EST IPC codes. The dataset groups green patents into four categories: company, individual, university and research institute/government agency. Throughout the entire period covered in the dataset (2014–2021), companies consistently accounted for more than 83 percent of all green patent applications, making them the dominant category of applicants.

Measure of Academic Freedom

Following Audretsch et al. (2024), we use the V-Dem Index of Academic Freedom (AFI). The V Dem Institute at the University of Gothenburg administers the V-Dem Electoral Democracy Index (V-Dem, 2024) and offers AFI data together with other democracy indices. The V-Dem indices capture the state of democratic institutions and values based on country experts’ evaluations (Coppedge et al., 2023). The Academic Freedom Index (AFI) assesses the levels of academic freedom across the world and is a result of collaboration between Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), and the V-Dem Institute (AFI, 2024).

The V-Dem Academic Freedom Index (AFI) aggregates five indicators: freedom to research and teach; freedom of academic exchange and dissemination; institutional autonomy; campus integrity; and freedom of academic and cultural expression (Coppedge et al., 2023). Academic freedom is understood as the right of academics to freedom of teaching and discussion, freedom in carrying out research and disseminating and publishing the results thereof, freedom to express freely their opinion about the institution or system in which they work, freedom from institutional censorship and freedom to participate in professional or representative academic bodies (UNESCO 1997 Recommendation concerning the Status of Higher-Education Teaching Personnel) (Coppedge et al., 2023, p. 317). The Academic Freedom Index is designed to provide an aggregated measure that captures the de facto realization of academic freedom, including the degree to which higher-education institutions are autonomous. The scale is from low to high (0–1) (Coppedge et al., 2023).

V-Dem uses a pool of over 3,700 country experts who produce judgements about the state of democracy or academic freedom in different countries. The resultant measures are checked for subjectivity by an algorithm that estimates both the degree to which an expert is reliable relative to other experts, as well as the degree to which their perception of the response scale differs from other experts (Papada et al., 2023). A "country expert" is a scholar or professional with deep knowledge of a country and of a particular political institution. Furthermore, the expert is usually a citizen or resident of the country (Coppedge et al., 2023).

Control Variables

We examine the impact of academic freedom on the innovation potential of countries through the number of green patent filings per capita. To ensure the accuracy and completeness of the results, several control variables are included in the analysis, as a country's innovation potential can vary significantly depending on its foreign economic policy and investment attractiveness. Following Opoku and Acheampong (2023), we control for trade openness (TO) and foreign direct investment (FDI). Trade openness is measured as exports + imports as a percentage of GDP (World Bank Group (2024a)). FDI is measured as net inflows and outflows of foreign direct investment as a percentage of GDP (World Bank Group (2024b)).

We use interaction between the Academic Freedom Index (AFI) and corruption proxied by the Transparency International's Corruption Perceptions Index (CPI) as a control variable in our model (Transparency International, 2021). Countries are scored on a scale from 0 to 100, where 0 indicates "highly corrupt" and 100 – minimal level of corruption. As the methodology changed in 2012, we have adjusted the older CPI values (2009–2011) by multiplying them by 10. The data obtained was standardised using the parameters of the base year 2012.

Model Testing

We introduce time lags of two (X2_) and five years (X5_), covering the periods 2012–2019 and 2009–2016 respectively. The use of time lags allows us to account for the impact of academic freedom on invention. We measure the short- and long-term impact of academic freedom, which reflect the real-world conditions: on the one hand, academic freedom can stimulate research activities, on the other hand, invention takes time to be translated into patents. To estimate this impact, we use a linear regression (Eq. 1):

$$\ln\left(GP_m\right) = \alpha_0 + \alpha_1 \times AFI + \sum_{i=1}^{4} \beta_i \times CV_i + \varepsilon, \tag{1}$$

where: $\ln\left(GP_m\right)$ is the logarithm of the number of applicants for "green patents" of type m per capita:

$m = 1 \ldots 4$ – types of applicants "green patents", where 1 – university, 2 – company, 3 – research institutions, 4 – individual, 5 – total;

AFI is the Academic Freedom Index;
CV_i is a set of control variables:
$i = 1 \ldots 4$, where 1 – trade openness (TO); 2 – net inflows of foreign direct investment percentage of GDP (FDI_{in}); 3 – net outflows of foreign direct investment percentage of GDP (FDI_{out}); 4 – Corruption Perceptions Index (CPI);
$\alpha_0, \alpha_1, \beta_i$ are the unknown coefficients to be estimated;
ε is the disturbance error term.

We do not include time and country fixed effects, as the focus of our study is on identifying general trends and relationships between key variables, rather than country or time-specific variations.[2] This approach allows us to focus on the direct impact of academic freedom and its interaction with other factors. However, we extend Eq. (1) to include the interaction (Bauer & Curran, 2005) between the academic freedom index and the level of corruption (Eq. 2):

$$\ln (GP_m) = \acute{\alpha}_0 + \acute{\alpha}_1 \cdot AFI + \sum_{i=1}^{3} \dot{\beta}_i \times CV_i + \theta_1 \cdot (AFI \times CPI) + \varepsilon, \tag{2}$$

where: $\acute{\alpha}_0, \acute{\alpha}_1, \dot{\beta}_i, \theta_1$ are the unknown coefficients to be estimated.

Including the interaction between AFI and CPI in the equation allows for a deeper understanding of how different levels of corruption can modify the effect of academic freedom on invention. Within the framework of institutional theory (Hall & Soskice, 2001), the ability of scientific institutions to operate effectively depends on the level of corruption in a country, as invention often requires regulation and support from the state. Academic freedom combined with low levels of corruption provides scientists and entrepreneurs with access to funding and intellectual property (IP) protection, which is critical for the development of new environmental technologies.

To explicitly identify how changes in corruption can strengthen or weaken the impact of academic freedom on invention, we apply differential Eq. (3) to determine the marginal effect (Esarey & Sumner, 2018):

$$\frac{\partial \ln (GP_m)}{\partial AFI} = \acute{\alpha}_1 + \theta_1 \cdot CPI, \tag{3}$$

This equation allows us to assess whether a reduction in corruption increases the positive impact of academic freedom on a country's invention potential. This approach deepens our understanding of the dynamics of the relationship between academic freedom, corruption and invention.

We estimate the standard errors (Eq. 4) and statistical significance (Eq. 5) of the marginal effect using the delta method (Tsionas, 2019). The introduction of a control variable – interaction between AFI and CPI – adds robustness to our model aimed at identifying the relationship between academic freedom and the number of green pat-

[2] We plan, however, to build on our model in future research and conduct a similar study with a breakdown of countries into developed and developing. This may help to mitigate the fact that we did not take fixed effects into account even though we have panel data.

ent filings, depending on the level of corruption. In other words, we assess whether the impact of academic freedom on invention varies depending on the level of corruption.

$$SE = \sqrt{Var\left(\acute{\alpha}_1\right) + CPI^2 \cdot Var\left(\theta_1\right) + 2 \cdot CPI \cdot Cov\left(\acute{\alpha}, \theta_1\right)}, \tag{4}$$

where: $Var\left(\acute{\alpha}_1\right)$ and $Var\left(\theta_1\right)$ are the variance of the coefficients $\acute{\alpha}_1$ and θ_1, respectively (i.e. the square of their standard errors);

$Cov\left(\acute{\alpha}_1, \theta_1\right)$ is the covariance between the estimates of the coefficients $\acute{\alpha}_1$ and θ_1.

$$p - value = 2 \cdot P\left(T > |t|\right), \tag{5}$$

where $P\left(T > |t|\right)$ is the probability that the random variable T, which has a t-distribution (Student's distribution) with the appropriate number of degrees of freedom, exceeds the absolute value of the calculated t-statistic:

$$t = \frac{\acute{\alpha}_1 + \theta_1 \cdot CPI}{SE}. \tag{6}$$

In addition to estimating the marginal effect, we use the Johnson-Neyman (J-N) method (Johnson & Fay, 1950) to identify the CPI bounds at which changes in academic freedom become statistically significant in the context of changes in corruption, adding a new dimension to understanding the complex interactions between these two variables. To visualise the results, we plot the J-N intervals on a graph (Long, 2024), which shows the areas of significant and insignificant impact of academic freedom depending on the level of corruption.

As our model uses many observations, we follow the recommendations on the use of standard errors for large samples (Pinzon, 2022). Before interpreting the results, we check the basic assumptions of the linear regression. Since statistical tests such as Shapiro–Wilk can be uninformative with large amounts of data, we analyse the skewness and kurtosis of the residuals and assess the normality of their distribution using graphical analysis: Q-Q (Normal P-P) plot (where the points should lie along the diagonal in the case of a normal distribution) and histograms of the residuals (which should have a shape close to the normal distribution). In addition, we perform diagnostic tests for the presence of autocorrelation of residuals (Durbin-Watson test), heteroscedasticity (Breusch-Pagan test), multicollinearity (variance inflation factor, VIF) and estimate the significance of the whole regression model (F-statistic) (Tsionas, 2019). SPSS and RStudio software were used for analysis, including packages for Breusch-Pagan test (lmtest), Johnson-Neyman intervals and graphs (interactions).

Analysis of Results

Data Description and Correlation Analysis

Summary statistics for the variables are presented in Table 1.

The analysis of the descriptive statistics shows a significant variation in the number of green patents between countries, especially for firms (Std. dev. = 1.921), indicating a high degree of diversity in the patenting activities of firms. The lowest variation is observed for individual applicants (Std. dev. = 1.174). All distributions have a negative skewness, indicating a shift to the left, with the largest shift for universities (−0.761). The kurtosis for most variables indicates a flat-topped distribution, especially for companies (−1.059). This implies the presence of frequent values with a smaller deviation from the mean.

The AFI values are between 0.021 and 0.978, with an average of 0.703 for the two-year time lag and 0.711 for the five-year time lag. The index shows a tendency for most countries to have high values, with a negative skewness, indicating that most countries have high values. CPI has values ranging from 11 to 92, with an average of 50.086 (two-year time lag) and 49.133 (five-year time lag), indicating a wide range of variables with a tendency towards a normal distribution. The coefficients of variation of the corruption index are low reflecting a moderate stability of this indicator. The results of Spearman's rank correlation, revealing statistically significant relationships between the variables, are presented in Table 2.

AFI is moderately strongly linked to the number of green patents, especially patent applications generated by companies and total patents with both two- and five year-time lags. This shows that academic freedom has a long-lasting effect on green patent output. CPI has a strong, statistically significant association with the number of patent filings, showing that the quality of institutions is important for stimulating green invention. And this is true both in the short and long term. Trade openness (TO) also has a positive effect on patents, especially for filings produced by universities and research institutions. Foreign direct investment and green patent applications do not have a strong relationship. FDI inflows have no significant effect on patents, while outflows of FDI are correlated with patent applications of different categories but in the short, two-year time lag term.

Regression Analysis Results for Models With a Two-year Time Lag

Table 5 presents the results of linear regression for all dependent variables (different types of green patent filings) with a 2-year time lag. Model (1) explains a significant proportion of the variation in the dependent variables (R Square ≈ 0.413–0.735), This indicates that the independent variables have sufficient explanatory power, which is slightly increased in model (2). High F-statistic values with high significance ($p < 0.001$) confirm the overall statistical significance of the models.

The results of model (1) show that academic freedom has a positive effect on the number of green patents filed by most categories of applicants, except for universities (H, H1, H2, H3, H4). In other words, the more academic freedom there is, the more patents are filed. In model (2), which looks at how AFI and CPI interact, the significance of AFI goes down and the effect for "Company" becomes negative (H1a). This means that in countries enjoying less corruption and more academic freedom, patent output by companies goes down. We offer explanations to this phenomenon when we discuss the moderating effects of corruption and the Johnson-Neyman confidence intervals in Table 5 below.

Table 1 Descriptive statistics

Variables			Min	Max	Mean	Median	Mode	Std. dev	Skewness	Kurtosis	N (valid)
Dependent variables											
Logarithmic number of green patents according to the type of applicant	Company	$\ln(Com)$	−18.593	−10.502	−14.217	−13.987	−18.593	1.921	−0.226	−1.059	375
	Individual	$\ln(Ind)$	−19.130	−12.723	−15.829	−15.670	−19.130	1.174	−0.307	−0.246	393
	University	$\ln(Univ)$	−20.354	−13.356	−15.994	−15.855	−20.354	1.335	−0.761	0.855	266
	Research Institution	$\ln(RI)$	−19.967	−12.200	−16.323	−16.187	−19.967	1.466	−0.235	−0.227	178
	Total	$\ln(Total)$	−19.130	−10.441	−14.411	−14.497	−19.130	1.935	−0.126	−0.910	497
Independent variable											
Index of Academic Freedom		X2_AFI	0,021	0.978	0.703	0.850	0.968	0.299	−1.074	−0.330	736
		X5_AFI	0,021	0.981	0.711	0.863	0.922	0.294	−1.107	−0.210	736
Control variable											
Trade openness, sum export and import (% of GDP)		X2_TO	15.282	382.348	89.849	74.628	15.282	57.128	2.190	6.772	725
		X5_TO	15.282	379.099	88.377	73.118	15.282	54.729	2.344	7.996	723
Foreign direct investment, net inflows (% of GDP)		$X2\_FDI_{in}$	−40.263	452.221	6.783	2.368	−40.263	29.744	9.551	108.374	712
		$X5\_FDI_{in}$	−22.412	279.361	6.113	2.464	−22.412	20.637	8.862	93.985	714
Foreign direct investment, net outflows (% of GDP)		$X2\_FDI_{out}$	−85.890	453.163	4.875	0.725	0.000	31.606	8.617	92.467	696
		$X5\_FDI_{out}$	−85.890	300.421	3.984	0.791	0.000	24.110	7.995	85.182	698
Corruption Perceptions Index Score		X2_CPI	11.000	92.000	50.086	44.000	38.000	19.960	0.453	−0.890	736
		X5_CPI	11.000	95.000	49.133	43.000	38.000	21.285	0.551	−0.870	736

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 2 Results of Spearman's correlation test

Variables	$\ln(Com)$	$\ln(Ind)$	$\ln(Univ)$	$\ln(RI)$	$\ln(Total)$	AFI	TO	FDI_{in}	FDI_{out}	CPI
two-year time lag										
AFI	0.442 ***	0.496 ***	0.238 ***	0.175 **	0.542 ***	1	0.288 ***	0.123 ***	0.162 ***	0.580 ***
TO	0.257 ***	0.355 ***	0.348 ***	0.530 ***	0.299 ***	0.288 ***	1	0.269 ***	0.220 ***	0.387 ***
FDI_{in}	−0.087 *	0.088 *	−0.015	0.071	−0.021	0.123 ***	0.269 ***	1	0.386 ***	0.054
FDI_{out}	0.301 ***	0.281 ***	0.293 ***	0.395 ***	0.381 ***	0.162 ***	0.220 ***	0.386 ***	1	0.384 ***
CPI	0.811 ***	0.616 ***	0.611 ***	0.564 ***	0.863 ***	0.580 ***	0.387 ***	0.054	0.384 ***	1
five-year time lag										
AFI	0.390 ***	0.464 ***	0.193 ***	0.109	0.520 ***	1	0.225 ***	−0.024	0.000	0.512 ***
TO	0.259 ***	0.343 ***	0.362 ***	0.537 ***	0.285 ***	0.225 ***	1	−0.060	−0.068 *	0.346 ***
FDI_{in}	0.003	0.034	0.045	0.028	0.018	−0.024	−0.060	1	0.375 ***	−0.040
FDI_{out}	−0.073	0.092 *	−0.035	−0.014	0.012	0.000	−0.068 *	0.375 ***	1	−0.033
CPI	0.733 ***	0.563 ***	0.559 ***	0.543 ***	0.777 ***	0.512 ***	0.346 ***	−0.040	−0.033	1

*** $-p<0{,}01$; ** $-p<0{,}05$; * $-p<0{,}1$

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

For "Individual", AFI is still positive, but its effect is weaker. Estimates show that the number of green patents increases by 0.932 points for a 1-point increase in AFI in model (2). This is different from the results in model (1), where AFI increases by 1.022 points, all other things being equal. This means that while academic freedom still increases the number of patents (H2), it does so to a lesser extent when the effect of the interaction between AFI and corruption is taken into account (H2a).

Academic freedom has a positive effect on "University" and "Research institutes" in model (2). The estimates show that the number of green patents increases by 1.764 and 2.425 points respectively for a 1-point increase in AFI in model (2). This is different from the results of model (1), where the increase in AFI is 0.222 and 0.931 points respectively, all other things being equal. This suggests that with higher levels of academic freedom, universities and research institutes tend to participate more actively in green patenting, especially when we adjust for the interaction between AFI and corruption. (H3a and H4a).

The regression coefficients reveal that academic freedom generally increases the number of green patent applications, but the effect is different for different types of applicants. Individuals, universities and research institutions benefit from greater academic freedom, while companies may suffer negative effects, depending on the level of corruption in the country. The effects of AFI are, however, more pronounced in the model accounting for the interaction of AFI with CPI.

Among the control variables, trade openness has a statistically significant positive relationship with the number of green patents per person in models (1) and (2), except for the “Total” category. The level of corruption has a statistically significant positive relationship with the number of patents in all categories of applicants ($p < 0.01$). Net inflows and outflows are significant only for the categories “Company” and “Individual” in both models, and for “Research institutes” in model (2). In other cases, the relationship is not significant. FDI inflows and outflows have a complex relationship involving an interplay of domestically oriented and international investment strategies for financing innovation. We found that the effects of FDI inflows and outflows often cancel each other out. The control variables FDI_{in} and FDI_{out} have a high level of multicollinearity in both models based on Eqs. (1) and (2) for the categories “Company” and “Research institutes”. This may lead to instability in the coefficient estimates.

The models in Eq. (2) show multicollinearity between AFI and CPI. This is to be expected, as we treat their interaction as a separate variable. The analysis of the model residuals showed that for most models, the skewness is close to zero, indicating a symmetrical distribution. Only for the categories “University” and “Research Institutes” the skewness values may indicate a slight asymmetry but are insignificant and, thus, unlikely to have an impact on the models. The kurtosis values for all models are close to zero or negative, which indicates a relatively “flat” distribution of the residuals. This implies that there are no significant deviations from the normal distribution. Only for the “University” category, the kurtosis is slightly above zero (0.467 and 0.378), which may indicate a slight concentration of values around the mean, but this deviation is also insignificant. Looking at the graphs, we can see that the data is normally distributed (see Tables 7-10 in Appendix). Overall, the analysis of the residuals did not show any major problems with normality.

Our model with the two-year lag confirmed that academic freedom and corruption have a big effect on the number of green technology patent filings. Academic freedom makes universities, research institutes and individual inventors file more patents, but its effect on companies is more uncertain and may be negative when we consider the interaction of corruption with academic freedom. We will address this result below when we discuss the Johnson-Neyman (J-N) intervals in Table 5. The interaction effect between academic freedom and corruption shows that the positive effect of academic freedom is stronger in countries with lower corruption, highlighting the need for a comprehensive approach to innovation policy that combines support for academic freedom with anti-corruption measures. Trade openness and FDI have a statistically significant positive relationship with the number of green patent application, while the impact of FDI is marginal.

Regression Analysis Results for Models With a Five-year Time Lag

Table 4 presents the results of linear regression for all dependent variables with a 5-year time lag. These models serve primarily as a comparative tool for assessing differences in the impact of academic freedom and other independent variables over a longer adjustment period. Model (1) explains a significant share of the variation in the dependent variables (R Square ≈ 0.374–0.631), which indicates that they have sufficient explanatory power, which is slightly increased in model (2). However, R Square values in the models with a 2-year time lag are higher. High, statistically significant F-statistic values ($p < 0.001$) confirm the overall statistical significance of the models. All of this suggests that academic freedom has a stronger effect in the short term, and in the longer term this effect might be mitigated by cultural and social factors and other elements of the economic and political situation (H, H1, H2, H3, H4).

As in the models with a 2-year time lag, academic freedom has a positive and significant effect at the $p < 0.01$ level for most categories of green patent applicants in Eq. (1), except for the "University" category (H3). In the models based on Eq. (2), the AFI coefficients are not statistically significant for individuals (H2a), universities (H3a) and research institutes (H4a).

This means that in the models with a 5-year time lag, the effect of AFI is much smaller than in the models with a 2-year time lag. At the same time, there is some improvement in the model with the AFI and CPI interaction as the control variable for the "Individual" category, whose coefficient becomes significant at the 5% level (0.019, $p < 0.05$). This suggests that people may need more time to adapt to changes in academic freedom, especially in places with high or low corruption.

Among the control variables, trade openness has a statistically significant positive relationship at the level of $p < 0.01$ with the number of green patents per person in models (1) and (2), except for the category "Company", where the significance level is $p < 0.05$. Net inflows and outflows are insignificant for all categories. The level of corruption has a statistically significant positive relationship with the number of patents in all categories of applicants, except for the Company and Individual categories in Eq. (2).

The model with a 5-year time lag is different from the models with a 2-year time lag. With the 5-year model, there is a high level of multicollinearity between the control variables FDI_{in} and FDI_{out}, but this is only for the "Research institutes" category. In the "Company" category, the VIF value decreased by half, which means that the coefficient is less likely to be unstable in this group. There was no significant multicollinearity for the other categories. At the same time, in the models based on Eq. (2), the multicollinearity between FDI and CPI is expected, since their interaction variable is included in the model.

When we compare the models with a 2-year and 5-year time lag, there are some differences in the skewness and kurtosis of the residuals. In the models with a 5-year time lag, there is a more obvious unevenness in the distribution of residuals, especially for the "Company" category, where the skewness has increased a lot. The increased right-hand side slope of the residuals suggests that the distribution of effects has shifted, possibly due to outliers or longer adjustment periods for certain companies.

We also saw similar results for kurtosis values. In models with a 5-year time lag, the distribution of residuals became more peaked, especially in the Company and Total categories. At the same time, for other groups, the kurtosis values remained close to zero or negative, indicating a relatively flat distribution. The visualisation of the results (see Tables 11-14 in Appendix) also shows some changes in the distribution of residuals.

The Durbin-Watson (DW) test is used to assess the presence of autocorrelation of the residuals in the 2-year and 5-year time lagged models. Models with a 2-year time lag show DW values in the range of 0.755–1.430 and models with a 5-year time lag – 0.645–1.480. The lowest DW values indicate strong positive autocorrelation of the residuals, while values closer to 2 indicate moderate positive autocorrelation. As the DW values in most models are significantly lower than 2, this indicates the presence of strong positive autocorrelation. Overall, the five-year time lagged models confirm the main findings of the study, while highlighting temporal variations in the impact of academic freedom and other variables.

Heteroscedasticity and Its Impact On the Interpretation of the Results

The Breusch-Pagan test for the 2-year time lag models shows statistically significant heteroskedasticity ($p < 0.01$) for most types of applicants. For patents filed by companies, the test value is 21.654 in the model without the AFI and CPI interaction and 35.286 in the model with the interaction, for individual applicants – 22.832 and 23.381, for universities – 22.985 and 27.101, and for the total number of patents – 20.467 and 24.861. The exception is patents filed by research institutes, where the test is not statistically significant (5.764 in the model without interaction and 5.053 in the model with interaction). These results indicate that the variability of the residuals is stable for this group. It is important to note that heteroscedasticity is more pronounced in the models with the interaction between AFI and CPI (model 2), which may indicate the need to correct standard errors or use alternative estimation methods.

In the models with a 5-year lag, there is a tendency for heteroscedasticity to increase, especially for companies (47.526 in all models, $p < 0.01$), universities (37.115 in all models, $p < 0.01$) and total patents (44.849 in all models, $p < 0.01$). In contrast, for individual applicants, the level decreased compared to the 2-year time lag. As in the previous case, the test is not statistically significant for patents filed by research institutes (5.444 in all models), which confirms the stability of the variance of the residuals in this group. The lag, therefore, has a significant effect on the variability of the residuals.

In general, the analysis shows that heteroskedasticity increases with a longer time lag, which may be due to:

(1) the cumulative effect of the institutional environment – the longer the observation period, the more factors (economic crises, policy changes, access to investment) affect patenting activity;
(2) strategic decisions by firms – larger firms are likely to adjust their patenting strategies depending on the economic context, which increases the variability in the longer term;
(3) changes in university funding – grant cycles and research trends can cause fluctuations in the number of patents.

Heteroscedasticity is found in several economic studies (Bollerslev, 1986; Deaton, 1992; Engle, 1982). Deaton (1992) notes that higher incomes are often associated with greater variability in expenditure patterns, as wealthier households may have a wider range of expenditures depending on their lifestyle, investments and savings. Similarly, in our case, the variability in patent activity of different categories of applicants can be explained by their economic resources, strategies and investment opportunities.

Companies have much greater resources to invest in R&D and innovation projects, which can lead to greater variability in patenting activity. Large companies have developed patenting strategies that often depend on changes in the market or industry. Such variability in the number of patents filed reflects not only financial capabilities but also the innovation strategies of a company. Individual applicants have fewer resources than companies, which may reduce the variability of their patents. However, even among individual applicants, heteroscedasticity can arise due to personal factors such as professional activities or interests in particular scientific fields, which in turn affect the intensity and focus of patenting activity. A boom in innovation in certain fields can temporarily increase patenting activity. Universities are often a source of innovative developments that can be filed in various scientific fields. However, their patent activity can also show considerable fluctuations due to changes in research interests, funding and partnerships with the private sector. Research institutes have a more stable patent activity due to limited specialisation in certain scientific fields and consistent funding, which limits the variability of patents. Overall, heteroscedasticity is natural and associated with different economic characteristics and strategic objectives of applicants, reflecting not only their financial capabilities but also innovation strategies, partnerships, access to resources and technology cycles.

Moderating Effect of Corruption

To gain a deeper understanding of the relationship between AFI and the number of green patents, we examined the moderating effect of corruption using CPI as a moderator (in models (2) with the interaction between AFI and CPI). The analysis of the marginal effect of AFI in the models with 2-year and 5-year time lags (see Tables 3 and 4, variable “marginal effect (3)”) allows us to better understand the mechanisms of its impact on the dynamics of green patents by different categories of applicants. To determine the marginal effect, we used the maximum CPI values for the respective periods: with a 2-year time lag, CPI = 92, with a 5-year time lag, CPI = 95. The results show that there are significant differences between the categories and that these effects vary over time.

In the models with a 2-year time lag, academic freedom has a significant negative effect on the number of patents filed by firms (−7.058, $p < 0.01$). This trend continues in the models with a 5-year time lag (−7.292, $p < 0.01$), indicating a stable effect in the long term. This may indicate that increased academic freedom, which promotes openness of knowledge and dissemination of ideas, does not always translate into increased green patenting activity in the private sector. Companies may be relying more on internal R&D mechanisms and using other IP protection strategies like trade secrets as an alternative to patenting. Universities and public research institutes publish their ideas in academic journal articles. “Open access to knowledge” in the context of patenting creates two competing effects:

(1) the open access effect – the more academic freedom, the more open publications, which reduces the need for patents;
(2) the knowledge spillover effect – strong academic freedom improves cooperation between universities, companies and the public sector, which should stimulate patenting.

For individual inventors, the effect of academic freedom is insignificant in the short run (2-year time lag) (0.754, $p > 0.1$). However, in the long term (5-year time lag) it becomes negative and statistically significant (−1.365, $p < 0.01$). This may indicate a gradual adaptation of the environment of individual inventors, where increased academic freedom reduces the need for patents due to increased opportunities for open knowledge sharing.

The dynamics are different for universities and research institutes. Universities show a positive effect of academic freedom on patenting in the short term (2-year time lag) (4.502, $p < 0.01$), supporting the idea that high levels of academic freedom contribute to the generation of knowledge and technology that is then described in patent filings. However, in the long term (5-year time lag), this effect diminishes (1.369, $p < 0.1$). For research institutes, a similar trend is observed: in the short term, academic freedom has a positive effect on patenting (5.162, $p < 0.01$), while in the long term this effect decreases, although it remains significant (2.338, $p < 0.05$). This may be due to the fact that research institutes have stable financial mechanisms and are less prone to changes in their patenting strategy.

Regarding the total patenting rate (Total), academic freedom has a negative marginal effect both in the short run (−2.408, $p < 0.01$) and in the long run (−5.177, $p < 0.01$). In the 5-year time lag, this negative effect increases, suggesting systemic changes in the innovation ecosystem under the influence of academic freedom. It is also important to note that in the areas where the effect becomes insignificant, there may be a structural shift in the way IP is protected. The results of modelling the interactions between academic freedom (AFI) and corruption (CPI) show that the impact of academic freedom on innovation activity is highly dependent on the level of corruption in a country. The estimation of Johnson-Neyman confidence intervals (Table 5) allows us to identify the critical thresholds of the CPI above which the effect of academic freedom changes from statistically significant to insignificant or vice versa. Given the methodological peculiarities of the calculation of the CPI, which varies between 0 and 100, the confidence intervals obtained should be interpreted with this range in mind.

In the models with a 2-year time lag, the effect of academic freedom for firms is statistically significant outside the range [16.00, 44.84], indicating that in countries with a very low CPI (high corruption) or, conversely, with an extremely high CPI (low corruption), the effect of AFI on company patenting is significant. This may be due to the fact that in the context of extreme corruption, companies may use informal mechanisms to protect IP, while in low-corruption countries, open access to knowledge and academic freedom foster business innovation and may put less pressure on companies to legally "encircle" their inventions.

For a 5-year time lag, the boundaries of significance shift: the effect of academic freedom is significant outside the range [−2.41, 36.68]. This means that the long-term

Table 3 Results of estimating the coefficients of regression analysis with two-year time lag

Variables		Company		Individual		University		Research institutes		Total	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constants	coef	−19.632 ***	−17.581 ***	−18.126 ***	−18.063 ***	−19.165 ***	−20.323 ***	−19.773 ***	−20.900 ***	−19.229 ***	−18.462 ***
	error	(0.216)	(0.610)	(0.154)	(0.389)	(0.247)	(0.712)	(0.341)	(0.912)	(0.155)	(0.396)
AFI	coef	0.739 ***	−1.993 **	1.022 ***	0.932 *	0.222	1.764 *	0.931 ***	2.425 **	0.695 ***	−0.357
	error	(0.234)	(0.796)	(0.178)	(0.535)	(0.256)	(0.926)	(0.355)	(1.177)	(0.176)	(0.530)
	VIF	[1.279]	[15.220]	[1.361]	[12.249]	[1.331]	[17.510]	[1.202]	[13.306]	[1.275]	[11.646]
TO	coef	0.002 *	0.003 ***	0.002 **	0.003 **	0.004 ***	0.003 **	0.007 ***	0.006 ***	0.001	0.002 **
	error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
	VIF	[1.413]	[1.586]	[1.517]	[1.757]	[1.698]	[2.067]	[1.908]	[2.141]	[1.419]	[1.544]
FDI_{in}	coef	−0.032 ***	−0.029 **	0.020 **	0.020 **	0.006	0.005	−0.031	−0.034 *	−0.006	−0.006
	error	(0.012)	(0.012)	(0.009)	(0.009)	(0.016)	(0.016)	(0.020)	(0.020)	(0.008)	(0.008)
	VIF	[17.057]	[17.112]	[8.549]	[8.566]	[5.363]	[5.380]	[28.115]	[28.536]	[9.845]	[9.845]
FDI_{out}	coef	0.031 ***	0.027 ***	−0.017 **	−0.017 **	−0.015	−0.013	0.030	0.035 *	0.008	0.007
	error	(0.011)	(0.010)	(0.008)	(0.008)	(0.017)	(0.017)	(0.019)	(0.020)	(0.007)	(0.007)
	VIF	[16.029]	[16.155]	[7.713]	[7.716]	[4.810]	[4.838]	[25.727]	[26.483]	[9.142]	[9.150]
CPI	coef	0.076 ***	0.031 **	0.024 ***	0.022 **	0.042 ***	0.067 ***	0.034 ***	0.058 ***	0.075 ***	0.057 ***
	error	(0.004)	(0.013)	(0.003)	(0.009)	(0.004)	(0.015)	(0.005)	(0.019)	(0.003)	(0.009)
	VIF	[1.408]	[20.028]	[1.533]	[17.263]	[1.642]	[19.384]	[1.490]	[18.457]	[1.445]	[16.251]
AFI * CPI	coef	–	0.055 ***	–	0.002	–	−0.030 *	–	−0.030	–	0.022 **
	error	–	(0.015)	–	(0.011)	–	(0.017)	–	(0.022)	–	(0.011)
	VIF	–	[47.551]	–	[39.776]	–	[47.847]	–	[39.769]	–	[36.645]
marginal effect (3)	coef	–	−7.058 ***	–	0.754	–	4.502 ***	–	5.162 ***	–	−2.408 ***
	error	–	(0.691)	–	(0.534)	–	(0.737)	–	(0.999)	–	(0.507)
R Square		0.686	0.697	0.413	0.413	0.450	0.456	0.480	0.485	0.735	0.737
F-statistic		160.283 ***	140.026 ***	53.556 ***	44.521 ***	42.467 ***	36.161 ***	31.352 ***	26.540 ***	266.137 ***	224.094 ***
Skewness (un)st. res		0.191	0.363	0.052	0.054	−0.210	−0.178	0.337	0.305	0.262	0.302

Table 3 (continued)

Variables	Company		Individual		University		Research institutes		Total	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Kurtosis (un)st. res	−0.049	0.294	−0.068	−0.061	0.467	0.378	−0.258	−0.379	0.267	0.402
Durbin-Watson	0.898	0.878	1.426	1.424	1.065	1.084	0.755	0.778	1.053	1.044
Breusch-Pagan	21.654 ***	35.286 ***	22.832 ***	23.381 ***	22.985 ***	27.101 ***	5.764	5.053	20.467 ***	24.861 ***
N	373	373	386	386	266	266	176	176	486	486

*** $-p<0.01$; ** $-p<0.05$; * $-p<0.1$. Errors are indicated in brackets. VIF values are in square brackets. (1), (2) and (3) are equations, see above. "(un)st. res." are unstandardized and standardized residual

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 4 Results of estimating the coefficients of regression analysis with five-year time lag

Variables		Company		Individual		University		Research institutes		Total	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constants	coef	−19.132 ***	−16.884 ***	−18.049 ***	−17.479 ***	−18.646 ***	−18.884 ***	−19.396 ***	−19.824 ***	−18.846 ***	−17.323 ***
	error	(0.263)	(0.640)	(0.159)	(0.322)	(0.272)	(0.684)	(0.352)	(0.847)	(0.184)	(0.377)
AFI	coef	1.428 ***	−1.546 *	1.216 ***	0.395	0.451	0.769	0.698 *	1.258	1.355 ***	−0.794
	error	(0.286)	(0.824)	(0.186)	(0.445)	(0.295)	(0.886)	(0.378)	(1.077)	(0.208)	(0.510)
	VIF	[1.177]	[10.174]	[1.269]	[7.328]	[1.265]	[11.414]	[1.154]	[9.320]	[1.192]	[7.464]
TO	coef	0.002 **	0.004 ***	0.004 ***	0.004 ***	0.006 ***	0.005 ***	0.006 ***	0.005 ***	0.003 ***	0.004 ***
	error	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	VIF	[1.137]	[1.279]	[1.157]	[1.299]	[1.297]	[1.686]	[1.248]	[1.468]	[1.149]	[1.217]
FDI_{in}	coef	−0.006	−0.003	0.007	0.008	0.001	0.000	0.021	0.021	−0.001	0.000
	error	(0.010)	(0.010)	(0.006)	(0.006)	(0.008)	(0.008)	(0.023)	(0.023)	(0.007)	(0.007)
	VIF	[8.301]	[8.337]	[3.965]	[3.975]	[4.260]	[4.303]	[15.090]	[15.090]	[4.716]	[4.723]
FDI_{out}	coef	0.000	−0.002	−0.003	−0.003	−0.002	−0.002	−0.011	−0.011	−0.002	−0.003
	error	(0.008)	(0.008)	(0.004)	(0.004)	(0.006)	(0.007)	(0.017)	(0.017)	(0.005)	(0.005)
	VIF	[8.282]	[8.304]	[3.979]	[3.983]	[4.261]	[4.304]	[15.030]	[15.031]	[4.728]	[4.731]
CPI	coef	0.059 ***	0.009	0.018 ***	0.004	0.029 ***	0.034 **	0.032 ***	0.041 **	0.058 ***	0.022 **
	error	(0.004)	(0.014)	(0.003)	(0.008)	(0.004)	(0.015)	(0.005)	(0.018)	(0.003)	(0.008)
	VIF	[1.301]	[18.363]	[1.407]	[13.240]	[1.408]	[18.807]	[1.353]	[17.354]	[1.336]	[12.067]
AFI * CPI	coef	–	0.060 ***	–	0.019 **	–	−0.006	–	−0.011	–	0.046 ***
	error	–	(0.016)	–	(0.009)	–	(0.017)	–	(0.020)	–	(0.010)
	VIF	–	[35.267]	–	[25.355]	–	[36.425]	–	[30.621]	–	[23.645]
marginal effect (3)	coef	–	−7.292 ***	–	−1.365 ***	–	1.369 *	–	2.338 **	–	−5.177 ***
	error	–	(0.775)	–	(0.498)	–	(0.799)	–	(1.009)	–	(0.527)
R Square		0.575	0.593	0.386	0.393	0.374	0.375	0.435	0.436	0.631	0.647
F-statistic		92.863 ***	82.935 ***	45.392 ***	38.839 ***	28.951 ***	24.065 ***	24.743 ***	20.582 ***	156.404 ***	139.596 ***
Skewness (un)st. res		0.515	0.827	−0.082	−0.049	−0.232	−0.230	0.200	0.191	0.325	0.673
Kurtosis (un)st. res		1.084	1.646	−0.254	−0.202	0.561	0.552	−0.463	−0.492	1.944	2.002

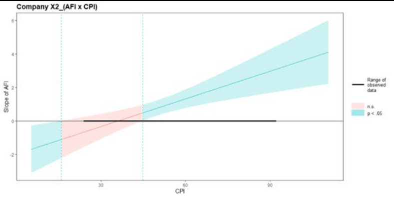
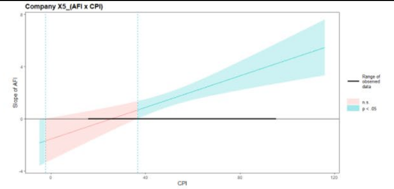
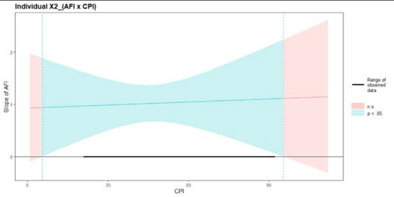
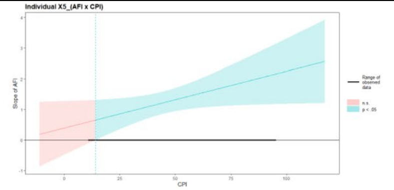
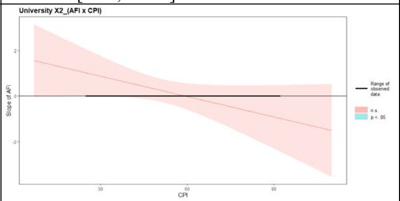
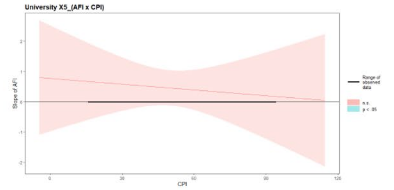
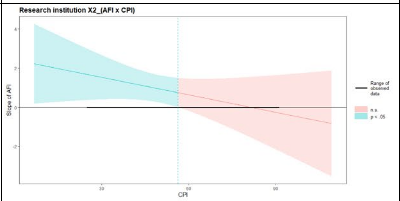
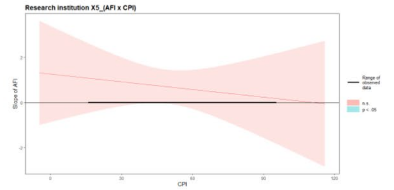
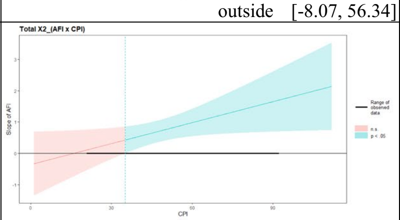
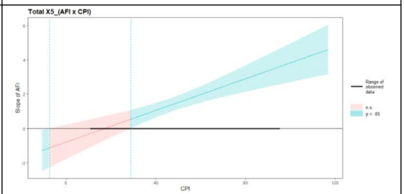
Table 4 (continued)

Variables	Company		Individual		University		Research institutes		Total	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Durbin-Watson	1.069	1.077	1.479	1.458	1.049	1.049	0.645	0.646	1.190	1.175
Breusch-Pagan	47.526 ***	47.526 ***	16.499 **	16.499 **	37.115 ***	37.115 ***	5.444	5.444	44.849 ***	44.849 ***
N	349	349	367	367	248	248	167	167	463	463

*** –$p<0.01$; ** –$p<0.05$; * –$p<0.1$. Errors are indicated in brackets. VIF values are in square brackets. (1), (2) and (3) are equations, see above. "(un)st. res." are unstandardized and standardized residual

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 5 Interaction Effect between AFI and CPI and confidence Intervals in regression models (2)

Model	Two-year time lag	Five-year time lag
Company	 outside [16.00, 44.84]	 outside [-2.41, 36.68]
Individual	 inside [5.42, 95.34]	 outside [-2106.18, 14.05]
University	 interval could not be found	 interval could not be found
Research institution	 outside [-8.07, 56.34]	 interval could not be found
Total	 outside [-438.75, 35.11]	 outside [-7.50, 28.76]

Range of observed data p < .05 n.s.

Source: Own calculation and visualization using RStudio

effect of AFI on firms is stronger in countries with a CPI of at least 36.68. Otherwise, this effect loses statistical significance. This result can be explained by the adaptation of firms' business strategies over time and by gradual changes in technology transfer mechanisms.

In the short term (2-year time lag), the significance of the AFI effect for individual inventors remains in the range [5.42, 95.34]. This indicates that in all countries, taking into account the actual minimum and maximum CPI values, academic freedom has a statistically significant impact on the innovation activity of individual inventors. This influence is clearly defined within the specified range of CPI values. However, in the models with a 5-year time lag, the picture is slightly different. The effect of AFI remains statistically significant outside the range [−2106.18, 14.05], which means that in countries with a CPI above 14.05, the effect of academic freedom on innovation activity becomes significant in the long term. This suggests an inverse relationship: the lower the level of corruption in a country (higher the CPI score), the greater the role of academic freedom in promoting invention. This interaction may indicate that individual inventors need more time to adapt their activities to the changing environment caused by corrupt practices and academic freedom. Therefore, in the long term, changes in corruption and academic freedom may have a more significant impact on patenting activity, as inventors are better able to adapt to these changes.

For research institutes, in the models with a 2-year time lag, the significance of the AFI effect is observed outside the range [−8.07, 56.34], indicating that this effect is only important when the CPI is below 56.34. In the models with a 5-year time lag, no significant CPI range was found for research institutes or universities (neither in the short nor in the long term). This may indicate that these categories of patenting activity are highly resilient to changes in the level of corruption. In other words, they may use patenting mechanisms regardless of the level of the CPI, which may be a consequence of domestic policies on funding innovation.

Conclusions

Table 6 below lists our hypotheses and summarizes the results. The regression coefficients reveal that academic freedom generally increases the number of green patent applications, but the effect is different for different types of applicants. Individuals, universities and research institutions overall seem to benefit from greater academic freedom especially in the models containing the interactive element when academic freedom is moderated by corruption. This is our first key finding, which is consistent with Audretsch et al., (2024). The effect of academic freedom mediated by corruption on universities and research institutes is more pronounced short-term (2-year lag), while its effect on individual inventors takes more time to materialize. Universities and publicly funded research institutes might be more immune to financial uncertainty than individual inventors. Furthermore, there is a possibility that long term universities operating in the context of low corruption and more academic freedom might opt for spin-offs or strategic collaborations with the private sector over applying for patent protection directly. And, of course, publishing is a default option for universities to showcase and claim their inventions (Siegel et al., 2004).

Our second key finding pertains to green patent output by companies. Companies account for more than 83% of all green patent applications in our sample, making them the dominant category of applicants. The private sector has a very complex relationship with academic freedom moderated by corruption. High levels of academic freedom accompanied by low levels of corruption decrease the green patent output by companies. Academic freedom, which promotes openness of knowledge and dissemination of ideas, does not always translate into increased green patenting activity

Table 6 Summary of results

List of hypotheses	Two-year time lag	Five-year time lag
H: There is a positive relationship between the Index of Academic Freedom (AFI) and green patent output	Confirmed	Confirmed
Ha: There is a positive relationship between AFI and green patent output using the interaction of AFI with the Corruption Perceptions Index (CPI) as a control variable	Not confirmed. The effect of the interaction of AFI and CPI is statistically significant, however. This indicates that the effect of AFI is moderated by CPI. Table 5 offers insights into these moderating effects	Not confirmed. The effect of the interaction of AFI and CPI is statistically significant, however. This indicates that the effect of AFI is moderated by CPI. Table 5 offers insights into these moderating effects
H1: There is a positive relationship between AFI and green patent output by companies	Confirmed	Confirmed
H1a: There is a positive relationship between AFI and green patent output by companies using the interaction of AFI with CPI as a control variable	Not confirmed. The relationship is negative. This means that in countries enjoying less corruption and more academic freedom, patent output by companies goes down. Table 5 offers insights into the moderating effects of CPI	Not confirmed. The relationship is negative. This means that in countries enjoying less corruption and more academic freedom, patent output by companies goes down. Table 5 offers insights into the moderating effects of CPI
H2: There is a positive relationship between AFI and green patent output by individuals	Confirmed	Confirmed
H2a: There is a positive relationship between AFI and green patent output by individuals using the interaction of AFI with CPI as a control variable	Confirmed	Not confirmed. But the AFI*CPI effect is positive and statistically significant implying that CPI climate takes time to exercise effect on individual inventors
H3: There is a positive relationship between AFI and green patent output by universities	Not confirmed	Not confirmed
H3a: There is a positive relationship between AFI and green patent output by universities using the interaction of AFI with CPI as a control variable	Confirmed at $p<0.1$. But the AFI*CPI effect is negative and statistically significant ($p<0.1$) implying that the effect of CPI climate has a reverse effect on universities	Not confirmed
H4: There is a positive relationship between AFI and green patent output by public research organizations	Confirmed	Confirmed at $p<0.1$
H4a: There is a positive relationship between AFI and green patent output by public research organizations using the interaction of AFI with CPI as a control variable	Confirmed	Not confirmed

Source: Own ownership

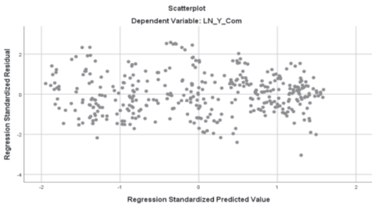
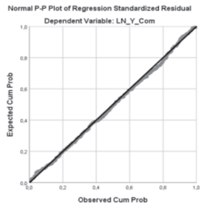
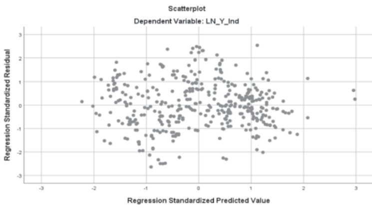
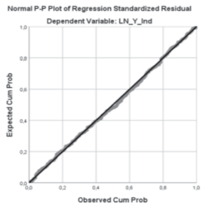
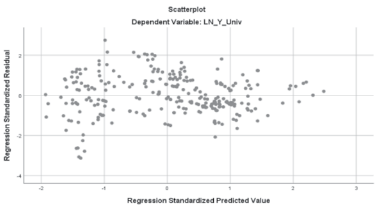
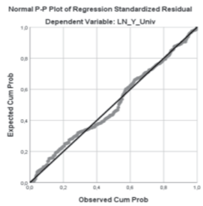
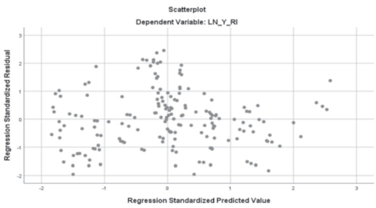
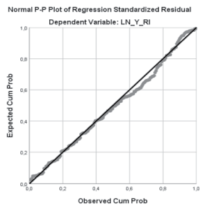
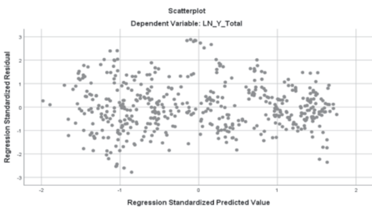
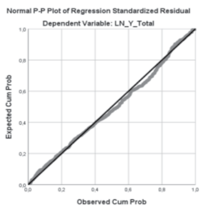
in the private sector. Companies may be relying more on trade secrets or other IP protection strategies as an alternative to patenting. By looking at the Johnson-Neyman confidence intervals (Table 5) for the interaction between AFI and CPI, we conclude that both extremes in regards to the level of corruption are impactful: in the context of extreme corruption, companies may use informal mechanisms to protect IP, while in low-corruption countries, open access to knowledge and academic freedom may foster internalization of business innovation when patenting is just one of the forms of IP management and protection.

Low corruption and high academic freedom usually go hand in hand. However, the interaction between the two might produce a system of mixed signals when it comes to innovation strategies in the private sector. Companies possess resources and an array of options of how to pursue the commercialization of their inventions. In "safe" environments involving low level of corruption and freedom of research protected by the government, they might opt for leveraging their inventions internally and relying on trade secrets. Elon Musk has reportedly spoken against the use of patents for his space technology company SpaceX (Duffy, 2022). The purpose of patenting is to protect IP rights for about twenty years. In theory this period of exclusive exploitation of inventions gives a company a head start to reach higher levels of competitiveness. Firms, both large and small, seek patent protection in pursuit of higher profits and for defensive reasons (Sichelman & Graham, 2010). Of course, patenting and maintaining costs, as well as the costs of litigation to enforce IP rights, are high, so companies may choose not to patent. Sichelman and Graham (2010) and Athreye et al. (2021) empirically ascertain that high costs, especially for small firms, are important deterrents of patenting. In general, companies of all sizes strive to maintain a balance between the risks associated with competitors stealing their secrets and expenses of legal protection and litigation. In "safe" environments, where the risks of unfair competition are low, companies have a variety of options of securing and leveraging their technological advantage.

What our study lacks is a more nuanced analysis of the effects of government policies on green innovation. Government policies like tax incentives, subsidies and enforcements of carbon emissions reductions have been instrumental in shaping green innovation strategies (Akhtaruzzaman et al., 2025). Policies that enhance judicial protection and stimulate R&D investment foster corporate green innovation in China (Cai et al., 2025). Future research can incorporate political factors and, thus, increase models´ complexity. Our main conclusion is that academic freedom is conducive to green patenting especially accompanied by low levels of corruption. However, companies respond to a complex set of incentives and engage in diverse innovation strategies. Future research can focus on the alternative indicators of green innovation output. However, patent applications remain a reliable source of insight into the invention process, which is the first stage of innovation. And our results reveal a strong link between academic freedom, control of corruption and green patent output. Thus, promoting academic freedoms and keeping corruption in check serve as important conditions of solving environmental challenges with the help of technology.

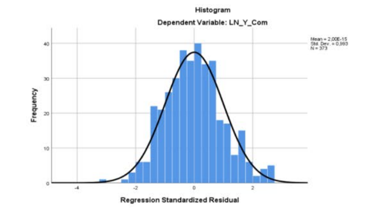
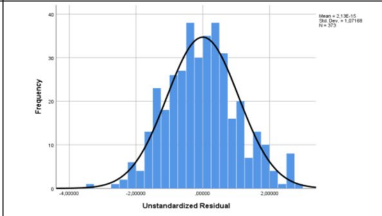
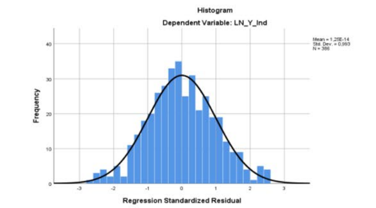
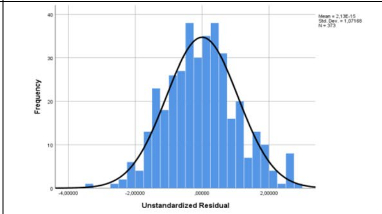
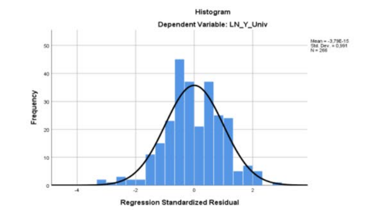
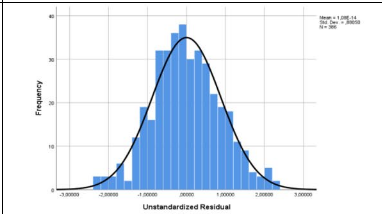
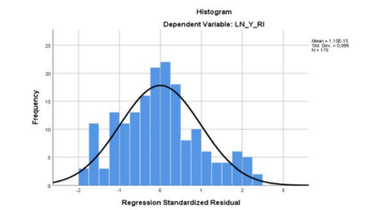
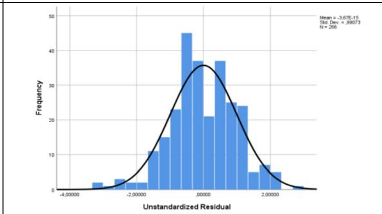
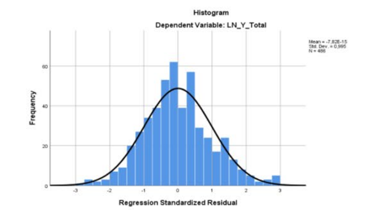
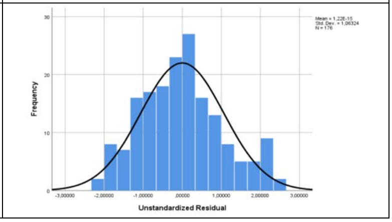
Appendix

Table 7 Scatterplot and Normal P-P plot for regression models (1) with two-year time lags

Models	Scatterplot	Normal P-P plot
Company		
Individual		
University		
Research Institutions		
Total		

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 8 Histograms of standardized and unstandardized residuals in regression models (1) with two-year time lags

Models	Regression Standardized Residual	Unstandardized Residual
Company	 	
Individual	 	
University	 	
Research Institutions	 	
Total	 	

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 9 Scatterplot and Normal P-P plot for regression models (2) with two-year time lags

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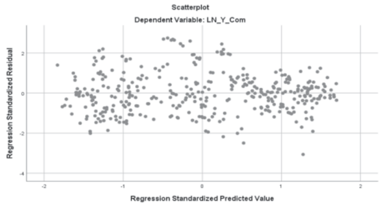
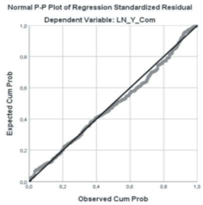
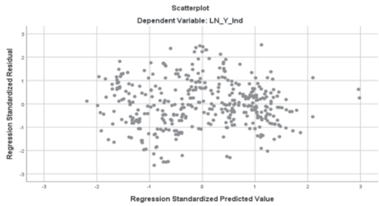
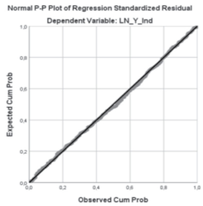
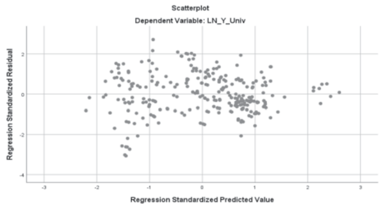
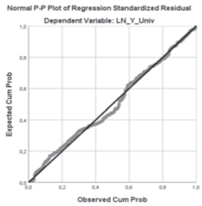
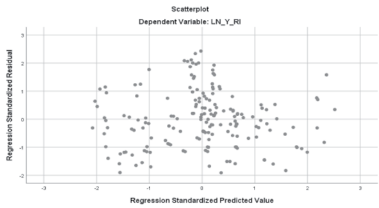
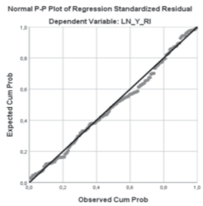
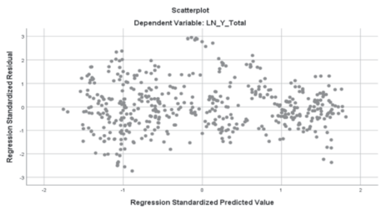
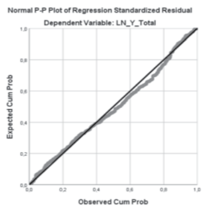
<tr><td>Company</td><td></td><td></td></tr>
<tr><td>Individual</td><td></td><td></td></tr>
<tr><td>University</td><td></td><td></td></tr>
<tr><td>Research Institutions</td><td></td><td></td></tr>
<tr><td>Total</td><td></td><td></td></tr>
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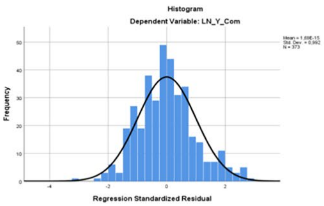
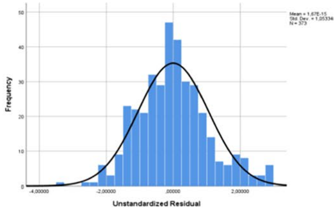
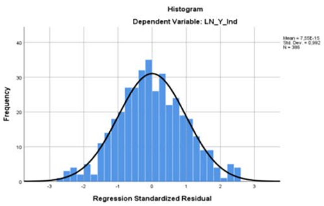
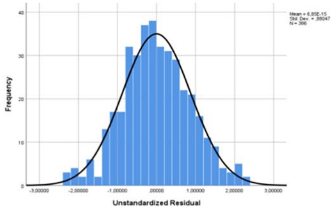
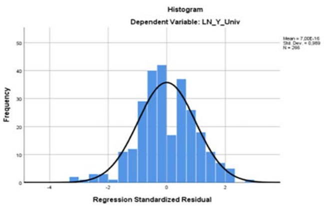
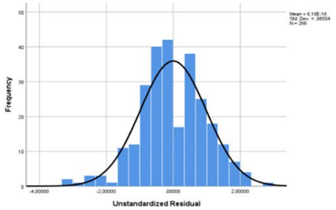
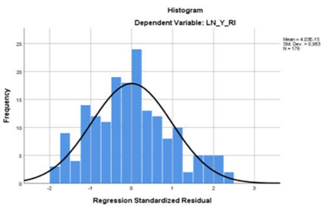
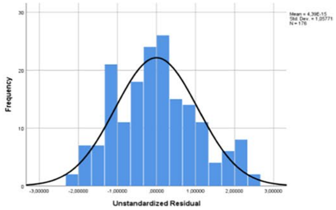
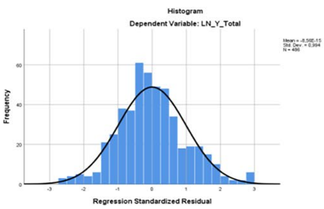
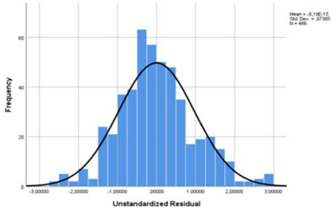
Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 10 Histograms of standardized and unstandardized residuals in regression models (2) with two-year time lags

Models	Regression Standardized Residual	Unstandardized Residual
Company		
Individual		
University		
Research Institutions		
Total		

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 11 Scatterplot and Normal P-P plot for regression models (1) with five-year time lags

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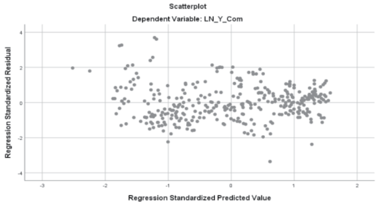
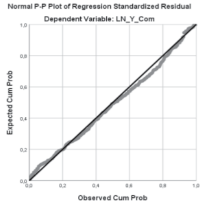
<tr><td>Company</td><td>
</td><td>
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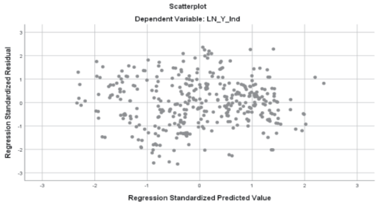
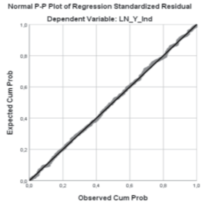
<tr><td>Individual</td><td>
</td><td>
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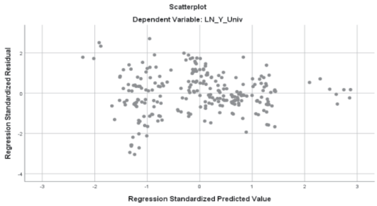
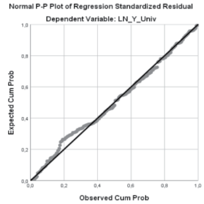
<tr><td>University</td><td>
</td><td>
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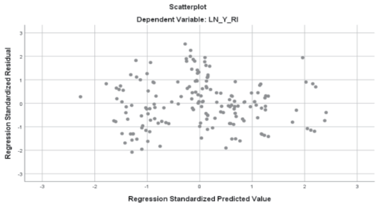
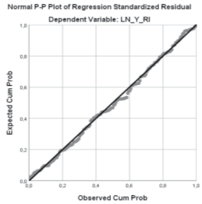
<tr><td>Research Institutions</td><td>
</td><td>
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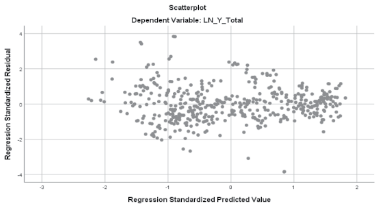
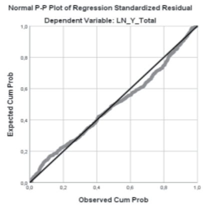
<tr><td>Total</td><td>
</td><td>
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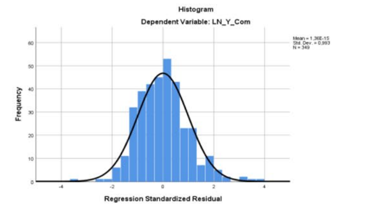
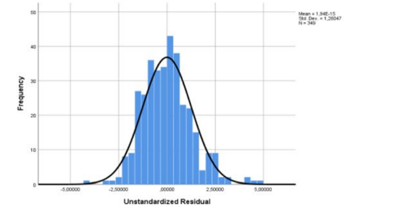
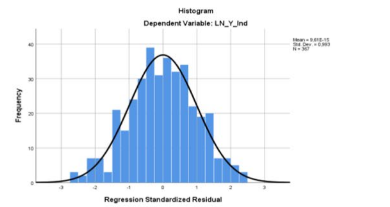
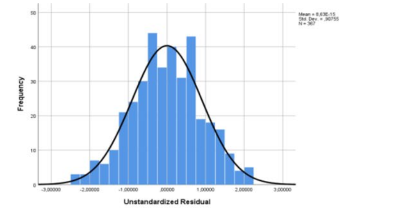
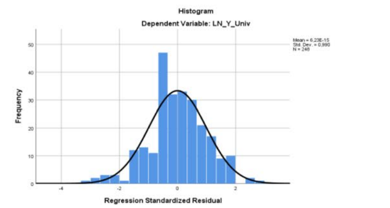
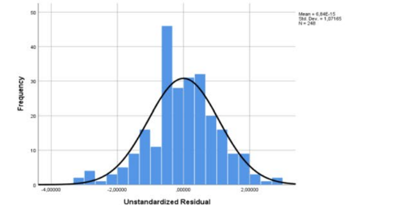
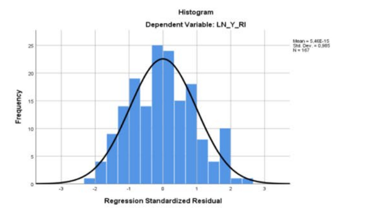
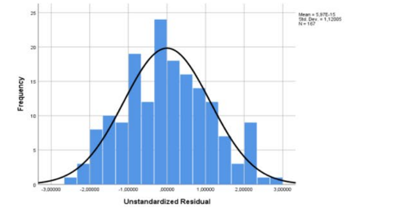
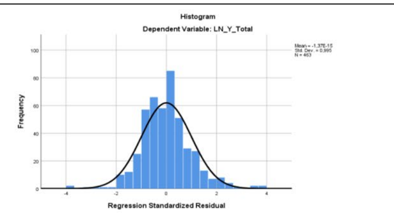
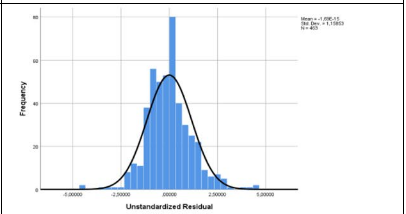
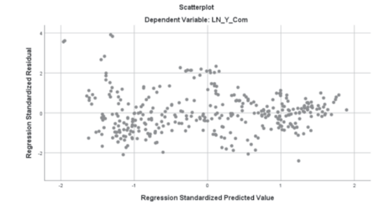
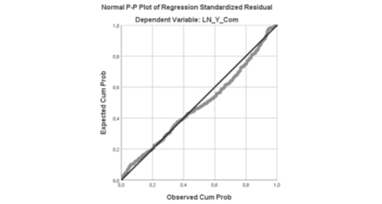
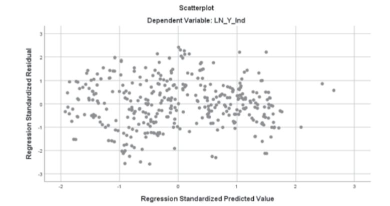
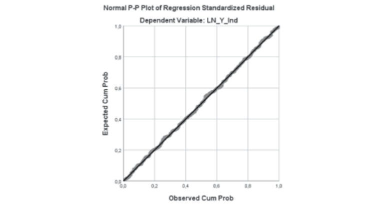
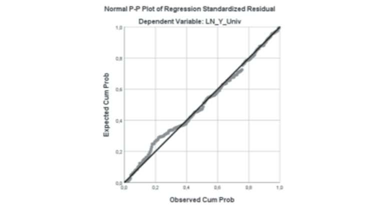
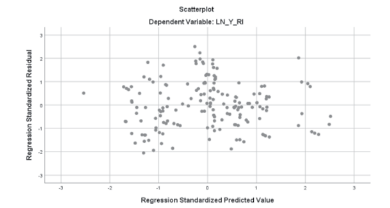
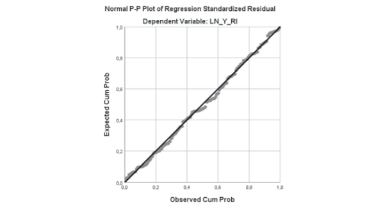
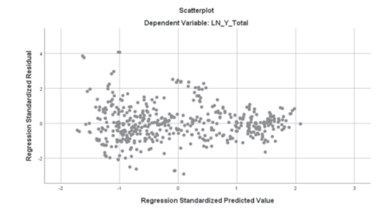
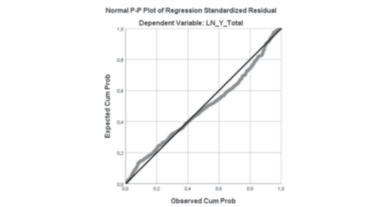
Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 12 Histograms of standardized and unstandardized residuals in regression models (1) with five-year time lags

Models	Regression Standardized Residual	Unstandardized Residual
Company		
Individual		
University		
Research Institutions		
Total		

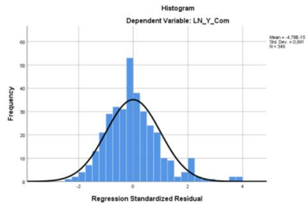
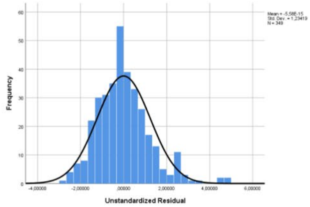
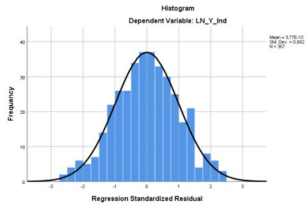
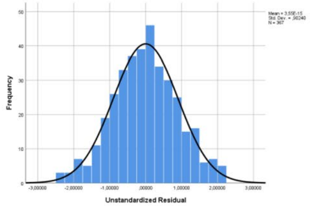
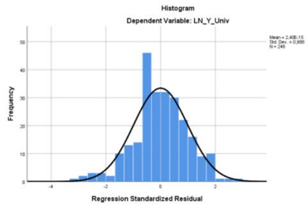
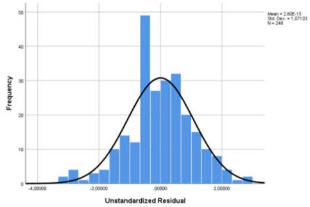
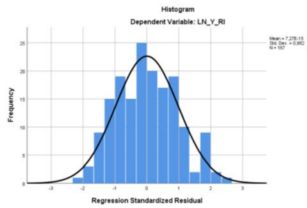
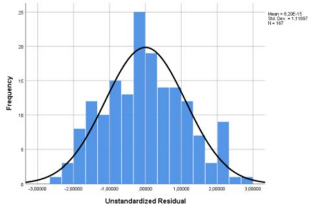
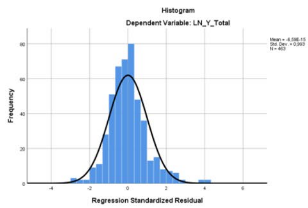
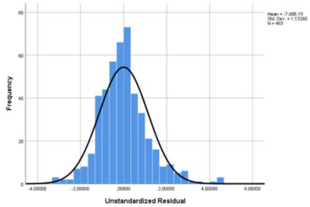
Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 13 Scatterplot and Normal P-P plot for regression models (2) with five-year time lags

Models	Scatterplot	Normal P-P plot
Company		
Individual		
University		
Research Institutions		
Total		

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Table 14 Histograms of standardized and unstandardized residuals in regression models (2) with five-year time lags

Models	Regression Standardized Residual	Unstandardized Residual
Company		
Individual		
University		
Research Institutions		
Total		

Sources: Own compilations and calculations by the authors based on data from the PatentScope (2023); V-dem dataset (V-dem, 2024); Transparency International (2021); DataBank World Bank Group (2024a, 2024b)

Authors' contributions Both authors contributed to the paper conceptualization and design. Maryna Demianchuk focused on data collection and analysis but also contributed to the first draft. Irina Ervits wrote the first draft and contributed to data collection and analysis. Both authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Declarations

Declaration of Interest statement The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Access to data The data for this paper is published on Mendeley Data, an open-source data repository. The link to the dataset is below:
Demianchuk, Maryna; Ervits, Irina (2025), "Dataset: Academic Freedom and Green Patenting by Different Participants of the National Innovation System", Mendeley Data, V1, https://doi.org/10.17632/mgxj33r325.1.
https://data.mendeley.com/datasets/mgxj33r325/1.

References

AFI (2024). *Academic Freedom Index*. Retrieved November 15, 2024, from https://academic-freedom-index.net/#top.

Aghion, P., Dewatripont, M., & Stein, J. C. (2008). Academic freedom, private-sector focus, and the process of innovation. *The RAND Journal of Economics,39*(3), 617–635. https://doi.org/10.1111/j.1756-2171.2008.00031.x

Akhtaruzzaman, M., Banerjee, A. K., & Boubaker, S. (2025). Government intervention and green innovation in renewable energy. *Energy Economics,145*, Article 108185. https://doi.org/10.1016/j.eneco.2025.108185

Athreye, S., Fassio, C., & Roper, S. (2021). Small firms and patenting revisited. *Small Business Economics,57*(1), 513–530. https://doi.org/10.1007/s11187-020-00323-1

Audretsch, D. B., Fisch, C., Franzoni, C., Momtaz, P. P., & Vismara, S. (2024). Academic freedom and innovation. *PLoS ONE,19*(6), Article e0304560. https://doi.org/10.1371/journal.pone.0304560

Bauer, D. J., & Curran, P. J. (2005). Probing interactions in fixed and multilevel regression: Inferential and graphical techniques. *Multivariate Behavioral Research,40*(3), 373–400. https://doi.org/10.1207/s15327906mbr4003_5

Bhattacharyya, S., & Jha, R. (2013). Economic growth, law, and corruption: Evidence from India. *Comparative Economic Studies,55*, 287–313. https://doi.org/10.1057/ces.2013.4

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics,31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bruneel, J., D'Este, P., & Salter, A. (2010). Investigating the factors that diminish the barriers to university-industry collaboration. *Research Policy,39*(7), 858–868.

Cai, J., Yuan, J., Yu, C., & Yu, C. (2025). Can the establishment of intellectual property demonstration cities stimulate green technology innovation of enterprises in China? *Journal of the Knowledge Economy,16*, 14907–14925. https://doi.org/10.1007/s13132-024-02548-x

Cervantes, M., et al. (2023). Driving low-carbon innovations for climate neutrality. *OECD Science, Technology and Industry Policy Papers*, 143. OECD Publishing, Paris. Advance online publication. https://doi.org/10.1787/8e6ae16b-en

Chavira, P. C., Shamsuzzoha, A., Kuusniemi, H., & Jovanovski, B. (2023). Defining green innovation, its impact, and cycle – A literature analysis. *Cleaner Engineering and Technology,17*, Article 100693. https://doi.org/10.1016/j.clet.2023.100693

Cobbinah, J., Osei, A., & Amoah, J. O. (2025). Innovating for a greener future: Do digital transformation and innovation capacity drive enterprise green total factor productivity in the knowledge economy? *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-025-02673-1

Comanor, W. S., & Scherer, F. (1969). Patent statistics as a measure of technical change. *Journal of Political Economy,77*(3), 392–398.

Coppedge, M., Gerring, J., Knutsen, C. H., Lindberg, S. I., Teorell, J., Altman, D., Bernhard, M. Cornell, A., Fish M. S., Gastaldi, L., Gjerløw, H., Glynn, A., Grahn, S., Hicken, A., Kinzelbach, K., Marquardt, K. L., McMann, K., Mechkova, V., Neundorf, A. et al. (2023). *V-Dem Codebook v13, Varieties of Democracy (V-Dem) Project*. Retrieved December 27, 2024, from https://v-dem.net/documents/24/codebook_v13.pdf.

Cvetanovic, S., & Sredojevic, D. (2012). The concept of national innovation system and economy's competitiveness. *Economic Themes,50*(2), 167–185.

Deaton, A. (1992). *Understanding consumption*. Oxford University Press.

Duffy, K. (2022). Elon Musk says SpaceX avoids using patents to build rockets because they're for the 'weak' and block innovation, *Business Insider,* Sep 22. Retrieved January 20, 2025, from https://www.businessinsider.com/elon-musk-spacex-patents-weak-build-starship-rockets-advance-2022-9.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica,50*(4), 987–1008.

Ervits, I. (2024). Developing indicators for the social benefits of university-industry collaborations. *International Journal of Corporate Social Responsibility,9*, Article 8. https://doi.org/10.1186/s40991-024-00097-9

Ervits, I., & Zmuda, M. (2018). A cross-country comparison of the effects of institutions on internationally oriented innovation. *Journal of International Entrepreneurship,16*(4), 486–503. https://doi.org/10.1007/s10843-018-0225-8

Ervits, I., Demianchuk, M., & Maslii, N. (2024). Dataset: The Effect of Environmental Policy on Green Patent Output by Different Participants of the National Innovation System. *Mendeley Data*, V1. https://doi.org/10.17632/rfjknyhsj3.1.

Esarey, J., & Sumner, J. L. (2018). Marginal effects in interaction models: Determining and controlling the false positive rate. *Comparative Political Studies,51*(9), 1144–1176. https://doi.org/10.1177/0010414017730080

European Union. (2007). *Charter of Fundamental Rights of the European Union*, 2012/C 326/02. Retrieved November 21, 2024, from https://www.refworld.org/legal/agreements/eu/2007/en/13901.

Florida, R. (2014). The creative class and economic development. *Economic Development Quarterly,28*(3), 196–205. https://doi.org/10.1177/0891242414541693

Freeman, C. (1987). *Technology and economic performance: Lessons from Japan*. Pinter Publishers.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy,31*(6), 899–933. https://doi.org/10.1016/S0048-7333(01)00152-4

Gao, Y., Zang, L., Roth, A., & Wang, P. (2017). Does democracy cause innovation? An empirical test of the popper hypothesis. *Research Policy,46*(7), 1272–1283. https://doi.org/10.1016/j.respol.2017.05.014

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature,28*(4), 1661–1707.

Hall, B. H., Link, A. N., & Scott, J. T. (2003). Universities as research partners. *The Review of Economics & Statistics,85*(2), 485–491. https://doi.org/10.1162/rest.2003.85.2.485

Hall, P. A., & Soskice, D. (2001). *Varieties of capitalism: The institutional foundations of comparative advantage*. Oxford University Press.

Hartung, K. (2025). *WIPO Statistics Show Increases in Worldwide Patent Applications*. Mechanical Patent Practice Group at McKee, Voorhees & Sease, PLC. Retrieved January 27, 2025, from https://www.filewrapper.com/wipo-statistics-show-increases-in-worldwide-patent-applications/.

Huang, H., & Xu, C. (1999). Institutions, innovations, and growth. *American Economic Review,89*(2), 438–443.

Johnson, P. O., & Fay, L. C. (1950). The Johnson-Neyman technique, its theory and application. *Psychometrika,15*, 349–367. https://doi.org/10.1007/BF02288864

King, J. L., Gurbaxani, V., Kraemer, K. L., McFarlan, F. W., Raman, K. S., & Yap, C. S. (1994). Institutional factors in information technology innovation. *Information Systems Research,5*(2), 139–169.

Knutsen, C. H. (2013). Democracy, state capacity, and economic growth. *World Development,43*, 1–18. https://doi.org/10.1016/j.worlddev.2012.10.014

Knutsen, C. H. (2015). Why democracies outgrow autocracies in the long run: Civil liberties, information flows and technological change. *Kyklos,68*(3), 357–384. https://doi.org/10.1111/kykl.12087

Larsson, R., Bengtsson, L., Henriksson, K., & Sparks, J. (1998). The interorganizational learning dilemma: Collective knowledge development in strategic alliances. *Organization Science,9*(3), 285–305.

Lee, Y. S. (2000). The sustainability of university-industry research collaboration: An empirical assessment. *Journal of Technology Transfer,25*, 111–133. 10.1023/A:1007895322042.

Lehmann, E. E., & Seitz, N. (2017). Freedom and innovation: A country and state level analysis. *Journal of Technology Transfer,42*, 1009–1029. https://doi.org/10.1007/s10961-016-9478-3

Long, J. (2024). *interactions / R /johnson_neyman.R*. Retrieved December 22, 2024, from https://github.com/jacob-long/interactions/blob/master/R/johnson_neyman.R.

Lundvall, B. -Å. (1992). *National systems of innovation. Towards a theory of innovation and interactive learning*. Pinter Publishers.

Mesot, J. (2023). *How academia contributes to the world's net zero ambitions*. World Economic Forum. Retrieved November 20, 2024, from https://www.weforum.org/stories/2023/01/how-academia-contributes-to-the-world-s-net-zero-ambitions/.

Mironov, M., & Zhuravskaya, E. (2016). Corruption in procurement and the political cycle in tunneling: Evidence from financial transactions data. *American Economic Journal: Economic Policy,8*(2), 287–321. https://doi.org/10.1257/pol.20140188

Motohashi, K. (2008). Growing R&D collaboration of Japanese firms and policy implications for reforming the national innovation system. *Asia Pacific Business Review,14*(3), 339–361. https://doi.org/10.1080/13602380802116773

Mungiu-Pippidi, A. (2015). Corruption: Good governance powers innovation. *Nature,518*, 295–297. https://doi.org/10.1038/518295a

Murphy, K. M., Shleifer, A., & Vishny, R. W. (1991). The allocation of talent: Implications for growth. *Quarterly Journal of Economics,106*(2), 503–530. https://doi.org/10.2307/2937945

Opoku, E. E. O., & Acheampong, A. O. (2023). Energy justice and economic growth: Does democracy matter? *Journal of Policy Modeling,45*(1), 160–186. https://doi.org/10.1016/j.jpolmod.2023.01.005

Papada, E., Altman, D. Angiolillo, F., Gastaldi, L., Köhler, T., Lundstedt, M., Natsika, N., Nord, M., Sato, Y., Wiebrecht, F., & Lindberg, S. I. (2023). *Defiance in the Face of Autocratization. Democracy Report 2023.* University of Gothenburg: Varieties of Democracy Institute (V-Dem Institute). Retrieved December 22, 2024, from https://www.v-dem.net/documents/29/V-dem_democracyreport2023_lowres.pdf.

PatentScope, 2023. WIPO. Simple search. Retrieved July 1, 2023, from https://patentscope.wipo.int/search/en/search.jsf.

Pinzon, E. (2022, October 6). *Heteroskedasticity robust standard errors: Some practical considerations*. The STATA Blog. Retrieved August 10, 2023, from https://blog.stata.com/2022/10/06/heteroskedasticity-robust-standard-errors-some-practical-considerations/.

Saeed, U. F., Kamil, R., & Appiah, K. O. (2025). Leveraging Green Technological Innovation for Corporate Value Creation: The Mediating Role of Environmental PerformanThein the Japanese Manufacturing Sector. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-025-02800-y

Shleifer, A., & Vishny, R. W. (1993). Corruption. *Quarterly Journal of Economics,108*(3), 599–617. https://doi.org/10.2307/2118402

Sichelman, T., and Graham, S. J.H. (2010). Patenting by Entrepreneurs: An Empirical Study, 17 Mich. Telecomm. Tech. L. Rev. 111. Retrieved December 22, 2024, from http://www.mttlr.org/volseventeen/Sichelman&Graham.pdf

Siegel, D. S., Waldman, D. A., Atwater, L. E., & Link, A. N. (2004). Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: Qualitative evidence from the commercialization of university technologies. *Journal of Engineering and Technology Management,21*, 115–142.

Takalo, S. K., Tooranloo, H. S., & Parizi, Z. S. (2021). Green innovation: A systematic literature review. *Journal of Cleaner Production,279*, Article 122474. https://doi.org/10.1016/j.jclepro.2020.122474

Taylor, M. Z. (2009). *International linkages* and national innovation rates: An exploratory probe. *Review of Policy Research,26*(1–2), 127–149. https://doi.org/10.1111/j.1541-1338.2008.00372.x

Tebaldi, E., & Elmslie, B. (2013). Does institutional quality impact innovation? Evidence from cross-country patent grant data. *Applied Economics,45*(7), 887–900. https://doi.org/10.1080/00036846.2011.613777
Tian, M., Su, Y., & Yang, Z. (2022). University-industry collaboration and firm innovation: An empirical study of the biopharmaceutical industry. *Journal of Technology Transfer,47*, 1488–1505. https://doi.org/10.1007/s10961-021-09877-y
Transparency International (2021). *Corruption Perceptions Index 2021*. Retrieved December 10, 2024, from https://www.transparency.org/en/cpi/2021.
Tsionas, M. G. (Ed.). (2019). *Panel data econometrics: Theory*. Elsevier: Academic Press.
UNESCO (1997). Recommendation concerning the Status of Higher-Education Teaching Personnel, 11 November 1997, Paris, France. Retrieved from https://www.unesco.org/en/legal-affairs/recommendation-concerning-status-higher-education-teaching-personnel
V-dem (2024). The V-Dem Dataset. Retrieved October 20, 2024, from https://v-dem.net/data/the-v-dem-dataset/.
van Waarden, F. (2001). Institutions and innovation: The legal environment of innovating firms. *Organization Studies,22*(5), 765–795. https://doi.org/10.1177/0170840601225002
Vrielink, J., Lemmens, P., & Parmentier, S. (2011). Academic freedom as a fundamental right. *Procedia - Social and Behavioral Sciences,13*, 117–141. https://doi.org/10.1016/j.sbspro.2011.03.009
Wang, M., Li, Y., & Cao, X. (2025). How climate commitment impact green technology innovation in enterprises: From the perspectives of cross-border knowledge search and digital transformation. *Journal of the Knowledge Economy,16*, 17940–17970. https://doi.org/10.1007/s13132-024-02453-3
WIPO (2019). *Industrial Property Statistics Glossary*. Retrieved March 23, 2019, from http://www.wipo.int/ipstats/en/statistics/glossary.html.
WIPO (2023). *IPC Green Inventory*. Retrieved December 22, 2023, from https://www.wipo.int/classifications/ipc/green-inventory/home.
World Bank Group (2024a). *DataBank. World Development Indicators. Exports and imports of goods and services (% of GDP)*. Retrieved December 22, 2024, from https://databank.worldbank.org/reports.aspx?source=2&series=BM.KLT.DINV.WD.GD.ZS&country=.
World Bank Group (2024b). *DataBank. World Development Indicators. Foreign direct investment, net inflows and outflows (% of GDP)*. Retrieved December 22, 2024, from https://databank.worldbank.org/reports.aspx?source=2&series=BM.KLT.DINV.WD.GD.ZS&country=.

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