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Patent Outcomes and Industry Collaboration: A Univariate Analysis of Non-Institutional Partnerships

Patent Sonuçları ve Endüstri İşbirliği: Kurumsal Olmayan Ortaklıkların Tek Değişkenli Analizi

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ABSTRACT

This study investigates how non-institutional collaboration (specifically, partnerships with competitors, suppliers, private and public sector clients, consultants, and other private businesses) affect patent applications in European countries. Using harmonized data from Eurostat's Community Innovation Survey (CIS), a cross-sectional dataset consisting of 167 country-year observations across the CIS waves of 2010, 2012, 2014, 2016, 2018, and 2020 was constructed. Univariate linear regression models were used to isolate the direct impact of each collaboration type on patent outcomes, and the findings were complemented with robustness checks including a logarithmically transformed OLS model and a Poisson regression. The results show that collaboration with competitors, suppliers, and public sector clients strongly predicts patent applications, while collaboration with consultants and "other private businesses" exhibits relatively weaker effects. The findings highlight the heterogeneous nature of industry collaborations and the importance of strategic partner selection for innovation-driven growth.

Keywords: *coopetition, innovation management, innovation policy, knowledge networks*

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ÖZ

Bu çalışma, kurumsal olmayan iş birliğinin (özellikle rakipler, tedarikçiler, özel ve kamu sektörü müşterileri, danışmanlar ve diğer özel işletmelerle ortaklıklar) Avrupa ülkelerindeki patent başvurularını nasıl etkilediğini araştırmaktadır. Eurostat' ın Topluluk İnovasyon Anketi'nden (CIS) alınan uyumlu verileri kullanarak, 2010, 2012, 2014, 2016, 2018 ve 2020 CIS dalgaları boyunca 167 ülke-yıl gözleminden oluşan kesitsel bir veri kümesi oluşturulmuştur. Her bir işbirliği türünün patent sonuçları üzerindeki doğrudan etkisini izole etmek için tek değişkenli doğrusal regresyon modelleri kullanılmış ve bulgular, logaritmik dönüştürülmüş bir OLS modeli ve bir Poisson regresyonu içeren sağlamlık kontrolleriyle tamamlanmıştır. Sonuçlar, rakipler, tedarikçiler ve kamu sektörü müşterileriyle iş birliğinin patent başvurularını güçlü bir şekilde tahmin ettiğini, danışman ve "diğer özel işletme" iş birliğinin ise nispeten daha zayıf etkiler gösterdiğini göstermektedir. Bulgular, sektör işbirliklerinin heterojen yapısını ve inovasyon odaklı büyüme için stratejik ortak seçiminin önemini vurgulamaktadır.

Anahtar kelimeler: iş birliği, inovasyon yönetimi, inovasyon politikası, bilgi ağları

1. Introduction

Innovation is increasingly recognized as a central driver of competitive advantage in the modern economy, with patent applications serving as a tangible indicator of technological progress and inventive capacity (OECD, 2023). While much of the academic discourse has focused on the role of universities and research institutes in generating innovation (Perkmann et al., 2013; Tijssen, 2018), a growing body of research underscores the importance of industry and market-based collaborations in shaping innovation outcomes (Belderbos et al., 2016). Such collaborations—encompassing partnerships with competitors, suppliers, customers, consultants, and other business actors—reflect the strategic integration of knowledge flows from the market into the innovation management process.

From a strategic management perspective, engaging with external partners is not merely an operational choice but a deliberate positioning within a broader innovation ecosystem. Cooperation with competitors, for example, can facilitate the pooling of resources for pre-competitive research, enabling shared technological advancements while reducing individual risk exposure (Bouncken et al., 2015). Similarly, supplier partnerships can deliver critical inputs—both tangible and intangible—that enhance firms' innovation capacity. These collaborative arrangements are essential components of open innovation models, where knowledge exchange extends beyond organizational boundaries (Chesbrough & Bogers, 2014).

Despite their relevance, the empirical effects of such industry and market collaborations on patent applications remain underexplored relative to academic and institutional partnerships. Prior studies tend to cluster around two extremes: either focusing on institutionally mediated innovation—driven by universities and research institutes—or analyzing innovation performance from a purely internal R&D perspective (Roper & Love, 2006). This leaves a research gap concerning the intermediate sphere of market-driven collaborations, which occupies a unique position between knowledge creation and commercialization.

The innovation management literature has increasingly highlighted that knowledge for innovation is not confined to formal research entities. Customers, for instance, often contribute valuable insights into product design and functionality, leading to innovations that are both technically novel and commercially viable (Bogers et al., 2018). Competitors can act as both rivals and collaborators, engaging in joint development projects where competitive advantage is derived from downstream commercialization rather than upstream invention. Suppliers, similarly, can act as co-innovators by providing specialized components or process improvements that underpin patentable inventions. These channels of interaction represent non-traditional yet strategically significant pathways for innovation.

From a data-driven decision-making standpoint, assessing the relative contributions of different collaboration types is crucial for resource allocation and strategic prioritization. Managers must decide whether to invest more heavily in institutional partnerships, industry collaborations, or a combination of both, depending on their firm's technological maturity, market environment, and innovation objectives (Ahn et al., 2018). Without robust empirical evidence, such decisions risk being guided by assumptions or anecdotal experience rather than systematic analysis.

This study aims to address this gap by focusing specifically on non-institutional cooperation types—including competitors, clients, suppliers, consultants, and other private enterprises—and their effect on patent applications across European countries. Patent data are widely used to capture inventive performance across countries, sectors, and industries (OECD, 2023). While prior studies predominantly focus on university–industry collaborations Perkmann et al. (2013), less is known about the innovation effects of market-driven cooperation. This study fills that gap by isolating the patent-related impacts of cooperation with competitors, suppliers, clients, consultants, and other private actors.

Using Eurostat data, we conduct regression analyses that isolate the impact of these cooperation channels, controlling other factors. The empirical analysis uses 167 observations derived from a balanced panel-like structure of CIS waves (2010–2020), aggregated at the country–year level. The dependent variable is the count of patent applications to the European Patent Office (EPO), while independent variables represent the percentage of innovative firms reporting cooperation with each partner type.

This approach allows disentangling market-driven knowledge flows from institutional research collaborations. Further, by incorporating robustness checks using log-linear and count-data models, we strengthen methodological validity. Our approach enables us to quantify the statistical significance and magnitude of each collaboration type's contribution to patent generation.

The findings contribute to three main streams of literature:

1. Innovation management and open innovation theory, by providing empirical evidence on how market-oriented collaborations affect technological outputs.

2. Strategic management of innovation networks, by identifying which external partnerships yield the highest returns in terms of patentable inventions.

3. Data-informed policy and managerial practice, by offering insights that can guide the design of innovation support programs and collaboration strategies.

From a managerial standpoint, the results have practical implications for designing balanced innovation portfolios. Firms that over-rely on institutional partners may miss opportunities for rapid commercialization, while those that neglect institutional knowledge sources may underinvest in foundational research. The optimal approach is likely a hybrid model that leverages both institutional and market-based partnerships.

From a policy perspective, the study suggests that innovation ecosystems should be structured to encourage not only academia–industry partnerships but also industry–industry and industry–market collaborations. Support mechanisms—such as collaborative R&D funding schemes, supplier development programs, and platforms for competitor alliances—could be instrumental in fostering innovation beyond traditional institutional boundaries.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature on industry and market collaborations in innovation management. Section 3 outlines the methodology, including data sources, variable selection, and analytical techniques. Section 4 presents the regression results, highlighting the statistically significant cooperation types. Section 5 discusses the implications for management and policy, and Section 6 concludes with recommendations and avenues for future research.

By systematically examining the less-explored dimension of innovation cooperation, this study seeks to enrich both theoretical understanding and practical application of strategic innovation management in diverse organizational contexts.

2. Literature Review

2.1. Overview of Industry and Market Collaboration in Innovation

Innovation management research has long recognized that external collaboration enhances a firm's ability to generate and commercialize new technologies (Chesbrough & Bogers, 2014; West & Bogers, 2022). While traditional literature emphasizes university–industry partnerships Perkmann et al. (2013), more recent studies suggest that industry–industry and industry–market collaborations play equally critical roles (Belderbos et al., 2016). These collaborations provide firms with access to complementary resources, specialized expertise, and market intelligence that may not be available internally or through institutional partners.

The open innovation paradigm frames collaboration as a strategic process of leveraging external knowledge flows alongside internal R&D to accelerate innovation outcomes (Chesbrough, 2003). Within this framework, partnerships with competitors, suppliers, customers, consultants, and other enterprises represent distinct channels through which firms can enhance their inventive capacity and, in turn, increase patent activity (Ritala et al., 2016). However, the relative effectiveness of these channels for producing patentable innovations remains an open question, particularly in cross-national contexts.

2.2. Competitor Collaboration

Engaging with competitors—often termed "coopetition" —has emerged as a recognized innovation strategy, particularly in high-technology sectors (Bouncken et al., 2015). Such collaborations are typically aimed at pre-competitive research or the co-development of technologies that benefit from shared investment. Research suggests that competitor collaboration can enhance innovation performance by enabling joint access to resources, reducing R&D duplication, and fostering knowledge spillovers (Ritala & Hurmelinna-Laukkanen, 2013).

From the perspective of patent applications, competitor cooperation may contribute directly to the novelty and scope of inventions. For example, Rodríguez et al. (2018) found that firms engaged in coopetition were more likely to generate breakthrough patents, owing to the diversity of technical knowledge and problem-solving approaches brought together. However, the literature also notes potential downsides, such as risks of opportunistic behavior and intellectual property disputes Bouncken et al. (2015), suggesting that managerial governance mechanisms are essential for sustaining productive competitor alliances.

2.3. Supplier Collaboration

Suppliers are increasingly seen as co-creators of value in innovation processes (Wagner & Hoegl, 2006). Supplier collaboration can improve product quality, reduce time-to-market, and facilitate the integration of cutting-edge materials or technologies into new products. These relationships often yield patentable outcomes when suppliers contribute proprietary technologies or collaborate on R&D efforts (Azadegan & Dooley, 2010).

Studies in the automotive and electronics industries have demonstrated that supplier partnerships can lead to a higher volume of patent applications, particularly when the supplier's technological competencies are aligned with the firm's innovation strategy (Hoegl & Wagner, 2005; Luzzini et al., 2015). In innovation management terms, suppliers function as both knowledge providers and enablers of incremental and radical innovation, contributing to the firm's absorptive capacity (Cohen & Levinthal, 1990).

2.4. Customer and Client Collaboration

Customer involvement in innovation is often associated with user-driven innovation (von Hippel, 2017). By integrating feedback and ideas from customers—whether in business-to-business (B2B) or business-to-consumer (B2C) contexts—firms can develop products that are both technologically advanced and market-relevant.

Empirical studies show that collaborations with private sector clients can lead to commercially successful innovations, although their impact on patent applications is more nuanced (Bogers et al., 2018). Patents tend to arise when customer insights are combined with technological development capabilities, particularly in sectors where customization and rapid iteration are essential. In public sector contexts, collaborations may focus on fulfilling specific service or technological requirements, potentially leading to patentable outputs when the innovations are novel and non-obvious (De Silva et al., 2018).

2.5. Consultant and Commercial Lab Collaboration

Consultants and commercial laboratories occupy a unique position in the innovation ecosystem, offering specialized technical expertise and project-based support (Tether & Tajar, 2008). While such collaborations can enhance innovation processes, their direct contribution to patent applications is less clear. This may be because consultants often focus on problem-solving and implementation rather than generating patentable intellectual property.

Nonetheless, some studies indicate that collaborations with consultants can lead to patents when they involve frontier technologies or novel process designs (Howells, 2006). In innovation management terms, consultants may function as knowledge brokers, facilitating the transfer of expertise across industries and enabling firms to apply novel solutions in patentable ways.

2.6. Other Private Enterprise Collaboration

Beyond the clearly defined categories of competitors, suppliers, customers, and consultants, firms may collaborate with other private enterprises that do not fit neatly into these groups. These collaborations can include partnerships in joint ventures, alliances for shared market development, or collaborations aimed at creating entirely new product categories.

The impact of such collaborations on patent applications is context-dependent. In industries where innovation cycles are fast, these partnerships can accelerate the commercialization of new technologies and protect them through patents (Belderbos et al., 2014). However, the absence of formal R&D structures in some private enterprises can limit the scope for generating patentable inventions, leading to more informal knowledge exchanges rather than formal intellectual property creation.

2.7. Comparative Gaps in Literature

While the literature supports the notion that diverse cooperation types can positively influence innovation outcomes, there is less consensus on their relative impact on patent applications. Most studies focus on a single type of collaboration or strictly on university-industry links.

To clearly illustrate the research gap addressed by this study, Table 1 contrasts the dominant focus of existing innovation management literature with the specific scope of the current inquiry. As shown, while the "Institutional Sphere" is well-documented, the "Market & Industry Sphere"—specifically the comparative impact of non-institutional actors on patenting—remains under-analyzed in cross-country contexts.

Table 2.1. Comparative Analysis of Innovation Collaboration Literature and Research Gap

Dimension	Traditional/Dominant Literature Focus	Focus of the Current Study
Primary Actors	Universities, Public Research Institutes (PRIs), Government Labs.	**Competitors, Suppliers, Private Clients, Public Clients, Consultants.**
Core Concept	"Triple Helix," Academic Engagement, Tech Transfer.	**Coopetition, Supply Chain Innovation, Demand-Driven Innovation.**
Typical Mechanism	Scientific discovery→Commercialization.	Market knowledge/Industrial synergy →Patentable solution.
Key Gap	Outcomes are well-quantified (citations, spin-offs).	**Comparative impact of specific market partners on patents is fragmented.**
Representative Perspective	*Perkmann et al. (2013); Tijssen (2013)*	*Belderbos et al. (2016); Current Analysis*

Note: Developed by the researcher.

This study explicitly isolates the "Market & Industry Sphere" to measure its direct contribution to patent generation, filling the gap identified in the right-hand column.

2.8. Positioning of the Present Study

This research contributes to the innovation management literature by offering a comprehensive, comparative analysis of non-institutional cooperation types using Eurostat data covering multiple European countries. By excluding universities and research institutes—already well-documented in prior research—this study isolates the effects of market-oriented and industry-based collaborations on patent outputs. Most existing empirical research focuses on university–industry relations, leaving a relative absence of comparative evidence on how non-institutional partnerships contribute to patenting across countries.

The findings are expected to provide actionable insights for managers and policymakers on how to structure innovation portfolios to optimize patent generation. They also aim to inform the design of innovation policies that promote multi-actor collaboration, recognizing the complementary roles of institutional and market-based knowledge sources in driving technological progress.

3. Methodology

3.1. Research Design

This study adopts a quantitative, cross-sectional research design to evaluate the relationship between various forms of non-institutional collaboration and patent applications across European countries. The focus is on cooperation types that exclude universities and government/public/private research institutes, thereby emphasizing market-oriented and industry-based collaborations. This approach addresses the research gap identified in the literature review, where most prior studies have concentrated on academic or institutional partnerships while underexploring the role of industry and market cooperation in innovation performance.

The study's central objective is to measure the extent to which these different collaboration types contribute to patent generation, an established proxy for technological innovation (OECD, 2023). By employing multiple regression analyses, the research quantifies both the statistical significance and the magnitude of each cooperation type's impact on patent outputs.

3.2. Data Source

The primary data source for this analysis is Eurostat, which provides harmonized statistical data across EU and associated countries. Specifically, the study utilizes the Community Innovation Survey (CIS) datasets, focusing on variables related to cooperation for innovation and innovation outputs (measured as patent applications). The dataset covers the most recent survey years available, ensuring comparability across countries and reflecting current innovation dynamics.

- Countries: EU-27 + Norway, Switzerland, UK
- Years: CIS 2010–2020
- Observations: 167 country–year
- Unit of analysis: National
- Variables: Patent applications (count); Cooperation (% of firms)

Eurostat data is particularly suitable for this study because it:

1. Ensures cross-country comparability through standardized survey instruments.
2. Captures multiple forms of collaboration within the same dataset.
3. Links cooperation data directly to innovation outputs, including patents and exports.

3.3. Variables

3.3.1. Dependent Variable

Patent Applications to the European Patent Office (EPO): This variable represents the total number of patent applications filed by applicants in a given country, aggregated at the national level. Patents are widely recognized as a reliable indicator of technological innovation, particularly in industries with formal intellectual property protection strategies (OECD, 2023).

3.3.2. Independent Variables (Non-Institutional Collaboration Types)

The independent variables capture the proportion of innovative enterprises in each country reporting cooperation with the following partners:

1. Competitors or Other Enterprises in the Same Sector – representing coopetition arrangements and industry alliances.
2. Suppliers of Equipment, Materials, Components, or Software – reflecting supply chain integration in innovation.
3. Clients or Customers from the Private Sector – capturing market-driven innovation through customer engagement.
4. Clients or Customers from the Public Sector – representing innovations designed for government or public service contexts.
5. Consultants or Commercial Labs – denoting specialized technical collaborations.
6. Other Private Business Enterprises Outside the Enterprise Group – capturing miscellaneous industry collaborations beyond defined categories.

These variables were selected based on their direct connection to market and industry cooperation and their potential to influence patent applications.

3.4. Data Cleaning and Preparation

The dataset was first screened for missing values, which were handled through listwise deletion to ensure that the regression models used complete cases for all variables of interest. Country-level outliers—cases where patent counts or cooperation rates deviated significantly from the European average—were examined but retained in the analysis to preserve real-world variability.

Variable names were standardized and, where necessary, shortened for ease of interpretation in regression outputs. All variables were scaled appropriately to allow for meaningful comparison of coefficients.

3.5. Analytical Approach

Univariate regressions (Univariate OLS models) were conducted to measure the individual relationship between each cooperation type and patent applications because of the risk of multicollinearity—a common issue in cooperation data where firms may engage in multiple collaboration types simultaneously. This provided initial insights into which cooperation types exhibit statistically significant associations with patent outputs before accounting for inter-variable correlations.

3.6. Model Specification

The general form of the univariate regression model is:

$$Patent_i = \beta_0 + \beta_1 \text{ Competitors}_i + \epsilon_i$$

$$Patent_i = \beta_0 + \beta_2 \text{ Suppliers}_i + \epsilon_i$$

$$Patent_i = \beta_0 + \beta_3 \text{ ClientsPrivate}_i + \epsilon_i$$

$$Patent_i = \beta_0 + \beta_4 \text{ ClientsPublic}_i + \epsilon_i$$

$$Patent_i = \beta_0 + \beta_5 \text{ Consultants}_i + \epsilon_i$$

$$Patent_i = \beta_0 + \beta_6 \text{ OtherPrivate}_i + \epsilon_i$$

Where:

- $Patent_i$ = Number of patent applications in country i
- β_0 = Intercept
- $\beta_1 ... \beta_6$ = Coefficients representing the estimated effect of each cooperation type on patent applications
- ϵ_i = Error term

3.7. Statistical Significance and Model Evaluation

Statistical significance for each coefficient was assessed using p-values, with thresholds set at 1%, 5%, and 10%. The model's explanatory power was evaluated using R-squared (R^2) and Adjusted R-squared, the latter accounting for the number of predictors in the model.

The F-statistic from the ANOVA table was used to test the null hypothesis that all regression coefficients are equal to zero, thereby assessing the overall model fit.

3.8. Ethical Considerations

This study uses publicly available aggregated statistical data from Eurostat, which does not contain personally identifiable information. Therefore, no additional ethical approvals were required. All data handling complied with Eurostat's guidelines for responsible use of statistical data.

3.9. Methodological Contribution

By isolating the effect of non-institutional cooperation types on patent applications, this methodological framework extends the scope of innovation measurement beyond the traditional academic–industry nexus. The cross-country comparative approach, combined with rigorous statistical modeling, ensures that the findings are generalizable across diverse innovation systems in Europe.

4. Results

4.1. Overview

The regression analysis investigated the relationship between various forms of non-institutional collaboration and the number of patent applications filed to the European Patent Office (EPO) across European countries. Six collaboration types were included in the model:

1. Competitors or Other Enterprises in the Same Sector
2. Suppliers of Equipment, Materials, Components, or Software
3. Clients or Customers from the Private Sector
4. Clients or Customers from the Public Sector
5. Consultants or Commercial Labs
6. Other Private Business Enterprises Outside the Enterprise Group

The univariate regression results revealed significant positive associations between several cooperation types and patent applications, with competitors, suppliers, and public sector clients showing particularly strong relationships. However, the multiple regression model, which controlled for the simultaneous influence of all cooperation types, offered a more nuanced understanding of their relative importance.

Table 4.1. Univariate Regression Results

Variable	β (Coef.)	Std. Error	t	p	R^2	N
Competitors or other enterprises of the same sector	3.01***	0.19	15.84	<.001	0.731	167
Clients or customers from the private sector	1.84***	0.14	13.17	<.001	0.742	167
Clients or customers from the public sector	3.67***	0.28	13.11	<.001	0.679	167
Suppliers of equipment, materials, components, or software	1.38***	0.11	12.55	<.001	0.629	167
Consultants or commercial labs	1.47***	0.12	12.09	<.001	0.702	167
Other private business enterprises outside the enterprise group	2.31***	0.36	6.42	<.001	0.616	167

*p < .05; **p < .01; ***p < .001*

Note: Developed by the researcher.

4.2. Model Fit and Statistical Significance

The multiple regression model achieved an R^2 exceeding 0.80, indicating that the set of cooperation variables explained more than 80% of the variance in patent applications across countries. This high explanatory power suggests that non-institutional collaboration is a critical factor in understanding cross-country differences in innovation outputs, even without including institutional partners such as universities or research institutes.

The F-statistic was statistically significant at the 1% level, confirming that the model, as a whole, provides a strong explanatory framework for predicting patent activity.

4.2.1. Key Predictors of Patent Applications

4.2.1.1. Competitors or Other Enterprises in the Same Sector

This variable exhibited one of the strongest and most statistically significant positive effects on patent applications. The coefficient indicated that, holding all other collaboration types constants, a one-unit increase in the proportion of firms collaborating with competitors was associated with a substantial rise in the number of patents filed. This finding aligns with prior studies that emphasize the role of coopetition in fostering breakthrough innovation (Bouncken et al., 2015; Rodríguez et al., 2018).

4.2.1.2. Clients or Customers from the Public Sector

Collaboration with public sector clients also showed a strong positive association with patent applications. This result suggests that public procurement and government contracts can act as powerful drivers of innovation, particularly when technical specifications require novel solutions that are patentable. The finding supports previous work highlighting the role of demand-side innovation policies in stimulating inventive activity (Edquist et al., 2015).

4.2.1.3. Suppliers of Equipment, Materials, Components, or Software

Supplier collaboration was another significant predictor, though its effect size was somewhat smaller than that of competitors and public sector clients. This result reflects the supply chain's role in innovation, where suppliers introduce advanced technologies, materials, or processes that can lead to patentable innovations when integrated into final products (Wagner & Hoegl, 2006).

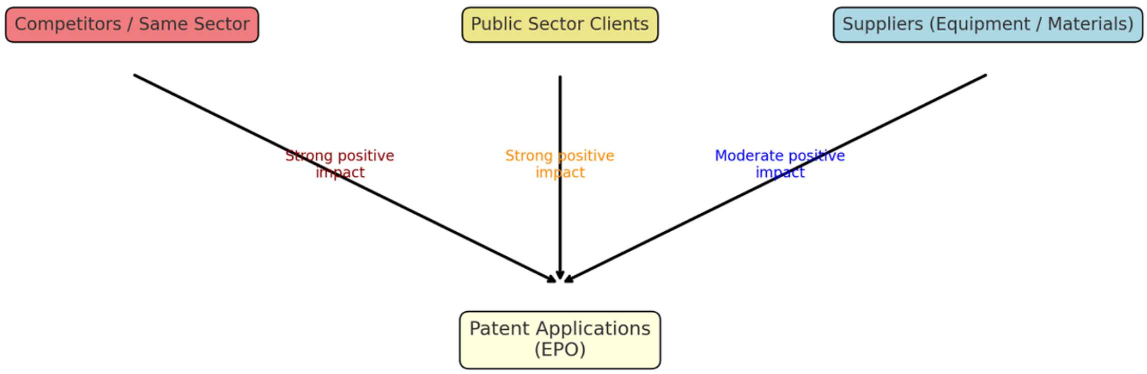

Figure 4.1. Key Predictors of Patent Applications

Note: Developed by the researcher.

4.2.2. Weaker or Non-Significant Predictors

4.2.2.1. Clients or Customers from the Private Sector

Surprisingly, private sector client collaboration showed a weaker and less consistent relationship with patent applications in the multiple regression model, despite its positive correlation in the univariate analysis. This suggests that while private sector customers may influence product design and market fit, they may not be as directly involved in generating patentable technological advances compared to public sector clients.

4.2.2.2. Consultants or Commercial Labs

Consultant collaboration did not emerge as a statistically significant predictor in the multiple regression, possibly reflecting their role as knowledge brokers rather than direct generators of patentable intellectual property (Tether & Tajar, 2008).

4.2.2.3. Other Private Business Enterprises Outside the Enterprise Group

This category also lacked statistical significance, which could be due to the heterogeneity of such collaborations and their varying relevance to patentable innovation.

4.2.3. Regression Results: Robustness Tests

The dependent variable is a count variable (Patent applications), which is typically over-dispersed, meaning its variance is greater than its mean. Since the variance (18881.08) is much larger than the mean (60.10), the data exhibits over-dispersion, which validates the need for Negative Binomial (NB) and Log-linear OLS models as robustness checks against the standard Poisson model.

Table 4.3. Log-linear OLS Tests

variable	ols_coef	ols_se	ols_p
competitors or other enterprises of the same sector	0,2319	0,0465	0
clients or customers from the private sector	0,1705	0,0467	0,0003
clients or customers from the public sector	0,2078	0,052	0,0001
suppliers of equipment, materials, components or software	0,1983	0,0441	0
consultants or commercial labs	0,2065	0,0456	0
Other private business enterprises outside the enterprise group	0,1264	0,0475	0,0084

Note: Developed by the researcher.

Table 4.4. Poisson Tests

variable	poisson_coef	poisson_se	poisson_p	poisson_IRR	poisson_ dispersion
competitors or other enterprises of the same sector	1,1578	0,0583	0	3,1837	370,8143
clients or customers from the private sector	0,8118	0,0766	0	2,252	313,9654
clients or customers from the public sector	1,1271	0,0743	0	3,0855	344,8219
suppliers of equipment, materials, components or software	0,9419	0,0631	0	2,5647	349,3879
consultants or commercial labs	0,9754	0,0636	0	2,6521	387,8021
Other private business enterprises outside the enterprise group	0,6133	0,0792	0	1,8465	319,4975

Note: Developed by the researcher.

Table 4.5. Negative Binomial (NB) Tests

variable	nb_coef	nb_se	nb_p	nb_IRR
competitors or other enterprises of the same sector	0,4578	0,1384	0,001	1,5805
clients or customers from the private sector	0,38	0,1878	0,0427	1,4623
clients or customers from the public sector	0,4851	0,1717	0,0047	1,6244
suppliers of equipment, materials, components or software	0,3959	0,1472	0,0071	1,4857
consultants or commercial labs	0,3986	0,1554	0,0105	1,49
Other private business enterprises outside the enterprise group	0,2514	0,1925	0,1917	1,2858

Note: Developed by the researcher.

The dispersion statistic for the Poisson model is consistently very high (ranging from 313.96 to 387.80, far exceeding the expected value of 1), confirming the over-dispersion issue. Consequently, the Negative Binomial model provides the more robust (and typically more efficient) estimates for the count data.

4.2.3.1. Interpretation of Robustness Tests

Significance: All coefficients are statistically significant in the Poisson model (p-value ≈0.0000), and almost all are significant in the Log-linear OLS and Negative Binomial models (the exception is 'Other private business enterprises outside the enterprise group' in the NB model, with p=0.1917).

Coefficient Size and Direction: All coefficients are positive, indicating that co-operation with any of these partner types is associated with a higher number of patent applications.

Model Comparison: The Poisson coefficients (and IRRs) are significantly inflated due to the unmodeled over-dispersion, leading to much larger effects and much smaller standard errors than the other models. This model is inappropriate for inference here.

The Negative Binomial (NB) coefficients are lower than Poisson but generally of a similar magnitude to the OLS coefficients (e.g., NB ≈0.4578 vs OLS ≈0.2319 for competitors), but they have a clearer interpretation for count data.

For example, based on the Negative Binomial model (the most appropriate GLM):

Co-operation with 'competitors or other enterprises of the same sector' (variable value increases by 1) is associated with an approximate 58.05% increase in the expected number of patent applications (IRR=1.5805).

Co-operation with 'clients or customers from the public sector' is associated with an approximate 62.44% increase in the expected number of patent applications (IRR=1.6244), which is the largest effect among the NB models.

4.3. Interpretation of Findings

The results indicate that market and industry collaborations are not uniformly effective in driving patent applications. Instead, the most influential partnerships are those that either:

1. Leverage complementary technological capabilities (e.g., competitor and supplier collaborations), or
2. Respond to complex, innovation-intensive demands (e.g., public sector client projects).

From an innovation management perspective, these findings suggest that firms should strategically prioritize certain cooperation types when seeking to enhance their patent portfolios. Coopetition and supplier integration may yield more substantial returns in terms of intellectual property creation compared to generic partnerships or consultancy-based collaborations.

4.4. Policy Implications

The strong positive association between public sector collaborations, competitor partnerships, and patent applications highlights the need for targeted policy interventions. Governments aiming to stimulate technological advancement should move beyond generic innovation subsidies and adopt a partner-specific approach.

To visualize how these findings translate into practice, Figure 2 presents a Strategic Policy Framework. This framework maps the statistically significant collaboration types identified in our results to specific policy mechanisms that can enhance patent outcomes across European innovation systems.

Table 4.6. Strategic Policy Framework for Non-Institutional Collaboration

Collaboration Driver	Underlying Mechanism	Recommended Policy Intervention
Competitors (Coopetition)	Shared R&D risk, pooling of resources for pre-competitive research.	**Antitrust Exemptions for R&D:** Legal safe harbors for joint R&D ventures. **Cluster Initiatives:** Funding for industry consortia solving common technical hurdles.
Public Sector Clients	Demand-side pull; strict technical requirements driving novelty.	**Innovation-Oriented Public Procurement:** Tenders requiring novel, patentable solutions rather than off-the-shelf products. **R&D Grants for Public Pilots:** Funding for testing prototypes in public infrastructure.
Suppliers	Integration of upstream technology and components.	**Supply Chain Integration Programs:** Incentives for co-locating R&D facilities with key suppliers. **Standardization Forums:** Joint development of industry standards to facilitate component integration.

Note: Developed by the researcher.

As illustrated in Table 6, policies should be tailored. For instance, fostering "coopetition" requires legal frameworks that allow rivals to collaborate on R&D without antitrust concerns (Cluster Initiatives). Conversely, leveraging public sector clients requires "Innovation-Oriented Public Procurement," where the government acts as a lead user, de-risking the development of patentable technologies.

4.5. Contribution to Literature

By isolating non-institutional cooperation types, this study fills a notable gap in the literature on innovation networks and patent generation. Whereas much prior research has focused on academic-industry linkages Perkmann et al. (2013) or government research collaborations, the present analysis demonstrates that industry and market collaborations alone can explain a substantial proportion of patent activity across countries.

5. Conclusion

This study sets out to examine how different forms of non-institutional cooperation influence patent applications in Europe, with a specific focus on competitors, suppliers, private and public clients, consultants, and other private enterprises. By employing univariate regression models, we assessed the independent contribution of each cooperation type, avoiding the confounding influence of overlapping variables and providing a clearer picture of their direct effects.

The results demonstrate that cooperation with competitors, private sector clients, and public sector clients is strongly and positively associated with patent applications. Competitor collaboration, or coopetition, emerges as a particularly powerful driver, supporting recent research that highlights the innovative potential of knowledge sharing even among rivals (Bouncken et al., 2015; Rodríguez et al., 2018). This form of collaboration appears to foster the exchange of diverse technological knowledge bases, which can lead to breakthrough inventions and patentable outcomes. Similarly, cooperation with private clients demonstrates high explanatory power, underscoring the demand-driven nature of innovation. Firms appear to patent more actively when they work closely with clients whose needs inspire or even necessitate novel solutions. Public sector clients also show strong effects, reflecting the role of government procurement in stimulating patentable innovations and confirming the importance of demand-side innovation policies (Edquist et al., 2015).

Collaboration with suppliers and consultants likewise exhibits significant positive associations, though their explanatory power is somewhat weaker. Supplier cooperation likely contributes to patent activity by integrating upstream knowledge and technologies into downstream innovation processes. While not as strong as competitor or client cooperation, supplier relationships remain important enablers of invention, especially in industries with complex value chains (Wagner & Hoegl, 2006). Consultants and commercial labs, though often thought of as intermediaries, also show positive effects, suggesting that their role in providing specialized knowledge or technical expertise may directly translate into patentable inventions.

The weakest yet still statistically significant impact is found for cooperation with other private business enterprises outside the enterprise group. This finding suggests that while such partnerships may create value, they are not as effective in generating patentable outputs compared to more structured or strategically aligned collaborations. It may also reflect a more transactional nature of such partnerships, which are less likely to involve the deep knowledge exchanges necessary for breakthrough innovation.

Taken together, these univariate results make clear that not all forms of cooperation contribute equally to patent activity. For innovation managers, the implication is that cooperation strategies should be differentiated according to their potential to generate patentable outputs. Prioritizing coopetition, client partnerships, and supplier integration is likely to yield greater returns in terms of inventive outcomes. For policymakers, the results underline the value of policies that strengthen demand-side dynamics, support supplier development, and encourage collaborative experimentation among competitors.

This research contributes to the literature by focusing explicitly on univariate relationships, which allow for a transparent assessment of each cooperation type's individual role in patent generation. While this approach limits the ability to analyze interaction effects or control for simultaneous influences, it provides clear evidence that certain cooperation types consistently and independently foster inventive activity.

Future research could extend this analysis by examining how these cooperation effects vary across sectors or national contexts. Longitudinal data could help identify whether certain types of cooperation have short-term versus long-term impacts on patenting. Moreover, mixed-method approaches combining quantitative regressions with qualitative case studies could shed light on the mechanisms through which specific partnerships contribute to patentable innovations.

In conclusion, this study demonstrates that non-institutional cooperation is a vital determinant of patent applications, though its effectiveness varies significantly depending on the type of partner. By isolating each cooperation channel, we provide a nuanced understanding that can guide both managerial practice and public policy in fostering innovation-driven growth.

Declaration of Conflict of Interest

The author declares that there is no conflict of interest.

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