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DISCUSSION PAPER

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Innovation Performance Through Collaborations With Public Research Organizations: Conducting and Signaling Mechanisms

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Abstract

We explore the association between signaling and conducting innovation collaborations with public research organizations and firms' revenues from firm and market novelties. Based on data from the German Community Innovation Survey 2023 and web-based indicators, firms conducting collaboration report higher revenues from market novelties, suggesting their relevance for the performance of more radical innovations. Firms signaling collaboration through website content report higher revenues from firm novelties, suggesting relevance for the performance of more incremental innovations. These findings indicate distinct mechanism in how collaborations with public research organizations relate to innovation performance.

Keywords University-Industry Transfer – Innovation Performance – Signaling
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1. Introduction

Collaborations between firms and public research organizations, including universities and research institutes, are critical enablers of firm-level innovation. By providing access to cutting-edge research, specialized expertise, and unique facilities, these partnerships allow firms to overcome internal limitations in their R&D capacities. Such collaborations equip firms to capitalize on emerging scientific advancements, unlock new market opportunities, and achieve sustainable growth (Veugelers, 2016; Stephan, 1996; Grimpe, Hussinger, & Sofka, 2023).

While the direct benefits of collaborating with public research organizations are well-documented—such as enhanced absorptive capacity, access to transformative technologies, and opportunities for interdisciplinary exchange (Laursen & Salter, 2006; García-Vega & Vicente-Chirivella, 2020)—the signaling effects of such collaborations have received less attention. Firms face significant challenges related to information asymmetries: external stakeholders, including customers, investors, and competitors, often lack visibility into firms' internal innovation processes, which may hinder the recognition of their capabilities and outputs (Merton, 1987). To bridge this gap, firms employ signaling mechanisms to effectively communicate their R&D activities and innovation potential.

Existing literature highlights patents and scientific publications as key signaling mechanisms. These traditional forms of R&D disclosure target investors and peers by providing verifiable evidence of innovative capabilities (Baruffaldi, Simeth, & Wehrheim, 2024; Liu, Du, & Pennings, 2024). However, their audience and accessibility are limited. Scientific publications often require technical expertise to interpret, and patents involve extensive disclosure of proprietary knowledge, exposing firms to the risk of competitive imitation (Polidoro & Theeke, 2012). As a result, these mechanisms are less effective for engaging customers who rely on accessible and interpretable information to assess product quality and innovation credibility.

This paper focuses on an alternative and underexplored signaling mechanism: firms' website disclosures of collaborations with public research organizations. Websites provide a unique platform for firms to communicate these partnerships in a manner that is both accessible to customers and less costly than patents or publications – both financially and in terms of knowledge disclosure. By highlighting collaborations in broad, non-technical terms, website disclosures enhance transparency while minimizing the risks associated with detailed knowledge sharing. Moreover, website signals can strengthen customer trust and differentiate products in competitive markets, particularly in cases of incremental innovation where distinctions are less apparent (Maier et al., 2024).

Using data from the German Community Innovation Survey 2023, and web-based indicators, this paper investigates how conducting and signaling collaborations with public research organizations are associated with firms' innovation performance. We analyze two dimensions of innovation: incremental innovations (firm novelties) and radical innovations (market novelties). Our results indicate that this distinction is crucial since the mechanisms driving the success of these innovations differ: conducting collaborations primarily supports the performance of radical innovations while signaling collaborations enhances the performance of incremental innovations.

The empirical analysis reveals distinct patterns. Firms conducting innovation collaborations with public research organizations report 13–36% higher revenues from market novelties, emphasizing the important role of such partnerships. Conversely, firms signaling these collaborations through website disclosures experience 10–31% higher revenues from firm novelties, suggesting the effectiveness of signaling in enhancing incremental innovations. These findings underscore the heterogeneous roles of collaboration and signaling in driving the performance of innovations with different levels of novelty.

This paper makes three key contributions to the literature. First, we extend the understanding of university-industry collaborations by disentangling the differential relationships between conducting and signaling collaborations with public research organizations on innovation performance. Second, we contribute to the signaling literature by emphasizing the role of website disclosures, a less costly yet effective mechanism for targeting customers and other non-expert audiences. Third, by integrating survey and web-based data, we provide a comprehensive empirical framework that bridges traditional and contemporary approaches to analyzing innovation.

2. Economic Framework

Collaborations between firms and public research organizations, such as universities and research institutes, have long been recognized as a cornerstone of firms' innovation strategies. These partnerships facilitate access to foundational research, advanced facilities, and specialized expertise, helping firms overcome limitations in their internal R&D capacities (Veugelers, 2016; Stephan, 1996). Beyond providing direct knowledge and resources, these collaborations enable firms to integrate interdisciplinary perspectives, fostering creativity and technological advancements that can lead to both incremental and radical innovations (Laursen & Salter, 2006; García-Vega & Vicente-Chirivella, 2020).

Conducting Collaborations and Innovation Performance

The primary benefit of conducting collaborations with public research organizations lies in knowledge transfer (Grimpe, Hussinger, & Sofka, 2023; Bianchi et al., 2015). Firms gain access to tacit and codified knowledge that can significantly enhance their innovation capacities (Gretsch et al., 2019). Public research organizations specialize in advancing basic research, which firms often lack the resources or risk tolerance to pursue independently. Through collaboration, firms can tap into cutting-edge scientific discoveries and leverage the expertise of researchers to develop and commercialize innovations that would otherwise remain inaccessible (Stephan, 1996; Conlé et al., 2023).

Such collaborations are particularly critical for supporting radical innovations, which often require a deep understanding of novel scientific principles or access to specialized technical capabilities. By addressing these knowledge gaps, public research organizations play a pivotal role in helping firms push the boundaries of existing technologies and enter new markets (Haus-Reve, Fitjar, & Rodríguez-Pose, 2019). However, these benefits are accompanied by challenges, including the need for significant investments in human capital, alignment of organizational goals, and management of intellectual property risks (García-Vega & Vicente-Chirivella, 2020).

Signaling Collaborations and Innovation Performance

While conducting collaborations can directly enhance a firm's innovation capacity, their success also depends on how effectively these efforts are communicated to external stakeholders. Signaling theory offers a lens to understand how firms address information asymmetries, particularly when the quality of their innovation processes or outputs is not immediately observable by customers, investors, or competitors (Spence, 1973; Grimpe, Kaiser, & Sofka, 2018). Signals such as patents and scientific publications have been widely used to convey a firm's innovative capabilities and the outcomes of its R&D collaborations (Baruffaldi, Simeth, & Wehrheim, 2024; Liu, Du, & Pennings, 2024).

However, these traditional signals are associated with limitations. Patents and publications primarily target investors and peers as they provide technical and verifiable evidence of innovation. Yet, they come with substantial costs, both financially and in terms of knowledge disclosure. Patents require an explicit description of the technical details of an innovation, potentially exposing firms to competitive risks (Polidoro & Theeke, 2012). Similarly, scientific publications involve sharing research findings that often provide competitors with insights into a firm's technological advancements (Gans, Murray, & Stern, 2017). These signaling mechanisms are also less effective for engaging customers who typically lack the technical expertise to interpret complex scientific or technical information.

In contrast, website disclosures offer a less costly and more versatile signaling mechanism, particularly suited for targeting customers and other non-expert audiences (Dahlke et al., 2024; Macchioni, Prisco, & Zagaria, 2024). Firms can use websites to highlight their collaborations with public research organizations in broad, accessible terms while avoiding the detailed knowledge disclosure required by patents or publications. This makes website signals an attractive option for firms seeking to enhance the perceived quality of their innovations without compromising proprietary information. By associating their products with reputable institutions, firms can leverage the credibility of public research organizations to build customer trust and differentiate their offerings in competitive markets (Maier et al., 2024).

Website disclosures are especially effective for incremental innovations, where the differentiation from competitors may not be immediately apparent. By signaling collaboration, firms can emphasize the quality and legitimacy of their products, encouraging customers to perceive them as superior to alternatives. This signaling strategy also aligns with the growing importance of digital communication channels in shaping consumer perceptions and purchasing decisions.

Roles of Conducting and Signaling Collaborations

The different roles of conducting and signaling collaborations underscore the strategic importance of partnerships with public research organizations in driving innovation performance. Conducting collaborations primarily enhances a firm's capacity to develop radical innovations by addressing critical resource and knowledge gaps. Meanwhile, signaling these collaborations through website disclosures amplifies their market impact, particularly for incremental innovations, by reducing information asymmetries and enhancing customer trust.

3. Data

3.1. Databases

The empirical analysis relies on cross-sectional data for approximately 3,900 firms from the German Community Innovation Survey 2023, enhanced with data on firms' website content in December 2022 from ISTARI, and patent information stemming from PATSTAT covering the period from 1974 to 2023. PATSTAT is merged with the Community Innovation Survey using the name-address matching according to Doherr (2023) provided by the ZEW Mannheim. The data from ISTARI is added to the Community Innovation Survey using firms' web addresses available in both datasets.

The German Community Innovation Survey is organized by the ZEW Mannheim on behalf of the German Federal Ministry of Education and Research. The survey is representative of firms with five or more employees in the German business sector. It focuses on questions about firms' innovation activities, whereas it covers further characteristics, such as revenues, industries, and age, too. Most importantly for our analysis, the German Community Innovation Survey 2023 asks firms about their conducted innovation collaboration with public research organizations.

ISTARI is a science start-up rooted in the work of Kinne & Lenz (2021) and Kinne & Axenbeck (2020) on web-based innovation indicators. Its data services are increasingly used as a resource for research (e.g.; Dahlke et al., 2024; Abbasiharofteh et al., 2023), and policy (ISTARI, 2024). The data provided by ISTARI corresponds to a probability index predicting the likelihood of a firm collaborating with public research organizations, generated by using a deep learning approach based on the firms' website texts following Kinne & Lenz (2021). The data covers all firms in Germany, Austria, and Switzerland having a website.

PATSTAT stems from the European Patent Office and covers information on firms' patent applications at the office.

3.2. Variable construction

Innovation performance – We are interested in the determinants of firms' innovation performance and what makes firm successful with their innovations. Thus, we focus on three different measures of innovation performance in our analysis:

Product innovation – Firms' revenues with new or significantly improved products or services. This measure comprises the performance of firms' product innovations.

Firm novelties – Firms' revenues with new or significantly improved products already existing on the market. This measure targets the performance of firms' more incremental product innovations.

Market novelties – Firms' revenues with new or significantly improved products not existing on the market. This measure targets the performance of firms' more radical product innovation.

Each revenue is generated in 2022, whereas the implemented products and services the revenues refer to have been implemented between 2020 and 2022.

Innovation collaboration – We concentrate on the individual and joint relationship of firms' innovation revenues with i) firms' conducted innovation collaborations with public research organizations, and ii) firms' signaled innovation collaborations with public research organizations.

Conducted innovation collaboration – Firms' conducted innovation collaborations with public research organizations is measured as a binary variable. It is equal to one if a firm conducted an innovation collaboration with a) public universities, or b) public research institutes between 2020 and 2022, and zero otherwise.

Signaled innovation collaboration – Firms' signaled innovation collaborations with public research organizations is measured by the estimated collaboration probability provided by ISTARI. The variable can take values between 0 and 1. A higher value indicates a higher probability of a firm having innovation collaborations with public research organizations based on the content it published on its website in December 2022. We describe the creation of the estimated collaboration probability in detail in Appendix A. Firms without a website receive the value of zero.

Firms' websites are a robust source of data for inferring their activities. Prior research demonstrated that they serve as comprehensive self-representations of firms, primarily targeting investors, customers, and the press. Moreover, unlike traditional mass media, such as print and broadcast media, websites allow firms to convey their identities, and activities comprehensively to all stakeholders (Dahlke, 2024). As a result, the estimated collaboration probabilities do not solely reflect the potential existence of collaboration but also the emphasis firms place on signaling such partnerships through their websites.

Control variables – We tackle omitted variable bias as potential sources of endogeneity by considering a variety of control variables in our empirical analysis. All control variables refer to the year 2022, if not specified differently.

Firm structure – Firm structure is represented by the number of employees in full-time equivalents, firm age in years, and binary variables for national and international group membership. Moreover, we cover export intensity, equal to a firm's export revenues over its total revenues, and a binary variable for public funding, equal to one if the firm received public financial support between 2020 and 2022. These variables account for resource availability, experience, and access to broader markets.

General innovation efforts – Innovation efforts include R&D intensity, measured as R&D expenditures over revenues, and its squared term to capture non-linear effects. Furthermore, a firm's patent stock, adjusted annually using a 15 percent depreciation rate, reflects accumulated innovation capacity, while process innovation is included as a binary variable, equal to one if the firm introduced a new or significantly improved process between 2020 and 2022.

External innovation efforts – External innovation efforts are captured through collaboration breadth, measured as the number of distinct types of innovation collaboration partners excluding public research organizations between 2020 and 2022, and the external R&D share, calculated as external R&D expenditures over total R&D expenditures. These variables reflect the firm's reliance on and diversity of external knowledge sources.

Market environment – Market environment controls include industry fixed effects for 21 industries based on the Nace Rev. 2 classification to address industry-specific factors interacted with a binary variable for being located in East Germany to capture industry specific regional differences remaining since the unification of Germany.

Data creation – Lastly, we include a binary variable indicating whether a firm was part of the training sample used to create the collaboration signal variable. This control accounts for potential biases introduced by the data generation process of the collaboration signal.

3.3. Descriptive statistics

Table 1 provides an overview of the key variables used in the analysis, offering insights into the characteristics of the firms included in the dataset. The sample comprises 3,862 firms drawn from the German Community Innovation Survey 2023. The descriptive statistics highlight the diversity of firms in terms of size, innovation activities, and collaboration with public research organizations, providing a robust foundation for exploring the relationship between conducting and signaling collaborations and innovation performance.

Innovation Performance – The mean turnover generated from new or significantly improved products or services is €13.94 million, with considerable variability across firms (standard deviation: €284.48 million). This variability reflects the heterogeneity in firms' innovation performance, ranging from those with no innovative activities to outliers with substantial revenues from innovation. When disaggregated, turnover from market novelties (radical innovations) averages €3.09 million, while turnover from firm novelties (incremental innovations) averages €10.85 million. These figures suggest that firms tend to generate more revenue from incremental improvements than from radical innovations, highlighting the importance of understanding the mechanisms driving the success of these two innovation types.

Innovation Collaboration – Approximately 22.8% of the sampled firms report conducting innovation collaborations with public research organizations between 2020 and 2022. In contrast, the mean website cooperation probability—a continuous proxy for signaling collaboration through websites between zero and one —stands at 27.2%. There is a moderate positive correlation between these two measures (r = 0.506). It indicates that while conducting and signaling collaborations are related, they capture distinct aspects of firms' engagement with public research organizations. Moreover, firms engaging in collaborations exhibit a substantially higher average website cooperation probability (61.6%) compared to non-collaborators (17.0%), suggesting that collaboration is often, but not always, accompanied by strategic signaling efforts.

Table 1: Descriptive Sample Statistics

Variable	Mean	Std. dev	Min	Max
Innovation variables				
Turnover with new/improved products/services (in mio. EUR)	13.943	284.475	0	16092.569
Turnover with market novelties (in mio. EUR)	3.094	72.982	0	4023.142
Turnover with firm novelties (in mio. EUR)	10.849	223.878	0	12069.428
Collaboration variables				
Collaboration with PRO (0/1)	.228	.42	0	1
Website cooperation probability with PRO (0-1)	.272	.37	0	1
Interaction term collaboration (0-1)	.14	.327	0	1
Control variables				
R&D intensity	.045	.198	0	5.833
Patent stock	.651	9.086	0	417.732
External R&D expenditure share	.054	.168	0	1
Cooperation breath	.938	1.661	0	8.000
Process innovation (0/1)	.805	.397	0	1
Number of employees as FTE	237.762	2666.346	.5	94591.000
Age	33.64	30.082	.5	266.500
National company (0/1)	.246	.431	0	1
Multinational company (0/1)	.178	.383	0	1
Public funding (0/1)	.331	.471	0	1
Export intensity (0-1)	.144	.248	0	1
Located in East Germany (0/1)	.373	.484	0	1
CoopProb training data (0/1)	.479	.5	0	1

N: 3,862

4. Empirical strategy

4.1. Estimation model

To investigate the relationship between conducting and/or signaling innovation collaboration with public research organizations with the performance of firm innovation, we employ the following empirical model:

$$I_i = \beta_0 + \beta_1 ConCol_i + \beta_2 SigCol_i + \beta_3 ConSigCol_i + \boldsymbol{Controls_i \beta_4} + \gamma + \epsilon_i,$$

where I_i is the revenue of firm i with new or significantly improved products and services. $ConCol_i$ is our binary variable for conducting innovation collaboration with public research organizations, $SigCol_i$ is our continuous measure for signaling innovation collaboration with public research organizations between zero and one, and $ConSigCol_i$ is the interaction term of both variables. The vector $Controls_i$ represents the described firm controls, and γ the described fixed effects differentiating between West- and East German industries. Finally, ϵ_i is the error term. We use ordinary least squares to estimate the parameters of the model. Moreover, we choose standard errors robust to heteroscedasticity.

4.2. Subsample selection

We concentrate on different measures of innovation revenues as dependent variables. Therefore, as we focus on the performance of innovation (What makes firms successful with their innovation?), and not their introduction (What makes firms innovative?), we estimate our empirical model for different subsamples of firms.

All firms – As a starting point, we use all firms responding to the 2023 Community Innovation Survey. Consequently, the estimated coefficients of β_1, β_2, and β_3 capture changes in I_i arising from variations in revenues through two mechanisms: i) changes in the number of firms generating innovative revenues (extensive margin), and ii) changes in the magnitude of revenues from innovation among innovating firms (intensive margin). This sample includes the largest number of observations, making it the least restrictive in terms of statistical power. However, it prevents identifying the separate mechanisms i) and ii).

Product innovators – Next, we use all firms responding to the 2023 Community Innovation Survey introducing new or significantly improved products or services between 2020 and 2022. Thus, we limit the variation captured by I_i to changes in the magnitude of innovative revenues (intensive margin), and effectively remove the variation related to the number of firms generating them (extensive margin). This sample is more restrictive in terms of statistical power as it removes non-innovators from the estimation, however it allows to separately investigate mechanism ii) focused on the relation between conducting/signaling collaboration and innovation performance.

Firm/Market innovators – Finally, to separately investigate the relationship between conduction/signaling collaboration and revenues from i) firm and ii) market novelties, we further divide the previous subsample of product innovators. First, to investigate the revenues with market novelties, we use only firms introducing new or significantly improved products or services new to the market between 2020 and 2022. Second, to analyze revenues with firm novelties in detail, we use only firms introducing new or significantly improved products or services new to the firm between 2020 and 2022.[1] While these two stratifications further reduce statistical power each, they enable a more detailed investigation into the types of innovation revenues and their relationship with conducting/signaling collaboration.

5. Results

5.1. Baseline results

Table 2 presents the results using the natural logarithm of revenues from product innovations as the dependent variable. Column (1) includes all firms, while Column (2) focuses on the subsample of product innovators. Interestingly, the key coefficients show contradictions between the two columns. In Column (1), conducting innovation collaboration with public research organizations is positive and statistically significant (C1: p=0.024). However, signaling such collaboration and its interaction with conducting collaboration are not significant. In contrast, Column (2) shows that conducting collaboration is not significant, but

[1] The 2023 Community Innovation Survey does not include a question on the introduction of firm novelties but focuses instead on the introduction of product innovations in general and market novelties in particular. Therefore, to investigate revenues from firm novelties in detail and to create a sample of firms introducing firm novelties specifically, we restrict the sample to firms that i) have revenues from firm novelties, or ii) introduced product innovations but no market novelties between 2020 and 2022.

signaling collaboration is both positive and statistically significant (C2: p=0.027). The interaction term remains insignificant.

This inconsistency resolves in Tables 3 and 4. Table 3 uses the natural logarithm of revenues from market novelties as the dependent variable, while Table 4 uses revenues from firm novelties. In both tables, Column (1) covers all firms, Column (2) focuses on product innovators, and Column (3) examines market and firm innovators, respectively.

Table 3 demonstrates that conducting innovation collaboration is significantly and positively associated with the performance of firms' market novelties, aligning with the pattern observed in Column (1) of Table 2 (C1: p=0.023, C2: p=0.041, C3: p=0.037). Across all columns, the coefficient for conducting collaboration is positive and statistically significant. Exponentiating these coefficients reveals that conducting innovation collaboration is associated with a 13 percent to 36 percent increase in revenues from market novelties.[2] However, signaling collaboration and its interaction with conducting collaboration remain statistically insignificant.

Table 4 aligns with the pattern observed in Column (2) of Table 2. It indicates a largely statistically significant and positive relationship between signaling innovation collaboration and revenues from firm novelties (C1: p=0.110, C2: p=0.006, C3: p=0.083). The exponentiation of the coefficients shows that an increase in the signaling variable from its minimum value (zero) to its maximum value (one) corresponds to a 10 percent to 31 percent increase in revenues from firm novelties. This time, conducting collaboration remains statistically insignificant, as well as the interaction term.

[2] Exponentiation: $(\exp(\widehat{\beta_1})-1)\times 100$.

Table 2: Conducting/Signaling Collaboration and Product Innovation Performance

Dependent variable: ln(turnover with new/improved products +1)	(1) All firms	(2) Product innovators
Collaboration with PRO (0/1)	.152**	.095
	(.076)	(.095)
Website cooperation probability with PRO (0-1)	.065	.211**
	(.064)	(.095)
Interaction term (0/1)	-.022	-.174
	(.117)	(.142)
R&D intensity	.186*	-.070
	(.105)	(.145)
R&D intensity^2	-.074***	.002
	(.022)	(.042)
Ln (patent stock +1)	.458***	.197**
	(.078)	(.078)
External R&D expenditure share	.249**	.204
	(.107)	(.145)
Ln(collaboration breath +1)	.096***	.086**
	(.031)	(.043)
Process innovation (0/1)	.167***	.009
	(.034)	(.055)
Ln(number of employees as FTE +1)	.261***	.499***
	(.019)	(.026)
Ln(age)	-.032	-.036
	(.022)	(.033)
National company (0/1)	-.102***	-.092*
	(.034)	(.052)
International company (0/1)	.124**	.234***
	(.057)	(.075)
Public funding (0/1)	-.001	-.008
	(.036)	(.051)
Export intensity (0-1)	.294***	.300***
	(.091)	(.111)
CoopProb training data (0/1)	-.090***	-.122***
	(.031)	(.045)
Constant	-.550***	-.671***
	(.086)	(.127)
Observations	3862	1750
R-squared	.344	.583

All Estimates are based on OLS. Robust standard errors are in parentheses.
*P-values correspond to: *** p<.01, ** p<.05, * p<.1*

Table 3: Conducting/Signaling Collaboration and Market Novelty Performance

Dependent variable: ln(turnover with market novelties+1)	(1) All firms	(2) Product innovators	(3) Market innovators
Collaboration with PRO (0/1)	.119**	.182**	.311**
	(.052)	(.089)	(.148)
Website cooperation probability with PRO (0-1)	-.004	.044	-.044
	(.036)	(.078)	(.183)
Interaction term (0/1)	.02	-.042	-.227
	(.085)	(.14)	(.246)
R&D intensity	.037	-.049	-.082
	(.073)	(.124)	(.237)
R&D intensity^2	-.019	.018	.040
	(.016)	(.033)	(.074)
Ln (patent stock +1)	.249***	.172**	-.041
	(.067)	(.081)	(.088)
External R&D expenditure share	.041	.034	.377
	(.056)	(.102)	(.332)
Ln(collaboration breath +1)	.061***	.079**	-.041
	(.020)	(.037)	(.076)
Process innovation (0/1)	.086***	.048	.023
	(.017)	(.037)	(.106)
Ln(number of employees as FTE +1)	.076***	.142***	.458***
	(.014)	(.026)	(.052)
Ln(age)	-.009	-.019	-.121*
	(.014)	(.028)	(.062)
National company (0/1)	-.042**	-.044	-.117
	(.018)	(.038)	(.101)
International company (0/1)	.089**	.201***	.323**
	(.037)	(.067)	(.129)
Public funding (0/1)	.000	.007	-.040
	(.023)	(.046)	(.097)
Export intensity (0-1)	.174***	.249**	.436**
	(.065)	(.108)	(.181)
CoopProb training data (0/1)	-.025	-.034	.013
	(.020)	(.040)	(.088)
Constant	-.254***	-.350***	-.546***
	(.053)	(.100)	(.208)
Observations	3862	1750	528
R-squared	.201	.271	.554

*Estimates are based on OLS. Standard errors are in parentheses. Industry-region fixed effects are included. P-values correspond to: *** p<.01, ** p<.05, * p<.1*

Table 4: Conducting/Signaling Collaboration and Firm Novelty Performance

Dependent variable: ln(turnover with firm novelties+1)	(1) All firms	(2) Product innovators	(3) Firm innovators
Collaboration with PRO (0/1)	.086	-.007	.019
	(.075)	(.107)	(.107)
Website cooperation probability with PRO (0-1)	.098	.269***	.173*
	(.061)	(.098)	(.100)
Interaction term (0/1)	-.059	-.225	-.145
	(.114)	(.157)	(.154)
R&D intensity	.092	-.130	-.001
	(.106)	(.166)	(.170)
R&D intensity^2	-.052**	.008	-.006
	(.022)	(.051)	(.047)
Ln (patent stock +1)	.414***	.199**	.159*
	(.079)	(.084)	(.082)
External R&D expenditure share	.195*	.139	.213
	(.102)	(.151)	(.152)
Ln(collaboration breath +1)	.079***	.073	.113**
	(.030)	(.047)	(.046)
Process innovation (0/1)	.134***	-.003	-.017
	(.033)	(.059)	(.060)
Ln(number of employees as FTE +1)	.235***	.452***	.490***
	(.019)	(.028)	(.028)
Ln(age)	-.023	-.018	-.023
	(.022)	(.036)	(.036)
National company (0/1)	-.106***	-.118**	-.104*
	(.032)	(.055)	(.055)
International company (0/1)	.087	.148*	.202**
	(.055)	(.082)	(.082)
Public funding (0/1)	.008	.012	-.012
	(.035)	(.057)	(.053)
Export intensity (0-1)	.178**	.147	.279**
	(.086)	(.120)	(.126)
CoopProb training data (0/1)	-.066**	-.080*	-.105**
	(.030)	(.048)	(.047)
Constant	-.507***	-.671***	-.685***
	(.085)	(.137)	(.138)
Observations	3862	1750	1558
R-squared	.289	.473	.576

Estimates are based on OLS. Standard errors are in parentheses. Industry-region fixed effects are included.
*P-values correspond to: *** p<.01, ** p<.05, * p<.1*

5.2. Robustness tests

We argue that signaling innovation collaboration is primarily used to enhance the performance of firms' product innovations. To ensure that our previous results are driven specifically by product innovations, rather than firms' overall innovativeness, we repeat our earlier estimations using cost-reducing process innovations as alternative dependent variables. Observing similar patterns as before would cast doubt on our theoretical and empirical framework, while the absence of statistically significant results for signaling innovation collaboration would support our argumentation.

Table 5 demonstrates the results of this exercise. Column (1) employs a binary variable indicating whether a firm introduced new or significantly improved processes between 2020 and 2022 that reduced average costs. Columns (2) and (3) use the percentage reduction in unit costs due to these new or improved processes in 2022 as the dependent variable. Columns (1) and (2) include all firms in the estimation sample, while Column (3) focuses on the subsample of firms that introduced cost-reducing process innovations during this period. Across all columns, there are no statistically significant results for signaling or conducting innovation collaboration.

Next, we analyze the relationship between conducting and/or signaling innovation collaboration with public research organizations and the likelihood of firms introducing product innovations. According to our argument, signaling collaboration primarily fosters the market performance of an innovation, becoming most relevant after implementation—though early signaling can also improve future market performance. In contrast, conducting collaboration with public research organizations is more relevant during the development and implementation phase of an innovation. Therefore, when examining the probability of firms implementing product innovations, conducting collaboration should play a more significant role than signaling collaboration.

Table 5: Conducting/Signaling Collaboration and Process Innovations

Dependent variables:	(1) Cost reduction innovation (0/1)	(2) Innovation cost reduction share (0-1)	(3) Innovation cost reduction share (0-1)
Subsample	*All firms*	*All firms*	*Process innovators*
Collaboration with PRO (0/1)	.041	.001	-.004
	(.031)	(.005)	(.013)
Website cooperation probability with PRO (0-1)	.001	-.003	-.011
	(.028)	(.003)	(.009)
Interaction term (0/1)	-.020	.002	.013
	(.046)	(.006)	(.017)
R&D intensity	.068	.041***	.104***
	(.069)	(.014)	(.029)
R&D intensity^2	.000	-.007**	-.019***
	(.016)	(.003)	(.005)
Ln (patent stock +1)	.012	-.001	.001
	(.020)	(.001)	(.003)
External R&D expenditure share	.104**	.012**	.002
	(.044)	(.005)	(.015)
Ln(collaboration breath +1)	.036***	.004**	.006
	(.014)	(.002)	(.005)
Ln(number of employees as FTE +1)	.023***	-.001*	-.012***
	(.006)	(.001)	(.002)
Ln(age)	-.009	-.003***	-.007**
	(.010)	(.001)	(.003)
National company (0/1)	.030*	.005**	.009
	(.017)	(.002)	(.008)
International company (0/1)	.009	.003	.011
	(.022)	(.003)	(.008)
Public funding (0/1)	.005	-.001	-.006
	(.016)	(.002)	(.006)
Export intensity (0-1)	.006	.001	.002
	(.033)	(.004)	(.014)
CoopProb training data (0/1)	-.011	-.001	-.001
	(.014)	(.002)	(.006)
Constant	.137***	.026***	.142***
	(.035)	(.004)	(.013)
Observations	3862	3813	824
R-squared	.045	.041	.205

*Estimates are based on OLS. Standard errors are in parentheses. Industry-region fixed effects are included. P-values correspond to: *** p<.01, ** p<.05, * p<.1*
Number of observation for variables related to innovation cost reduction share in the full sample equals 3813 due to the non-response of the firms.

Table 6 investigates this relationship using three binary dependent variables. Column (1) employs a binary variable equal to one if a firm introduced a product innovation between 2020 and 2022. Column (2) uses a binary variable equal to one if a firm introduced a market novelty during the same period, and Column (3) uses a binary variable equal to one if a firm introduced a firm novelty. In each column, conducting innovation collaboration is more statistically significant and has a greater magnitude than signaling collaboration. We interpret these results as further evidence of the robustness of our findings.

6. Conclusion

Firms' collaborations with public research organizations are crucial facilitators of innovation (Bianchi et al., 2016; Gretsch et al., 2019; García-Vega & Vicente-Chirivella, 2020). These partnerships provide access to the tacit knowledge embedded within public research organizations (Haus-Reve et al., 2019; Veugelers, 2016) and enhance the visibility of firms' innovation efforts when strategically communicated (Nasirov & Joshi, 2023; Baruffaldi et al., 2024). This study examines theoretically and empirically how conducting and signaling innovation collaborations with public research organizations independently and jointly influence innovation performance, emphasizing the distinct roles of these mechanisms.

First, it establishes firms' websites as low-cost signaling mechanisms for communicating collaborations. This expands the signaling literature, which has primarily focused on high-cost mechanisms like patents and publications (Gans et al., 2017; Liu et al., 2024). Second, by examining both radical (market novelties) and incremental (firm novelties) innovations, the study reveals distinct pathways through which collaborations with public research organizations might influence innovation performance. Finally, the study shows that signaling collaborations is particularly effective for incremental innovations, contrasting with the established role of patents and publications in supporting radical innovations (Polidoro and Theeke, 2012).

Table 6: Conducting/Signaling Collaboration and Product Innovation Propensity

Dependent variables:	(1) Product innovation (0/1)	(2) Market novelty (0/1)	(3) Firm novelty (0/1)
Collaboration with PRO (0/1)	.069**	.074***	.051
	(.034)	(.028)	(.035)
Website cooperation probability with PRO (0-1)	.005	.036	.020
	(.033)	(.023)	(.032)
Interaction term (0/1)	.025	.024	.006
	(.050)	(.041)	(.051)
R&D intensity	.475***	.459***	.216***
	(.075)	(.077)	(.080)
R&D intensity^2	-.109***	-.099***	-.058***
	(.016)	(.018)	(.017)
Ln (patent stock +1)	.070***	.082***	.075***
	(.016)	(.019)	(.016)
External R&D expenditure share	.186***	.011	.164***
	(.049)	(.030)	(.049)
Ln(collaboration breath +1)	.012	.026**	.002
	(.015)	(.011)	(.015)
Ln(number of employees as FTE +1)	.012*	.007*	.014**
	(.006)	(.004)	(.006)
Ln(age)	-.020*	-.009	-.013
	(.011)	(.008)	(.011)
National company (0/1)	-.012	-.001	-.020
	(.019)	(.013)	(.019)
International company (0/1)	.011	.010	.009
	(.025)	(.019)	(.025)
Public funding (0/1)	.04**	.014	.046**
	(.018)	(.013)	(.018)
Export share	.152***	.121***	.075**
	(.037)	(.032)	(.038)
CoopProb training data (0/1)	-.009	-.009	-.006
	(.016)	(.011)	(.017)
Constant	.388***	.056**	.334***
	(.039)	(.027)	(.040)
Observations	3862	3862	3862
R-squared	.11	.164	.073

Estimates are based on OLS. Standard errors are in parentheses. Industry-region fixed effects are included.
*P-values correspond to: *** p<.01, ** p<.05, * p<.1*

The empirical findings confirm the essential role of collaborations with public research organizations in driving radical innovations, as reflected in higher revenues from market novelties. The coefficient magnitudes reported in Table 3 suggest that firms engaging in these collaborations realize a 13% to 36% increase in revenues from market novelties. When contextualized against the average turnover of €3.09 million from market novelties, this equates to an additional €390,000 to €1.13 million in revenue for the average firm. These findings indicate the potential of knowledge transfer facilitated by innovation collaborations with public research organizations. They provide firms with access to cutting-edge research and specialized expertise, enabling them to overcome R&D limitations and push technological boundaries (Haus-Reve, Fitjar, & Rodríguez-Pose, 2019).

Signaling collaborations through website disclosures strongly correlates with increased revenues from firm novelties, representing incremental innovations. Firms that signal innovation collaborations with public research organizations achieve revenue increases of 19% to 31%, equivalent to an additional €2.05 million to €3.35 million, based on an average turnover of €10.85 million from firm novelties. This association indicates the effectiveness of signaling in addressing market information asymmetries, particularly when product differentiation is less apparent (Maier et al., 2024). By showcasing affiliations with public research organizations on websites, firms might enhance customer trust and perceptions of product quality. As a result, for incremental innovations, where market success often depends on reputation and perceived quality, website signaling seems to emerge as a practical strategy.

The absence of statistically significant interaction effects between conducting and signaling collaborations suggests that these mechanisms function largely independently. Conducting collaborations primarily supports radical innovations, while signaling collaborations enhance market recognition for incremental innovations. This distinction underscores the need for firms to align collaboration and communication strategies with their specific innovation objectives (García-Vega & Vicente-Chirivella, 2020).

These findings offer tentative insights for both managers and policymakers seeking to optimize the impact of firms' collaborations with public research organizations on innovation performance.

For managers, conducting collaborations with public research organizations seems important for radical innovations, as these partnerships provide access to advanced knowledge and resources. Conversely, for incremental innovations, signaling collaborations through website disclosures enhances market success, most likely by fostering customer trust and visibility (Merton, 1987). Firms should integrate website disclosures into broader communication strategies, including branding and stakeholder engagement, to maximize their signaling effectiveness. Notably, in contrast to conducting collaborations, signaling collaborations appears less critical for market novelties, suggesting that firms focused on radical innovations can prioritize direct knowledge transfer and collaboration activities without overemphasizing signaling efforts.

For policymakers, supporting firms' collaborations with public research organizations requires a dual emphasis on facilitating knowledge transfer and enhancing partnership visibility. Initiatives such as smaller grants or recognition programs can encourage firms to utilize cost-effective signaling tools like websites (Lanahan & Armanios, 2018), particularly for incremental innovations. However, for radical innovations, policymakers should prioritize the support of conducting innovation collaboration to foster actual knowledge transfer (Veugelers, 2016).

This study has several limitations that require further investigation. First, the cross-sectional nature of the data limits causal inference. Longitudinal research could better capture the dynamic effects of conducting and signaling collaborations over time, including potential lagged or cumulative impacts of signaling on innovation performance.

Second, the focus on German firms may constrain the generalizability of the findings. Comparative studies across regions with diverse innovation and science systems could uncover how contextual factors influence the interplay between conducting and signaling collaborations.

Finally, websites represent a special signaling mechanism. In addition to the traditional disclosure strategy of firms such as secrecy, patenting or publishing (Gans et al., 2017; Liu et al., 2024), websites allow firms to communicate their innovation efforts in accessible, non-technical language, targeting customers and non-expert stakeholders. Their cost-effectiveness, flexibility and confidentiality make them particularly valuable for incremental innovation. However, future research should explore how firms integrate websites with other digital tools such as social media (e.g., Mumi et al., 2019; Nijssen & Ordanini, 2020) and online marketplaces (Mavlanova et al., 2012) to develop consistent signaling strategies that meet the diverse needs of the market and stakeholders.

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Appendix A – Estimation of collaboration probability

Website information – Firms' collaboration probability with public research organizations is estimated based on web-scraped data provided by ISTARI. The data is scraped during December 2022 following the methodology of Kinne and Axenbeck (2020). Website addresses originate from the Orbis database by Bureau van Dijk (Dahlke et al., 2024).

Training data – The training data for the machine learning model that generates the collaboration probabilities is based on the Mannheim Innovation Panel. The panel is an annual, representative survey of firms in the German enterprise sector with five or more employees. Specifically, the training and testing data include a sample of 4,393 firms from the German Community Innovation Survey 2023, which is part of the Mannheim Innovation Panel.

The sample selection criteria for the training data were as follows:

a) *Website ownership:* Each firm in the sample must have an active website.
b) *Consistent collaboration:* Firms must demonstrate consistent collaborations over time: If a firm participated in the German Community Innovation Survey in 2021, 2019, or 2017, it had to report continuous collaboration or non-collaboration with public research organizations across all surveys.

The share of consistently collaborating firms within the sample was 15 percent.

Test statistics – The machine learning model, achieved an F1 score of approximately 0.7, reflecting a reasonable balance between precision and recall. This performance aligns with expectations, as predicting firms' collaborations with public research organizations is likely more challenging than predicting firms' product innovator status, which Kinne and Lenz (2020) achieved with an F1 score of 0.8. Figure A.1 depicts the confusion matrix of the model, Figure A.2 depicts the Precision-Recall (PR) and the Receiver Operating Characteristic (ROC) curve of the model, both demonstrating a reasonable performance of the model estimated by ISTARI.

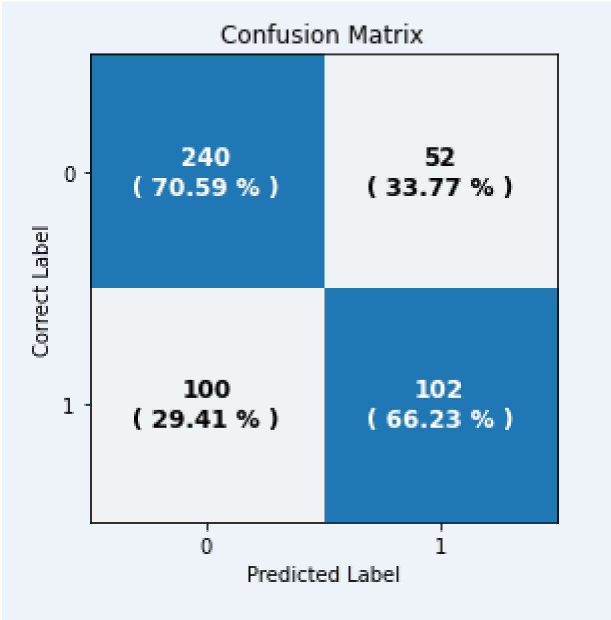

Figure A.1: Confusion Matrix

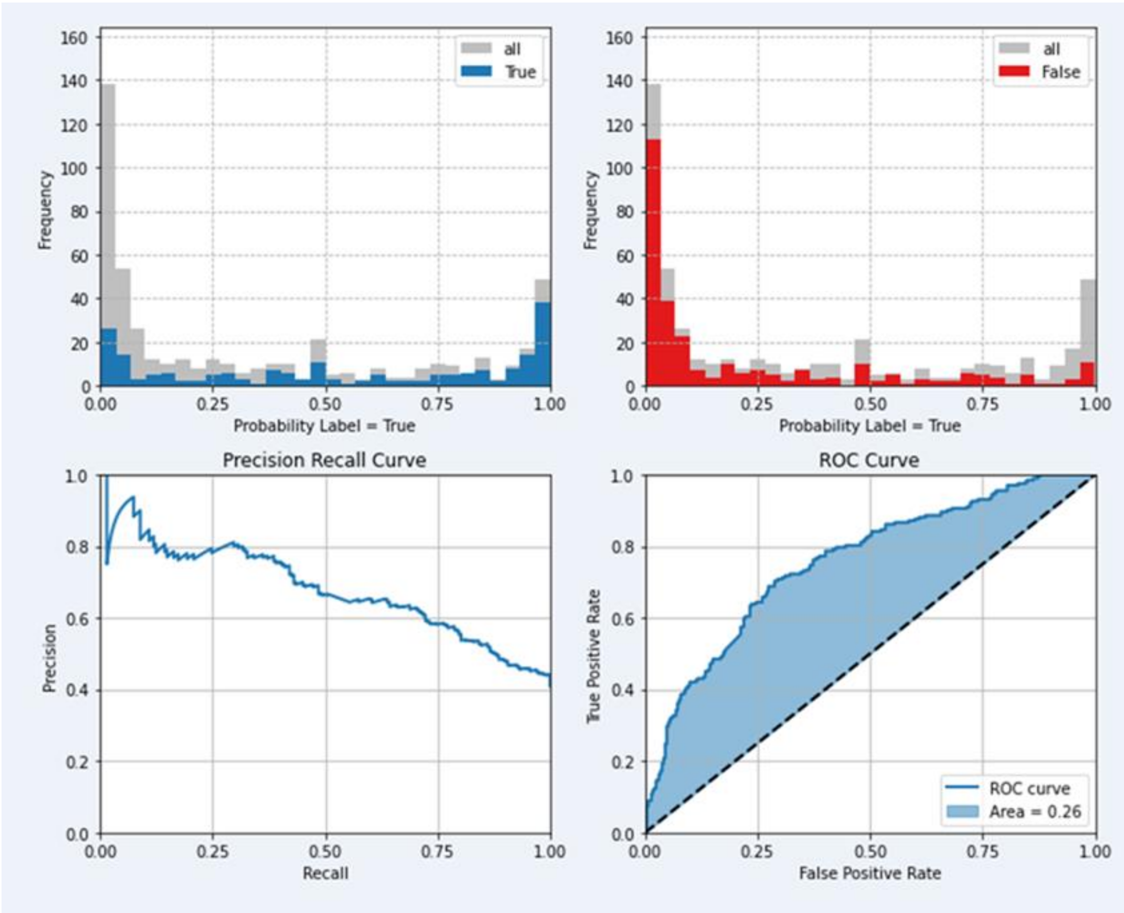

Figure A.2: PR and ROC curves

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