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Geopolitical Shocks and Nanotechnology Innovation Resilience: Patent Evidence from G7 and BRICS Economies

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Abstract

Background: Patent databases are large-scale information systems that record codified technological activity and can support data-driven monitoring of innovation resilience under systemic disruption.

Objective: This study examines whether major geopolitical and macroeconomic shocks are associated with changes in nanotechnology patent application trajectories across application domains and whether these changes differ between G7 countries and the five original BRICS countries.

Methods: The study combines bibliometric identification of application domains with patent data from the PatentInspiration database for the period 2004–2023. The inferential panel includes seven G7 countries and the five original BRICS countries, namely Brazil, India, Russia, China, and South Africa. Deviations around the Global Financial Crisis, the COVID-19 pandemic, and the war in Ukraine are estimated using event-study PPML models and PPML difference-in-differences models. For the aggregate models, statistical inference is based on a CR2 cluster-robust covariance matrix with clustering at the country level and Satterthwaite-adjusted degrees of freedom; country-specific models are reported only as descriptive point estimates without p-values.

Results: After correcting for clustering and the small number of clusters, statistically significant negative deviations during the Global Financial Crisis were observed in healthcare in 2009, in agriculture in both years, and in food in both years. In the 2022–2023 period, only the 2022 deviations in cosmetics and agriculture were statistically significant; during the COVID-19 pandemic, no aggregate deviation was statistically significant. No aggregate BRICS-G7 DiD estimate was statistically significant. The country-specific models therefore serve only as a descriptive decomposition, and their point estimates indicate substantial internal heterogeneity within the BRICS group.

Conclusion: Patent data provide a useful basis for domain-sensitive monitoring of innovation trajectories; however, after correction, robust statistical evidence is concentrated in only a subset of period-domain combinations. The aggregate models provide no statistically significant evidence of a systematic difference between BRICS and G7, and differences between individual countries should be interpreted as descriptive patterns rather than as independently inferentially confirmed effects.

Index Terms

Patent analytics; Technology intelligence; Innovation resilience; Nanotechnology applications; PPML; G7; BRICS.

1 INTRODUCTION

Technological innovation in contemporary economies is increasingly shaped not only by market demand and scientific progress, but also by geopolitical tensions, institutional environments and the resilience of international production and knowledge linkages.

The debate on technology sovereignty shows that states and supranational entities seek not only to support technological diffusion, but also to secure access to critical technologies, infrastructured knowledge and strategic capabilities (Edler et al., 2023). At the same time, global shocks such as the COVID-19 pandemic, financial crises and geopolitical conflicts disrupt global value chains, regional innovation systems and corporate strategies (Fischer et al., 2024; Herold & Marzantowicz, 2023; Sheth & Uslay, 2023). These processes are also important from the perspective of socio-economic analysis, because innovations do not emerge in isolation in laboratories, but in relation to institutions, financing, international cooperation, regulation, supply networks and the ability of economies to absorb systemic shocks (Fagerberg et al., 2018; Lundvall, 2007).

Patent records are used here as structured information on formalized technological activity. They combine time stamps, institutional affiliation, domain-specific terminology and application-date metadata, making them suitable for tracing changes in technological search and specialization. Patent analytics is therefore relevant not only to innovation economics, but also to information management and technology intelligence, where semi-structured patent records are converted into comparable indicators for monitoring technological change (Abbas et al., 2014; Abraham & Moitra, 2001; Daim et al., 2006).

A growing stream of bibliometric, patentometric and technology-intelligence research uses large information systems to map emerging domains, trace knowledge flows and identify shifts in technological specialization (Daim et al., 2006; Donthu et al., 2021). Related applied informatics studies have used bibliometric evidence to analyze, for example, focusing on digital pricing and e-commerce logistics (Kunharyanto et al., 2025; Poláček et al., 2024), illustrating how data-driven mapping can connect information systems with socio-technical and business phenomena. Patent analytics extends this logic from scholarly publication records to formalized technological records, where application dates, institutional origin and domain terminology can be used to observe technology trajectories over time.

The effects of crises on innovation cannot be understood simply as an automatic decline in technological activity. Empirical studies show that financial crises may reduce patenting particularly in industries dependent on external financing, because they constrain resources for long-term research and development projects (Hardy & Sever, 2021). In some areas, however, the pandemic not only disrupted innovation processes, but also redirected technological effort toward new application areas (Bloom et al., 2021; Jeon et al., 2023; Yildirim, 2023). This implies that the same macroeconomic or geopolitical shocks may generate different patent application trajectories across sectors and countries. This assumption is particularly important for the analysis of horizontal high-tech fields, in which technological knowledge diffuses across markets while remaining dependent on specific institutional, material and informational infrastructures.

Nanotechnology represents a suitable empirical case of such a horizontal and enabling technological field. In the literature on general purpose technologies, the key characteristics are pervasiveness, cumulative improvement and the capacity to create complementarities across downstream sectors (Bresnahan & Trajtenberg, 1995). Studies focused directly on nanotechnology show that patent activity in this field displays broad sectoral dispersion and has the potential to support innovation across a range of industrial and societal domains (Shea et al., 2011). Due to the specific physicochemical properties of nanomaterials, nanotechnology can contribute to the development of new materials, targeted drug-delivery systems, diagnostics, cosmetic innovations, smart food packaging, nanosensors, nanopesticides and nanofertilizers (Ashaolu, 2021; He et al., 2019; Lowry et al., 2019; Malik et al., 2023; Nile et al., 2020). Its significance is therefore not only technological, but also economic and social, because it reaches into healthcare, food security, sustainable agriculture, consumer markets and regulatory debates on the safety of new materials.

At the same time, the cross-sectoral nature of nanotechnology complicates the assessment of its innovation resilience. On the one hand, nanotechnology may act as a source of technological renewal and radical innovation in various application domains. On the other hand, its development often depends on specialized inputs, research infrastructure, validation and testing capacities, regulatory rules, patent protection and international knowledge flows. The perspective of national innovation systems emphasizes that the ability to create and use new technologies depends on institutional arrangements, educational and research capacities, the business environment and linkages among actors (Lundvall, 2007; Lu et al., 2024). The literature on global value chains and innovation systems also shows that participation in international production networks alone does not necessarily guarantee technological growth unless it is supported by domestic capabilities and absorptive capacity (Fagerberg et al., 2018; Fischer et al.,

2024). From the perspective of sectoral innovation systems, it also cannot be expected that healthcare, cosmetics, agriculture and food will respond identically to the same shocks, because they differ in their knowledge bases, actors, demand structures, regulatory intensity and market structures (Malerba, 2002; Trčka et al., 2025; Svoboda et al., 2026).

Beyond the perspectives of national and sectoral innovation systems, contemporary innovation research increasingly conceptualizes technological development as a process embedded in broader innovation ecosystems and socio-technical arrangements. Technological change is shaped not only by scientific capabilities or market incentives, but also by the quality of interactions among universities, firms, governments and regulatory institutions, as well as by the stability of international knowledge networks through which expertise, infrastructure and resources circulate (Etzkowitz & Leydesdorff, 2000; Geels, 2004; Adner, 2017). From this perspective, geopolitical shocks are not merely external disturbances affecting economic performance; they reshape the institutional environment in which innovation takes place by influencing collaboration opportunities, investment decisions, access to research infrastructures and strategic policy priorities. Patent applications can therefore be interpreted not only as indicators of inventive activity but also as observable manifestations of how innovation ecosystems respond and adapt to changing geopolitical and institutional conditions.

Existing literature has primarily addressed the general development of nanotechnology, its application potential, safety and regulatory issues, or the broader problem of innovation-system resilience (Doak et al., 2023; Rasmussen et al., 2025; Saldívar-Tanaka & Hansen, 2021). Recent research has also begun to examine how geopolitical shocks and regulatory exposure are associated with nanotechnology patenting across selected advanced economies (Svoboda et al., 2026). However, less attention has been paid to whether major geopolitical and macroeconomic shocks are reflected in the patent trajectories of specific nanotechnology application domains across the full G7 benchmark and the five original BRICS countries, and whether broad geopolitical groupings conceal substantial sectoral and national heterogeneity. This distinction is important because aggregate comparisons between economic blocs may obscure markedly different trajectories across application domains and individual national innovation systems. Although patent data do not capture overall innovation performance, they represent an established indicator of formalized technological activity and have long been used to monitor changes in innovation, technological specialization and directions of technological development (Daim et al., 2006; Griliches, 1990).

This study therefore analyses the development of patent application activity in nanotechnology during the period 2004-2023. It focuses on four application domains, namely healthcare, cosmetics, agriculture and food, which were identified through bibliometric search and subsequently verified in terms of patent continuity. The reference group consists of all G7 countries, while the comparison group consists of the BRICS countries included in the dataset: Brazil, India, Russia, China and South Africa. The aim is not to claim that these domains exhaust the entire field of nanotechnology, but to create an analytically comparable panel that makes it possible to examine whether the Global Financial Crisis of 2008–2009, the COVID-19 pandemic of 2020–2021 and the war in Ukraine in 2022–2023 were reflected in changes in patent trajectories and whether these changes differ across sectors and countries.

The analysis is positioned at the intersection of innovation-system research, technology intelligence and comparative technology policy. It links the literature on geopolitical and macroeconomic shocks with a specific enabling technology, examines resilience at the level of application domains and uses the G7 benchmark to interpret the trajectories of BRICS countries without assuming that BRICS forms an internally homogeneous group.

Accordingly, nanotechnology is not treated here as a material-science problem. It is used as an empirical case for analyzing how formalized technological activity, observed through patent applications, changes across countries and application domains during systemic disruption. We focused on the following research questions:

- **RQ1:** Which nanotechnology application domains can be identified in the scholarly literature and at the same time display sufficient continuity of patent activity in the G7 reference group?
- **RQ2:** Are major geopolitical, macroeconomic, and systemic shocks associated with significant changes in patent trajectories in the selected domains?
- **RQ3:** Do these changes manifest asymmetrically across selected countries and application domains, and can distinct patterns of vulnerability and stability therefore be identified in the analyzed sample?

The remainder of the article is structured as follows. The Materials and Methods section explains the bibliometric identification of application domains, the construction of the patent application panel and the use of PPML event-

study and PPML difference-in-differences models. The Results section presents aggregate and country-specific effects of the three analyzed shocks. The Discussion section interprets the findings in relation to innovation systems, sectoral heterogeneity, technology intelligence and technology policy. The Conclusion summarizes the main empirical findings, limitations and future research directions.

2 MATERIALS AND METHODS

2.1 Research design and patent analytics workflow

The research design is sequential and combines bibliometric identification of application domains, patent retrieval and statistical modelling of count data. The bibliometric phase identifies nanotechnology application domains visible in the scholarly literature. The patent phase verifies whether these literature-based domains display sufficient continuity of patent applications for longitudinal analysis. The modelling phase then tests whether major shocks are associated with deviations in patent trajectories and whether these deviations differ between the full G7 benchmark and BRICS countries.

The analytical workflow is sequential. It starts with bibliometric domain identification, continues with patent information retrieval and panel construction, and ends with PPML event-study and difference-in-differences models. Patent databases are treated as structured information sources that record application dates, institutional origin and domain-specific terminology. The workflow is therefore designed to transform patent records into comparable indicators of technology dynamics across countries and application domains.

2.2 Identification of nanotechnology application domains

The first phase of the research focused on identifying nanotechnology application domains that display thematic stability in the scholarly literature and at the same time provide a suitable basis for subsequent patent analysis. The domain-identification procedure builds on the literature-based classification framework previously applied by Svoboda et al. (2026), while the present study introduces a different selection criterion based on patent continuity and restricts the inferential analysis to four domains. In line with recommendations for bibliometric mapping of technological fields (Donthu et al., 2021), a multi-source procedure combining the Scopus database and the Scite citation aggregator was used. Scopus served as the main source for the systematic search of peer-reviewed literature, while Scite was used as a supplementary citation-oriented triangulation tool to examine whether the application domains identified through the primary Scopus search also appeared in broader citation and interpretive contexts. Scite was not used to assess database coverage or retrieval completeness.

The Scopus search was conducted on 2 February 2026 using a Boolean query that combined general nanotechnology entities with terms denoting an application or sectoral context:

> (("nanomaterial" OR "nanomaterials" OR "nanoparticle" OR "nanoparticles" OR "nanocomposite" OR "nanocomposites" OR "nanofiber" OR "nanofibers" OR "nanostructure" OR "nanostructures") AND ("area" OR "application" OR "field" OR "sector" OR "branch"))

The search was limited to peer-reviewed scholarly publications. No time filter was applied, because the aim was not to capture only current developments, but to map the application spectrum of nanotechnology over the course of its scholarly development. Scite was subsequently used through three thematically related queries: In which areas are nanotechnologies used? What are the most common industrial and sectoral application areas of nanotechnologies reported in the scientific literature? In which application areas are nanotechnologies most frequently applied across scientific and applied research?

Scite was not used in this study as a standalone coverage database or as a replacement for standard bibliographic search. Its role was supportive and triangulatory: after the primary Scopus search, it was used to verify whether the identified application areas also appear in broader citation and interpretive contexts of the scholarly literature. This procedure is particularly useful for horizontal technologies such as nanotechnology, where application contexts often do not appear under uniform terminology. After the outputs had been obtained, thematic consolidation followed: synonyms and semantically related terms were merged, specialized applications were assigned to broader

analytical domains, and isolated occurrences without repeatability across sources were not interpreted as separate application areas.

Only domains meeting three predefined criteria were included in the patent phase. First, the domain had to be identified in the primary Scopus search. Second, it had to recur in the supplementary citation-oriented mapping. Third, it had to display sufficient continuity of patent activity in the G7 reference group. Patent continuity was operationalized as the absence of two consecutive zero-count years in the twenty-year G7 patent application time series. This criterion was applied to the G7 reference trajectory used for domain selection, not to every individual country series. The patent-continuity criterion was included so that an area present in the literature but too weak in patent activity would not automatically be considered suitable for longitudinal modelling.

On the basis of this filter, healthcare, cosmetics, agriculture and food were selected as the final domains. The selection of these four domains is substantively defensible because they represent socioeconomically important areas in which nanotechnology can function as a radical or strongly transformative innovation while also entering safety, validation and regulatory debates. In healthcare, this concerns diagnostics, drug-delivery systems and nanomaterials in medical applications; in cosmetics, consumer products with direct contact with the human body; in agriculture, nanopesticides, nanofertilizers and sensors; and in food, packaging, food safety and nanoformulations. Other nanotechnology application areas are not rejected. Rather, they either did not provide the same stable combination of literature visibility, patent continuity and regulatory relevance, or would require a different domain-specific design. The selected set is therefore not a map of the entire field of nanotechnology, but a reproducible and methodologically defensible basis for comparative analysis of patent trajectories.

2.3 Patent data and inferential sample

The bibliometric identification of application domains was followed by patent analysis, whose aim was to verify whether the areas identified in the literature also display continuous technological activity and to create a data basis for the longitudinal and comparative analysis of patent application trajectories. Patent data were used as a proxy indicator of formalized innovation activity.

Patent data were obtained on 4 July 2026 from the PatentInspiration database. This database was selected as a unified tool for data extraction and aggregation because it enables thematic searches in international patent records using Boolean operators, work with bibliographic data, time filters, classification metadata, patent families and the construction of time series by country and application area. According to its documentation, PatentInspiration is based on EPO DOCDB data and contains bibliographic data from more than 100 countries, including titles, abstracts, applicants, inventors, citations, classifications and family information; it also reports weekly database updates and full texts from the main patent authorities. The patent search followed the bibliometric phase and was based on general nanotechnology terms, specifically nanomaterial, nanoparticle, nanocomposite, nanofiber and nanostructure in both singular and plural forms, combined with terms for the individual application domains.

PatentInspiration was selected as a unified full-text search and aggregation interface rather than as a substitute for primary patent data sources. Its bibliographic foundation is based on EPO DOCDB; however, unlike DOCDB itself, it also enables patent claims and descriptions to be searched within a single consistent workflow. Directly replacing this interface with DOCDB would therefore not be methodologically equivalent: DOCDB does not contain full texts, and reproducing the same search would require linking bibliographic data with separate full-text collections and subsequently harmonizing their coverage. The same Boolean queries, searched fields, time filters and stemming procedure were applied consistently across all countries, years and application domains. This provides procedural consistency in dataset construction, but it does not necessarily imply identical retrieval completeness across all patent collections. Publicly available information on PatentInspiration indicates broader bibliographic than full-text coverage, with claims and descriptions available more comprehensively for some patent authorities than for others; however, a complete and current authority-by-field coverage matrix is not publicly available. The resulting patent counts should therefore be interpreted as database-dependent measures of retrieved patent activity rather than as exhaustive counts of all potentially relevant patent documents. Keywords used:

> ("nanomaterial" OR "nanomaterials" OR "nanoparticle" OR "nanoparticles" OR "nanocomposite" OR "nanocomposites" OR "nanofiber" OR "nanofibers" OR "nanostructure" OR "nanostructures") AND (domain term)

The patent set was constructed primarily using full-text keywords combining a nanotechnology block and a domain block. This procedure was chosen because nanotechnology is a horizontal enabling technology and its applications are dispersed across many technological classes. Svoboda et al. (2026) emphasize that nanotechnology innovations are characterized by interdisciplinary diffusion and by the ability to transform application environments, which supports the need for a broader retrieval framework based on the intersection of nano terms and domain terms. Using IPC or CPC as the main exclusive filter could lead to the loss of relevant patents: nanotechnology classifications often capture the material or technological principle but not the application domain, whereas sectoral classifications capture the application but may not explicitly distinguish nanotechnology content. Full-text retrieval in the title, abstract, claims and description therefore better corresponds to the aim of this study, namely to identify the intersection between nanotechnology terms and specific application areas.

For the final analysis, the domains healthcare, cosmetics, agriculture and food were used. In the case of healthcare, the subfields of medicine and pharmacy were merged to avoid underestimating patent activity due to terminological differences. The analysis covered the period from 2004 to 2023, making it possible to observe developments before and after three disruptive episodes: the Global Financial Crisis of 2008–2009, the COVID-19 pandemic of 2020–2021 and the war in Ukraine in 2022–2023.

Three operational decisions are important for interpretation. First, countries were assigned according to the institutional origin of the patent, that is, the origin of the institution associated with the patent record. The country variable therefore expresses institutional origin, not the patent office or jurisdiction in which the record was filed. Second, the year refers to the patent application date. The dependent variable is therefore the annual number of patent applications in a country-application domain-year combination. Third, the publication lag of patent applications must be considered. Because the final data collection took place in July 2026, the vast majority of applications with application dates in 2022 and 2023 should already have been published and included in database indexes. Later indexing of individual records or harmonization changes in database records cannot, however, be completely ruled out.

The inferential sample consisted of twelve countries. The reference group included all G7 countries: the United States, Canada, Japan, Germany, Italy, France and the United Kingdom. The BRICS comparison group included Brazil, India, Russia, China and South Africa. The results must be interpreted with regard to the different data profiles of individual countries: China has an exceptionally large scale of patenting and strongly affects the aggregate BRICS result, while South Africa has very low numbers of patent applications and frequent zero values. Patent data for all countries are provided in the Supplementary Materials, Tables S1–S4.

The dataset was aggregated at the country-by-domain-by-year level. The exported patent application counts were used as full counts and no additional fractional counting was applied. This choice is consistent with the aim of monitoring visible patent application activity by institutional origin rather than measuring fractional inventive contribution across organizations or jurisdictions.

2.4 Statistical strategy

The statistical analysis was divided into two main steps. The first step used event-study PPML models to determine whether patent activity in a given domain deviated from its previous local trajectory in the shock year and in the immediately following year. The second step used PPML difference-in-differences models to test whether the responses of BRICS countries differed from the response of the full G7 group. This two-step strategy makes it possible to distinguish an overall time-associated break in the patent trajectory from a relative difference between BRICS and G7.

PPML was selected because the dependent variable is a non-negative count variable, differs substantially across countries and domains and may include low values or zeros in smaller series. PPML allows absolute patent application counts to be analyzed directly and avoids logarithmic transformation of zero-valued observations. This is consistent with count-data econometrics and with the broader use of Poisson pseudo-maximum likelihood estimators in multiplicative models under heteroskedasticity (Cameron & Trivedi, 2013; Silva & Tenreyro, 2006). Estimated coefficients were transformed into percentage effects using the standard expression 100 x [exp(coefficient) - 1].

Each shock was operationalized as a two-year window consisting of the year in which the shock emerged and the immediately following year. The Global Financial Crisis was represented by 2008–2009, the COVID-19 pandemic by 2020–2021 and the war in Ukraine by 2022–2023. This operationalization was selected because patent application activity does not necessarily respond to systemic shocks within a single calendar year. Patent applications are usually preceded by research, administrative preparation, validation processes and decisions concerning intellectual property protection. The two-year window also keeps the model specification comparable across the three disruptive episodes.

Event-study PPML models were estimated separately for each application domain and each shock period and included country fixed effects and country-specific local linear trends. The aggregate DiD models included country and year fixed effects. Statistical inference for the aggregate event-study and BRICS-G7 DiD models was based on cluster-robust standard errors at the country level. Given the small number of countries, only 12, a bias-reduced CR2 correction for the small number of clusters was applied together with Satterthwaite-adjusted degrees of freedom for individual coefficient tests. This procedure accounts for both heteroskedasticity and arbitrary within-country dependence of errors across years (Bertrand et al., 2004; Cameron & Miller, 2015; Pustejovsky & Tipton, 2018). The country-specific PPML DiD models always compare one focal country with the seven G7 countries and therefore contain only a single treated country cluster. They are consequently retained solely as a descriptive decomposition of the point estimates, without p-values, confidence intervals, or claims of statistical significance. The models identify time-associated changes in patent trajectories and relative differences between BRICS countries and G7. They do not isolate one definitive causal mechanism, because the analyzed shocks may operate simultaneously through financing, demand, sanctions, collaboration networks, supply-chain disruptions and regulation.

3 RESULTS

3.1 Inferential sample and comparison logic

The inferential analysis is based on a panel that includes the full G7 group and all five analyzed BRICS countries. The analysis focuses on four nanotechnology application domains, namely healthcare, cosmetics, agriculture and food, and is based on a twenty-year time series of patent applications.

Across the full dataset of 960 country × domain × year combinations, annual absolute patent application counts ranged from 0 to 11 480. The range was 0-11 480 in healthcare, 0-2 121 in cosmetics, 0-1 996 in agriculture, and 0-7 176 in food.

The results are presented at three levels. Complete annual patent application counts by country, application domain, and year are provided in the Supplementary Materials, Tables S1–S4. Tables 1 and 2 report percentage point estimates and p-values based on CR2 cluster-robust inference at the country level with Satterthwaite-adjusted degrees of freedom. Tables 3 to 5 present only a descriptive decomposition of country-specific point estimates; p-values and indicators of statistical significance are not reported for these models.

3.2 Aggregate impact of shocks in the full country panel: Event-study PPML

During the Global Financial Crisis, a statistically significant negative deviation was observed in healthcare only in 2009, in agriculture in both 2008 and 2009, and in food in both years; the deviations in cosmetics did not reach the 0.05 significance level. During the COVID-19 pandemic, no deviation was statistically significant. During the war in Ukraine period, only the negative deviations in cosmetics and agriculture in 2022 were statistically significant, while the remaining estimates were not statistically significant.

Table 1. *Event-study PPML: Deviation of patent application activity from the pre-shock trajectory in the G7 + BRICS panel.*

Domain	2008	2009	2020	2021	2022	2023
Healthcare	*-11.4%* *p = 0.130*	**-25.0%** **p = 0.019**	*-6.2%* *p = 0.356*	*-3.7%* *p = 0.494*	*-9.1%* *p = 0.312*	*-16.8%* *p = 0.365*
Cosmetics	*-30.0%* *p = 0.068*	*-34.2%* *p = 0.066*	*-5.3%* *p = 0.674*	*-7.4%* *p = 0.648*	**-19.8%** **p = 0.023**	*-26.5%* *p = 0.116*

Domain	2008	2009	2020	2021	2022	2023
Agriculture	**-30.3% p = 0.043**	**-33.4% p = 0.036**	*-10.9% p = 0.473*	*-9.3% p = 0.451*	**-17.0% p = 0.032**	*-15.9% p = 0.114*
Food	**-20.0% p = 0.019**	**-30.8% p = 0.043**	*-8.0% p = 0.224*	*-6.4% p = 0.407*	*-11.4% p = 0.060*	*-21.6% p = 0.110*

Note: Each cell reports the estimated percentage effect and the corresponding p-value based on a CR2 cluster-robust covariance matrix with clustering at the country level and Satterthwaite-adjusted degrees of freedom. The number of clusters is 12. Values with $p < 0.05$ are shown in bold, while values with $p \geq 0.05$ are shown in italics.

3.3 Relative responses of BRICS countries compared with G7: PPML DiD

The second level of the analysis examines the aggregate difference between the BRICS group and the G7 group. Although some point estimates are positive and their signs suggest relatively more favorable development in BRICS, after the CR2 correction no BRICS-G7 DiD coefficient was statistically significant at the 0.05 level in any domain or year. The aggregate results therefore provide no statistically significant evidence that the BRICS group responded systematically differently from G7 to any of the shocks examined.

Table 2. *PPML DiD: BRICS countries compared with the full G7 group.*

Domain	2008	2009	2020	2021	2022	2023
Healthcare	*+10.1% p = 0.456*	*+34.9% p = 0.213*	*+2.8% p = 0.795*	*+16.4% p = 0.516*	*+28.4% p = 0.407*	*+68.9% p = 0.215*
Cosmetics	*+37.7% p = 0.188*	*+49.7% p = 0.257*	*-10.1% p = 0.114*	*+8.1% p = 0.761*	*+2.6% p = 0.892*	*+15.1% p = 0.667*
Agriculture	*+57.1% p = 0.171*	*+29.1% p = 0.445*	*-3.1% p = 0.777*	*+12.0% p = 0.405*	*+7.6% p = 0.831*	*+28.7% p = 0.512*
Food	*+20.7% p = 0.147*	*+46.8% p = 0.104*	*+10.8% p = 0.149*	*+16.8% p = 0.444*	*+22.9% p = 0.438*	*+55.5% p = 0.220*

Note: Each cell reports the estimated percentage effect and the corresponding p-value based on a CR2 cluster-robust covariance matrix with clustering at the country level and Satterthwaite-adjusted degrees of freedom. The number of clusters is 12. Values with $p < 0.05$ are shown in bold, while values with $p \geq 0.05$ are shown in italics.

The signs of the aggregate point estimates may be influenced particularly by the large scale of Chinese patent activity; however, this compositional interpretation does not constitute statistical confirmation of a BRICS-G7 difference. Internal differences among countries are therefore presented only descriptively in the subsequent analysis.

3.4 Responses of individual BRICS countries compared with G7 during the Global Financial Crisis

The following country-specific PPML models serve solely as a descriptive decomposition of the aggregate result. During the Global Financial Crisis, the point estimates for Brazil are positive across all four domains in both years; positive estimates are also observed for Russia and, in some domains, for China, whereas India shows a mixed to negative profile and South Africa is strongly affected by very low patent counts and zero values.

These country-specific patterns cannot be interpreted as independently statistically confirmed effects for individual countries. Their contribution is limited to describing the direction and magnitude of the point estimates, showing that the aggregate BRICS category may conceal substantially different national trajectories.

Table 3. *Descriptive PPML DiD decomposition: point estimates for individual BRICS countries relative to the full G7 group during the Global Financial Crisis, 2008–2009.*

Domain	Brazil 2008	Brazil 2009	India 2008	India 2009	Russia 2008	Russia 2009	China 2008	China 2009	South Africa 2008	South Africa 2009
Healthcare	+55.6%	+71.1%	-2.3%	+24.8%	+56.3%	+128.0%	+5.6%	+25.6%	-100.0%	+172.8%
Cosmetics	+374.8%	+599.6%	-44.2%	-44.1%	+1.7%	+32.5%	+37.2%	+32.5%	-100.0%	-31.7%

Domain	Brazil 2008	Brazil 2009	India 2008	India 2009	Russia 2008	Russia 2009	China 2008	China 2009	South Africa 2008	South Africa 2009
Agriculture	+246.7%	+306.7%	-81.3%	-32.3%	+103.9%	+112.8%	+69.2%	+18.3%	-100.0%	-100.0%
Food	+106.4%	+119.8%	-30.9%	-7.5%	+43.0%	+163.3%	+20.2%	+38.0%	+87.5%	+377.9%

Note: The cells report only country-specific PPML point estimates transformed into percentage differences relative to the G7 group. P-values and inferential significance indicators are not reported because each specification includes one focal country and seven G7 control countries, and therefore only a single treated country cluster. The estimates are interpreted exclusively descriptively in terms of their direction and magnitude.

3.5 Responses of individual BRICS countries compared with G7 during the COVID-19 pandemic

The country-specific results for the COVID-19 pandemic period are also interpreted exclusively descriptively. The point estimates suggest relative weakening in Brazil and Russia across several domains, a mixed to more favorable profile for India and China in selected domain-year combinations, and extreme volatility in South Africa associated with very low patent counts.

Table 4. *Descriptive PPML DiD decomposition: point estimates for individual BRICS countries relative to the full G7 group during the COVID-19 pandemic, 2020–2021.*

Domain	Brazil 2020	Brazil 2021	India 2020	India 2021	Russia 2020	Russia 2021	China 2020	China 2021	South Africa 2020	South Africa 2021
Healthcare	-29.3%	-42.3%	+10.7%	+32.3%	-25.1%	-64.0%	+6.0%	+24.3%	-100.0%	-100.0%
Cosmetics	-6.3%	-44.8%	+11.0%	+15.8%	-18.8%	-56.2%	-10.5%	+21.1%	-100.0%	-100.0%
Agriculture	+12.3%	-26.7%	-2.6%	+124.5%	+35.0%	-46.1%	-6.4%	+16.6%	-25.7%	-100.0%
Food	+0.5%	-33.7%	+54.4%	+61.3%	-17.4%	-65.4%	+12.2%	+23.9%	-29.6%	-8.2%

Note: The cells report only country-specific PPML point estimates transformed into percentage differences relative to the G7 group. P-values and inferential significance indicators are not reported because each specification includes one focal country and seven G7 control countries, and therefore only a single treated country cluster. The estimates are interpreted exclusively descriptively in terms of their direction and magnitude.

The descriptive decomposition therefore suggests a mosaic of different national trajectories rather than statistically confirmed country-specific differences. In particular, the estimates for South Africa should be interpreted only as indicative directional patterns in a small patent series with frequent zero counts.

3.6 Responses of individual BRICS countries compared with G7 during the war in Ukraine

During the 2022–2023 period, the country-specific point estimates show a markedly negative profile for Russia and Brazil, a positive profile for China, and a mixed profile for India. These values help describe why the signs of the aggregate BRICS estimates may differ from the trajectories of some individual group members; however, because each model contains only a single treated country cluster, they do not support standalone statistical inference for individual countries.

Table 5. *Descriptive PPML DiD decomposition: point estimates for individual BRICS countries relative to the full G7 group during the war in Ukraine, 2022–2023.*

Domain	Brazil 2022	Brazil 2023	India 2022	India 2023	Russia 2022	Russia 2023	China 2022	China 2023	South Africa 2022	South Africa 2023
Healthcare	-44.2%	-63.0%	-8.8%	-18.6%	-83.9%	-91.3%	+37.3%	+83.5%	+183.9%	+101.5%
Cosmetics	-29.2%	-54.5%	+11.8%	-12.8%	-82.2%	-80.9%	+10.3%	+30.3%	+516.6%	+395.7%
Agriculture	-61.5%	-80.2%	-57.2%	+42.8%	-79.2%	-93.2%	+19.4%	+43.8%	+144.5%	+78.5%
Food	-42.7%	-65.0%	+6.9%	+45.7%	-85.2%	-90.4%	+31.3%	+68.0%	+63.9%	+12.5%

Note: The cells report only country-specific PPML point estimates transformed into percentage differences relative to the G7 group. P-values and inferential significance indicators are not reported because each specification includes one focal country and seven G7 control countries, and therefore only a single treated country cluster. The estimates are interpreted exclusively descriptively in terms of their direction and magnitude.

Table 5 therefore represents only a descriptive decomposition. The direction and magnitude of the point estimates suggest divergent trajectories for Russia, Brazil, China, and India after 2022; however, these estimates cannot be interpreted as statistically confirmed country-specific effects.

3.7 Summary of the main findings in the full G7 specification

During the Global Financial Crisis, after the CR2 correction, statistically significant negative deviations in the aggregate event-study model were concentrated in healthcare in 2009, agriculture in both years, and food in both years. Cosmetics showed negative point estimates, but their p-values remained above the 0.05 level. No aggregate BRICS-G7 DiD difference was statistically significant during this period; national profiles are therefore interpreted only descriptively.

The COVID-19 pandemic represents the least conclusive period in terms of corrected inference. Neither the event-study models nor the aggregate BRICS-G7 DiD models produced any coefficient that was statistically significant at the 0.05 level. The cross-country differences reported in Table 4 are only descriptive point estimates and do not constitute independently valid inferential tests.

During the war in Ukraine period, only the negative deviations in cosmetics and agriculture in 2022 were statistically significant in the aggregate event-study model. Neither the estimates for 2023 nor the aggregate BRICS-G7 DiD coefficients were statistically significant. The markedly different signs of the point estimates for Russia, Brazil, and China are therefore used only as a descriptive decomposition of the aggregate pattern.

The comparison across application domains shows that the statistical support for deviations is not uniform across healthcare, cosmetics, agriculture, and food. The largest number of corrected statistically significant deviations appears during the Global Financial Crisis, whereas during the COVID-19 period no domain shows a statistically significant deviation, and after 2022 significance is limited to cosmetics and agriculture in 2022. The country-specific tables complement this picture only descriptively.

Overall, the corrected inference does not support the original broad claim of robust negative deviations across all domains during the Global Financial Crisis and the war in Ukraine. Instead, it supports the narrower conclusion that statistically significant deviations are specific to particular combinations of shock, year, and application domain. At the same time, no aggregate BRICS-G7 difference was demonstrated, and the internal heterogeneity of the BRICS countries remains a descriptive rather than inferential finding.

4 DISCUSSION

4.1 Interpretation from the perspective of innovation systems

The results should be interpreted as limited inferential evidence at the aggregate level, complemented by a descriptive decomposition of national trajectories, rather than as statistical confirmation of the resilience or vulnerability of individual countries. They show that some combinations of shock and application domain deviate from their previous trajectories, whereas others lack statistical support after correcting for clustering.

The observed heterogeneity suggests that geopolitical shocks should be understood as institutional transformations rather than isolated economic events. Patent applications reflect cumulative processes of scientific collaboration, investment, regulatory adaptation, knowledge exchange and intellectual property strategies rather than immediate technological responses (Jasanoff, 2004). Consequently, changes in patent trajectories capture the combined effects of disruptions to international collaboration, research infrastructures, financing opportunities and policy priorities. Such patterns are consistent with the view that innovation emerges within interconnected innovation ecosystems whose performance depends on interactions among actors and institutions rather than on the capabilities of individual organizations alone (Etzkowitz & Leydesdorff, 2000; Adner, 2017). Innovation resilience therefore reflects not only technological capabilities but also the capacity of innovation ecosystems to reorganize knowledge production under conditions of uncertainty (Geels, 2004).

From a theoretical perspective, the aggregate models do not provide statistically significant evidence of a systematic difference between G7 and BRICS. However, the descriptive point estimates for individual countries suggest that a common group category may conceal divergent national trajectories. These differences should be regarded as a basis

for further research into institutional capacities, research infrastructure, market structure, technological specialization, and international linkages, rather than as independently confirmed country-specific effects.

At the same time, the results support a domain-differentiated perspective only in a limited sense: corrected statistical significance varies across healthcare, cosmetics, agriculture, and food, as well as across the individual shock periods. Descriptive estimates for individual countries further suggest differing directions of development, but inference for these estimates is not valid when there is only a single treated country cluster.

The findings are relevant to debates on global value chains, technological sovereignty, and the vulnerability of knowledge-intensive systems; however, mechanisms such as sanctions, restrictions on collaboration, input shortages, or policy changes are not directly tested. The negative point estimates for Russia and Brazil and the positive estimates for China after 2022 therefore represent possible descriptive patterns rather than inferentially confirmed consequences of specific institutional mechanisms.

4.2 Implications for technology intelligence and policy monitoring

From a technology-intelligence perspective, the results indicate that patent analytics can function as one input to monitoring systems for strategic technologies. Patent information systems contain structured and semi-structured records on application dates, institutional origin, terminology and technology fields. When combined with bibliometric domain mapping and count-data models, these records can help identify where technological activity changes after systemic disruptions.

For technology monitoring, this implies that a single aggregate nanotechnology indicator may fail to capture differences across application domains. Country-specific point estimates can serve as exploratory signals for further analysis rather than as independently statistically confirmed assessments of national resilience. Decision-support systems should therefore report not only the country, application domain, and shock period, but also the inference method used and the associated uncertainty.

The same analytical logic can be transferred to other enabling technologies such as artificial intelligence, robotics, semiconductors or green technologies, provided that domain definitions and patent queries are specified transparently. In such cases, the main value lies in comparing domain-specific trajectories rather than relying on a single aggregate indicator.

4.3 Limitations

Several limitations of the study should be noted. First, raw patent application counts capture only formalized technological activity and do not by themselves measure the quality of inventions, their commercial value, scientific impact or actual market application. This qualification concerns the count indicator used in this article, not patent data in general. Patent quality and value can be studied through forward citations, family size, claims, legal status, renewal behavior, co-inventorship networks or specialized valuation indicators (Hall et al., 2005; Harhoff et al., 1999; Trajtenberg, 1990). Patent application counts are therefore useful for international and longitudinal comparison, but they provide only a partial picture of innovation performance (Daim et al., 2006; Griliches, 1990). Future studies should combine count-based patent analytics with patent-quality and patent-value indicators.

Second, a further limitation concerns differences in full-text coverage across patent collections. In this study, country refers to the institutional origin associated with the patent record, whereas the availability of claims and descriptions depends on the relevant publication authority or collection. Because the analytical dataset was retained as aggregated country × application-domain × year counts, document-level differences in full-text availability cannot be reconstructed from the present dataset. If such coverage differences are systematically related to filing routes used by applicants from different countries, they may affect absolute cross-country comparisons. The results should therefore be interpreted as comparative trajectories obtained using a consistently applied retrieval procedure rather than as exhaustive measures of national patenting activity.

Third, the study identifies time-associated changes in patent application trajectories, not definitive causal mechanisms. The analyzed shocks are macro-level and geopolitical events that may operate through several channels at the same time, including financing, supply chains, sanctions, demand shifts, regulation and collaboration networks. Because the analysis uses application date, the year assigned to each observation reflects the application

year rather than the later publication year. This reduces, but does not eliminate, timing concerns: patent applications are preceded by invention and internal research activity.

The third limitation concerns the composition of the BRICS comparison group. The aim of this study was to analyze the five original BRICS countries, Brazil, Russia, India, China and South Africa, relative to the full G7 benchmark. The analysis therefore concerns the original BRICS configuration rather than the subsequently expanded BRICS membership. This is substantively important for interpretation and comparability over the 2004–2023 study period, but it also increases the compositional sensitivity of the results. China has an exceptionally large scale of patenting and specific institutional incentives and therefore strongly influences the aggregate BRICS effect. A control interpretation without China would lead, especially in 2022–2023, to a much more negative picture of BRICS relative to G7 because the declines of Russia and Brazil would dominate. This result is not the main estimate of the study, however, because the research objective was to examine the five-country BRICS comparison group considered in the analysis. South Africa is included as one of the five original BRICS countries, but its patent series contain very low counts and frequent zeros; country-specific results for South Africa should therefore be interpreted as indications of direction and volatility in a small patent series, not as evidence as robust as that for larger patent systems.

The fourth limitation concerns the number of clusters and the structure of the country-specific models. The aggregate tests use the CR2 correction with Satterthwaite-adjusted degrees of freedom; however, the individual-country models contain only a single treated country cluster. Their results therefore do not have a standalone inferential interpretation and are used only to describe the direction and magnitude of the point estimates.

5 CONCLUSION

This study shows that the response of nanotechnology patent activity to major geopolitical and macroeconomic shocks is not uniform but depends on the specific application domain and period. The strongest statistically supported decline was identified during the Global Financial Crisis, particularly in healthcare, agriculture, and food. By contrast, the COVID-19 pandemic was not associated with a statistically significant aggregate deviation in any of the examined domains. In the 2022 to 2023 period, statistically significant negative deviations were observed only in cosmetics and agriculture in 2022. At the same time, the aggregate DiD models provided no statistically significant evidence that the development of patent activity in the analyzed BRICS countries systematically differed from that in the G7. The divergent national trajectories observed in the point estimates should therefore be interpreted as descriptive heterogeneity rather than as statistically confirmed country-specific effects.

The main scientific contribution of this study is the finding that the resilience of technological development to systemic shocks cannot be reliably assessed solely at the level of aggregated technological sectors or geopolitical groups of countries. In the case of a horizontal technology such as nanotechnology, responses to the same external disruption differ across application domains and may also vary substantially across individual national innovation systems. Innovation resilience should therefore be understood as a domain-dependent characteristic of technological trajectories rather than as a uniform property of a technology or a group of economies. This conclusion extends the intersection of research on innovation systems, technological resilience, and patent analytics by explicitly incorporating the application-domain dimension.

The study also shows that patent data can be used to identify changes in technological trajectories during systemic disruptions, but their interpretation must distinguish between general temporal deviations, differences across technological domains, and heterogeneity among individual countries. Future research should extend this perspective by incorporating indicators of patent quality and economic value, as well as institutional characteristics of individual innovation systems, in order to identify more precisely the mechanisms underlying differences in the capacity of technological domains to absorb external shocks.

ADDITIONAL INFORMATION AND DECLARATIONS

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Data Availability: The patent application count data underlying the analysis are provided in the Supplementary Materials (Tables S1–S4), available as an online appendix to this article (Supplementary files).

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