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Are Research Spin-Offs More Innovative? Evidence from a Matching Analysis

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Abstract

The purpose of the paper is to analyze whether research spin-offs, that is, spin-offs from either research institutes or universities, have greater innovation capabilities than comparable knowledge-intensive firms created in other ways. Using a sample of about 1,800 firms from high-innovative sectors, propensity score matching is used to create a sample of control firms that are comparable to the group of spin-offs. The paper provides evidence that the investigated 123 research spin-offs have more patent applications and more radical product innovations on average compared to similar firms. The results also show that research spin-offs' superior innovation performance can be explained by their high level of research cooperation activities and by location effects. Being located in an urban region and proximity to parent institutions is conducive for innovation productivity.

Keywords: Spin-Offs, Innovation Performance, Propensity Score Matching, Locational Factors, Cooperation

JEL classification: M13, O18, R3

1 Introduction

The creation of new companies, particularly in knowledge-intensive industries, is a topic of high interest in the recent literature (e.g., Audretsch and Fritsch; 1994; Audretsch and Feldman; 1996; Zucker et al.; 1998). Numerous studies stress the unique role of spin-off companies as a special method of firm foundation (Klepper and Sleeper; 2005; Mustar et al.; 2006). Spin-offs are seen as mediators for transferring knowledge between research facilities and companies, thereby creating knowledge spillovers (Keeble et al.; 1998). In addition, spin-offs appear to have higher survival rates and higher employment growth than firms created by other means (Egeln et al.; 2004; Koster; 2006). Thus, many authors attempt to discover the significant determinants of innovativeness and economic development of these firms. Some studies focus on locational conditions, including proximity to collaboration partners, and how such conditions interact with the founder's human capital (Beise and Stahl; 1999; Egeln et al.; 2004).

In an earlier paper, Lejpras and Stephan (2011) I study the relationship between cooperation, locational conditions, and firm performance for spin-offs using a structural equation model that employs the partial least squares method (Tenenhaus et al.; 2005). The results show that a firm's innovativeness and its performance are related, and that a firm's cooperation activities are a main driver of its innovativeness. However, in that paper, when spin-offs were compared with a sample of other high-tech firms created in other ways, no statistical significant evidence of superior performance by spin-offs was found. In this paper, I again investigate whether research spin-offs are more innovative compared to similar knowledge-intensive firms created in other ways. Furthermore, I also shed light on the factors that contribute to spin-offs' innovativeness. My analysis is based on data from East-German firms collected in a large survey that contains 123 spin-offs and about 1,600 companies from high-innovative industries. The sample includes companies active in manufacturing medical and optical instruments, research consultancies, and the IT sector. The average age of the spin-offs in the sample is 10 years and they have on average nine employees, which implies that my study is based on established spin-offs and not early start-up spin-offs. The data that I use also allow me to distinguish between spin-offs from research facilities and those from universities (Egeln et al.; 2004; Meyer; 2003;Pirnay et al.; 2003). In the empirical analysis, propensity score matching is applied to create a control group of firms created in other ways that are similar to the sample of spin-offs not only in regard to their innovation efforts (R&D intensity), but also with regard to their profitability, age, industry, location attributes, and cooperation activities. Several measures for innovation output are used. The introduction of both product and process innovations during the last two years is employed, including radical product innovation and own developed processes. Patent applications and number of patents are also analyzed. To the best of my knowledge, only a few other researchers have studied spin-offs' innovation productivity using propensity score matching (PSM) (Cantner et al.; 2011). One advantage of this approach is that the endogeneity problem, which arises from the particular features of spin-offs that make them difficult to compare to other forms of firm creation, is explicitly addressed when using PSM.

The results from the matching analysis show that differences in innovation capabilities between the spin-off group and the control group are significantly reduced after matching, confirming that major parts of the observed differences can be explained by spin-off characteristics, for example, high R&D and cooperation intensity. However, the results show that there is still a delta in the innovation productivity of spin-offs even after matching due to a higher introduction of radical product innovations by spin-offs and because they have more patent applications. A more fine-tuned analysis that distinguishes between spin-offs from a research institute and those from a university shows that, compared to the control group, it is the university spin-offs that are more likely to hold patents, whereas the research institute spin-offs are more likely to have introduced radical product innovations. The different models tested also reveal that spin-offs' higher innovation productivity can be explained by their higher cooperation intensity as well as by certain location attributes, such as closeness to the parent research institute.

The structure of the paper is as follows. The next section summarizes the literature on the innovative performance of academic spin-offs. Section 3 describes methods and data used. Section 4 presents the estimation results. Section 5 concludes and discusses some general implications of this study.

2 Literature Review

There is no commonly accepted definition of a "spin-off" in the literature. The vast majority of studies define a spin-off as a firm whose intellectual capital originates from its parent institution, such as a university, research institute, or another company(Mustar et al.; 2006)), but even these definitions vary widely when it comes to the details of this connection. The various types of ties discussed in the literature include different forms of support from parent institutions for spin-offs that range from knowledge transfer (occurring, e.g., through personnel links or provision of technology and/or existing products) to equity financing (Colombo et al.; 2010; Klepper and Sleeper, 2005; Meyer, 2003).

The unique role of spin-off companies in the innovation process as a means of knowledge transfer is stressed in the literature (Pérez and Sánchez; 2003). Spin-offs show higher survival rates and stronger employment growth than start-up companies (Longhi; 1999). Spin-offs do not respond to market conditions in the same way as other kinds of entry; nonfavorable and niche markets are particularly conducive to spin-offs (Klepper and Sleeper; 2005). A large number of spin-off studies look for and analyze the determinants of the creation and development of spin-off firms; namely, geographical proximity to skilled labor and university research, variety of support, and collaboration activities. **?**argue that spatial proximity to the sources of knowledge, particularly skilled labor and research, stimulates knowledge transfer and strengthens the innovative activities of firms. Intellectual human capital plays a pivotal role in the growth and location of the high-innovative industry. Similarly, Lockett et al. (2005) stress the importance of the transferability of technologies, that is, the industry-specific critical design and production techniques embodied in skilled personnel, for the formation of spin-off firms.

Spin-offs generally are assumed to have a lead in terms of performance indicators compared to firms created by other means (Zhang; 2009). Particularly in the early stages of firm evolution, most spin-offs are dependent on the knowledge and resources of their parent institution, for example, their founders often work at the parent institution during the product development phase (Walter et al.; 2006). Due to this situation, spin-off companies are ready to market their products earlier than firms founded in other ways and hence achieve higher performance sooner (Koster, 2006). Zahra et al. (2007) argue that stable and sufficient financial resources can be one factor behind the success of spin-offs because it allows them to concentrate on their nonfinancial resources, such as access to skilled labor or cooperation partners. Many studies indicate that key to the success of spin-offs is their capacity to create strategic alliances with a variety of actors, as well as their integration in diverse networks of interactive relationships and partnerships in various fields (Baba et al.; 2009). Having strategic alliances and networks with, for example, parent institutions, academic teams, research facilities, large firms, or SMEs assists spin-offs in acquiring and coordinating resources for technological and scientific development. The results of the study by Jensen and Thursby (2001) on the licensing practices of U.S. universities make clear that most university inventions could not be made by either the inventor or the firm standing alone. Due to the fact that the vast majority of licensed inventions are in an embryonic phase, the university technology managers consider inventor cooperation in further development crucial to commercial success.

Firms from science-intensive sectors such as biotechnology tend to locate close to the main universities, even if they are not spin-offs (Audretsch et al. 2005). Since proximity matters, good quality transport infrastructure should also have a positive influence on the cooperation intensity and innovation performance of spin-offs (Audretsch and Dohse; 2007). The issue of the geographical proximity of cooperation partners is extensively investigated in the literature. However, no clear and consistent conclusions have been reached regarding the role proximity to the collaboration partners plays in the innovation activity of firms. On the one hand, many analysts emphasize that, for several reasons, proximity is decisive for cooperation and thus innovation activity (Audretsch et al.; 2005). First, intraregional collaboration allows face-to-face interaction and informal contacts between scientists, private firms, and public institutions. Informal communication leads to mutual trust between cooperation partners, and trust reduces the fear of know-how leaks. In this way, proximity increases the propensity to collaborate on R&D projects and assures rich knowledge transfer and exploitation, enhancing the chances of successful commercialization. On the other hand, Audretsch and Stephan (1996) find that the vast majority (approximately 70%) of the ties between biotechnology companies and their cooperation partners (university-based scientists and other companies) are interregional. Spatial proximity is not important if face-to-face contact between collaboration partners is carefully planned instead of by chance. Moreover, companies do not rely on locally-based scientific networks if the university-based scientists are less involved in knowledge exploitation, and more interested in increasing it (Audretsch and Feldman; 1996).

3 Method

The study compares the innovation performance of research spin-offs with that of a group of companies having similar characteristics but created in other ways. To date, very few studies on spin-offs use propensity score matching. One such study,Cantner et al. (2011) analyzes 128 academic spin-offs using a survey and matches them with 128 nonacademic startups. Rubin (1997) and Rosenbaum and Rubin (1984; 1985) show that a propensity score analysis of observational data can be used to create groups of treated and control units that have similar characteristics, and that comparisons can be made within these matched groups. In this study, the sample of spin-offs is the "treated" group for which I match a "control" group of similar firms. For each firm in the sample, let S_i be a spin-off indicator that equals 1 when the firm is created as a spin-off and 0 otherwise. The propensity score of being a spin-off is defined as the conditional probability of being a spin-off given a set of observed co-variates, X_i,

$$p\left(S_i\right) = \Pr\left(S_i = 1 \left| X_i \right.\right) = E\left[S_i \left| X_i \right.\right]$$

Propensity score matching relies on two key assumptions (Rosenbaum and Rubin, 984). The first, the conditional independence assumption (CIA), requires that conditional on the propensity score, potential outcomes are independent of treatment assignment. The CIA assumes that selection into treatment occurs only on observable characteristics. Hence, unbiased treatment effect estimates are obtained when all relevant covariates are controlled for. The second assumption is the common support or overlap condition, meaning that firms must have a positive probability of either merging or not merging rather than just having the same covariate values. In sum, propensity score matching relies on the "strong ignorability" assumption, which implies that for common values of covariates, the choice of treatment is not based on the benefits of alternative treatments.

Let Y_{i1} denote the innovation performance of spin-off and Y_{i0} the innovation performance of non-spin-off firms and observe and, hence, as one observes only one status per firm, the observed outcome can be written as $Y_i = S_i \cdot Y_{i1} + (1 - S_i) \cdot Y_{i0}$. Accordingly, let $E\left[Y_{i1} \left| S_i = 1 \right.\right]$ and $E\left[Y_{i1} \left| S_i = 0 \right.\right]$ denote average outcomes of the innovative performance of spin-offs and non-spin-offs firms, respectively. The effect of interest is the difference between the expected innovative performance of the spin-offs firms and that which the firms would have exhibited if they were not spin-offs:

$$\tau\left|_{S_i=1}\right. = E\left[Y_{i1}\left|S_i = 1\right.\right] - E\left[Y_{i0}\left|S_i = 1\right.\right] \tag{1}$$

In the classical causal effect evaluation framework, this denotes the expected treatment effect on the treated. Here, it denotes the difference in expected outcome for a spin-off due to the fact that it was created as a spin-off. Since I do not have the counterfactual evidence of what would have happened if a firm had not been created as a spin-off, the second is unobservable. However, it can be estimated using the group of matched non-spin-offs by $E\left[Y_{i0}\left|S_i = 0\right.\right]$ and the effect from being a spin-off on innovation outcomes is then estimated by the difference in the average outcome between the merged and non-merged innovative performance:

$$\tau^e = E\left[Y_{i1}\left|S_i = 1\right.\right] - E\left[Y_{i0}\left|S_i = 0\right.\right] \tag{2}$$

If the spin-off and non-spin-off firms systematically differ in their firm characteristics, Equation (2) will be a biased estimator of Equation (1) (Dehejia and Wahba; 2002; Caliendo and Kopeinig; 2008).

To evaluate the sensitivity of results with respect to different matching specifications, and also to explore the effect of control variables related to cooperation activities and location conditions on observed outcomes, I test three model specifications in the propensity score estimation. The models are

Model I: $P(S_i = 1)$=f(profits, age, industry, sales, no employees, r&d intensity, federal state)

Model II: $P(S_i = 1)$=Model I + cooperation

Model III: $P(S_i = 1)$=Model II + location factors

In Model I, the basic characteristics of a company are included. In Model II, the variables of Model I are included and cooperation activity is added. In the third model, settlement types and location characteristics are added to the mix as well. This means, for instance, that after matching according to Model III, the spin-offs and their controls should not only be balanced with regard to their basic characteristics, for example, age or size in terms of revenue, but also in terms of their cooperation activity and locational conditions. This is important because if it true, as conjectured, that both cooperation and location are important determinants of innovation productivity, then both determinants should be included in the matching.

Modelling the comparison between spin-offs and comparison firms as selection on observable characteristics has several advantages. First, with this approach it is easy to focus on different outcome variables, whereas with a model based on selection by unobservables (e.g., Heckman selection models) one usually focuses on a single outcome variable. It should be noted that in the PSM framework, no assumption as to linear relationships between variables is necessary; basically, the functional form of the relationship between treatment and outcomes is very flexible. In addition, in principle it is possible to combine PSM with linear regression models (Cantner et al.; 2011). This is interesting when covariates in addition to those included in the Probit model for propensity score estimation are included in the linear regression model.

4 Empirical Analysis

4.1 Data and test results for the balancing assumption

The analysis is performed by using the micro-level data collected by the German Institute for Economic Research (DIW Berlin) in a large survey. This survey, carried out on behalf of the German Ministry of Education and Science, was titled "Current Situation and Outlook of East-German Firms." It was sent to 30,000 firms located in East Germany in the year 2004 and yielded a response rate of about 20%. The survey contained a question regarding the origin of the company. Based on answers to this question, I can differentiate between company and research spin-offs, and for the latter I can further distinguish between spin-offs that were formed from a university and those that were created by a research institute.

The survey specifically focused on locational factors, collaboration, and networking, as well as on the innovation activities of firms. The questionnaire included 49 questions pertaining to general information about the firm and its activities, business and competition situation, innovation and R&D activities, and collaboration and networking, as well as questions about locational conditions. A potential limitation of this study is that in addition to quantitative indicators (e.g., number of patent applications or turnover), the analysis uses the firms' own assessments of business situation and locational conditions, raising the potential for bias in the answers. Indeed, it is possible that a firm's assessment of locational conditions may not match objective reality (e.g., perceived vs. actual distance from university or airport). However, the perceptions, objectively true or not, of potential decisionmakers are crucial because these perceptions can affect decisions they may make about where to locate their economic activities(Audretsch and Dohse 2007, Czarnitzki and Hottenrott 2009, Egeln, Gottschalk, and Rammer 2004). Figure 1 shows the geographical distribution of the spin-offs, illustrating that a high share of them are located either in agglomerated regions (e.g., Berlin or Dresden) or in urbanized regions (e.g., Jena and Rostock). Only a small fraction of spin-offs is located in rural regions.

Table 1a shows means of spin-offs (treated) and other firms (controls), the first column for the unmatched and the second for the matched. In PSM, I selected 1:1 nearest-neighbor matching for its simplicity. I imposed the common support restriction for PSM as well as the no replacement option, which implies that each spin-off has a unique control company assigned as its match. As a consequence of these choices, the control sample that the treated sample contain the same number of firms. Even though it industry type might be an important influence on innovative performance, the relatively small number of observations made it infeasible to match by industry. To account for industry effects, I chose to distinguish between medium/high-tech manufacturing and knowledge-intensive services (KIBS), which are included as respective dummy variables in the analysis.

The pseudo-R^2s for the various Probit models are between 0.17 for Model I, 0.20 for Model II and 0.23 for Model III, which is satisfactory. Figure 1A shows that common support holds for Model III in this case. Note that the number of observations can vary between models due to missing values and also due to completely determination of successes (spin-off) or failures (control) in the Probit estimation for a specific combination of categorical variable values, in particular for the federal state dummies.

For the matched samples, the balancing assumption holds, meaning that all variables considered as covariates in the Probit models should not be significantly different between spin-offs and controls. For instance, spin-offs are significantly less profitable compared to their peers but this difference disappears after matching. Spin-offs are on average about 10 years old and have about nine employees; the unmatched peers are on average 13 years old and have on average six employees. Again, this difference balances out after matching. Moreover, that the majority of spin-offs are from knowledge-intensive industries (72%); only 28% are from medium or high-tech manufacturing. Table 1A in the Appendix shows a further differentiation of the sample with respect to industries at the two-digit level. Most spin-offs are from industries that have the NACE two-digit codes 33 and 74, which signify instruments manufacturing and R&D consultancy services, respectively.

Table 1a also shows that the spin-offs in the sample have a rather high R&D intensity (measured as R&D personnel/employees) at 36%. Before matching, other firms that are also active in knowledge-intensive industries have about a 10% R&D intensity; however, the matched control firms have almost as high R&D intensity on average as the spin-offs and therefore difference in R&D intensity is not statistically significant.

Table1a: Comparison of spin-offs with other firms before and after matching based on Model III[1]

[1]Note that the results for federal states dummies are omitted from the Tables but available from the author upon request

Variable	Sample	Mean Treated	Control	%Bias	%Reduct Bias	t-test t	p>t
profitability	Unmatched	3.1529	3.4083	-23.9		-2.58	0.01
	Matched	3.1529	3.1281	2.3	90.3	0.18	0.861
age (yrs)	Unmatched	10.182	13.052	-18.8		-1.62	0.106
	Matched	10.182	10.496	-2.1	89.1	-0.22	0.827
Industry type							
medium/high-tech manufacturing	Unmatched	0.28099	0.50903	-47.9		-4.85	0
	Matched	0.28099	0.21488	13.9	71	1.19	0.235
KIBS	Unmatched	0.71901	0.49097	47.9		4.85	0
	Matched	0.71901	0.78512	-13.9	71	-1.19	0.235
Sales (mill euro)	Unmatched	1.1284	3.4883	-11.9		-0.93	0.353
	Matched	1.1284	1.0174	0.6	95.3	0.57	0.572
Employment	Unmatched	9.3802	6.5794	20.2		1.83	0.067
	Matched	9.3802	8.3595	7.4	63.6	0.73	0.467
R&D intensity	Unmatched	36.198	10.073	97.4		13.28	0
	Matched	36.198	35.488	2.7	97.3	0.16	0.871

Table 1b shows interesting results regarding the location pattern of spin-offs. More than 51% of the spin-offs are located in high-density agglomerations, and almost 16% in high-density urbanized regions: in short, more than 85% of the spin-offs are located in these types of regions. In the survey, firms were asked whether a specific location factor was important for them, and then to rate the quality of that factor in the location in which they were located on a scale where 1 = poor, 2 = medium, and 3 = good. Therefore, the means reported here are conditional on whether firms answered that the respective location factor is important for them. As all means are around 2.5, it can be concluded that firms both assessed the factors as important as well as gave a relatively good rating to the supply of qualified labor, closeness to research institutes, and universities related to their respective locations. This finding could also be connected to the fact that, as just discussed, most spin-offs are located in agglomerated/urban regions, which are the regions where universities and research institutes are located. The ratings are significantly different for spin-offs and the unmatched sample, but are no longer significantly different when comparing spin-offs with the matched sample. This means that the firms in the matched sample are exposed to similar location conditions as are the spin-offs.

Table 1b: Comparison of spin-offs with other firms before and after matching based on Model III (results for federal states dummies omitted)

Variable	Sample	Mean Treated	Control	%Bias	%Reduct Bias	t-test t	p>t
Location types							
high-density region in agglomeration	Unmatched	0.5124	0.30253	43.6		4.78	0
	Matched	0.5124	0.57851	-13.7	68.5	-1.03	0.304
lower-density region close to agglomeration	Unmatched	0.03306	0.10397	-28.3		-2.52	0.012
	Matched	0.03306	0.03306	0	100	0	1
rural region close to agglomeration	Unmatched	0.03306	0.09025	-23.9		-2.16	0.031
	Matched	0.03306	0.03306	0	100	0	1
high-density urban region	Unmatched	0.15702	0.09603	18.4		2.14	0.033
	Matched	0.15702	0.1157	12.4	32.3	0.93	0.351
lower-density region close to urban center	Unmatched	0.04959	0.11336	-23.4		-2.17	0.03
	Matched	0.04959	0.02479	9.1	61.1	1.02	0.31
rural region close to urban center	Unmatched	0.09917	0.10758	-2.8		-0.29	0.774
	Matched	0.09917	0.08264	5.4	-96.6	0.45	0.656
rural region	Unmatched	0.06612	0.08303	-6.4		-0.65	0.515
	Matched	0.06612	0.04132	9.4	-46.6	0.85	0.394
Location factors							
Supply of qualified labor	Unmatched	2.5455	2.0079	33.9		3.63	0
	Matched	2.5455	2.5041	2.6	92.3	0.2	0.842
Closeness to university	Unmatched	2.6116	1.1762	69.4		7.87	0
	Matched	2.6116	2.3967	10.4	85	0.75	0.452
Closeness to research institute	Unmatched	2.5041	0.89531	81.7		9.68	0
	Matched	2.5041	2.2397	13.4	83.6	0.93	0.351

Notes: Location types according to the definition provided by The German Federal Institute for Research on Building, Urban Affairs and Spatial Development

Table 1c shows the differences in means for the cooperation frequencies of spin-offs and the different comparison samples. Cooperation frequency is measured on a Likert scale where 1 means there was no cooperation activity, 2 signifies very low/seldom cooperation, 3 indicates occasional cooperation, and a score of 5 means that the firm engaged in very frequent cooperation. Table 1c reveals that spin-offs mainly cooperate in the fields of product and process development and have higher cooperation intensities on average compared to the unmatched controls. However, for the matched sample these differences disappear and spin-offs and their matched peers are very similar in terms of both who they cooperate with and how often.

Table 1c: Comparison of spin-offs with other firms before and after matching based on Model III (results for federal states dummies omitted)

Variable	Sample	Mean Treated	Control	%Bias	%Reduct Bias	t-test t	p>t
Cooperation frequency							
basic research	Unmatched	2.3802	1.4801	69		8.7	0
	Matched	2.3802	2.3388	3.2	95.4	0.21	0.836
product development	Unmatched	3.1405	2.2043	66.3		7.01	0
	Matched	3.1405	3.1736	-2.3	96.5	-0.18	0.861
process development	Unmatched	2.6942	1.8014	64.3		7.41	0
	Matched	2.6942	2.6198	5.4	91.7	0.38	0.706
education	Unmatched	2.3884	2.0303	27.2		2.95	0.003
	Matched	2.3884	2.405	-1.3	95.4	-0.1	0.923
distribution	Unmatched	1.9091	1.956	-3.6		-0.37	0.712
	Matched	1.9091	2.1074	-15.3	-323.2	-1.18	0.238

4.2 Results for Outcome Variables from Matching

The main results of the analysis are shown in Tables 2 to 4. Table 2 contains the results for all 123 research spin-offs, that is, for both university and research institute spin-offs. The first two columns of Table 2 reveal that spin-offs are superior in terms innovation productivity when compared to a nonmatched comparison group of all firms created in other ways and the differences are statistically significant in almost all outcome variables except for process innovations. Ninety percent of the spin-offs have introduced product innovations, whereas less than 70% of the nonmatched peers have done so. The table also shows that 46% of spin-offs have introduced radical production innovations (new to the market innovation), but only 20% of the comparison group has done so. The average turnover share of radical innovations is 16% for spin-offs, but less than 5% for the other firms. Though the share of introducing process innovation (38%) is not significantly higher for spin-offs, the share of self-developed process innovations is significantly higher for spin-offs (31%) than for other firms (13%). The major difference in terms of innovation productivity is with regard to patent applications. Of the spin-offs, 43% have applied for a patent right, but less than 13% in the comparison group have done so.

Most of the observed differences are significantly reduced when the matched control group is used for the comparison. One of the major determinants for innovation output is R&D intensity. When this characteristic is employed in the estimating propensity scores, only half the differences regarding the share of firms introducing new products remain, and this is even further reduced once the location factors are taken into account (Model III). In Model III, the observed difference between spin-offs (90.2%) and the matched sample (84.4%) is no longer statistically significant. What remains significant, however, is both the share of radical product innovation in turnover (at a 10% level of significance) and the share of firms having filed patent applications (at a 1% level of significance). Thus, it can be concluded that, in general, a higher share of spin-off' turnover comes from radical product innovations (16.4%) compared to their peers, for which this share of turnover is only about 10%. In addition, and most notably, spin-offs are more likely to have applied for patents than are their peers.

Table 2: Results on innovation productivity for all spin-offs

	Spin-Offs	ΔAll Firms	ΔMatched (n=123)		
In past two years	(n=123)	(n=1,572)	Model I	Model II	Model III
Product Innovation (in %)	90.2	-20.8***	-9.8**	-10.0**	-5.8
Radical Product Innovation (in %)	46.3	-25.9***	-12.2**	-15.8**	-9.1
Share in Turnover (%)	16.4	-11.8***	-5.5*	-8.6***	-6.4*
Process Innovation (in %)	38.3	-6.8	0	0	0
Process Innovation Own (in %)	30.9	-17.2***	-11.4*	-1.7	-6.6
Patent Applications (in %)	43.1	-29.7***	-16.3***	-17.5***	-18.2***
Patents (number)	1.29	-0.84***	7.3	28.3	69.4
Pseudo-R^2 Probit Model			0.173	0.200	0.234

Note: Standard errors obtained from bootstrapping with 999 replications, * significant at 10%, ** significant at 5%, *** significant at 1%

Table 3 differentiates between different types of research spin-offs. When I compare just the 89 university spin-offs with their peers, I find that they are more likely to have introduced product innovations (90% vs. 80%, Model III) and also are more likely to have applied for patents (47% vs. 29%). Overall, the results of Table 3 are in accordance with Table 2.

Table 3: Results on innovation productivity for university spin-offs

	Spin-Offs	ΔAll Firms	ΔMatched (n=89)		
In past two years	(n=89)	(n=1562)	Model I	Model II	Model III
Product Innovation (in %)	90.5	-21.0***	-12.0**	-4.9	-9.8*
Radical Product Innovation (in %)	44	-23.6***	-8.4	-11	-4.9
Share in Turnover (%)	13.7	-9.0***	-1.2	-7.4**	-2.1
Process Innovation (in %)	33.3	-1.8	-3.8	-1.3	-2.5
Process Innovation Own (in %)	27.4	-13.7***	-4.8	-8.5	-3.7
Patents (in %)	47.6	-34.2***	-20.5***	-17.1**	-18.3**
Patents (number)	1.36	-0.91***	-0.1	-0.13	1.3*
Pseudo-R^2 Probit Model			0.172	0.202	0.231

Note: Standard errors obtained from bootstrapping with 999 replications, * significant at 10%, ** significant at 5%, *** significant at 1%

Table 4 shows the results for the 39 research institute spin-offs. Here, the results from Model III demonstrate that the main difference between the research institute spin-offs and their counterparts is both the likelihood of having introduced radical innovations and the share of turnover attributable to radical product innovations. Overall, the spin-offs from research institutes obtain 22% of their revenues from radical innovations, whereas in the peer group this is less than 6%. Recall that after matching, spin-offs and their peer group are most similar in terms of characteristics, in particular R&D efforts, but also in their cooperation activities and location conditions.

Table 4: Results on innovation productivity for research institute spin-offs

	Spin-Offs	ΔAll Firms	ΔMatched (n=39)		
In past two years	(n=39)	(n=1488)	Model I	Model II	Model III
Product Innovation (in %)	89.7	-20.5***	-12.8	-13.5	0
Radical Product Innovation (in %)	51.3	-30.8***	-7.7	-21.6*	-26.3**
Share in Turnover (%)	22.4	-17.6***	-13.9**	-16.9***	-16.7***
Process Innovation (in %)	48.7	-17.3**	-15.8	-5.4	-7.9
Process Innovation Own (in %)	38.5	-25.1***	-10.3	-2.7	-18.4
Patents (in %)	33.3	-19.9***	-20.5*	-16.2	-2.6
Patents (number)	1.15	-0.69***	0.03	-0.86	-0.92
Pseudo-R^2 Probit Model			0.1485	0.183	0.231

Note: Standard errors obtained from bootstrapping with 999 replications, * significant at 10%, ** significant at 5%, *** significant at 1%

Comparing Models I, II, and III in Table 4 shows that the greatest reduction in significance regarding innovation productivity is from Model II to Model III. Therefore, one tentative conclusion is that locational differences largely explain the observed differences in innovation productivity between spin-offs and other firms. I also tested whether there is any significant difference with regard to public support that spin-offs receive. The only difference I found is for support from the federal state, which is significantly higher for spin-offs compared to unmatched firms, but not significant for matched firms. Thus, the higher innovation productivity of spin-offs is not due to them receiving more subsidies or more public support.

5 Conclusions

Generally speaking, the literature is very positive about the innovation capabilities of spin-offs. One reason for this assumed high innovation productivity has to do with resource and knowledge transfer from the parent institution as well as the inherent knowledge and skills embodied in spin-off founders. However, there is, to date, only limited empirical evidence on the assumed superior innovation productivity of spin-offs. In any comparison between spin-offs and companies created in other ways, it is essential to ensure that the comparison group is actually similar to spin-offs in terms of innovation input (R&D intensity), cooperation activities, and location conditions. In this paper I used propensity score matching to create a group of firms that is comparable in its characteristics to the spin-offs. Indeed, I find that the differences in innovation productivity between spin-offs and other firms are reduced to a large extent after matching. However, a few significant differences in innovation productivity remain. Basically, it is both the share of radical product innovation as well as number of patent applications that are higher for the spin-offs, even after controlling for the above-mentioned factors in the propensity matching. Therefore, my results confirm that spin-offs demonstrate superior innovation productivity compared to their peers. I can only speculate as to the reasons for this observed difference, but tend to agree with assumptions made in the literature that it is the high degree of knowledge transfer from the parent institutions to the spin-off as well as continued cooperation with the parent institution that is the most plausible explanation. This study also differentiates between university and research institute spin-offs and finds that the latter have a higher share of their turnover attributable to radical product innovation, whereas the university spin-offs are more likely to have applied for patents compared to their peers. Since it is unclear whether a patent will lead to a market launch and thereby to an innovation, spin-offs from research institutes are apparently already a step ahead in commercializing their innovations. From this finding a tentative conclusion might be drawn that innovation policies focusing on early stages might be most useful for university spin-offs, while public support for commercialization of radical product innovations might be most relevant for spin-offs from research institutions.

A Appendix Tables and Figures

Table 1A: Industries of spin-offs and matched sample

NACE	Description	Spin-offs	Matched
24	chemicals and chemical products	4	5
29	machinery and equipment	1	9
30	electrical and optical equipment	1	—
31	electrical machinery and apparatus	3	6
33	medical, precision and optical instruments, watches and clocks	26	12
34	transport equipment	—	3
35	and other transport equipment	—	1
70	real estate activities	1	—
71	renting of machinery and equipment	—	3
72	computer and related activities	23	19
73	research and development	35	19
74	other business activities	29	44
80	education	—	2
	Total	123	123

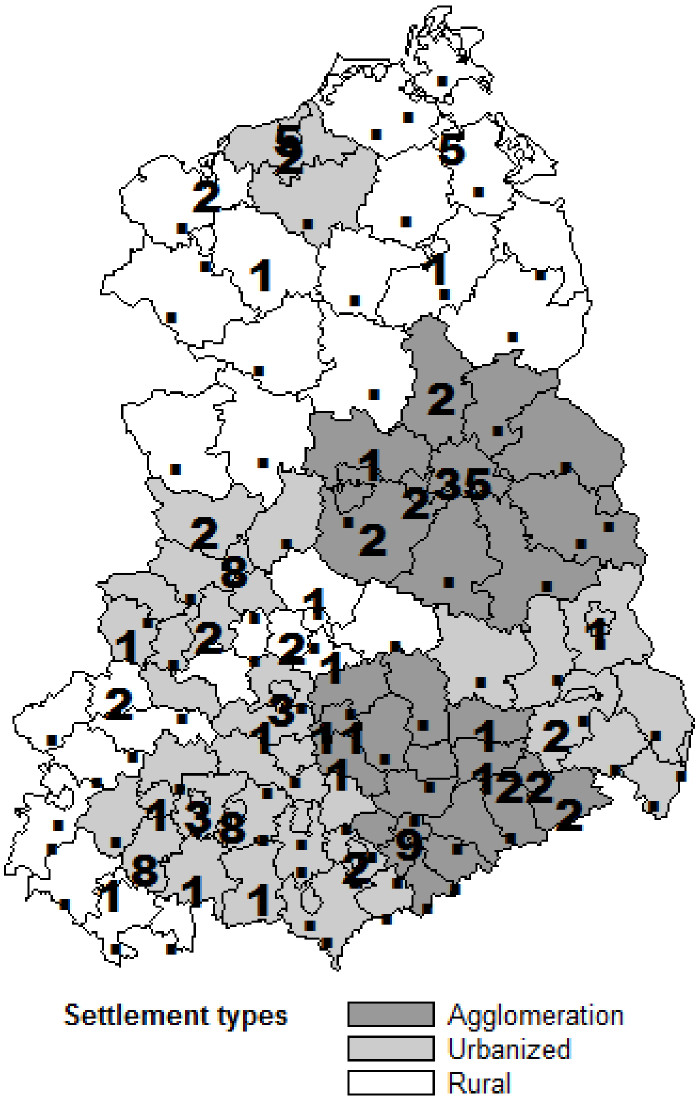

Figure 1: Regional distribution of spin-offs and location types

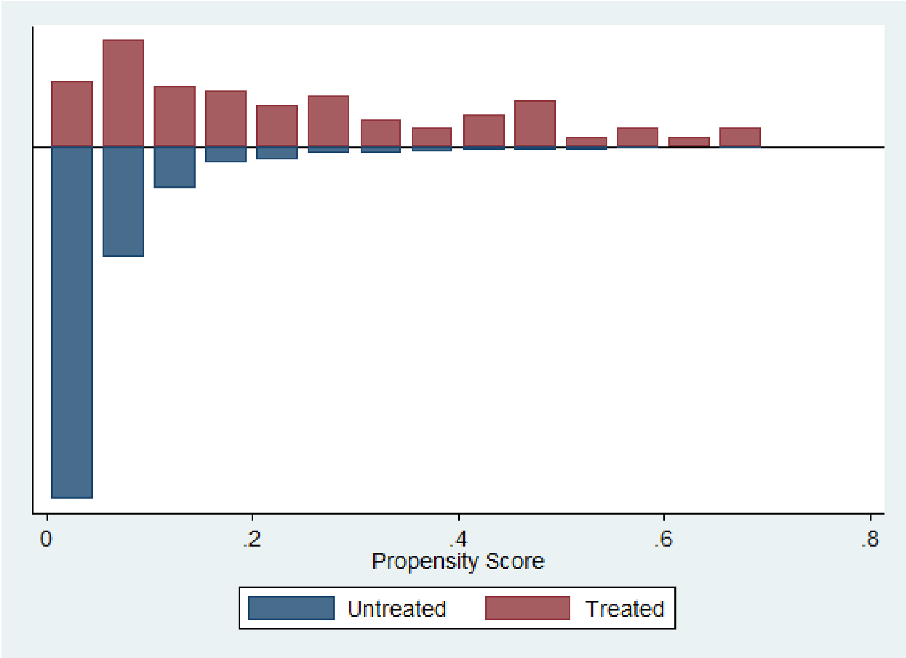

Figure 2: Distribution of propensity scores, Model III

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