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The Impact of Technology Characteristics on the Formation of Exploration and Exploitation Alliances - Insights from the Solar Photovoltaic Industry

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Abstract

The literature has identified exploration and exploitation alliances as two ideal-type modes firms use to collaboratively develop and commercialize technologies. Previous studies have investigated the antecedents and performance effects of a firm?s balance between exploration and exploitation in alliance formation. Yet, currently, we lack a sufficient understanding of how a firm?s choice to explore or exploit via alliances might depend on the characteristics of the firm?s technology. Drawing on data from 1079 partnerships in the solar photovoltaic industry, in this paper we test how the complexity, maturity and tacitness of technological knowledge affect a firm?s propensity to form exploration and exploitation alliances. We find that a higher tacitness of technological knowledge raises, whereas a higher technological maturity reduces the likelihood of entering exploration alliances. Moreover, we show that different sub-types of exploitation alliances, such as production and marketing alliances, differ in the degree to which they are related to specific technology characteristics. We conclude that understanding a firm?s choice to explore or exploit through alliances requires an in-depth understanding of the specific technology pursued. In addition, our work provides empirical support for recent studies that have called for a more fine-grained differentiation of alliances according to their position on the exploration-exploitation continuum. Jelcodes:O32,O31

THE IMPACT OF TECHNOLOGY CHARACTERISTICS

ON THE FORMATION OF EXPLORATION AND EXPLOITATION ALLIANCES –

INSIGHTS FROM THE SOLAR PHOTOVOLTAIC INDUSTRY

ABSTRACT

The literature has identified exploration and exploitation alliances as two ideal-type modes firms use to collaboratively develop and commercialize technologies. Previous studies have investigated the antecedents and performance effects of a firm's balance between exploration and exploitation in alliance formation. Yet, currently, we lack a sufficient understanding of how a firm's choice to explore or exploit via alliances might depend on the characteristics of the firm's technology. Drawing on data from 1079 partnerships in the solar photovoltaic industry, in this paper we test how the complexity, maturity and tacitness of technological knowledge affect a firm's propensity to form exploration and exploitation alliances. We find that a higher tacitness of technological knowledge raises, whereas a higher technological maturity reduces the likelihood of entering exploration alliances. Moreover, we show that different sub-types of exploitation alliances, such as production and marketing alliances, differ in the degree to which they are related to specific technology characteristics. We conclude that understanding a firm's choice to explore or exploit through alliances requires an in-depth understanding of the specific technology pursued. In addition, our work provides empirical support for recent studies that have called for a more fine-grained differentiation of alliances according to their position on the exploration-exploitation continuum.

Keywords: Exploration, exploitation, ambidexterity, alliances, technology characteristics, technology partnerships, R&D partnerships,

1 INTRODUCTION

A large and quickly growing literature stresses the importance of alliance as an important means for enhancing the innovative capacity of firms. In particular, it is pointed out that, amid trends towards increasing speed of innovation and rising complexity of products, firms can no longer rely on in-house capabilities for innovation. Instead when developing and commercializing their products they increasingly rely on external partners who provide complementary resources and serve as a source of learning in fields where a company might possess little expertise (e.g., Mowery et al., 1998; Rosenkopf and Almeida, 2003)

Previous studies have investigated the effect of alliance formation on innovation and firm performance and looked at antecedents that influence the propensity of firms to engage in inter-firm collaborations. In this context, more recently, scholars have started to differentiate alliances into exploration and exploitation alliances according to the motivations underlying their formation (Koza and Lewin, 1998; Rothaermel, 2001). While exploration alliances are formed by firms to enhance the search for new products and opportunities, e.g., R&D alliances, exploitation alliances are used to enhance the firm's capability for the commercialization of existing technologies, e.g., production and marketing alliances (Lavie and Rosenkopf, 2006; Rothaermel and Deeds, 2004). It has been suggested that a firm's balance between exploration and exploitation alliances depends on a variety of firm-internal and environmental factors, such as the firm's absorptive capacity (Rothaermel and Alexandre, 2009) and environmental dynamism (Lavie and Rosenkopf, 2006). However, up to this point, we lack a sufficient understanding of how a firm's propensity to focus on exploration or exploitation in alliance formation may depend on the specific technology it pursues. Technologies differ on a number of dimensions, such as the complexity, maturity or the tacitness of the knowledge they draw upon (Grant, 1996). Although it seems possible that these technology characteristics affect a firm's balance on exploration vs. exploitation in alliance formation (Singh, 1997), existing studies have not systematically investigated their effect on the degree to which a firm focuses on either of the two alliance modes.

Addressing this gap in the literature, in this paper we investigate the question how technology *characteristics affect a firm's propensity to form exploration and exploitation alliances*. Towards this end, we draw on data for 1079 alliances in the solar photovoltaic industry. This industry lends itself as research setting as technology plays a key role for firm strategies in the sector and – in the face of a high pace of innovation and market growth – firms have made extensive use of inter-firm collaborations. As part of our analysis, we test a number of specific hypotheses related to how technology characteristics affect alliance formation. Besides testing differences between exploration and exploitation alliances, we respond to a recent call by Parmigiani and Rivera-Santos (2011) and test how alliance types which in previous empirical studies have been subsumed under the category of 'exploitation alliances' differ with regard to their antecedents.

We find support for our hypotheses that a higher tacitness and a lower maturity of technological knowledge positively affect the likelihood of firms to form exploration alliances. Moreover, the propensity of a firm to enter exploitation alliances with a stronger exploratory component, such as production alliances, is higher for a higher tacitness of technological knowledge. Contrary to expectations, we do not find the complexity of a firm's products to have a significant effect on its balance between exploration and exploitation alliances.

Our study contributes to a more detailed understanding of the antecedents of alliance formation. We suggest that understanding a firm's propensity to form an exploration or exploitation alliances requires taking a close look at the characteristics of the technology the firm pursues, which in turn are likely to be dependent on the industry and the firm's position in the value chain. In addition, our findings support studies that have called for a more fine-grained categorization of alliances according to their position on the exploration-exploitation continuum. We provide empirical evidence that alliance types which so far have been collectively treated as 'exploitation alliances' differ with regard to their antecedents. As a result, our study helps to further disentangle the contingency factors that may drive firms to invest in specific forms of alliances.

The rest of this paper is structured as follows: Section 2 reviews the literature on exploration and exploitation alliances and discusses the role of technology characteristics in alliance formation to derive a number of hypotheses. Section 3 describes the method and data used in this study. Based on a presentation of the results in section 4, section 5 discusses the implications for theory and practice. This paper concludes by outlining the main limitations, suggestions for future research as well as a summarizing the main findings.

2 THEORY & HYPOTHESES

The literature on organizational learning distinguishes two ideal-typical ways in which firms can learn: exploration and exploitation. According to March (1991, p. 71), "exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, and innovation. Exploitation includes such things as refinement, choice, production, efficiency, selection, implementation and execution". Early work drawing on the taxonomy developed by March (1991) has concentrated on how firms can balance the trade-off between the two modes of learning using intra-organizational measures, e.g. by implementing organizational structures that allow firms to simultaneously explore and exploit. More recently, researchers have applied March's framework to study how firms leverage external resources to enhance inter-organizational learning. In this context, an important field of application has been the investigation of strategic alliances, which Gulati (1998) defined as "voluntary agreements between independent firms to develop and commercialize new products, technologies or services". Lavie and Rosenkopf (2006), for example, distinguish between exploration and exploitation alliances, where the former “engage partners in R&D that may lead to innovative technologies and applications” and the latter being “alliances for commercializing and using existing technologies” (p, 799). [1]

Previous studies have investigated how firms balance exploration and exploitation in alliance formation to achieve maximum performance. As the main outcome of these research efforts, it was found that the balance between exploration and exploitation chosen by firms depends on both organizational factors, such as firm performance, capabilities and routines (Lavie et al., 2011; Park et al., 2002; Rothaermel, 2001) and factors residing in the firm’s environment, such as industry turbulence and market uncertainty (Beckman et al., 2004; Rothaermel, 2001). While these studies have contributed to a much better understanding of how firms make use of exploration and exploitation alliances, we currently lack a sufficient understanding of how characteristics of the technologies that alliances are designed to develop or commercialize might affect a firm’s propensity to form exploration or exploitation alliances. The literature on the knowledge-based view stresses the importance of technological knowledge as a key resource of firms (Barney, 1991; Conner and Prahalad, 1996; Grant, 1996). The characteristics of knowledge, such as the degree to which it can be effectively communicated, have been shown to decisively influence organizational learning processes. For example, Conner and Parahald (1996) suggest that the benefits of firms that can be derived from knowledge-based resources depend on choosing an organizational structure that fits the characteristics of knowledge. Given their impact on firm-internal learning and innovation processes and previous studies that have demonstrated their effect on alliance formation (Singh, 1997; Steensma and Corley, 2000), it seems possible that the properties of technological knowledge may also influence firms’ balance between exploration and exploitation in firm-external learning. In the following, we therefore derive hypotheses on how three characteristics of technological knowledge – complexity, maturity and tacitness – may affect a firm’s choice to form exploration and exploitation alliances.

Complexity of technological knowledge

Singh (1997) defines a complex technology as an “applied system whose components have multiple interactions and constitute a nondecomposable whole”. This definition contains three important characteristics that contribute to the complexity of technological knowledge: 1) a systemic nature of the technology, i.e. a product architecture that consists of a larger number of elemental units which are usually organized in hierarchies of subsystems, 2) multiple interactions, i.e., a network of ‘nonsimple’

[1] A somewhat related distinction between different alliances was made by Rothaermel and Deeds (2009). However, in their analysis, they do not strictly cluster alliance types based on the purpose of the alliance but depending on whether the partner of the firm is located up- or downstream in the firm’s value chain.

relationships that link the different system units and 3) non-decomposability, i.e. system performance significantly decreases as soon as one removes elemental units or subsystems.

Due to the aforementioned characteristics, already small variations in the system elements and their interfaces can have significant effects on the performance of complex technologies (Perrow, 1994). To ensure reliable operation and avoid product failures, firms pursuing more complex technologies therefore need to put more effort into understanding the detailed interaction between components and closely configure them to achieve maximum system performance. Not surprisingly, therefore high technology complexity has been found to be connected with a higher propensity of firms to enter alliances (Singh, 1997). Such alliances help firms to acquire the necessary capabilities, share costs and reduce the risk of investments related to the development and commercialization of complex technologies (Bayona et al., 2001; Singh, 1997). Generally, both exploration and exploitation alliances contribute to the aforementioned objectives and may therefore be suited to deal with complex technologies. Yet, according to Ashby's law the possibility of a system to control disturbances of another system is higher, the larger its variety (Ashby, 1958). Exploration alliances, by definition, allow firms to achieve a higher degree of variety in the governance of technologies than exploitation alliances. Therefore, we would expect a higher complexity of technologies to be connected with a stronger use of exploration alliances compared to exploitation alliances.

While the distinction between exploration and exploitation is useful, according to Parmigiani and Riviera-Santos (2011) and Lavie and Rosenkopf (2006) alliances usually comprise elements of both exploration and exploitation, such that they form a continuum rather than representing distinct categories. For example, although previous studies have classified production and marketing alliances as exploitation alliances, one might assume that production alliances have a stronger exploratory component as they may require the transfer of technological knowledge, whereas marketing alliances usually focus on the distribution of existing technological artifacts. Apart from testing the effect of technological complexity on the propensity to form exploration and exploitation alliances, we therefore test how this technology characteristic may influence a firm's choice to form exploitation alliances with a stronger or weaker exploratory component. We phrase our first two hypotheses:

H1a: The larger the technological complexity of a firm's product, the more likely the firm is to form an exploration rather than an exploitation alliance.

H1b: The larger the technological complexity of a firm's product, the more likely the firm is to form an exploitation alliance which involves a stronger exploratory component.

Maturity of technological knowledge

One technology characteristic that might influence a firm's balance between forming exploration and exploitation alliances is technological maturity, which, following Hoppmann et al. (2013), we define as the "stage of a technology in the technology life-cycle". In early stages of the technology life-cycle there is large uncertainty about technology characteristics, important merit dimensions and the market potential of the technology (Murmann and Frenken, 2006; van de Vrande et al., 2009). This uncertainty about which technological design may turn out as the winner requires firms to invest in and experiment with a broader set of potential technological solutions (Janney and Dess, 2004). Over time, as firms develop a better understanding and certain technological solutions turn out as superior, product innovation efforts of firms become more focused and routinized to form so-called technological paradigms (Abernathy and Utterback, 1978; Dosi, 1982).

Research on alliances has found that to mitigate the uncertainties at the beginning of the technology life-cycle, firms make use of alliances to share risks and costs of technology development (Hagedoorn et al., 2000; Kogut, 1991; Rosenkopf and Schilling, 2007; Sanchez, 1993). Since, when using alliances, firms can leverage complementary capabilities of partners, alliances allow firms to build a portfolio of real options that help reduce uncertainties (Grant and Baden-Fuller, 2004; Kogut, 1991; Vassolo et al., 2004). Exploration alliances are well suited to contributing to a diversified portfolio of technologies. Therefore, we would expect exploration alliances to play a particularly important role during the early stages of the technology life-cycle, whereas exploitation alliances may become more important as a technology matures. Supporting this claim, it has been recommended that under technological uncertainty firms reach out to non-redundant partners to enlarge the pool of technological opportunities (Duysters, 1996; Goerzen, 2007; Laursen and Salter, 2006). Alternatively, it seems possible that firms counterbalance an internal focus on either exploration or exploitation by focusing on the other mode in cross-firm collaboration. For example, Stettner and Lavie (2013) find that exploring via externally oriented modes, such as acquisitions and alliances, while focusing on exploitation internally, enhances firm performance. As the basis of our study, we assume that the need of firms to explore during times of high technological uncertainty outweighs their tendency to counterbalance an internal focus on exploration by forming exploitation alliances. In analogy to the first two hypotheses, we therefore phrase two further hypotheses on the effect of technological maturity on a firm's propensity to form exploration vs. exploitation alliances:

H2a: The larger the technological maturity of a firm's product, the less likely the firm is to form an exploration rather than an exploitation alliance.

H2b: The larger the technological maturity of a firm's product, the less likely the firm is to form an exploitation alliance which involves a stronger exploratory component.

Tacitness of technological knowledge

Finally, previous research has made a distinction between tacit and explicit knowledge (Simonin, 1999; Zander and Kogut, 1995). Tacit knowledge is knowledge that is non-verbalized, intuitive and unarticulated (Polanyi, 1962), i.e. solely carried in the minds of individuals. Due to its unarticulated nature, it cannot be easily transmitted through formal communication but often relies on close observation, interpersonal contact and learning-by-doing (Collins, 1974; Teece, 1977). This makes it harder for firms to identify, evaluate and absorb tacit knowledge (Hitt et al., 2006; Szulanski and Cappetta, 2003). Collins and Hitt (2006), for example, show that the transfer of tacit knowledge between business units and firms requires building relational capital through frequent communications, on-site meetings and partner visits. Explicit knowledge, on the contrary, can be coded and articulated. As a result, it can be more easily transferred across longer distances, e.g. in manuals, templates, blueprints or embedded in artifacts, such as products or machinery (Inkpen, 1998; Nonaka and Takeuchi, 1995; Simonin, 1999).

In the literature, exploration alliances have been closely connected with tacit and exploitation alliances with explicit knowledge. For example, Lavie and Rosenkopf (2006) posit that exploration alliances "enabl[e] partners to share tacit knowledge and develop new knowledge", whereas exploitation alliances leverage and combine partner's existing capabilities through exchanges of explicit knowledge" (p.799). Similarly, Rothaermel (2001) suggests that exploration alliances allow firms to get "close enough to share tacit knowledge such as basic R&D". He claims that, on the other hand, exploitation alliances "focus on complementarities among the allied partners as they exchange explicit knowledge" (p. 690). In fact, it seems likely that, although exploration alliances may include the transfer of artifacts, the primary goal of exploration alliances lies in learning about technologies by exchanging knowledge that cannot be easily acquired on the market (Arora and Gambardella, 1994; Hamel, 1991). The transfer of explicit knowledge, e.g. the distribution of products in marketing alliances, has been shown to often require the simultaneous transfer of implicit knowledge for technologies to be correctly understood and used (Collins and Hitt, 2006). Yet, it seems plausible that exploitation alliances might have a stronger focus on the transfer of explicit knowledge embedded in artefacts rather than tacit knowledge components. Accordingly, we phrase our two last hypotheses:

H3a: The larger the tacitness of technological knowledge of a firm’s product, the more likely the firm is to form an exploration rather than an exploitation alliance.

H3b: The larger the tacitness of knowledge of a firm’s product, the more likely the firm is to form an exploitation alliance which involves a stronger exploratory component.

3 METHODS

3.1 Research Setting and Sample

We tested our hypotheses drawing on data from the solar photovoltaic (PV) industry. The solar PV is a suitable research setting for analyzing the effect of technological characteristics on exploration and exploitation alliances as 1) there are several PV technologies with different characteristics which may turn out to become the ‘winning technologies’, 2) technology has played a key role for firm strategies in the sector and 3) in the face of a highly dynamic environment, firms have made extensive use of alliances.

As the time frame for our analysis, we chose 1998 to 2012. The solar cell was invented in 1954 by the Bell Laboratories and has since been used in a variety of applications, such as powering satellites or oil platforms. Yet, a notable PV industry did not emerge before policy makers put in place demand-side support for solar PV in the early 1990s (Hoppmann et al., 2013). For example, whereas the cumulative installed PV capacity amounted to 502 MW in 1994, this number increased to 102,156 MW – more than the 200-fold – in 2012. The time frame chosen for our analysis therefore covers a large part of the industry evolution.

The unit of analysis in our study is the single alliance.[2] Our sample includes 1109 private and public firms in all parts of the value chain. PV systems are made up of PV modules, which convert sunlight into electricity, and so-called balance of system, which includes racking, AC/DC converters and wiring. PV modules, in turn, are based on different PV sub-technologies. The dominant technology – assuming more than 87 percent of the market in 2012 – is crystalline silicon PV, followed by thin-film PV (e.g., cadmium telluride, amorphous silicon and copper indium gallium selenide) and emerging PV technologies (e.g., dye-sensitized and organic PV). Wafer-based c-Si has the highest energy conversion efficiency. It is manufactured using a multi-stage process in which silicon is cast into ingots, cut into wafers, further processed to cells and finally assembled to modules. Modules based on thin-film or emerging PV, on the contrary, are manufactured by depositing a thin layer of semi-

[2] Several other studies investigating the antecedents of exploration and exploitation alliances choose the firm-year as the unit of analysis. Compared to this, choosing the alliance as the unit of analysis has the advantage of allowing to draw on firm and technology characteristics of both alliances partners as explanatory variables.

conductor on a carrier material, e.g. glass. Since this significantly reduces the amount of semiconductor material required, thin-film or emerging PV, possess a significantly lower material intensity than wafer-based c-Si PV which might give them a cost advantage in the longer run. Our analysis covers the entire value chain from the processing of the semiconductor material to the manufacturing of modules to the installation of the PV system. However, a key criterion for the firm to be included in our sample was its involvement in developing, commercializing or marketing PV technology, i.e. we excluded firms that are active only in financing.

3.2 Variables

3.2.1 Dependent Variable

Following Koza and Lewin (2000) and Lavie and Rosenkopf (2006), we operationalize exploration alliances as those alliances that include knowledge generating R&D agreements, whereas exploitation alliances were operationalized as those alliances that comprise an agreement involving joint marketing and service, OEM/VAR, licensing, production or supply. Information on inter-firm agreements was obtained from the Factiva database. A precondition for being considered for our analysis was that agreements involved at least one firm. Moreover, we did not consider agreements for which we were unable to find the year during which the alliances was established. Our search yielded 1079 alliances for which we extracted the announcement year, the partner's identified and the type of agreement. Each alliance could involve more than one agreement type. In contrast to previous studies, however, we decided to not create a separate category for hybrid alliances but assigned an alliance involving simultaneous exploration and exploitation to both categories. To test hypotheses 1b, 2b, 3b, we subdivided the category of exploitation alliances into exploitation alliances involving production and those involving marketing and supply. Production alliances are more likely to involve a stronger focus on learning and the exchange of intangible knowledge, whereas marketing and supply alliances can be assumed to focus on the distribution of existing goods. Therefore, we use production alliances as a measure for exploitation alliances with a stronger and marketing and supply alliances as a measure for exploitation alliances with a weaker exploratory component (see hypotheses 1b, 2b and 3b).

3.2.2 Independent Variables

Our hypotheses relate exploration and exploitation alliances with three independent variables: Complexity, maturity and tacitness of technological knowledge.

In line with the definition presented in section 2, we measure technological complexity as the degree to which the product of a firms is composed of interrelated elements. In the PV sector the complexity of the product increases as it advances along the value chain. Whereas ingots and wafers as pre-products of PV modules possess a relatively simple product architecture, the final PV system consists of a large number of interrelated components. Consequently, in this study we measured the technological complexity of a firm's products by identifying its position in the value chain. Information on a firm's value chain position was obtained by scanning a firm's website and publicly available documents. Based on its products, we then assigned the firm to a specific category of technological complexity: 1 for ingots and wafers, 2 for cells and modules and 3 for entire PV systems. Similar to our procedure for coding alliance types, firms that covered several value chain steps were assigned several categories of technological complexity. The final variable used in our regression is the average complexity of the two alliance partners.

As stated in section 2, the maturity of technological knowledge is defined as the stage of the technology in the technology life-cycle. Similar to Hoppmann et al. (2013) and employing a categorization that is commonly used in the industry itself, this study we operationalized technological maturity by differentiating three generations of PV technologies: wafer-based crystalline silicon, thin-film PV and emerging PV. Crystalline silicon PV was invented in 1954 by the Bell Laboratories and constitutes the most mature PV technology. Thin-film PV was developed in the 1970s and possesses a medium level of maturity. Emerging PV, finally, is the least mature and has only just reached commercial stage. To classify a firm's product according to its maturity, we collected all PV patents filed by a specific firm (if any), identified the PV technologies pursued by the firm and assigned a maturity level reaching from 1 (crystalline silicon) to 3 (emerging PV). For firms pursuing different PV technologies at the same time we calculated the average complexity of the technologies pursued. In analogy to the procedure used for technological complexity, the final variable used in our regression is the average maturity of the technologies pursued by the two alliance partners.

Finally, to measure the tacitness of technological knowledge we exploited the fact that explicit knowledge can be coded and transferred across larger differences, whereas tacit knowledge requires close observation and interpersonal contact. Previous studies have found a close correlation between distance of partners and the type of knowledge that can be effectively transferred (see section 2). Therefore, in this study we use geographic proximity between the alliance partners as a proxy for the tacitness of knowledge with a higher geographical distance implying a lower tacitness of technological knowledge. To calculate the geographical distance between alliance partners, in a first step we used web-based research to obtain the addresses of all companies in our sample. The firm addresses were subsequently geocoded and the resulting coordinates used to calculate the geographic distance based on the WGS coordinate system.

3.2.3 Controls

When testing our hypotheses, we controlled for several firm- and industry-specific factors that might influence a firm’s balance between exploration and exploitation alliances. First, previous studies have found firm size to have an impact on a firm’s propensity to form exploration and exploitation alliances (Beckman et al., 2004; Rothaermel and Deeds, 2004). We therefore includes three dummy variables that categorize alliances according to whether they are formed between two large, two small or a combination of small and large companies. Companies were defined as small if their number of employees was smaller than 250 or their revenue did not exceed 50M USD (source). Data on revenues and employees was obtained from Orbis and corporate websites. Second, a firm’s knowledge stock may affect its tendency to form exploration and exploitation alliances. We proxied the knowledge stock by the total number of patents a firm had filed prior to entering the alliance. Third, since exploration and exploitation in alliances may depend on prior experience with each of the two modes, we controlled for prior partnering experience. For this purpose, we included a count of all prior alliances formed by a focal firm at the time of entering the alliance. Fourth, prior research has demonstrated that exploration and exploitation in the solar photovoltaic industry may be strongly affected by public measures put in place to support the industry. We therefore control for year- and country-specific public R&D expenses. Public R&D data was obtained from IEA. Since market growth has been suggested to affect firm balances between exploration and exploitation, we also control for annual market growth. Fifth, it seems likely that alliances between firms and research institutes have a particularly high likelihood of being exploration alliances. Hence, in our model we use a dummy variable as a control which takes the value of ‘1’ if the alliances involves a research institute. Sixth, a firms tendency to enter exploitation alliances may be higher if it is located in a low-labor cost country which offers favorable conditions for manufacturing. We therefore constructed a dummy variable that takes the value of 1 if the firm is located in China or India as the most prominent low-cost locations in the PV industry. Finally, we captured unobserved time-specific effects by including a series of time dummies.

3.3 Analysis

Since our dependent variable is categorical, we used binary logistic regression to estimate our model. Table 1 reports the descriptive statistics and correlations for our variables. Table 2 contains the models that estimate the likelihood of a firm to form an exploration vs. exploitation alliance (hypotheses 1a, 2a and 3a). In addition, Table 3 contains the models that estimate the likelihood of a firm to enter exploitation alliances with a weaker vs. a stronger exploratory component (hypotheses 1b, 2b and 3b).

Table 1: Descriptive Statistics

	Variable	N	Mean	Std. Dev	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Exploration alliance	1,078	.23	.42	0.00	1.00	1.00													
2	Manufact. exploitation alliance	1,078	.47	.50	0.00	1.00	-.51**	1.00												
3	Marketing exploitation alliance	1,078	.30	.46	0.00	1.00	-.36**	-.62**	1.00											
4	Firm knowledge stock	1,078	1.97	1.86	0.00	7.55	.19**	-.15**	-.01	1.00										
5	Firm size small & small	1,078	.17	.37	0.00	1.00	-.05	.05	-.00	-.28**	1.00									
6	Firm size small & large	1,078	.45	.50	0.00	1.00	-.01	-.05	.06*	-.05	-.41**	1.00								
7	Research Institute	1,078	.10	.29	0.00	1.00	.47**	-.23**	-.18**	.06*	-.11**	.02	1.00							
8	Market growth	1,078	8.34	.99	5.31	10.31	-.08*	.10**	-.04	-.05	.07*	-.02	-.04	1.00						
9	Public R&D	1,078	3.58	2.13	-2.59	6.59	.05	-.05	.02	.10**	.08*	.01	.01	-.00	1.00					
10	Silicon price	1,078	4.56	.59	3.63	5.39	.04	-.11**	.08**	.01	-.07*	.01	.04	-.59**	-.09**	1.00				
11	Low-cost Location	1,078	.27	.44	0.00	1.00	-.10**	-.07*	.16**	-.04	-.08*	.02	-.02	.15**	-.41**	-.06*	1.00			
12	Technological Complexity	784	1.93	.43	1.00	3.00	-.01	-.01	.01	-.11**	.17**	.07	-.04	.01	.19**	-.13**	-.20**	1.00		
13	Technological Maturity	671	1.60	.69	1.00	3.00	.26**	-.06	-.19**	.27**	.15**	.04	.20**	.09*	.12**	-.02	-.25**	.09*	1.00	
14	Technological Tacitness	1,078	14.25	2.26	0.00	16.89	-.12**	-.07*	.19**	.09**	.02	.04	-.10**	.12**	.10**	-.10**	.26**	.02	-.05	1.00

In both, Table 2 and 3 we first present a model that contains only controls. Subsequently, independent variables are individually added to the model. The hypotheses are tested with the model that contains all independent variables and controls. To bring our data closer to normal form, geographic distance as a proxy for tacitness of technological knowledge is included in logarithmic form. In the following, we discuss the results against the background of our hypotheses derived in section 2.

4 RESULTS

Pertaining to hypotheses 1a and 1b, we posited that a larger complexity of a firm's products raises the likelihood that the firm enters and exploration rather than an exploitation alliance and chooses exploitation alliances that have a stronger focus on exploration. Our results do not offer support for none of these hypotheses. The coefficients in models 5a and 5b for technological complexity are not significant, therefore not corroborating hypotheses 1a and 1b. Furthermore, models 2a and 2b demonstrate that model fit decreases when adding technological complexity as an explanatory variable, providing further evidence that this variable does not contribute to explaining firm's propensity to enter exploration vs. exploitation alliances.

Hypotheses 2a and 2b suggested that a higher maturity of a firm's products implies a higher propensity to a) form exploration rather than exploitation alliances and b) form exploitation alliances which involve a stronger exploratory component. Model 5a in Table 2 provides support for hypothesis 2a. A higher technological maturity of a firm's products is significantly ($p < 0.01$) related to its propensity to enter an exploration alliance. Since we operationalized our variable for technological maturity in a way that a higher value indicates a lower technological maturity, the positive sign of the regression coefficient indicates a higher likelihood to enter exploration alliances if technological maturity is low. Yet, at the same time, our results do not provide support for hypothesis 2b. Model 5b in Table 3 reveals that the technological maturity does not increase a firm's propensity to choose a manufacturing exploitation rather than a marketing exploitation alliance.

In keeping with hypothesis 3a and 3b we find a positive relationship between the tacitness of technological knowledge of a firm's product and its propensity to a) enter exploration rather than exploitation alliances and b) exploitation alliances with a higher exploratory component. Regression coefficients for technological tacitness are significant ($p < 0.01$) and negative. In our operationalization, a higher value for the technological tacitness variable indicates a lower degree of technological tacitness. Hence, a higher degree of technological tacitness is connected with a higher propensity to form an exploration alliance (Model 5a) and a higher likelihood of entering exploitation alliances which involve a strong exploratory component (Model 5b).

Finally, with regard to the controls, our findings suggest that alliances involving research institutes have a significantly higher likelihood of being exploration alliances. Similarly, exploration alliances are significantly less likely to be formed if one of the partners is located in a low-country, i.e. China or India. In models 1b to 5b firm size, public R&D and firm location affect the likelihood of firms to form more and less exploratory exploitation alliances. However, the effect of these control variables becomes insignificant as soon as the main independent variables – technological maturity, complexity and tacitness – are added. Summarizing our findings, Table 4 provides a summary of our hypothesis tests.

Table 2: Results of regression analyses
(dependent variable: likelihood of exploration vs. exploitation alliance)

	Model 1a	**Model 2a**	**Model 3a**	**Model 4a**	**Model 5a**
Intercept	193.4208 (196573.9994)	219.3785 (221271.7341)	115.4258 (220237.2457)	190.9085 (193103.1359)	115.1228 (219782.0876)
Firm knowledge stock	0.2728*** (0.0499)	0.2276*** (0.0579)	0.0519 (0.0727)	0.2882*** (0.0504)	-0.0325 (0.0847)
Firm size small & small (dummy)	0.5512 (0.2774)	0.7682 (0.3283)	0.373 (0.383)	0.5971 (0.279)	0.3575 (0.4507)
Firm size small & large (dummy)	0.1103 (0.1971)	0.3644 (0.2216)	0.1676 (0.2229)	0.1522 (0.1986)	0.3594 (0.256)
Research Institute (dummy)	3.4686*** (0.3028)	3.5568*** (0.4242)	2.9466*** (0.3541)	3.4382*** (0.3041)	3.0901*** (0.5019)
Market growth	0.3117 (0.9233)	-0.0342 (1.0099)	1.5951 (1.0985)	0.3682 (0.9232)	1.6056 (1.2247)
Public R&D	0.0112 (0.047)	-0.0221 (0.0531)	-0.019 (0.0562)	0.034 (0.0482)	-0.0186 (0.0656)
Silicon price	-50.6397 (49962.5901)	-56.2343 (56239.935)	-34.0567 (55977.0023)	-49.8543 (49080.4117)	-33.6438 (55861.316)
Low-cost Location	-0.6372*** (0.2376)	-0.9362*** (0.2652)	-0.8081*** (0.2858)	-0.4772* (0.2482)	-0.7394** (0.3351)
Technological Complexity		-0.0653 (0.2445)			0.1046 (0.3155)
Technological Maturity			0.5629*** (0.1568)		0.9937*** (0.193)
Technological Tacitness				-0.09*** (0.0381)	-0.1436*** (0.0541)
Year dummies	Yes	Yes	Yes	Yes	Yes
Cox & Snell R-squared	0.226	0.208	0.239	0.230	0.272
Nagelgerkes R-squared	0.344	0.312	0.342	0.350	0.393
N	1,078	784	671	1,078	566

* p<0.1, ** p<0.05, *** p<0.01

Table 2: Results of regression analyses

(dependent variable: likelihood of manufacturing vs. marketing exploitation alliance)

	Model 1b	**Model 2b**	**Model 3b**	**Model 4b**	**Model 5b**
Firm knowledge stock	-0.0984 (0.0438)	0.0255 (0.051)	0.0715 (0.0686)	-0.0722 (0.0449)	0.1183 (0.0763)
Firm size small & small (dummy)	-0.2396 (0.2348)	0.0405 (0.2885)	-0.6516* (0.3817)	-0.1697 (0.2374)	-0.543 (0.4592)
Firm size small & large (dummy)	-0.3577** (0.1686)	-0.3393* (0.1889)	-0.2848 (0.2028)	-0.3289* (0.1699)	-0.1989 (0.2209)
Research Institute (dummy)	0.7029 (0.5703)	0.2201 (0.7614)	1.5382* (0.8148)	0.6961 (0.5716)	0.9425 (0.9168)
Market growth	-0.0663 (0.6915)	0.078 (0.7576)	0.3134 (0.9442)	0.0543 (0.692)	0.1066 (0.9955)
Public R&D	-0.1221*** (0.0407)	-0.1198** (0.047)	-0.068 (0.0548)	-0.0903** (0.0417)	-0.0201 (0.063)
Silicon price	-2.2161 (9.3375)	2.1154 (10.4022)	5.5678 (12.6054)	-0.5926 (9.3464)	2.8962 (13.3053)
Low-cost Location	-0.9963*** (0.1837)	-0.7377*** (0.2046)	-0.6322*** (0.2399)	-0.7876*** (0.1925)	-0.4108 (0.2721)
Technological Complexity		-0.1705 (0.2084)			-0.2348 (0.2805)
Technological Maturity			0.1683 (0.1708)		0.1876 (0.2095)
Technological Tacitness				-0.1382*** (0.0413)	-0.1194** (0.0572)
Intercept	11.3506 (43.3975)	-7.4073 (48.1479)	-24.2723 (58.6845)	5.5613 (43.4192)	-9.9312 (61.9456)
Year dummies	Yes	Yes	Yes	Yes	Yes
Cox & Snell R-squared	0.071	0.063	0.074	0.085	0.094
Nagelgerkes R-squared	0.091	0.085	0.098	0.115	0.126
N	833	599	479	833	410

* p<0.1, ** p<0.05, *** p<0.01

Table 4: Summary of hypothesis tests

No.	Hypothesis	Supported?
H1a	The larger the technological complexity of a firm's product, the more likely the firm is to form an exploration rather than an exploitation alliance.	No
H1b	The larger the technological complexity of a firm's product, the more likely the firm is to form an exploitation alliance which involves a stronger exploratory component.	No
H2a	The larger the technological maturity of a firm's product, the less likely the firm is to form an exploration rather than an exploitation alliance.	Yes
H2b	The larger the technological maturity of a firm's product, the less likely the firm is to form an exploitation alliance which involves a stronger exploratory component.	No
H3a	The larger the tacitness of technological knowledge of a firm's product, the more likely the firm is to form an exploration rather than an exploitation alliance.	Yes
H3b	The larger the tacitness of knowledge of a firm's product, the more likely the firm is to form an exploitation alliance which involves a stronger exploratory component.	Yes

5 DISCUSSION

In the following, we discuss the implications of our results. We first point out the main contributions to the literature on exploration and exploitation alliances in section 5.1. Subsequently, in section 5.2, we elaborate on a number of practical implications that follow from our empirical findings. Finally, we outline the most important limitations of our study and make suggestions for future research in section 5.3.

5.1 Theoretical Implications

Our study makes several important contributions to the literature on exploration and exploitation alliances. First, we provide empirical support for the notion that a firm's propensity to balance between exploration and exploitation in alliance formation is affected by technology characteristics. In particular, we find that the technological maturity reduces, whereas a higher tacitness of technological knowledge enhances the likelihood that a firm enter exploration vs. exploitation alliances. It seems that, in line with the arguments presented in section 2, exploration alliances are particularly valuable and important in the early stages of a technology in the life-cycle when there is a considerable amount of technological uncertainty. Similarly, a higher tacitness of knowledge may require the formation exploration alliances as exploitation alliances, such as manufacturing or marketing partnerships, involve a stronger focus on the exchange of tangible goods and artefacts. Although previous studies have connected the maturity and tacitness of technological knowledge with R&D activities of companies, to our knowledge this study is the first to systematically test the influence of technology characteristics on firm's balance between exploration and exploitation alliances. By stressing technology characteristics as an important drive of a firm's propensity to form exploration vs. exploitation alliance, our study complements the existing literature which has usually focused on industry and firm characteristics when studying the antecedents of exploration and exploitation alliances.

Second, while we provide evidence that maturity and tacitness of technological knowledge affect a firm's balance between exploration and exploitation alliances, we do not find the technological complexity of a firm's products to have a similar effect. We see two main explanations for this finding. As a first potential reason, a firm's propensity to form exploration vs. exploitation alliances may not depend only on the complexity of the product itself but the overall technological complexity, including the processes firms use to develop and manufacture these products. Product and process complexity are not necessarily positively related. For example, in the PV industry relatively simple products, such as ingots and wafers, require highly complicated machinery for their production. The manufacturing of modules and the installation of the PV systems, on the other hand, is based on relatively simple processing steps. As a result, while product complexity rises along the PV value chain, this is not necessarily true for overall technological complexity. Since exploration alliances may also involve R&D related to manufacturing processes and equipment, they might be triggered by overall technological complexity, rather than product complexity. This would explain why we do not find a clear connection between product complexity and a firm's tendency to make use of exploration alliances. A second potential reason is that marginal rather than total product complexity affects a firm's balance between exploration and exploitation alliances. In fact, although products become more complex along the PV value chain, firms at later stages of the value chain may not have to deal with the overall complexity but only have to touch upon specific sub-systems when adding value. Especially when products are highly modular, such as in the case of PV, the marginal complexity firms face may be relatively small even though the product as a whole is very complex. The fact that we measure the influence of overall, rather than marginal complexity, might explain why we do not find a positive relationship between product complexity and a firm's propensity to form exploration rather than exploitation alliances.

Finally, our findings provide empirical support for previous studies that have called for a more fine-grained distinction of alliances on the exploration/exploitation continuum (Parmigiani and Riviera-Santos, 2011). We find that even among alliances which in previous studies have been summarized under the term 'exploitation alliances' there are different subtypes which involve a stronger or weaker exploratory dimension and are differently related to technology characteristics. In particular, a higher tacitness of technological knowledge seems to be related with a stronger use of exploitation alliances in the field of manufacturing, whereas a lower tacitness raises the likelihood of firms entering alliances in the field of marketing, i.e. supply and distribution. This finding seems plausible insofar as marketing alliances may involve primarily the exchange of tangible goods and artefacts, whereas manufacturing alliances have been shown to require learning and the transfer of knowledge related to production processes.

5.2 Practical Implications

Besides contributing to a better understanding of the antecedents of exploration and exploitation alliances, our study may help inform decisions of corporate managers and policy makers. For managers, our findings imply that the necessity to build capabilities in exploration and exploitation alliances depends on the characteristics of the technology. In early stages in the technology life-cycle and for technologies strongly based upon tacit knowledge, firms may need to put a particular emphasis on enhancing their capacity to form exploration alliances. It seems likely that the capabilities to identify the need for alliances, screening potential partners and governing such alliances differs from those of exploitation alliances. For example, in joint R&D projects the concrete outcome is often difficult to define up-front and may strongly change in the course of the collaboration. As a result, the success of exploration alliances may more strongly depend on developing close ties to a number of trusted partners, rather than a mere reliance on formal, well-developed contractual relationships. Our analysis may inform the extent to which a firm needs to implement facilitating resources and capabilities for different products of its portfolio that differ in their technology characteristics.

For policy makers, our analysis might be of interest as it provides a first indication on the measures that can be used to foster innovation in a particular industry. Depending on the characteristics of the technology in focus, policy makers might focus on providing support for different types of innovation alliances. For example, while for technologies that strongly rely on tacit knowledge, a key task of policy makers lies in fostering exploration alliances, e.g. by providing support for collaborative R&D, products involving a lower degree of technological tacitness might benefit more strongly from measures targeted at supporting the formation of exploitation alliances, such as export subsidies. Also, since the propensity of firms to focus on exploration vs. exploitation alliances changes over the technology life-cycle, measures used by policy makers to support a specific industry might have to evolve to follow the specific needs firms have.

5.3 Limitations and Future Work

Our study has several limitations which present promising avenues for future research. First, future research should investigate the extent to which our findings are generalizable to sectors other than the PV industry. While the PV industry with its high technological diversity presents a good opportunity to observe the effect of technology characteristics on alliance formation, the industry is special in that products are modular and the industry as a whole is still relatively young. It would be interesting to investigate whether our results also hold for industries characterized by highly integrated products or a lower number of competing alternative technologies.

Second, we provide first evidence on the relation of technological characteristics and the likelihood to form exploration vs. exploitation alliances. However, our study does not provide any insights into the question how the alliance type, in turn, affects the capabilities required by firms to form and govern such alliances. Given that different technologies may require a different focus of firms in terms of forming exploration and exploitation alliances, what are the capabilities that need to be built? Do they differ between the two alliance types and in which regard? Providing answers to these questions may help derive more detailed managerial implications about how to successfully balance a firm's portfolio of exploration and exploitation alliances.

Finally, while our study demonstrates that different sub-types of exploitation alliances may differ with regard to their antecedents, we lack a sufficient understanding of how a firm's focus on different alliances within exploitation affects firm performance. Previous studies have provided evidence that balancing exploration and exploitation may lead to superior performance. Yet, does this hold true also for different types of alliances that differ in the degree of exploration within the exploitation category. Further research seems warranted that takes a closer look at firm's motives to form different types of exploitation alliances and the consequence this has for firm performance.

6 CONCLUSION

In this paper we analyzed how technology characteristics affect a firm's propensity to enter exploration vs. exploitation alliances. Previous research has particularly focused on investigating the role of firm and industry characteristics as antecedents for exploration and exploitation alliances. Therefore, in this study, we drew upon a sample of 1079 alliances in the solar photovoltaic industry to test whether the complexity, maturity and tacitness of technological knowledge affect a firm's balance between the different alliance types. Moreover, responding to recent calls for a more differentiated perspective on exploration and exploitation alliances, we investigated whether the likelihood of forming different sub-types of exploitation alliances depend on technology characteristics. Contrary to expectations, we do not find technological complexity to have a significant effect on a firm's focus on either exploration or exploitation alliances. A lower maturity and a higher tacitness of knowledge positively affect a firm's propensity to enter exploration alliances. Tacitness also was found to be connected with a stronger focus on exploitation alliances which involve a stronger exploratory component. Our study contributes to a better understanding of the antecedents of exploration and exploitation alliances. In particular, we suggest that firms might have to tailor their alliancing focus and capabilities to the specific characteristics of the technologies they pursue. Moreover, our study demonstrates the need to further differentiate between and investigate the drivers of different sub-types of exploitation alliances.

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