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Who innovates longer: Efficiency in R&D, Technological Exit and the Role of Technological Knowledge ? Evidence from German Innovators

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Abstract

This paper deals with the long term efficiency of firm?s innovation activities and the charac-teristics of a firm?s technological knowledge base as drivers of innovation efficiency. Starting from the beginning of the technological life cycle for photovoltaic technologies (PVTs) in 1964, the innovation efficiency in PVTs is analyzed for 294 German firms until 2012. A novel approach is employed in order to determine long term innovation efficiency at the firm level. Since innovation efficiency is not directly observable, a latent variable is utilized. The idea is is followed that different forms of firms? technological exit can be associated with different innovation efficiency levels. Applying an ordered probit model and a two-step maximum like-lihood selection ordered probit estimation model, the role of technological knowledge for in-novation efficiency is highlighted. By considering multiple sources of a sample selection bias, the representativeness of the applied concepts and the gained results are discussed.

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Abstract

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Key words: R&D efficiency, efficiency measurement, technological diversification, technological knowledge, knowledge synergies.

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1. Introduction

The Resource based view (RBV) highlights technological knowledge as an important strategic firm resource (Wernerfelt 1984, Barney 1991, Petraf 1993). This is even true for low tech firms since technological knowledge, at least to a certain degree, constitutes the basis for production process of products and services (Patel/Pavit 1997). Building on these arguments, Grandstand (1998) develops the concept of the technology based view (TBV) of the firm, which puts emphasis on high tech firms and the strong competitive relevance of their technological knowledge base. According to the TBV, a diverse technological knowledge base is the core of profitable innovation and competitive advantage. Thereby, the competitive value of a firm's technological knowledge base is affected by dynamic changes. Technological developments accompanied by technological progress, increased product and process complexity (Grandstrand/Sjölander 1990, Patel/Pavitt 1997), technology fusion (Kodama 1986) and the evolvement of platform technologies (Kim/Kogut 1996) require a firm's dynamic capability to continuously reconfigure and renew its existing resources and especially its technological knowledge base (Eisenhard/Martin 2000, Teece 2007). A promising strategy for dealing with these dynamics and for ensuring long term innovativeness and competitiveness is addressed by the concept of corporate technological diversification. According to this concept, a firm should concentrate on technological areas with the most technological and economic potential in the present. Simultaneously, it is necessary to relocate or expand innovation activities into new technological areas when time has come. Time has come, when the potential within established technological areas begins to decline or promising potential within newly evolving technological areas arises.

Several scholars have given empirical proof of a positive effect of technological diversification on firm performance indicators like market value (Nesta/Saviotti 2006) and on innovation performance indicators like R&D expenditures, patents, patent citations, publications and publication citations (Garcia-Vega 2006, Leten et al. 2007). Although traditional performance studies on technological diversification sensitize for the importance of technological entry and technological knowledge accumulation at the firm level, all of them suffer from at least two substantial shortcomings. Firstly, they abstain from an explicit post technological entry view. Long term efficiency of innovation activities within newly entered technological areas is not explicitly addressed and works just as an implicit basic assumption. Secondly, an exclusive focus is on technological entry as process of effectively entering new technological areas. Exit from technological areas as disinvestment strategy constitutes a widely under-researched dimension of technological diversification.

This paper combines and addresses both research gaps simultaneously. It goes beyond prior findings by focusing on innovation efficiency from a post technological entry view. Technological exit as a consequence of long term innovation inefficiency is explicitly considered. Emphasis is on the following two research questions: (1) Are there differences in the efficiency of firms' innovation activities after entering a new technological area and how can they be assessed empirically? As a second step, an evaluation is made whether technological knowledge is really on the core of efficient innovation as proposed by the RBV and TBV. It is examined (2) which characteristics of a firm's technological knowledge base increase or hamper the efficiency of innovation activities within a new technological field.

The paper proceeds as follows: Chapter two highlights the main challenges arising from innovation efficiency measurement and the shortcomings of metrics suggested by existing literature. In chapter three the applied data and the novel methodological approach for specifying innovation efficiency and its technological knowledge oriented determinants are introduced.

Subsequently, the descriptive statistics are presented. Results are reported and discussed in chapter four. Chapter five closes with a conclusion.

2. Innovation efficiency and technological exit

A major challenge concerning the empirical analysis of innovation efficiency in the context of technological diversification arises thorough a proper assessment of innovation efficiency. In general, no broadly accepted metrics exist. The product development cycle time is one of the most popular and often applied efficiency indicator for innovation activities (Griffin 1993). Thereby, short cycle times are associated with increased innovation efficiency. However, cycle times reveal nothing about the economic value of innovations or their associated efficiency in terms of output/input relations. Especially the partly unobvious and intangible, multidimensional and complex character of the innovation output lead to a limited determinability of efficiency in form of output/input relations (Pappas/Remer1985). Although there are several output related efficiency indicators proposed by scholars, such as the number of successful innovation projects per number of failed innovation projects, the discounted sum of all future project paybacks in relation to of the sum of all innovation project related investments (McGrath/Romeri 1994), patents grants per R&D expenditures (Deng et al. 1999), R&D spending per patent (Bowonder et al. 2000) or patent citations per R&D expenditures (Lin/Chen 2005); all of them are strong simplifications and abstain form a comprehensive assessment. Innovation efficiency is a considerably more complex construct which is difficult to determine since:

- it is determined by and finds manifestation within multiple dimensions (e.g. financial, technical, customer, competition, organizational) (Lazarotti et al. 2011);
- it is determined by and finds manifestation on different levels (e.g. project level, individual level, team level, firm level) (Kim/ Oh 2002);
- it is characterized by process dependency. Innovation occurs within different phases. The efficiency of one phase effects the efficiency of subsequent phases and thus, the efficiency of the whole innovation project (Pillai et al. 2002);
- it is characterized by objective and easily quantifiable elements (e.g. financial figures) (McGrath/Romeri 1994) and qualitative elements which are difficult to measure(Kim/ Oh 2002, Pillai et al. 2002);

- it is determined by the interplay of interdependent systems (e.g. input, process, output system) with different requirements (e.g. assets, personnel, organizational) and efficiency (García-Valderrama 2005).

In this paper, a novel firm level indicator for long term innovation efficiency within newly entered technological areas is applied. Characterizing long term innovation efficiency as being not directly observable, technological exit is used as a latent variable for long term innovation efficiency measurement. Technological exit from a technological area is considered as a consequence of long term innovation inefficiency. Only if a certain efficiency level within technological areas can be realized, continuing innovation activities are to be expected in the long term. Innovation efficiency is at the core of successful innovation activities, at the overall firm level as well as within single technological areas. If a sufficient efficiency level of innovation activities within a technological area is not reached in the long term, a release and reallocation of the committed scarce resources like personnel and financial resources will most likely lead to more efficient resource allocations. The technological exit based conceptualization of long term innovation efficiency furthermore allows the implicit consideration of all possible static and dynamic dimensions of innovation efficiency.

Taking a step further with the core argument of technological exit as suitable approach for innovation efficiency assessment implies that different modes of firms' technological exit may be associated with different innovation efficiency levels. As a consequence, the ordinal efficiency information linked to persistent innovators and different technological exit types is exploitable for analytical purposes fitting the requirements of an ordered probit model. A latent innovation efficiency variable can be derived.[1] For determining different levels of innovation efficiency within one single technological area, five technological exit types are distinguished. (1) Persistents: Persistents are firms which have not yet left the technological area. They continuously conduct innovation activities after entering a technological area. For these firms, the expected long term efficiency is sufficient to justify the continuation of innovation activities within a technological area. (2) M&As: This exit mode covers all cases of mergers and acquisitions, leading to technological exit of the original firm. Although firms which are subject to a M&A exit are not active (independent) innovators anymore, their innovation efficiency is assumed to be as high as for persistents or just slightly below. It can be expected that only those firms are targeted which show a sufficiently high innovation efficiency level within their technological areas. In this context, DeTienne (2010) shows that, at least in certain high

[1] The idea of using ordinal information about firm failure for profitability assessment was initially suggested by Krüger and von Rhein (2009) in the context of industrial dynamics and industrial life cycle research. The authors assume a latent relationship between different forms of market exit and different degrees of firm profitability.

tech industries, reaching innovation excellence and then being acquired by an incumbent firm is a deliberate strategy for startup and spin-off firms. The re-integration of subsidiaries and collaborative organizational forms are also included. (3) Related out-diversification comprises all innovators which terminate innovation activities within a technological area and continue innovation activities within related, familiar or new technological areas. Technological areas are considered as related if their underlying knowledge bases are characterized by synergies in form of complementarities or similarities (Breschi et al. 2003). For firms which pursue related out-diversification, the long term innovation efficiency level in the concerned technological area is not expected to be high enough for satisfying continuing innovation activities. However, it is sufficient to allow the exploitation of knowledge synergies in related technological areas. An (4) unrelated out-diversification is pursued by innovators which terminate innovation activities within a certain technological area and continue innovation activities within unrelated, familiar or new technological areas or which terminate all innovation activities and focus on imitation or non-innovation based business activities. The expected long term innovation efficiency does not justify ongoing innovation activities within the concerned or even a related technological area. Nevertheless, after technological exit, at least some general knowledge and resources can productively be used in unrelated technological areas, e.g. knowledge concerning the management of multiple projects, laboratory equipment or supplier networks. The last exit type is (5) total firm exit which include all forms of overall firm failure, namely liquidation and bankruptcy. The expected long term innovation efficiency for firms which pursue a total firm exit is not sufficient to justify the continuation of any innovation activity.

3. Data and Methodological Approach

The analyses carried out in this paper set a technological focus on entry, exit and innovation efficiency within the technological area of photovoltaic technologies (PVTs). This is especially meaningful since PVTs are still in the growth phase. Promising future technological and market potential still exists. Focusing on such a non-mature technology reduces exogenous impacts on innovation efficiency which lie beyond the sphere of a firm's influence. Possible exogenous impacts are diminishing technological potential caused by obsolescence of knowledge or shrinking market potential on the output side of technology application. Patent applications as a commonly accepted indicator for innovation and technological knowledge are used. Especially in PVTs patents are considered as important strategic mean to protect innovations (Braun et al. 2010, Breyer 2012). The observation starts with the beginning of the technology life cycle for PVTs in Germany in 1964, where the first PVT patent was applied by a German firm. All German firms which applied for at least three PVT patents between 1964 and 2012 are considered, leading to a sample size of 294 PVT innovators.[2] Patent data was collected from PATSTAT and DEPATIS.[3] PVTs are defined in conformity with the WIPO Green Inventory (GI) Scheme. The GI is a hierarchical scheme which differentiates alternative energy production technology groups and their subordinated technological areas by IPC classes. According to the GI, PVTs constitute an independent technological area within alternative energy technologies. On the overriding level, PVTs belongs to the technological group solar technologies. Patent data was completed with data gained by an extensive review of the historical background of all sample firms. A variety of secondary sources like official trade registers, trade publications, commercial firm registers from Hoppenstedt, Buergel and LexisNexis, web material and the BSW member list were used. For every firm, the year of foundation, connections to other firms, changes of the name, the legal status, the location, and the ownership structure were identified. Companies which changed their name, legal form or headquarter within Germany during the observation period were treated as continuing entities. For all sample firms, the year of the first PVT application was treated as year of technological entry. Necessary data was gained from multiple sources. For technological exit the following methodology is utilized:

3.1. Conceptualization of different technological exit types

All sample firms were assigned to one efficiency level which could be (1) Persistents, (2) M&A, (3) related out-diversification, (4) unrelated out-diversification or (5) total firm exit.
Data on persistent, M&A and total firm exit modes is based on secondary data gained form official trade registers, trade publications, commercial firm registers like Hoppenstedt and Buergel, LexisNexis, web material and the BSW member list. [4] For the case of out-diversification, the year of the latest PVT patent application plus eight years was considered as year of out-diversification. Related out-diversification occurs when at least one patent in a PVT related technological area was applied for within eight years after the last PVT-patent. A patent application is treated as PVT related if one or more of its associated IPC classes fall into at least one technological sector which also comprises at least one IPC class which is defined as PVT by the GI. Technological sectors are differentiated by the ISI-OST INPI clas-

[2] German firms are all firms with Head Quarter in Germany.
[3] EP and DE-patent applications are considered. DEPATIS is the German patent office. The combination of both data sources enhances data validity, especially in the early years of the observation, before the establishment of the EPO in 1978. Data was matched manually.
[4] BSW (Bundesverband Solarwirtschaft e.V.) is the German association for Solar.

sification developed by the WIPO (Schmoch 2008). Unrelated out-diversification covers all cases in which a firm does not apply for any patents or only for non PVT related patents within eight years after the last PVT-patent.

Applying this methodological approach results in a situation where the exit type is only determinable for marked oriented technological exits (total exits and M&A) until 2012. In contrast, technological out-diversification types and the persistent type are only valid observable for firms which enter before 2005, taking the eight year window of out-diversification into consideration.[5] For later entering firms, the correct exit type is not determinable in the sense of not yet being observable. In consequence, this leads to two different observation samples: (1) The selection sample which includes only those firms for which the unobservable outcome (innovation efficiency) is determinable by the observable latent variable (technological exit type); (2) the full sample which also includes firms for which the unobservable outcome is not determinable by the observable latent variables because the technological exit type is not yet observable.

3.2. Dependent Variable

The dependent variable, namely the long-term innovation efficiency of an innovator in PVTs, is an unobservable variable. It is measured by the categorization of different technological exit types as latent variable. The ordinal information behind technological exit types is exploited to assess different levels of innovation efficiency. As discussed earlier in chapter 2, the following rankings with regard to the innovation efficiency (IE) level are proposed:

Ranking I:

$$\mathrm{IE}_{\text{Persistent innovators}} = \mathrm{IE}_{\text{M\&A}} > \mathrm{IE}_{\text{related out-diversification}} > \mathrm{IE}_{\text{unrelated out-diversificaton}} > \mathrm{IE}_{\text{total firm exit.}}.$$

And

Ranking II:

$$\mathrm{IE}_{\text{Persistent innovators}} > \mathrm{IE}_{\text{M\&A}} > \mathrm{IE}_{\text{related out-diversification}} > \mathrm{IE}_{\text{unrelated out-diversificaton}} > \mathrm{IE}_{\text{total firm exit.}}.$$

[5] The year 2012 is the most recent year for which out-diversification can be determined. Taking a time lag up to 18 month between the formal patent application and the appearance of this application within patent databases into account, later years are not valid at the time where the study was conducted.

3.2. Independent Variables

There are two connected research aims of this study. Alongside the empirical assessment of innovation efficiency differences between firms without having data on innovation efficiency (dependent variable), the research interest is on the analysis of technological knowledge as core determinant of innovation efficiency, as proposed by the RBV and the TBV (independent variables). Thus, the following technological knowledge variables are considered in the ordered probit estimation models:

Pre-entry related technological knowledge: The stock of knowledge and experience accumulated by a firm within PVT related areas before entering PVTs is expected to contribute positively to innovation efficiency within PVTs. Several scholars have shown that related diversification outperforms unrelated diversification because of knowledge based economies of scale and scope, resulting from efficiency enhancing potential for knowledge synergies. This potential is realized in form of knowledge spill-overs or cross fertilization (Piscitello 2000, Breschi et al. 2003, Suzuki/Kodama 2004, Nesta/Saviotti 2005, Leten et al, 2007). Within this study, different quantity and quality levels of a firm's prior technological knowledge are considered by different technological entry types. In total, five entry types are considered by dummy variables: (1) De novo entrants are all firms which enter PVTs within five years after foundation.[6] De novo entrants possess no prior technological knowledge. (2) Spin-offs are all academic and private spin-offs. Founders accumulate knowledge and expertise from R&D and marketing of their parents during their prior employment. This often builds the basis for the spin-offs innovation activities (Argarwal et al. 2004). Therefore, spin-offs are assumed to build their PVT innovation activities on pre-entry core PVT knowledge and on related PVT knowledge. (3) Parents-linked entrants are innovators which are economically associated to an incumbent firm but legally independent form the incumbent. In general, parents-linked entrants have access to the parent's technological knowledge stock which is frequently at least to some degree related to the parents-linked entrant's innovation activities. Within a strategically intended swap out of certain innovation activities into newly founded subsidiaries, often also some core technological knowledge for the parents-owned innovation activities is transferred. Thus, parents-linked innovators are associated with pre-entry related and core technological knowledge. (4) Related diversifiers enter PVTs at least six years after foundation. Eight years or less before entering PVTs they applied at least for one patent related to PVTs. (5) Unrelated diversifiers enter PVTs at least six years after foundation. Eight years or less before entering PVTs, they applied only for PVT unrelated patents or for no pa-

[6] Entry is realized in the year of the first PVT patent application.

tents overall. According to the out-diversification exit type determination in chapter 3.1, technological relatedness is considered by the ISI-OST INPI classification. Table 1 illustrates the matches between exit types and entry types.

Table 1. Exit types per entry type.

	De Novo	Rel. Div	Unrel. Div	Parents-linked	Spin-Off	Sum
Persistent	7	37	4	13	7	**68**
M&A	12	7	3	9	2	**33**
Rel. Div-out	9	22	3	5	1	**40**
Unrel. Div-out	13	7	8	0	0	**28**
Total exit	24	0	4	2	0	**30**
n.a.	21	35	21	12	6	**95**
Sum	**86**	**108**	**43**	**41**	**16**	**294**

PVT innovation expertise and experience: Organizational learning theory suggests that beyond the accumulation of experience from innovation successful activities, even learning from failures contributes significantly to the generation of superior knowledge within a technological area. Once a firm begins to innovate within PVTs, a path dependent learning process is initiated. As innovation activities within a technological area increase, a firm becomes more and more familiar with the relevant dynamics and developments, chances and threats as well as its technology specific strengths and weaknesses. This accumulated knowledge and experience may put a firm ahead of competitors' innovation activities (Argyris/Schön 1978). The longer and the more intense a firm conducts innovation activities within PVT, the higher the expected superior PVT knowledge is from failure and success. With a higher stock of superior PVT knowledge, higher innovation efficiency is to be expected. Two origins of PVT experience and learning are considered. Firstly, the intensity of PVT innovation activities by the average number of PVT patent application per year in which a firm conducts PVT innovation (**yPVTpat**). Secondly, the natural logarithm of the duration of PVT innovation activities, reflecting learning curve effects (**ln(PVTdur)**).

Control for Industry affiliation: PVTs are applied within diverse industries. Different industrial settings and industry specific productivity levels may affect the PVT innovation efficiency of a firm. This holds particularly true for service industries where innovation and patenting intensity might be significantly lower compared to non-service industries. A dummy variable is introduced to control for this effect. It takes the value of one if a firm's industrial affiliation is not a service industry, 0 otherwise (**d_nonServ**).

Control for firm size/age at entry: Furthermore it is controlled for impacts on innovation efficiency resulting from the firm size**.** A significant proportion of the sample firms is characterized by a small and medium size. Since these firms are not affected by disclosure obligation, continuous data on firm size like revenue or number of employees is not publicly available. This is particularly challenging for firms which do not exist anymore. Assuming a positive and strong correlation between firm size and firm age (Evans 1987), the natural logarithm of the firm age when entering PVTs is included as a proxy to control for a possible bias resulting from size effects (**ln(entry age)**.

3.3. Descriptive Statistics

Table 2 reports the descriptive statistics for the full sample as well as for the selection sample. The full sample comprises all firms which enter PVTs between 1964 until 2012, independently from the observability of the exit type. The selection sample covers all firms which enter from 1964 until 2004. For all of these firms, the exit type is determinable. Firms which enter later than 2004 are only considered if their exit type was observable. This is the case for M&A and total exits. In total, 294 firms fall into the full sample and 199 firms into the selection sample. For both samples nearly 80 percent of the firms are not associated to service industries. The duration of innovation activities within PVTs is lower for the full sample whilst the average age at entry and the average number of yearly PVT patents is higher within the full sample than within the selection sample. The composition of entry types differs slightly. In both samples related diversifiers constitute 37 percent and spin-offs 5 percent of all entries. A minor change occurs for parents-linked entries, which account for 14 percent of all entries within the full sample and for 15 percent of all entries within the selection sample. A more intensive dynamic becomes obvious for de novo firms and unrelated diversifiers. In the full sample 29 percent of all entries are de novo, compared to 33 percent for the selection sample. Unrelated diversifiers realize a share of 15 percent in the full sample and 11 percent in the selection sample.

Table 2. Descriptive Statistics.

	Full Sample		**Selection Sample**	
N	294		199	
Share d_nonServ	78.6%		78.9%	
ln(duration)	2.00		2.23	
ln(age)	2.35		2.24	
yPVT patents	1.70		1.34	
		Share		**Share**
De Novo	86	29.3%	65	32.6%

Unrel. Div	43	14.6%	22	11.1%
Rel. Div	108	36.7%	73	36.7%
Parents-linked	41	13.9%	29	14.6%
Spin-off	16	5.4%	10	5.0%
Total	**294**	**100%**	**199**	**100%**

4. Estimation Method and Results

In order to determine the effects of the firm's technological knowledge base on a firm's innovation efficiency within PVTs, an ordered probit model is applied. The core idea of a probit model is that an observable ordinal response variable is characterized by a latent continuous metric. Therefore, the range of an N (0,1) distribution is divided into k categories defined by k-1 cut points c, $c_1, c_2 \ldots c_{k-1}$. Every firm within the sample is assumed to have score as a linear combination of one or more predictors x plus an error term with a standard normal distribution:

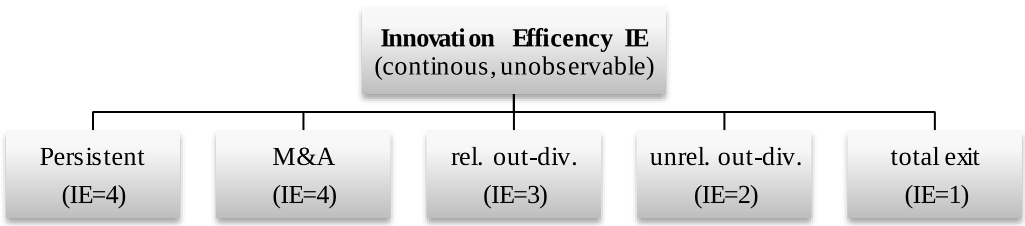
$$y_i^* = x_i \times \beta + \epsilon_i, \qquad \epsilon_i \sim \mathcal{N}(0,1), \qquad i = 1, \ldots, N.$$

The observed ordinal variable y takes values from 1 to k, whereby c represents the threshold parameters:

$$y_i = k \;\leftrightarrow\; c_{k-1} < y_i^* \leq \; c_k.$$

Based on this score and the cut points as threshold parameters, the probabilities for each firm realizing IE=1, 2.., k is estimated. Thus, the ordered probit model allows taking a continuous variable like innovation efficiency into account by deriving predictable ordinal outcomes. Given the assumption that several categories of innovation efficiency levels can be distinguished based on the observable ordinal information behind technological exit types (IE= 1, 2, k), 1 indicates the lowest innovation efficiency and k the highest innovation efficiency. Subsequently, 5 categories of innovation efficiency are distinguished and ordered. Based on the ordinal information of different technological exit types, the following ranking is applied:

Illustration 1. Innovation efficiency and categorical –Ranking I



In a first estimation step, only firms with an observable technological exit mode are considered (selection sample) within an ordered probit model. Results are reported in table 3. Model 1 estimates only the coefficients of the control variables. The non-service variable is not significant, indicating that there is no general difference in the innovation efficiency between service firms and non-service firms innovating in PVTs. The coefficient of the age variable is positive and highly significant, indicating higher innovation efficiency for older and larger firms. In model 2, the pre-entry knowledge dummies are introduced. Innovators which enter PVTs with no prior knowledge (de novo entrants) are used as base category. The coefficient of the spin-off and the parents-linked variables are positive and significant at the 0.01 level. This confirms prior empirical evidence concerning a positive influence of pre-entry related and core technological knowledge on innovation efficiency. In line with these findings, the coefficient for related diversifiers is also positive and significant at the 0.05 level, which is acceptable. For unrelated diversifiers, no significant innovation efficiency effect is proven. Although these firms have some knowledge in unrelated technological areas or at least some general knowledge concerning business operations, this knowledge is not sufficient to put unrelated diversifiers ahead of de novo firms in terms of innovation efficiency. Furthermore, compared to model 1, the age variable turns insignificant. A plausible explanation can be found in the implicit consideration of age and size effects within the pre-entry knowledge effects which are assessed by different entry types. Different entry types can be associated with different firm age and size, e.g. de novo firms, spin-offs and parents-linked firms are likely to be considerably younger and smaller than diversifiers. Nevertheless, the age variable is kept in the model to allow controlling for possible intra-entry type size effects. Model 3 includes all variables. The pre-entry knowledge variables and the control variables remain unchanged in magnitude, direction and significance. The variables for PVT innovation expertise and experience are both highly significant and positive. A higher average number of yearly PVT patent applications as well as a longer duration of firms PVT innovation activities contributes positively to higher innovation efficiency within PVTs. Subsequently, a t-test was performed to test for differences in the efficiency effect for the significant pre entry knowledge types. The null hypothesis of coefficient equality cannot be rejected, indicating that the intensity of the innovation efficiency effect does not differ for different kinds of pre entry technological knowledge associated to spin-offs, parents linked firms and related diversifiers. To sum up, the following relationship can be stated: $IE_{\text{Spin of}} = IE_{\text{parents-linked}} = IE_{\text{related div.}} > IE_{\text{unrelated div.}} = IE_{\text{de novo}}$.

In models 4-6, a modified ranking of the observable ordered outcomes is applied, assuming a higher innovation efficiency for persistent innovators than for merged or acquired firms: $IE_{Persistent} > IE_{M\&A} > IE_{related\ div\text{-}out} > IE_{unrelated\ div\text{-}out} > IE_{total\ exit}$ (Ranking RII).

Contrary to the prior estimations, the innovation efficiency of persistent innovators is assumed to exceed the innovation efficiency realized by merged or acquired firms. Model 4 only includes the control variables. Compared to R1, the firm age variable is also positive and highly significant at the 0.01 level whilst the non-service dummy is noticeable larger and turns weakly significant at the 0.1 level. This indicates higher innovation efficiency for non-service firms in the case of R2. Nevertheless, given the subsequent results, this finding should not be overstated. Adding the dummy variables for pre-entry knowledge in model 5 and for PVT innovation expertise and experience in model 6, the non-service variable becomes insignificant for both estimation models. In general, the estimation results in model 5 and 6 for R2 seem initially quite similar compared to the results for R1 in model 2 and 3 concerning magnitude, direction and significance of the estimated coefficients. A t-test, however, reveals the equality of the coefficients for spin-offs and parents-linked firms at the 0.01 significance level whilst the coefficient for related diversifiers is significantly different from spin-offs and parent-linked firms at the 0.1 significance level. Accordingly, for Ranking II the following empirical relationship holds true: $IE_{Spin\ of} = IE_{parents\text{-}linked} > IE_{related\ div.} > IE_{unrelated\ div.} = IE_{de\ novo}$. The likelihood ratio test is highly significant in the case of both rankings, indicating a good model fit. A comparison of the LR test for both models however indicates superiority of R1.

So far, a selected sample of 199 firms for whom the exit type is observable, is applied. Firms with no observable outcome (=exit type) are not considered. Particularly the necessary time window for the determination of out-diversification exit types leads to a huge number of censored observations with no observable outcomes. Methodically, the exclusion of these censored observations may lead to a selection bias, implying that the applied sample is not representative anymore. In the case of this kind of sample selection bias, Heckman (1979) shows that an ordinary ordered probit leads to inefficient estimation results. As the descriptive statistics in table 2 indicate, firms in the selected (censored) sample are characterized by a lower age at entry, a longer duration of PVT activities, a lower average number of yearly PVT patents and a different structure of innovator types according to their pre-entry technological knowledge. Consequently, a possible selection bias should be considered to ensure the efficiency of the results. In general, sample selection is a concern whenever the response variable is observed only if a selection condition is met. In our case this selection condition consists of the combination of two necessary conditions: (1) technological entry after 2004 and (2) no marked based (observable) technological exit afterwards. In order to take a possible selection bias into consideration, a two-step maximum likelihood ordered probit selection model suggested by Miranda and Rabe-Hesketh (2006) is applied to obtain consistent parameter estimates. This model fits our statistical setting in which the outcome variable is a categorical one and the selection condition can be expressed by a combined binary variable. The selection model estimation results for ranking 1 and ranking 2 are reported in column 7 and 8, whereby '-P' denotes the ordered probit estimation part and '-S' the selection equation part. The selection equation allows for constructing an estimate of the probability that the efficiency level for a specific firm is observed whilst accounting for the non-representativeness of the selection sample. The coefficients of the selection equation reveal that the censored sample is biased trough a lower share of spin-offs (-0.69) and unrelated diversifiers (-0.56), significant at the 0.1 level, independently of the chosen ranking. For both rankings, the selection sample is furthermore biased towards firms with a lower average number of yearly PVT patents (-0.1 at the 0.05 level) and towards firms with a higher duration of PVT innovation activities (1.02 at the 0.01 level). A subsequent Likelihood Ratio test of independent equations reveals that the parameter λ is not significantly different from zero, valid for both rankings. This implies a non-significant correlation between the latent variable for innovation efficiency (dependent response variable) and the selection variable in the applied estimation model. Taking the average yearly PVT patent variable as an example, this infers that a decreasing average yearly number of PVT patents raises the probability of being in the selection sample, yet being in the selection sample has no significant effect on the estimated outcome (innovation efficiency). This can be argued in an analogous manner for all other independent variables included in the model. Considering these results, sample selection is a not a serious concern within the given estimation models. The results of the probit estimation part reveal no significant differences compared to the ordinary ordered probit model, using the censored sample set. The cut parameters are just ancillary parameters and coefficients of the model. They are better fitted in the case of ranking 1. In line with the results of the Likelihood ratio test of model 3 and 4, this implies a superior discriminatory power of ranking 1 compared to ranking 2.

Within the given research setting, a second source of selection bias may arise in form of self-selection. By way of reminder, the relevant sample firms had been selected by the condition of applying for at least three PVT applications. On the one side, this selection condition is necessary to exclude "accidental" patenting in PVTs. However, this selection condition may also cause a self-selection problem. Compared to the very first technological entrants, later entering innovators have to apply for at least three patents within a successively decreasing time window to be included in the sample. This may lead to a sample in which more recent technological entrants are characterized by more regular and more intensive PVT innovation activities. To deal with this issue, a control sample was applied. Within this control sample all innovators fulfilling the following criteria are considered: (1) They apply for at least one PVT patent in at least two different years and (2) the time gap between a firm's PVT patent applications does not exceed three years. All firms within this sample are considered as regular and intensive PVT innovators, independently from a bias caused by entry time. In total, 235 firms fall into the control sample of regular innovators. Results are reported in column 9-P and 9-S of table 3. The results of the ordered logit and selection estimation, using only data of regular PVT innovators, confirm the robustness of the proposed relationship: $IE_{\text{Spin of}} = IE_{\text{parents-linked}} = IE_{\text{related div.}} > IE_{\text{unrelated div.}} = IE_{\text{de novo}}$.

Table 3. Estimation results.

	Ordinary OP						OP selection model – logit and selection parts				Regular Innovators	
	Rank R1			Rank RII			Logit RI	Selection RI	Logit RII	Selection RII	Logit RI	Selection RI
	(1)	(2)	(3)	(4)	(5)	(6)	(7-L)	(7-S)	(8-L)	(8-S)	(9-L)	(9-S)
Spin-off		1.90*** 4.00	1.28*** 3.15		1.90*** 4.43	1.65*** 3.72	1.75*** 3.03	-0.69* -1.76	1.59*** 2.99	-0.69* -1.75	1.74*** 2.83	-0.46 -1.10
Parents-linked		1.33*** 4.69	1.20*** 3.96		1.21*** 4.438	1.03*** 3.85	1.18*** 3.82	-0.31 -1.08	1.00*** 3.18	-0.30 -1.02	1.41*** 3.87	-0.15 -0.51
Rel. Div		0.95*** 2.88	0.78** 2.25		1.02*** 4.68	0.70** 2.19	0.76** 2.15	-0.26 -0.76	0.66* 1.83	-0.26 -0.76	1.35*** 2.81	-0.11 -0.29
Unrel. Div		0.12 0.37	0.15 0.44		0.12 0.40	0.03 0.09	0.13 0.36	-0.56* -1.77	-0.02 -0.04	-0.56* -1.74	0.36 0.82	-0.44 -1.20
yPVT patents			0.27*** 3.60			0.16*** 3.04	0.26*** 3.44	-0.10** -2.50	0.15** 2.00	-0.10** -2.44	0.21** 2.49	-0.08* -1.93
ln(duration)			0.56*** 3.47			0.62*** 4.69	0.60*** 2.70	1.02*** 7.37	0.71** 1.97	1.02*** 7.38	0.58** 2.11	0.95*** 6.50
d_nonServ	0.30 1.54	0.07 0.36	-0.01 -0.03	0.36* 1.89	0.14 0.69	0.05 0.23	-0.01 -0.03	-0.03 -0.14	0.05 0.24	-0.34 -0.17	-0.04 -1.11	0.09 0.40
ln(age)	0.19*** 3.63	0.08 0.91	0.05 0.57	0.22*** 4.47	0.11 1.25	0.10 1.12	0.05 0.51	-0.15 -1.60	0.09 0.92	-0.15 -1.58	-0.14 -1.11	-0.19* -1.87
Cons								-0.64** -2.00		-0.65** -2.01		-0.72** -2.02
c1								0.96* 1.75		1.17 1.29		0.96 1.32
c2								1.62*** 2.95		1.84** 2.11		1.27* 1.78
c3								2.31*** 4.23		2.51*** 3.01		1.99*** 2.86
c4										3.06*** 3.75		
λ								0.09 0.25		0.19 0.24		0.19 0.36
No. obs.	199	199	199	199	199	199	294	294		294		235
No. censored obs.							95	95		95		80
Pseudo R^2	0.035	0.1139	0.1736	0.0418	0.1112	0.1556						
Ll	-241.34	-221.48	-206.57	-294.41	-273.08	-260.22		-346.32		-399.96		-260.56
LR chi2/ Wald chi2	17.23***	56.96***	86.77***	25.68***	68.35***	95.88***		67.37***		86.89***		50.27***

Significance levels indicated by ***(0,01), **(0,05), *(0,1), z-values are reported in line 2, base category= de novo firms

A further methodological concern lies in the applied time frame for out-diversification. Changes of the time window length are capable to substantially influence the outcome of the response variable realized by the sample firms. In order to test the robustness of our results with regard to the eight years window for out-diversification, a reduced time window of four years is considered. Halving the out-diversification time frame to four years changes several characteristics of the sample data. Firstly, the composition of the selection sample changes. The size of the selection sample increases since the year of out-diversification is now observable for some firms. Additionally, a change in the exit mode may occur for some firms. Secondly, for firms within the selection sample which pursue out-diversification exit modes, the average number of yearly PVT patents increases and the duration of PVT innovation activities decreases. In total, 255 firms fall into the new selection sample which uses a four years window for determining out-diversification exit modes. Also for the reduced time window estimation setting, a two-step ordered probit selection model is applied. Results are reported in table 4. Model 10-P reports the results of the ordered probit part of the estimation and model 10-S the selection part for the case of Ranking 1 (RI). 11-P denotes the ordered probit part of the estimation model for Ranking 2 (RII) and 11-S the selection part.

Compared to the coefficient estimations based on the eight year window variables for RI (model 3), the coefficient estimates for the reduced four year window (Model 10) remain quite similar in terms of magnitude, direction and significance level. A subsequently performed t-test for checking the equality of coefficient reveals, however, that pre-entry technological knowledge associated to spin-offs and parents-owned companies has a higher effect on innovation efficiency than pre-entry related technological knowledge, significant at the 0.1 level. The following relationship concerning pre-entry technological knowledge types as drivers of innovation efficiency according to Ranking I is proven: $IE_{\text{Spin-Off}} = IE_{\text{parents-linked}} > IE_{\text{related div.}} > IE_{\text{unrelated div.}} = IE_{\text{de novo}}$ which differs from model 7.

The selection part of model 10 (10-S) shows a clear difference in the composition of the selection sample compared to the initial selection sample resulting from an eight year window (model 7). Whilst in model 7-S a bias towards a significant lower number of spin-offs and unrelated diversifiers within the selection model became evident, no bias concerning the individual pre-entry knowledge entry types is observable in model 10-S which uses the four year window for out-diversification. As to be expected, a bias within the selection sample towards firms with a lower average number of yearly PVT patents and firms with a higher duration of PVT innovation activities still remains. Moreover, the LR test of independent equations reveals no significant difference of the parameter λ from zero, indicating the absence of a sample selection bias when applying the selection sample.

Table 4. Estimation results – reduced time window for out-diversification exit modes.

	OP selection model – logit and selection parts			
	Probit RI (4y)	Selection RI (4y)	Probit RII (4y)	Selection RII (4y)
	(10-P)	(10-S)	(11-P)	(11-S)
Spin-off	1.66*** 3.04	0.01 0.01	1.43*** 3.55	-0.05 -0.06
Parents-linked	1.10*** 3.87	0.02 0.06	0.87*** 3.55	-0.03 -0.07
Rel. Div	0.77** 2.08	0.06 0.12	0.56** 2.01	0.15 0.03
Unrel. Div	0.41 1.38	-0.41 -0.94	0.35 1.28	-0.45 -1.06
yPVT patents	0.19*** 2.77	-0.16*** -2.75	0.14*** 2.69	-0.16*** -2.81
ln(duration)	0.61*** 3.26	1.48*** 6.62	0.54*** 3.42	1.47*** 6.69
d_nonServ	0.04 0.65	-0.48 -1.45	0.09 0.49	-0.05 -1.49
ln(age)	0.06 0.65	-0.22 -1.59	0.12 1.51	-0.22 -1.62
Cons		0.18 0.04		0.23 0.52
c1		0.67* 1.66		0.55 1.49
c2		1.23*** 3.01		1.11*** 2.93
c3		1.83*** 4.35		1.69*** 4.27
c4				2.09*** 5.16
λ		-0.11 -0.29		-0.41** -1.29
No. obs.	294	294		294
No. censored obs.	39	39		39
Replications				
Pseudo R²				
Ll		-301.42		-375.49
LR chi2/ Wald chi2		62.41***		61.04***

Significance levels indicated by ***(0,01), **(0,05), *(0,1), z-values are reported in line 2, base category= de novo firms

Also the estimation results for ranking II are quite similar when comparing the result gained by applying an eight years frame for out-diversification and a four years frame. The four years frame lead to an increase within the significance level of the related diversification entry variable from 0.1 to 0.05. Also the significance level of the coefficient for the yearly average number of patents and the duration of PVT innovation activities increases form initially five percent in model 8-L to one percent in model 11-P. A subsequent t-test performed to validate the equality of the pre-entry technological knowledge coefficients confirms the relationship

$IE_{Spin\text{-}Off} = IE_{parents\text{-}linked} > IE_{related\ div.} > IE_{unrelated\ div.} = IE_{de\ novo}$. Entering PVTs with technological knowledge associated to spinoffs and parents-linked firms is associated with a higher long term PVT innovation efficiency compared to innovators which enter PVTs per related diversification. Nevertheless, pre-entry related technological knowledge contributes significantly to a higher innovation efficiency compared to firms which enter with no related technological knowledge or no technological knowledge overall. With regard to innovation efficiency within PVT, our results suggest that it makes no significant difference whether a firm enters without any technological knowledge or with unrelated technological knowledge. Since the same selection sample as in model 10 is applied, the absence of a selection bias when estimating the coefficients based on the section sample can be confirmed.

5. Conclusion

This paper deals with the empirical assessment of a firm's long term innovation efficiency within newly entered technological areas and knowledge based determinants. A focus is set on photovoltaic technologies (PVTs). In a first step, a novel innovation efficiency indicator is applied. Assuming long term innovation efficiency as a non-observable outcome, a latent variable is derived from the ordinal information of different technological exit types. This indicator is capable to reflect the comprehensiveness und multidimensional character of long term innovation efficiency. In a second step, the influence of different technological knowledge based determinants is proven. In line with prior research, the results confirm a significant influence of innovation expertise and experience within a technological area on the innovation efficiency within this area. More efficient innovators in PVTs are characterized by a higher average number of yearly PVT applications and a longer duration of their innovation activities within PVTs. Furthermore, statistical evidence is found for the relevance of related pre-entry knowledge for innovation efficiency. Pre-entry technological knowledge associated to innovators which enter PVTs as spin-offs, parents-linked firms and related diversifiers contributes positively to higher innovation efficiency. In contrast, non-related pre-entry technological knowledge has no significant effect. Results are robust within different conceptual and estimation settings.

A main concern when observing different innovation efficiency levels based on technological exit types lies in a well-considered choice of the time window for determining out-diversification. Since out-diversification is a widely under-researched area, a first pragmatic approach is applied within this paper. The time window is set on 8 years, assuming that this time frame reflects a good approximation of the average knowledge depreciation within PVTs (Braun et al. 2010). A reduction to 4 years performed as robustness check does not significantly change the results.

Moreover, different potential sources of selection biases are considered. First, a selection bias may result from the unobservablity of the outcome variable for some firms. A two-step ordered probit selection model is applied to take into consideration that the unobservability of the latent outcome variable may lead to a biased estimation (selection) sample, containing only firms for which the outcome is observable. An additional form of selection bias is possible in the form of self-selection. This bias may occur since for the initial sample only firms are included which applied for at least three PVT patents. In consequence, this can lead to more regular and intensive PVT innovators in more recent years of the observation period. To account for this, a subsample of regular innovators is built and used for an independent estimation. The results underline the robustness of the estimated coefficients when applying the full sample. Nevertheless, one remaining source of selection bias has to be accepted within the given estimation setting. All firms within the sample are characterized by at least three PVT applications. On the one hand, this selection condition is expedient in order to exclude all cases of “accidental” PVT innovation activities. On the other hand, it also leads to the exclusion of all firms which intentionally expand innovation activities into PVT but fail prior to the third patent application.

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