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Co-ownership and patent filing rates in Brazilian Heis (2020–2024): Panel evidence

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Abstract

This study investigates the association between co-ownership and patent filing rates in Brazilian higher education institutions (HEIs) from 2020 to 2024, aiming to assess whether formal collaboration and public funding jointly influence universities' performance in technological protection after controlling for scientific output and institutional heterogeneity. Using an observational HEI × year panel design, the research integrates public administrative data from the Revista da Propriedade Industrial (RPI) and the National Institute of Industrial Property (INPI) on invention patent (PI) and utility model (MU) filings, Scopus data on scientific production, and FINEP data on public research funding. The modeling strategy employs negative binomial regression (NB2) with a log link and an offset of ln(Scopus + 0.5), including year and region fixed effects. An additional specification incorporating the interaction between co-ownership and funding was estimated as a complementary analysis. The results reveal a highly concentrated patenting structure, dominated by invention patents, and show positive bivariate associations between filings, co-ownership, and funding. However, in multivariate models adjusted for scientific scale and institutional heterogeneity, none of the three co-ownership measures exhibit statistically significant direct effects. A small yet significant interaction between co-ownership and funding emerges only for invention patents, suggesting limited conditional influence. Overall, formal collaboration alone does not increase patent filing rates once contextual factors are considered, and the national system remains concentrated. These findings indicate that improving intellectual property performance in universities requires coordinated strategies that integrate collaboration quality, technology transfer mechanisms, and effective funding environments rather than simply expanding the number of partnerships.

Keywords: Patents, Innovation, Universities, Public funding.

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1. Introduction

Universities occupy a central position in innovation systems by generating knowledge, forming networks, and activating technology-transfer mechanisms, including open-innovation practices, that sustain competitiveness and socioeconomic development [1, 2]. Recent literature emphasizes that more robust outcomes emerge when public research, firms, and governments are institutionally articulated with appropriate governance and aligned incentives, an updated perspective on the Triple Helix model applied to the Sustainable Development Goals (SDGs) [3] and on syntheses of barriers and facilitators in university–industry collaboration [4]. European evidence likewise shows that institutional characteristics and funding structures influence university patenting and co-patenting with firms [5]. In Brazil, recent analyses highlight expansion under stringent constraints and regional asymmetries in public funding [6] underscoring the relevance of measuring how collaboration and public financing translate into knowledge protection via patents in higher education institutions (HEIs), whether through researchers' motivational factors [7] or the partnership dynamics observed at São Paulo state universities [8].

Within this debate, university intellectual property (IP) is treated both as an indicator of technological capacity and as a channel for transfer (licensing, co-patenting, and revenues), yet its dynamics depend on organizational arrangements, absorptive capacity, and the regulatory environment [9-11]. Comparative evidence also shows that Bayh-Dole-inspired legal frameworks have reshaped IP management in universities and spurred international reforms, although the mere formalization of rights and linkages does not guarantee results in the absence of effective institutional intermediation [12, 13].

In the context of innovation-driven economies, universities play a dual role as knowledge producers and active participants in technology transfer processes. Recent research emphasizes that academic excellence and institutional reputation directly affect the performance of innovation ecosystems and startup environments, reinforcing the strategic relevance of higher education institutions (HEIs) for regional competitiveness [14]. Furthermore, universities engage in patenting not only for the protection of intellectual property but also to pursue income generation, institutional recognition, and social impact through technology transfer, although they continue to face persistent challenges related to bureaucracy, financial constraints, and limited incentives [15].

At the same time, studies of university–industry collaboration point to benefits—direct innovation and indirect gains, such as learning and network formation—as well as limits: co-ownership/co-patenting signals structured interaction, but by itself, does not capture relational intensity, project quality, or contractual governance arrangements. Organizational/cognitive proximities influence these dimensions, the role of intermediaries, and property rights rules [13, 16-19]. This ambivalence is particularly salient in systems with a growing scientific base but uneven distributions of R&D and absorptive capacities, where the mere formalization of ties does not ensure protectable outcomes without effective institutional mediation and active management of patent portfolios.

Recent Brazilian scholarship reinforces that the university IP field is concentrated and unequal across areas and institutions, with long institutional trajectories and specific accumulations, as evidenced by rankings and analyses showing a high share of HEIs among the largest filers and marked concentration in a few universities [20-22]. These patterns align with systemic diagnoses that describe a historically dominant institutional core and its effects, linked to resource allocation and relative performance [23]. In parallel, recent analyses argue that improving technological outcomes also requires strengthening intrafirm R&D and appropriation mechanisms within companies, rather than expecting that isolated incentives will automatically turn into private expenditures and patents [24].

This picture resonates with debates in the Global South, where institutional architecture and the unequal distribution of scientific and industrial capacities shape the conversion of science into protectable technology (e.g., differences in governance, funding, and sectoral windows) [25-27]. Recent evidence suggests that Organisation for Economic Co-operation and Development (OECD)-inspired arrangements yield results only when adapted to the stage of development and local production structures, often prioritizing technology adoption and diffusion before frontier innovation and calibrating technology-transfer (TT) and IP instruments to existing business and academic capabilities [26, 28]. In such contexts, estimating associations among formal collaboration, public funding, and patent filings requires models that control for scientific exposure/scale and institutional heterogeneity (research profile, university type, regulatory regime), lest size effects be confounded with substantive effects [5, 29].

Despite descriptive advances, analytical gaps persist: positive bivariate relationships among collaboration, funding, and filings coexist with more cautious multivariate findings once controls for scientific scale, fixed effects, and research structure are imposed; furthermore, there is no consensus about the temporal stability of these relationships. Few studies combine an HEI×year panel, count models with a scientific exposure offset, and disaggregation by title type (invention patents vs. UMs), while explicitly considering modulation by public funding in mutually aligned specifications. This article is situated in this space, employing an observational design and maintaining strict alignment among research questions, methods, and results.

In Brazil, research productivity grants provided by the National Council for Scientific and Technological Development (CNPq) have been instrumental in shaping scientific performance and institutional excellence. Evidence from the field of production engineering shows that grant-holding researchers achieve higher publication rates, greater postgraduate supervision, and more innovation-related outcomes than non-grantees, indicating that funding mechanisms effectively stimulate academic productivity [30]. These findings highlight the relevance of financial incentives and research-support policies for the development of science and technology capacity within HEIs—a dimension empirically tested in this study through Finep funding and co-ownership indicators.

In line with these objectives, this study estimates the association between co-ownership and the patent-filing rate of Brazilian HEIs from 2020 to 2024 in an HEI×year panel adjusted for scientific exposure and institutional heterogeneity. Specifically, we aim to: (i) examine the relationship between FINEP funding and filings in an HEI×year panel under the same adjustments; (ii) explore heterogeneity by type of co-ownership (academic vs. firm/other) and by title (invention patents vs. UMs) in specifications aligned with the main model; and (iii) characterize the distribution and concentration of filings across HEIs in the analyzed quinquennium using the same universe and counting rules.

Consistent with these aims, we formulate the following hypotheses: (i) there is an association between co-ownership and HEI patent-filing rates (2020–2024) when estimated in an HEI×year panel adjusted for scientific exposure and institutional heterogeneity; (ii) FINEP disbursements are associated with filing rates under the same adjustments; and (iii) the strength of the association between co-ownership and rates varies by type of co-ownership (academic vs. firm/other) and by title (invention patents vs. UMs) in specifications aligned with the main model. Finally, as a descriptive question, we ask how filings are distributed across HEIs over the quinquennium and what level of concentration is observed.

2. Method

2.1. Design and Unit of Analysis

This is an observational study structured as an HEI×year panel covering the period from 2020 to 2024. The unit of analysis is institution i in year t. The outcome is the annual count of patent filings and UMs in which the HEI appears as an applicant, either alone or in co-ownership. For co-owned applications, we assign one occurrence per HEI per application, thereby disallowing within-HEI double-counting. By construction, the sum across HEIs may exceed the national total, which is consistent with the applicant-based perspective and the formation of the panel.

2.1.1. Conceptual Model

The conceptual model organizes the empirical relationships among co-ownership, public funding, research structure, and filing outcomes at the HEI×year level. Academic output, measured in Scopus, is treated as the exposure (offset) in an NB2 specification (log link), ensuring that coefficients are interpreted as effects on filing rates conditional on the scientific scale. Co-ownership is operationalized in three views, each estimated in a separate specification: (i) academic co-ownerships (with universities, institutes, and foundations); (ii) co-ownerships with firms/other entities; and (iii) the share of filings in co-ownership (0–1). Public funding (FINEP) operates both as a direct determinant of filings and as a moderator of the co-ownership–filings association (interaction term). Arrows indicate expected associations; no strict causal interpretation is assumed (Figure 1).

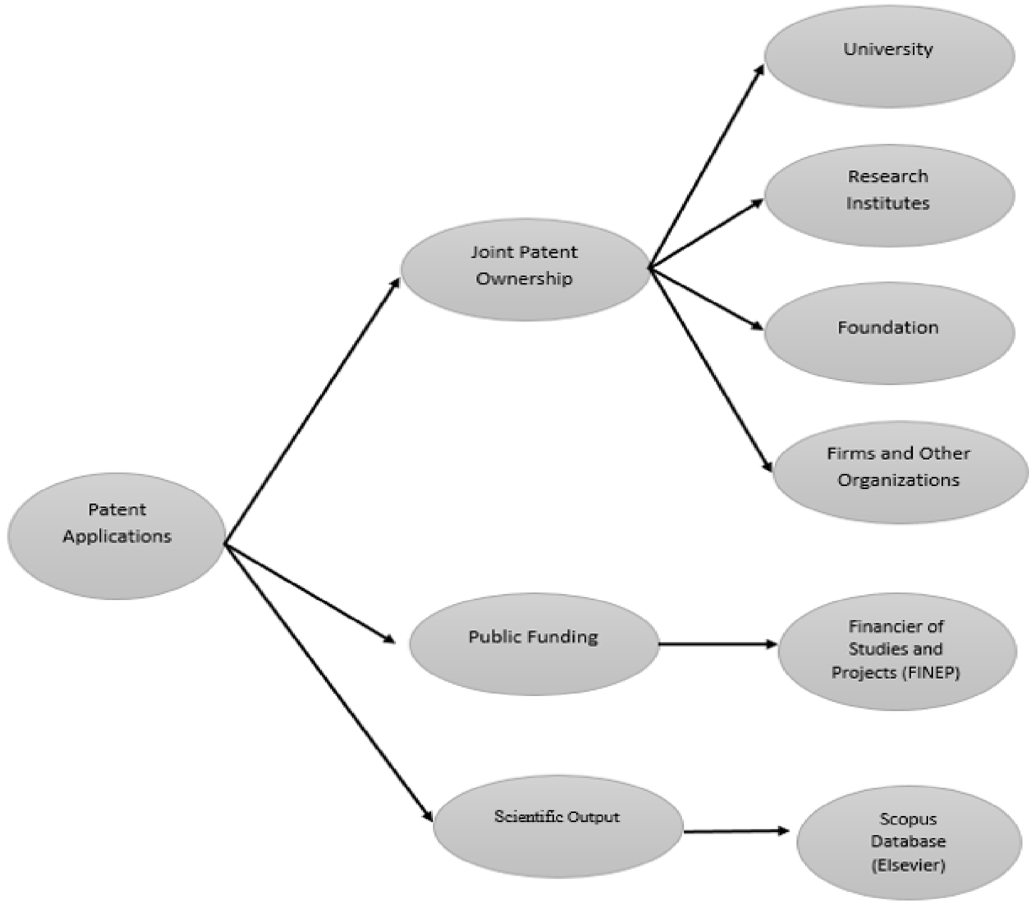

Figure 1.
Conceptual model of study variables.

2.2. Data Sources, Collection, and Temporal Scope

Patent data are sourced from the Brazilian Patent and Trademark Office's Industrial Property Gazette (INPI/RPI), which combines the Official Publication (PDF) with structured files (XML/TXT). To unambiguously identify the filing act, we use Code 2.1 ("application filed"), recording, for each observation, the application number and date, the title type (invention patent or UM), and the applicants. Extraction and initial processing were performed in Python with scripts that decompress weekly RPI bulletins and convert records into standardized base spreadsheets (field and format normalization). We use only public INPI data (applicant names, filing date and number, invention patent/UM codes), regardless of the 18-month confidentiality period. We do not expect coverage impacts for 2020–2023, although we note possible undercoverage in 2024 due to confidentiality concerns.

Measures of scientific scale and institutional structure were compiled from Scopus (HEI × year indexed output), CAPES (Coordination for the Improvement of Higher Education Personnel) and FINEP (public funding). Nominal reconciliation of institutions employed an alias dictionary and, when available, Scopus Affiliation IDs, with manual verification for any discrepancies. We maintained provenance/version logs for each extraction and applied filters. We conducted accounting checks (including consistency of invention patent and UM counts, as well as year-wise and co-ownership-type aggregates).

2.2.1. Data-Collection Records

Table 1 documents, for each variable/dataset, the source, collection date, applied parameters/filters, and operational notes, ensuring traceability of the 2020–2024 HEI×year panel. In particular, Scopus provides the main exposure (offset) $\ln(\text{Scopus}_{it} + 0.5)$—with an annualized proxy when a yearly series is incomplete. Code 2.1 (application filed) in INPI/RPI unambiguously identifies invention patent and UM filings, including co-owned applications.

Table 1.
Data-collection records.

Variable / Dataset	Source / Platform	Collection date	Filters or applied parameters	Notes
Invention Patents and utility models (UMs)	INPI – Industrial Property Gazette (RPI)	September 12, 2025	Code 2.1 (applications filed); 2020–2024	Co-owned applications included.
Scientific output	Plataforma Sucupira / Scopus	April 4, 2025/ September 8, 2025	Filtered by institution and year (2020–2024)	Aggregated by HEI over the period.
Public funding	FINEP – Transparency Portal (projects and disbursements)	September 12, 2025	Mapping executor → HEI; values for 2020–2024	Disbursements for contracted operations/releases made.
Alias / key dictionary	Prepared by the authors	2025	Nominal reconciliation (aliases, acronyms, English names) and use of Affiliation ID	Integrated into the OSF repository.

Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024; plus the authors' OSF repository (alias dictionary).

2.3. Variable Construction

The dependent variable is the annual count of filings per HEI (total invention patents + UMs). Heterogeneity analyses are replicated separately for invention patents and for UMs. Because the substantive interest lies in rates, the models include an offset in the linear predictor. The leading offset is

$$\ln\left(\text{Scopus}_{it} + 0.5\right),$$

Where Scopus_{it} denotes the HEI's indexed output in Scopus by year. The key predictors capture co-ownership in three views (each estimated in a separate specification): (i) annual count of co-ownerships with firms/other non-academic partners; (ii) annual count of academic co-ownerships; and (iii) the share of the HEI's filings in co-ownership (0–1). Controls include year fixed effects, region fixed effects, and, when available, institutional characteristics (e.g., legal status and field composition).

2.4. Modeling strategy

The main model employs a negative binomial (NB2) count family with a log link, which is suitable for overdispersion, and incorporates a scientific scale offset. Let y_{it} be the filing count and $\mu_{it} = \mathbb{E}[y_{it} \mid X_{it}]$. We specify

$$\text{Var}(\, y_{it} \mid X_{it}\,) = \mu_{it}\{1 + \alpha\, \mu_{it}\}, \alpha > 0,$$

With linear predictor

$$\ln(\mu_{it}) = \beta_0 + \beta_1 \, \text{CoTitEmp}_{it} + \beta_2 \, \text{CoTitAcad}_{it} + \theta' Z_{it} + \ln(\text{offset}_{it}) + \lambda_t + \delta_r;$$

IRR = exp (β); pseudo-R^2 de McFadden.

and report incidence-rate ratios (IRRs) as exp (β), alongside McFadden's pseudo-R^2. Here, Z_{it}gathers controls, $\lambda_t$are year fixed effects, and $\delta_r$are region fixed effects. The inference relies on robust standard errors clustered by HEI. Incidence rate ratios (IRR = exp(β)) are reported along with 95% confidence intervals. To examine whether the effect of co-ownership varies with public funding, an additional specification including the co-ownership × funding interaction was estimated, and separate models were fitted for invention patents and MU.

2.5. Diagnostics, Specification Selection, and Robustness

The choice of the negative binomial (NB2) model rests on evidence of overdispersion in the count data, assessed via the dispersion parameter ($\alpha > 0$) and the Pearson chi-square/degrees-of-freedom ratio. We compared Poisson and NB2 fits using AIC, BIC, and McFadden's pseudo-R^2, complemented by residual deviance analysis. We also inspected leverage and re-estimated models, excluding influential observations, to verify the stability of the estimates. This strategy confirmed the adequacy of NB2 relative to the simple Poisson model, yielding a specification consistent with the observed data properties. Sensitivity analyses preserve the panel logic and include: (i) alternative offsets (faculty and researcher counts); and (ii) alternative specifications (Poisson).

2.6. Reproducibility and Reporting

All statistical analyses were conducted in IBM SPSS Statistics v. 31, using the Generalized Linear Models (GENLIN) procedure. We estimated negative binomial (NB2) and Poisson regressions with a log link, robust (sandwich) variance, and Pearson chi-square scale adjustment to correct for overdispersion. We also fitted Generalized Estimating Equations (GEE) to obtain complementary goodness-of-fit measures, such as McFadden's pseudo-R^2. Specifications included year and region fixed effects as well as alternative offsets (Scopus publications and number of PhD researchers), as appropriate to each model.

The analytic datasets were frozen as of the dates recorded in the Open Science Framework (OSF), ensuring temporal traceability and transparency across study steps. To standardize institutional identification, we applied an alias dictionary that unified spelling variants and abbreviations. The public replication package on OSF includes the consolidated panel, intermediate spreadsheets, the alias dictionary, and the final tables exported from SPSS.

2.7. Ethical Considerations and AI-Assisted Writing

This study uses exclusively public and administrative data with no individual identification, aggregated at the HEI×year level. There was no human-subject intervention, no direct interaction with participants, and no processing of sensitive personal data; therefore, IRB/ethics review does not apply, without prejudice to good practices in information governance and security (access control and provenance documentation via OSF).

Writing and editorial polishing received assistive support from generative AI for paraphrasing, style harmonization, and consistency checks in terminology. AI was not used for data collection, cleaning, or statistical analysis. All quantitative procedures (panel construction, NB2 with offset, fixed effects, cluster-robust standard errors, lags, and Poisson checks) were implemented and verified in SPSS v31 by the authors, with reproducibility ensured by the provided scripts. The authors critically reviewed all AI-assisted content for factual accuracy and methodological adherence; no results, numbers, or interpretations beyond those generated by the study's script were introduced.

2.8. Data and Code Availability

Scripts for extraction, cleaning, linkage, and modeling; the HEI×year panel (with variables necessary to reproduce tables and figures); and the institutional alias dictionary will be made publicly available after peer review under a permissive license. Raw RPI/INPI files (in PDF and XML/TXT formats), which may be subject to use restrictions, will not be redistributed; however, they can be fully reconstructed from the original public sources and the accompanying control spreadsheets. The repository will include comprehensive documentation of data collections, transformations, and file versions, ensuring transparency and reproducibility across all stages of the study.

3. Results

3.1. Coverage and Sample Composition

Applying the sequential filters to applications published in INPI/RPI between 2020 and 2024 yielded 7,494 records in the raw final portfolio and 6,649 in the consolidated final portfolio (HEI×year panel)—counted by applicant, with one occurrence per HEI for co-owned applications (Table 2). We retain the caveat of possible undercoverage in 2024 due to the 18-month confidentiality period that applies.

Table 2.
Applied filters and analytical portfolio (2020–2024).

Filter	Description	Number of filings
Total applications by applicant	All patent applications were considered, with each applicant counted separately, as many applications involve multiple applicants.	43,027
UMs and invention patents	Selected utility model (UM) and invention patent applications (codes BR 20 and BR 10). International revalidations and certificates of addition were excluded.	46,272
Years 2020–2024	A five-year window was selected to ensure sufficient data for statistical analysis, excluding outdated or irrelevant information.	42,476
Raw final portfolio	Includes HEI applications (universities, public and private colleges, federal education institutes, military institutes, and research-support foundations).	7,494
Consolidated final portfolio (panel)	The portfolio used in the analyses consisted of filings from HEIs that appeared in the Top 50 ranking, which ultimately covered 61 institutions due to ties occupying the same ranking position.	6,649

Note: In co-ownerships, a single application may be counted for more than one applicant; this rule is consistent with the HEI-based panel construction described in the Method.
Source: Authors, based on INPI/RPI (invention patent and UM filings; applicant-level counts; 2020–2024).

3.2. Distribution by HEI: Ranking and Dispersion

Deposit concentration is summarized by the HEI ranking (2020–2024), with UFCG (373), UFMG (351), and USP (275) standing out (Table 3); the cumulative share reaches 53.96% at the 14th position.

Table 3.
Ranking of patent deposits by HEI (2020–2024).

Rank	Institution	Patent filings (%)
1	Institutos Federais de Educação, Ciência e Tecnologia (IFs)	574 (8.63%)
2	Universidade Federal de Campina Grande (UFCG)	373 (5.61%)
3	Universidade Federal de Minas Gerais (UFMG)	351 (5.28%)
4	Universidade de São Paulo (USP)	275 (4.14%)
5	Universidade Federal da Paraíba (UFPB)	266 (4.00%)
6	Universidade Estadual de Campinas (UNICAMP)	240 (3.61%)
7	Universidade Federal de Pernambuco (UFPE)	208 (3.13%)
8	Universidade Estadual Paulista Júlio de Mesquita Filho (Unesp)	186 (2.80%)
9	Universidade Federal do Ceará (UFC)	185 (2.78%)
10	Universidade Federal do Rio de Janeiro (UFRJ)	181 (2.72%)
11	Universidade Federal de Uberlândia (UFU)	154 (2.32%)
12	Universidade Estadual de Londrina (UEL)	153 (2.30%)
13	Universidade Federal de Pelotas (UFPel)	150 (2.26%)
14	Universidade Federal Rural de Pernambuco (UFRPE)	146 (2.20%)
	Universidade Federal de Sergipe (UFS)	146 (2.20%)
15	Universidade Federal do Maranhão (UFMA)	141 (2.12%)
16	Universidade Federal de Viçosa (UFV)	140 (2.11%)
17	Universidade Federal de Santa Catarina (UFSC)	132 (1.99%)
18	Universidade Federal do Paraná (UFPR)	120 (1.80%)
19	Serviço Nacional de Aprendizagem Industrial (SENAI)	119 (1.79%)
20	Universidade Federal do Rio Grande do Norte (UFRN)	118 (1.77%)
21	Universidade Federal do Pará (UFPA)	112 (1.68%)
22	Universidade Federal de São João del-Rei (UFSJ)	109 (1.64%)
23	Universidade Tecnológica Federal do Paraná (UTFPR)	107 (1.61%)
24	Universidade Federal de Alagoas (Ufal)	104 (1.56%)
25	Fundação Universidade Federal de São Carlos (UFSCar)	99 (1.49%)
26	Universidade Federal da Bahia (UFBA)	94 (1.41%)
27	Universidade Federal do Piauí (UFPI)	92 (1.38%)
28	Universidade Federal de Juiz de Fora (UFJF)	84 (1.26%)
29	Universidade Federal de Lavras (UFLA)	78 (1.17%)
	Fundação Universidade de Brasília (mantenedora) (FUB) + Universidade de Brasília (UnB)	78 (1.17%)
30	Universidade Federal de Santa Maria (UFSM)	75 (1.13%)
31	Universidade Federal do Rio Grande do Sul (UFRGS)	74 (1.11%)
	Universidade Federal do Rio Grande (FURG)	74 (1.11%)
32	Universidade Federal do Espírito Santo (UFES)	67 (1.01%)
33	Universidade Federal de Mato Grosso do Sul (UFMS)	65 (0.98%)
34	Universidade Federal Rural do Semiárido (UFERSA)	62 (0.93%)
35	Universidade Federal Fluminense (UFF)	60 (0.90%)
36	Universidade Estadual da Paraíba (UEPB)	59 (0.89%)
37	Universidade Tiradentes (UNIT)	58 (0.87%)
38	Universidade Federal de Ouro Preto (UFOP)	57 (0.86%)
39	Universidade Federal de Goiás (UFG)	52 (0.78%)
40	Universidade Federal de Itajubá (UNIFEI)	48 (0.72%)
41	Universidade do Estado do Rio de Janeiro (UERJ)	44 (0.66%)
42	Universidade Estadual de Maringá (UEM)	41 (0.62%)
	Universidade Estadual do Oeste do Paraná (Unioeste)	41 (0.62%)
43	Universidade Federal do Recôncavo da Bahia (UFRB)	38 (0.57%)
44	Fundação Universidade Federal de Mato Grosso (UFMT)	36 (0.54%)
	Universidade Católica de Pernambuco (UNICAP)	36 (0.54%)
	Universidade Estadual do Norte Fluminense Darcy Ribeiro (UENF)	36 (0.54%)
45	Fundação Oswaldo Cruz (Fiocruz)	33 (0.50%)
	Universidade Federal de Alfenas (UNIFAL)	33 (0.50%)
46	Fundação Universidade Federal do ABC (UFABC)	32 (0.48%)
47	Fundação Universidade Federal do Pampa (Unipampa)	29 (0.44%)
	Universidade Federal de São Paulo (UNIFESP)	29 (0.44%)
	Universidade Federal do Vale do São Francisco (UNIVASF)	29 (0.44%)
	Universidade Estadual de Ponta Grossa (UEPG)	29 (0.44%)

48	Universidade Federal dos Vales do Jequitinhonha e Mucuri (UFVJM)	27 (0.41%)
49	Fundação de Ensino Superior do Vale do Sapucaí (mantenedora) (Univás)	24 (0.36%)
	Universidade do Estado do Pará (UEPA)	24 (0.36%)
50	Universidade Estadual de Santa Cruz (UESC)	22 (0.33%)

Note: In co-ownerships, a single application may be counted for more than one applicant; this rule is consistent with the HEI-based panel construction described in the Method section.
Source: Authors, based on INPI/RPI (invention patent and UM filings; applicant-level counts; 2020–2024).

The HEI-wise distribution of filings is right-skewed, with a long tail, high concentration among top institutions, and upper-end outliers in the box plot (Figure 2).

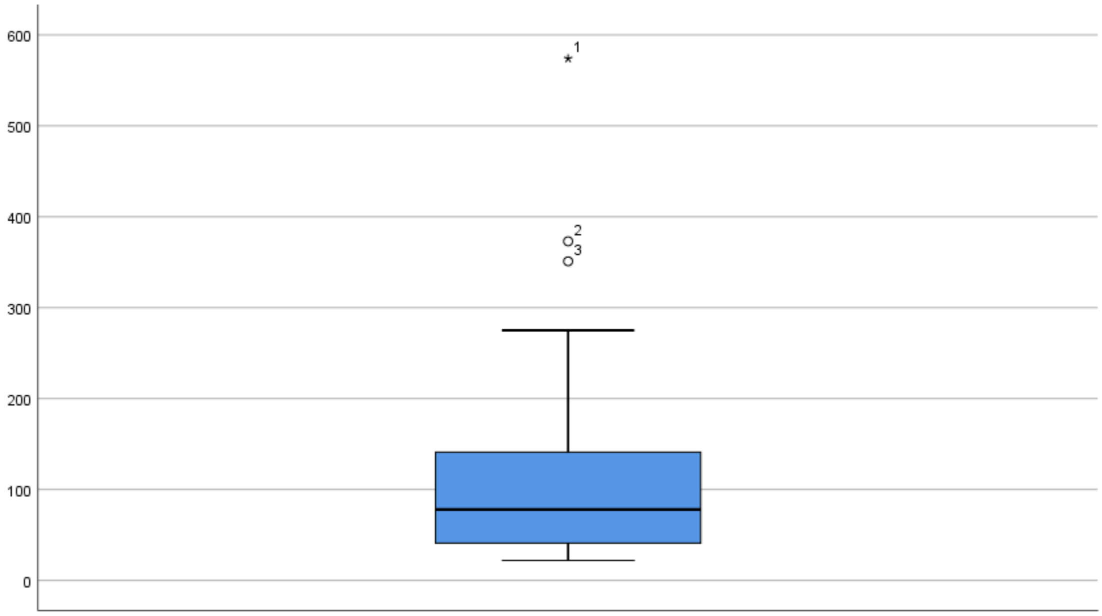

Figure 2.
Dispersion of patent filings across HEIs (box plot, 2020–2024).
Note: Values by HEI follow the same applicant-level counting rule as the ranking; outliers reflect institutions at the top of the distribution.
Source: Authors, based on INPI/RPI (invention patent and UM filings; applicant-level counts; 2020–2024).

3.3. Patent Types (Invention Patents vs. UMs)

Invention patents predominate over UMs at most HEIs (Figure 3). A subset of institutions—e.g., UFPB, UFU, UFSC, and UFRN—shows a higher share of UMs, indicating a more diversified protection strategy.

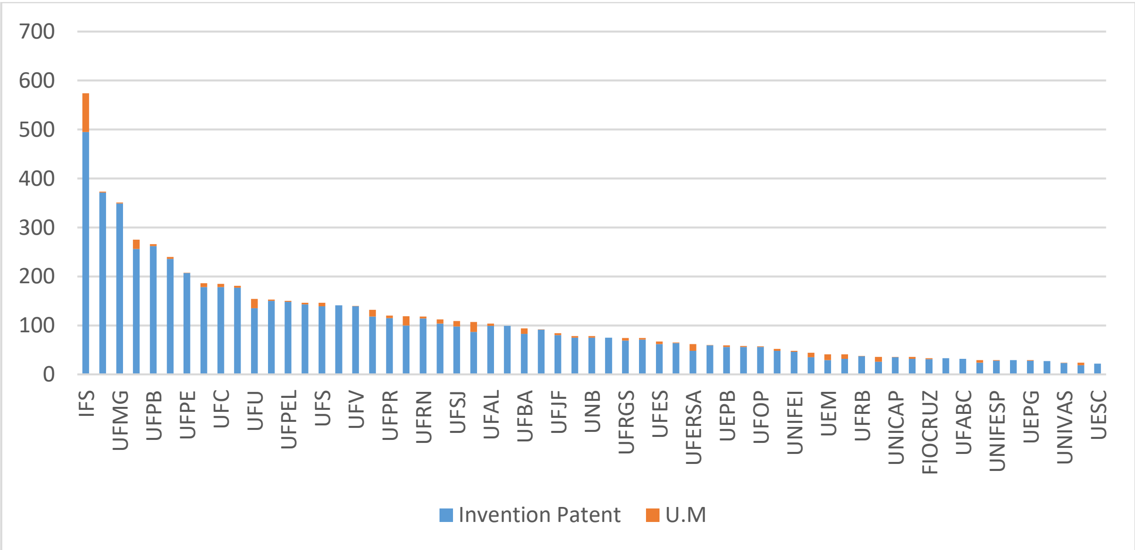

Figure 3.
Comparison of UM and invention patent filings by HEI (2020–2024).
Note: Values by HEI follow the same applicant-level counting rule as the ranking.
Source: Authors, based on INPI/RPI (invention patent and UM filings; applicant-level counts; 2020–2024).

3.4. Bivariate Associations

Spearman correlations between patent filings and co-ownership measures are positive and statistically significant ($p < 0.01$) for all metrics. The most significant associations are observed for total co-ownership ($\rho = 0.770$), co-ownership with universities ($\rho = 0.758$), and co-ownership with firms/other entities ($\rho = 0.573$) (Table 4).

Table 4.
Spearman correlations between patent filings and co-ownership measures (HEIs, 2020–2024).

	Patent filings	Co-ownership with universities	Co-ownership with institutes	Co-ownership with foundations	Co-ownership with firms/other	Total co-ownership
Patent filings	1.000					
Co-ownership with universities	0.758**	1.000				
Co-ownership with institutes	0.650**	0.723**	1.000			
Co-ownership with foundations	0.472**	0.552**	0.335**	1.000		
Co-ownership with firms/other	0.573**	0.493**	0.429**	0.480**	1.000	
Total co-ownership	0.770**	0.878**	0.741**	0.640**	0.741**	1.000

Note: Spearman coefficients; $N = 61$HEIs; $p < .01$(**) denotes two-tailed significance.
Source: Authors, based on INPI/RPI (invention patent and UM filings; applicant-level counts; 2020–2024).

As a complement, Table 5 reports Spearman correlations between patent filings and FINEP disbursements (2020–2024). Associations are positive and statistically significant in all years ($p < 0.01$), with the strongest observed in 2024 ($\rho = 0.660$) and for the total over the period ($\rho = 0.661$).

Table 5.
Spearman correlations between patent filings and FINEP disbursements (annual, 2020–2024; and total).

	Patent filings	Finep - 2020	Finep - 2021	Finep - 2022	Finep - 2023	Finep - 2024	FINEP – Total
Patent filings	1.000						
Finep - 2020	0.388**	1.000					
Finep - 2021	0.518**	0.758**	1.000				
Finep - 2022	0.568**	0.651**	0.768**	1.000			
Finep - 2023	0.512**	0.629**	0.711**	0.733**	1.000		
Finep - 2024	0.660**	0.574**	0.638**	0.697**	0.707**	1.000	
FINEP – Total	0.661**	0.722**	0.801**	0.846**	0.873**	0.928**	1.000

Note: Spearman coefficients; $N = 61$HEIs; $p < .01$(**) denotes two-tailed significance.
Source: Authors, based on INPI/RPI and FINEP (HEIs, 2020–2024).

3.5. Multivariate Estimates (NB2)

We fit an NB2 model with a log link, an offset for scientific output (Scopus), year, and region fixed effects, and cluster-robust standard errors at the HEI level. Results are reported as IRR = exp(β) with 95% CIs, N, McFadden's pseudo-R^2, and the α (overdispersion) parameter. In the NB2 models with the Scopus offset, we do not observe statistically significant effects for the three co-ownership operationalizations across the separate specifications (Tables 6).

Table 6.
Negative binomial (NB2) with log link and offset (annual Scopus publications per HEI), year, and region fixed effects, cluster-robust SEs by HEI.

Variable	IRR (exp(β))	95% CI (lower)	95% CI (upper)	p-value
Year 2020	0.946	0.678	1.320	0.744
Year 2021	0.747	0.548	1.017	0.064
Year 2022	0.740	0.582	0.942	0.014
Year 2023	1.264	0.971	1.642	0.081
Year 2024 (ref.)	1.000	—	—	—
Center-West	0.113	0.045	0.286	<0.001
Northeast	0.513	0.207	1.270	0.149
North	0.193	0.081	0.458	<0.001
Southeast	0.216	0.085	0.547	0.001
South (ref.)	1.000	—	—	—

Note: $n = 295$; $\alpha = 2.028$; McFadden's pseudo-R^2=0.018. IRRs are relative to the stated reference categories (Year 2024; South).
Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024. Estimates computed in IBM SPSS Statistics v31 (GENLIN/GEE).

3.6. Heterogeneity and Moderation by Public Funding

Specifications by partnership type replicate the NB2 with log link, Scopus offset, year and region fixed effects, and cluster-robust SEs by HEI. Results are reported as IRR, with 95% CIs, p-values, N, α, and McFadden's pseudo-R^2, maintaining strict adherence to analytical design. See Tables 7 (co-ownerships with firms/other), 8 (academic co-ownerships), and 9 (share of co-ownership, 0–1).

Table 7.
NB2 (co-ownerships with firms/other), Scopus offset ln [Scopus + 0.5], year and region fixed effects, cluster-robust SEs by HEI.

Variable	IRR (exp(β))	95% CI (lower)	95% CI (upper)	p-value
Co-ownerships with firms/other	0.990	0.979	1.000	0.051
Year 2020	1.121	0.937	1.342	0.213
Year 2021	0.833	0.688	1.009	0.062
Year 2022	0.765	0.642	0.911	0.003
Year 2023	0.930	0.784	1.103	0.403
Year 2024 (ref.)	—	—	—	—
Center-West	0.517	0.323	0.826	0.006
Northeast	2.093	1.348	3.251	0.001
North	1.666	0.760	3.652	0.203
Southeast	1.267	0.706	2.274	0.428
South (ref.)	—	—	—	—
Constant	0.018	0.012	0.026	<0.001

Note: $N = 295$; dispersion α(GENLIN) = 1.575; McFadden's pseudo-$R^2 = 0.022$.
Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024. Estimates computed in IBM SPSS Statistics v31 (GENLIN/GEE).

Table 8.
NB2 (academic co-ownerships), Scopus offset ln [Scopus + 0.5], year and region fixed effects, cluster-robust SEs by HEI.

Variable	IRR (exp(β))	95% CI (lower)	95% CI (upper)	p-value
Academic co-ownerships	0.999	0.994	1.004	0.729
Year 2020	1.134	0.940	1.369	0.189
Year 2021	0.837	0.686	1.022	0.080
Year 2022	0.768	0.642	0.918	0.004
Year 2023	0.942	0.794	1.119	0.500
Year 2024 (ref.)	—	—	—	—
Center-West	0.513	0.306	0.861	0.012
Northeast	2.130	1.290	3.517	0.003
North	1.665	0.738	3.756	0.219
Southeast	1.089	0.576	2.056	0.793
South (ref.)	—	—	—	—
Constant	0.016	0.010	0.024	<0.001

Notes: $N = 295$; dispersion α(GENLIN) = 1.932; McFadden's pseudo-R^2 (GENLIN) = 0.018. Offset: ln ($Scopus_{it}$ + 0.5), not annualized. IRRs are from GENLIN; 95% CIs and $p$are from GEE (independent correlation; robust variance; clusters by HEI).
Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024. Estimates computed in IBM SPSS Statistics v31 (GENLIN/GEE).

Table 9.
NB2 (share of co-ownership, 0–1), Scopus offset ln [Scopus + 0.5], year and region fixed effects, cluster-robust SEs by HEI.

Variable	IRR (exp(β))	95% CI (lower)	95% CI (upper)	p-value
Share of co-ownership (0–1)	0.454	0.157	1.313	0.145
Year 2020	1.117	0.937	1.332	0.217
Year 2021	0.817	0.675	0.988	0.037
Year 2022	0.759	0.636	0.906	0.002
Year 2023	0.928	0.782	1.102	0.392
Year 2024 (ref.)	—	—	—	—
Center-West	0.584	0.384	0.891	0.012
Northeast	2.412	1.547	3.761	<0.001
North	2.034	0.824	5.023	0.124
Southeast	1.338	0.701	2.555	0.377
South (ref.)	—	—	—	—
Constant	0.021	0.012	0.037	<0.001

Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024. Estimates computed in IBM SPSS Statistics v31 (GENLIN/GEE).
Notes: $N = 295$; dispersion α(GENLIN) = 1.411; McFadden's pseudo-R^2 (GENLIN) = 0.023. Offset: ln ($Scopus_{it}$ + 0.5), not annualized. For the main row, IRR (exp(β)) is from GENLIN; 95% CIs and $p$are from GEE (independent correlation; robust variance; clusters by HEI).

3.7. Additional Specification: Interaction Between Co-ownership and Funding

We estimated the co-ownership × funding interaction in an NB2 model with a Scopus offset, year, and region fixed effects, and cluster-robust SEs by HEI. Coefficients by funding level are reported as IRR with 95% CIs, p-values, N, α(overdispersion), and McFadden's pseudo-R^2. In the specification for invention patents (compared to UMs), the interaction is statistically significant (IRR ≈ 1.001; p =0.021) and of small magnitude; in the remaining specifications, the interaction is not significant (Table 10).

Table 10.
NB2 model for patents with Co-ownership × Funding (FINEP) interaction.

Variable	IRR (exp(β))	95% CI (lower)	95% CI (upper)	p-value
Region (ref. = South)				
Center-West	0.521	0.393	0.690	<0.001
Northeast	1.739	1.384	2.184	<0.001
North	0.872	0.635	1.197	0.396 (ns)
Southeast	1.076	0.818	1.416	0.601 (ns)
Total co-ownership	0.992	0.984	0.999	0.036
Funding (log+1)	0.787	0.715	0.867	<0.001
Co-ownership × Funding (log+1)	1.001	1.000	1.002	0.021

Notes: NB2 model with log link; offset ln ($\text{Scopus}_{it} + 0.5$); year and region fixed effects; cluster-robust standard errors by HEI. ns = not significant.
Source: Authors, based on INPI/RPI (invention patent and UM filings), Scopus (HEI×year output) and FINEP (public funding), 2020–2024. Estimates computed in IBM SPSS Statistics v31 (GENLIN/GEE).

4. Discussion

Recent scholarship on university innovation converges on the role of collaboration and public funding in knowledge protection. However, it diverges in terms of the intensity and stability of these relationships once differences in scientific scale and context are taken into account. Against this backdrop, our results—anchored in an HEI×year panel (2020–2024), counts of invention patents and UMs, and control for scientific exposure—revisit the central question: to what extent is co-ownership associated with patent filing rates among Brazilian HEIs when estimated with an offset and year/region fixed effects?

The empirical results presented here align with the systematic review conducted by Moletta and Pilatti [15] which found that financial sustainability, academic recognition, and technology transfer are the primary drivers of patenting in universities, while structural and institutional barriers continue to limit innovation outcomes. Similarly, our findings suggest that although collaboration and public funding are positively associated with patenting activity, these factors alone are insufficient to overcome the persistent organizational constraints that shape HEIs' technological output.

The interpretation is organized along three complementary axes: the relationship between FINEP disbursements and filing rates under the same adjustments; variation in the association by type of co-ownership (academic vs. firm/other) and by title (patents vs. UMs) in specifications aligned with the main model; and the distribution/concentration of filings across HEIs over the quinquennium. This structure preserves the observational focus of the findings and adheres to the analytical design.

Results indicate intense concentration and asymmetry in filings across HEIs, with a long tail, upper-end outliers, and the predominance of invention patents over UMs, with institutional variation. At the bivariate level, we observe positive and significant associations between filings and co-ownership (total, with universities, and with firms/other entities), as well as between filings and FINEP, with a particular emphasis on 2024 and the period as a whole; the disbursements themselves display high correlations across recent years, suggesting temporal consistency. In multivariate adjustment (NB2 with offset and year/region fixed effects), the three co-ownership operationalizations do not exhibit statistically significant direct effects when estimated in separate specifications; the same pattern holds under the Poisson model. The co-ownership and funding interaction is significant for patents, with a small magnitude and limited substantive interpretation, and does not replicate in the other specifications.

These results also resonate with the broader dynamics of the Brazilian postgraduate and research system. As demonstrated by Lievore, et al. [31] the expansion and diversification of postgraduate programs across regions between 1995 and 2014 fostered scientific growth but also reinforced structural asymmetries in research capacity and funding distribution. Such asymmetries may partly explain the heterogeneity in patenting performance observed among HEIs in different regions, despite similar access to public incentives.

Regarding the general hypothesis, which posited an association between co-ownership and filing rates conditional on exposure and institutional heterogeneity, the multivariate evidence does not support it in the separate specifications, despite positive bivariate alignments. Controls for scientific scale, fixed effects, and the covariate structure absorb a relevant share of the raw association, such that co-ownership on its own does not translate into a statistically detectable increase in rates.

For public funding, the evidence is mixed. Bivariate statistics reveal a positive association between FINEP and filings, indicating temporal regularity in investments. In the adjusted models, there is no broad, consistent direct effect of funding on rates; however, we find an indication of modulation through the interaction with co-ownership for patents, which is small in magnitude and lacks systematic replication. A parsimonious reading is that funding is associated with filings and may condition the relationship between formal collaboration and intellectual protection in specific scenarios, without constituting a robust direct effect across all model configurations.

Proposed heterogeneity manifests only partially. Separate estimations by co-ownership type (academic vs. firm/other) do not yield significant direct effects under the same set of controls, offering no apparent multivariate differences between types. By title, however, the interaction with funding appears for invention patents and not for UMs, suggesting segment-specific sensitivity for inventions when collaboration and funding co-occur, albeit modestly.

The descriptive question on distribution and concentration is confirmed. The system exhibits intense concentration and asymmetry of filings across HEIs, with the predominance of patents in the context within which the remaining findings should be interpreted for the Brazilian science, technology, and innovation system.

This empirical pattern aligns with systemic diagnoses documenting the historical formation of a concentrated institutional core, with implications for resource allocation and relative performance [23]. In recent reviews, the author describes expansion under budgetary constraint and the need to demonstrate sound use of funding and quality, which contextualizes the long tail of filings and the heterogeneous institutional strategies observed [23].

In the university–industry collaboration axis, the contrast between positive bivariate signals and the absence of robust direct effects in adjusted models is consistent with the literature on U–I governance and absorptive capacity. The Triple Helix perspective posits that innovation outcomes are contingent upon structured interactions among universities, firms, and government, mediated by governance rules and institutional incentives, including SDG-oriented agendas [3, 32]. The presence of co-ownership in patent databases does not fully capture the organizational and market conditions necessary to convert collaboration into measurable performance, which is consistent with the attenuation of effects in the model with offset and fixed effects.

Analyses of the national context highlight the importance of intrafirm R&D and the need for firms to be capable of absorbing knowledge, enabling collaboration to yield technological advancements, including in intellectual property. Recent arguments suggest that isolated incentives do not automatically translate into private expenditure or protected outputs, particularly in the context of competitive and regulatory conditions [24]. This reading helps explain why positive descriptive signals diminish when controlling for scientific scale and heterogeneity, and why the funding modulation emerged in a contained manner for patents.

Regarding public funding, comparative studies show that institutional frameworks and transfer mechanisms are crucial to aligning incentives for the generation, appropriation, and diffusion of knowledge, with updated evidence on the trajectory of Bayh–Dole and its implications for university IP management [11, 33]. In parallel, the influence of public research on industrial R&D appears conditional on collaboration, capabilities, and spillovers: public funding has positive but heterogeneous effects on private expenditures and innovative outputs, typically mediated by university–industry linkages [17, 34, 35]. These findings are consistent with the pattern observed here (positive bivariate association and a small yet significant interaction effect for patents in adjusted specifications) and align with evidence that property rights and governance rules shape commercialization [36].

The observational nature of the HEI×year panel design does not authorize causal inference. Although NB2 with offset, fixed effects and cluster-robust errors device reduce bias from observable and time-invariant unobservables, residual confounding remains possible, as does endogeneity from partnership selection and reallocation of efforts over time. Associations should be read as conditional on the control set and panel structure.

There are limitations in the measurement of key variables. Co-ownership captures formal linkages in invention patent/UM applications but does not measure relational intensity, project quality, contractual governance, or absorptive capacity. The Scopus-based offset serves as a proxy for scale/exposure, but is subject to measurement error due to field coverage, indexing lags, and affiliation variation. For funding, construction records from FINEP require executor→HEI mappings and deduplications; even with reconciliation, residual linkage errors cannot be ruled out.

The relationship between funding and filings may involve lags that vary by field and type of outcome. We conducted exploratory checks with 1- and 2-year lags (< 1 and $t < -2$), and coefficients remained stable, with no substantive change in interpretation. As these tables are not included in this version, we record the caveat and leave more granular lag estimations (by field and, ideally, with intra-annual granularity) to future work.

From an econometric standpoint, although NB2 is coherent with observed overdispersion and was contrasted with the Poisson model, specification choices influence the detection of minor effects. Multicollinearity among co-ownership dimensions and institutional predictors can increase uncertainty and reduce statistical power. The co-ownership × funding interaction—significant only for patents and small in magnitude—requires caution, as interaction estimates are sensitive to scale, parameterization, and controls.

There are unit-of-analysis and external validity limits. Inferences operate at the institutional level; we do not infer behaviors of researchers, laboratories, or specific projects. The Brazil 2020–2024 setting—with its institutional architecture and funding environment—frames the interpretation of results and constrains generalization to other contexts without adaptation.

Despite rigorous procedures for provenance, alias reconciliation, and versioning, integrating public sources (INPI/RPI, Scopus, FINEP) involves residual identification and coverage mismatches. Harmonization choices were documented and replicated; even so, small imprecisions may attenuate estimates and contribute to the lack of significance in direct effects under full adjustment. These limitations justify a parsimonious interpretation of the findings and suggest extensions using relational-intensity measures, impact metrics beyond counts, and longer windows with explicit lag modeling.

5. Conclusions

For 2020–2024, the study characterizes a system of university intellectual protection marked by high concentration and asymmetry across HEIs, with the predominance of invention patents over UMs. At the bivariate level, formal collaboration and public funding are positively associated with filings. However, in a multivariate adjustment with a scientific exposure offset and year/region fixed effects, co-ownership alone shows no statistically significant direct effect on filing rates. Funding-related modulation emerges narrowly for patents, with a small magnitude and no replication in other specifications. Taken together, these results provide an empirical picture that is consistent with the study's observational design and the institutional heterogeneity described earlier.

Substantively, the evidence suggests that formal linkages, by themselves, do not guarantee greater protection intensity once scientific scale and temporal/regional heterogeneity are controlled for. The bivariate association with funding and the punctual interaction for patents indicates that relationships among collaboration, financing, and intellectual protection are conditioned by institutional and contextual features, rather than by linear, universally direct mechanisms. Accordingly, initiatives to enhance intellectual property outcomes within HEIs are likely to depend on combinations of qualified collaboration, organizational capacity, and a genuinely functional funding environment.

Practical implications follow from the coherence between results and limitations. In policy and management terms, strategies that integrate firm collaboration, institutional arrangements for technology transfer, and the strengthening of internal capabilities are more promising than simply increasing the number of partnerships. From a research perspective, the findings motivate extensions using relational-intensity measures, project trajectory tracking, and impact metrics beyond counts, as well as longer time windows with explicit modeling of lags between funding and outcomes. These directions can refine our understanding of how collaboration and financing translate into adequate knowledge protection within the Brazilian university system.

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