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Liquidity events and VC-backed academic spin-offs: the role of search alliances

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Abstract

Despite the emergent importance of liquidity events (IPOs and trade sales) as performance indicators for VC-backed academic spin-offs, empirical research on the drivers of liquidity events relating to such spin-offs has been limited. In adopting a search perspective, we analyze how different alliance types impact on VC-backed academic spin-offs' chances of realizing a liquidity event. We find that market search alliances increase a spin-off's likelihood of a liquidity event, whereas technology search alliances reduce this likelihood. However, the latter effect is mitigated when the spin-off has a founding team with prior market experience. We explore the implications for practice and policy of the development and success of VC-backed academic spin-offs.

Keywords: liquidity event, academic spin-offs, alliances, search

1. Introduction

Technology ventures are innovative start-ups that bridge science and technology using venture capital (VC) as a primary source of funding (Wry et al., 2014). Many are created either by university scientists aiming to commercialize technology developed in the academic setting (Mustar et al., 2008), or by entrepreneurs searching for technology developed at universities to apply to specific market opportunities (Shane, 2000). Both types of technology ventures have become known and are studied as ‘academic spin-offs’ (ASOs) (Wright et al., 2007). ASOs are an extreme form of technology ventures that experience conflicting demands of the academic and commercial world (Ambos and Birkinshaw, 2010) and face a high level of market ambiguity (Molner et al., 2019). From a policy perspective, ASOs that receive capital – so-called VC-backed ASOs – are the most attractive (Mustar et al., 2008), as they are growth-oriented and may therefore contribute most prominently to economic growth (Zhang, 2009).

However, empirical evidence shows that they rarely evolve into sizable, robust and commercially successful independent players (Wright et al., 2007). Rather than entering the product market (Moeen and Agarwal, 2017), these ventures tend to use other, less studied value-capturing mechanisms such as trade sales or IPOs in the market for corporate control (Wright and Fu, 2017). Therefore, researchers are increasingly interested in the market for corporate control, i.e., the likelihood of liquidity or exit events,¹ as a performance measure for such firms (Meoli et al., 2013; Moeen and Agarwal, 2017; Moeen, 2017). The market for corporate control seems to be particularly dominant during periods of industry incubation, when novel technologies have not yet found their way to the market (Moeen and Agarwal,

¹ We use the terms “liquidity” and “exit” interchangeably (Aggarwal and Hsu, 2014).

2017). It is this period of industry emergence that gives rise to technology ventures, and VC-backed ASOs in particular.

Existing research on the exit probability of technology ventures points mainly to the importance of sending out quality signals to overcome problems of information asymmetry, in particular having a prominent partner on board has been shown to increase acquisition probability (e.g., Colombo et al., 2019; Hoehn-Weiss and Karim, 2014; Reuer et al., 2012; Cattaneo et al., 2015; Meoli et al., 2013). While this signaling perspective provides a useful angle from which to explain how investors' reactions to ventures differ according to the prominence of the alliance partners with whom they engage, it does not consider the vast variety of rationales for pursuing such alliances. To counter the shortcomings of these theories, Wright and Clarysse (2020) call for research using behavioral theories to explain technology ventures' choices in their development paths.

We follow this recommendation by building on research by Andries et al. (2013) and Gruber et al. (2008, 2013). Andries et al. (2013) show that after founding, ASOs engage mainly in experimental activities when searching for optimal product–market combinations. Gruber et al. (2008, 2013) have already shown the importance of identifying different potential applications when founding a technology venture based on a particular technology. However, they fail to adequately address the problem of technology entrepreneurs' bounded rationality. Members of the founding team are unlikely to have diverse commercial insights (Vanaelst et al., 2006), and if they do, these are typically limited to considering the diversity of product markets (Fern et al., 2012; Gruber et al., 2013). Hahn et al. (2018) have found evidence that ventures founded by scientists engage in collaborative search specifically in order to reduce the costs of the search process or broaden the range of search opportunities. However, the authors also warn that such collaborations may lead to rigidity. Hence, it appears that collaborative search does not always have a positive impact.

We build on these emerging insights to address the following research question: *to what extent does VC-backed ASOs' use of alliances to search for market applications or novel technological solutions impact on their chances of realizing a liquidity event?* The sample used to address this research question consists of 157 VC-backed ASOs that have developed and commercialized technologies originating from universities in the UK. These firms were founded between 1995 and 2010 and engaged in technology and/or market searches by forming alliances. Alliances are voluntary arrangements between organizations involving exchange, sharing, or co-development of products, technologies, or services (Gulati, 1998). Our results show that market search alliances increase VC-backed ASOs' likelihood of liquidity events, whereas technology search alliances reduce this likelihood. Furthermore, we find that the negative effect of technology search alliances on the likelihood of liquidity events is mitigated when the ASO has a founding team with prior market experience. We discuss the implications of these findings for research and policy.

2. Theory and Hypotheses

It has long been recognized that firms face challenges resulting from a lack of market information (Knight, 1921). Searches are a means to address these frictions associated with imperfect knowledge and are central to the functioning of markets (Hayek, 1945). This evolutionary view of markets is also fundamental to understanding the drivers of economic growth, especially in the Schumpeterian tradition (Aghion and Howitt, 1992; Aghion and Festré, 2017). ASOs' lack of market information and the search processes in which they engage are extensions of this tradition.²

In order to generate business opportunities by linking their technological resources with identified market demand, ASOs must possess two interdependent types of knowledge:

² We thank an anonymous reviewer for pointing this out to us.

technological knowledge and market knowledge (Nerkar and Roberts, 2004). On the one hand, technological knowledge is important as it enables firms to develop and build products that meet customer demand (Clarysse et al., 2011). Greater technological knowledge offers opportunities to develop a greater number and wider variety of innovative solutions (Gruber et al., 2013). On the other hand, ASOs need a good understanding of the market in which they wish to sell their products or services. Market knowledge allows them to assess which market to enter, and complements technological knowledge by enabling new ventures to judge how technological knowledge can be used to address market needs (Shane, 2000). Market knowledge also informs firms about how to develop new products and services that better satisfy customer needs than existing products (Katila, 2005).

Going beyond the role of technological and market knowledge, Danneels (2002) introduces the concepts of customer and technological competence. In addition to knowledge of customer needs and preferences, customer competence includes understanding of purchasing procedures, distribution and sales, and access to customers, as well as communication channels for exchanges of information between the firm and its customers during development and commercialization. Similarly, technological competence is broader than technological knowledge insofar as it also includes design and engineering, product and process design equipment, manufacturing facilities and know-how, and procedures for quality control. Since a larger set of business opportunities increases a firm's growth options, ASOs need to engage in search processes to fuel the accumulation of both types of competence.

The notion of searching as originally formulated in the behavioral theory of the firm (Cyert and March, 1963). A fundamental premise of behavioral theory is that sets of alternative actions are not available to actors *ex ante*, but must be constructed through searching. Organizational searches have been conceptualized as a problem-solving activity in which firms solve problems by combining different knowledge elements (Nelson and Winter,

1982). The organizational search literature distinguishes between search processes undertaken to gain new technological knowledge and those carried out to gain new market knowledge (Sidhu et al., 2007). Technology searching is the process of identifying, selecting and coupling new technologies required to meet earlier identified customer needs. Similarly, market searching is the process of exploring and scanning the market to identify potential market applications based on existing, proprietary technologies.

Technology searches typically involve well-structured problems, which allow problem solvers to rely on algorithms to search for solutions (Jeppesen and Lakhani, 2010). Such algorithms inform problem solvers about the necessary steps and potential pathways to finding the best solution (Dunbar, 1998). The algorithmic nature of technology searching enables both definition of the problem that needs to be resolved and identification of the path to reach the solution (Amabile, 1983). However, this does not mean that problems encountered in technology searches are easy to solve (Simon, 1973); it simply means that those problems and their associated solution criteria are relatively easy to articulate. In contrast, market searches typically involve ill-structured problems, since the criteria for assessing solutions are unclear. The heuristic nature of market searching makes it much more challenging to identify pathways to solutions (Amabile, 1983). Accessing and assessing new market knowledge is more challenging and difficult than gaining new technological knowledge, as knowledge about markets is typically tacit in nature, and customer needs are often unarticulated (Von Zedtwitz and Gassman, 2002).

Technology searches are planning-oriented, whereas market searches are a discovery-based activity, as relevant knowledge can only be developed through in-market experimentation (McGrath and MacMillan, 1995). To explore a range of potential market opportunities, discovery-based market searching implies a series of small investments in different market segments (McGrath, 2010). The objective of discovery-based market

searches is to learn as much as possible about each market segment as cheaply as possible by postponing large resource commitments until assumptions are validated.

It is difficult to initiate the search process before an ASO is founded since there is no prior experiential market knowledge in the pre-founding team to identify a viable long-term technology–market combination (Grégoire et al., 2010). The lack of pre-founding experience makes ASOs unique in comparison with other innovative startups that are founded by employees of industry incumbents (Agarwal et al., 2017). ASOs therefore engage in alliances with other organizations to economize on search costs (Hahn et al., 2018). Previous research typically distinguishes between explorative and exploitative alliances, based on the function in the value chain fulfilled by the alliance (e.g., Rothaermel and Deeds, 2004). This tradition associates exploration with activities upstream in the value chain relating to technology, such as R&D. Conversely, exploitation is associated with activities downstream in the value chain relating to the market, such as distribution. Pure explorative alliances are conduits for exploring new opportunities (see quadrant (4) in Figure 1), while pure exploitative alliances are used to exploit existing opportunities (see quadrant (1) in Figure 1) (Koza and Lewin, 2000). However, this dichotomy is an oversimplification, as exploration and exploitation may occur at both the technology and market level. In addition to pure exploration and exploitation, Danneels (2002) suggests two intermediate cases: leveraging technological competence and leveraging customer competence. The former involves exploiting existing technological competences while exploring new market competences, whereas the latter involves exploiting existing market competences while exploring new technological competences. In essence, these two intermediate cases reflect the processes of market and technology searches, respectively.

ASOs may engage with alliance partners to scan markets in which to leverage their technological resources (see quadrant (3) in Figure 1), or may access external technology to

develop new solutions to serve their existing customers (see quadrant (2) in Figure 1). Market search alliances are alliances in which the ASO's technological knowledge is complemented by an alliance partner's market knowledge in order to explore the value of the ASO's technology in the market served by the alliance partner. Technology search alliances are alliances in which the ASO's market knowledge is complemented by the alliance partner's technological knowledge. Figure 1 shows the link between the ASO's existing and new market/technological competences and types of alliance.

---INSERT FIGURE 1 HERE---

In the next section, we explore how market and technology search alliances influence the likelihood of liquidity events for VC-backed ASOs³.

2.1 Market search alliances

One of the main challenges confronting technology ventures and ASOs in particular is to establish which market segments to target (Molner et al., 2019). They must explore and scan the market to identify potential applications based on their existing technologies. This process of technology-to-market linking can best be described as combining technological competences with information on customer preferences and market demand. The main challenge of market searches is to identify and evaluate end-user domains where the technology can be meaningfully applied. Since ASOs typically are set up to commercialize technology scoring relatively low on the technology readiness scale (Mankins, 1995), ASOs still have to engineer products that make use of the underlying technology that forms the reason for founding the ASO. The ASO must decide on product features, taking into consideration the needs and preferences of target customers. However, the process of technological development and market selection is highly uncertain, often ambiguous and

³ As we focus in this paper on the role of hybrid alliances aimed as at exploring new product-market combinations, we do not consider pure exploitative and pure explorative alliances in the hypothesis development. However, we do control for these alliances in our statistical models.

inherently unpredictable, making it very hard for academic entrepreneurs, who typically lack specific industry experience, to assess the likely potential of a business opportunity.

The literature on ASOs has shown that many university inventions are very explorative, at early stages of technology maturity and facing considerable amounts of market ambiguity (Clarysse et al., 2011; Molner et al., 2019). Considerable time may be spent in searching for appropriate product markets for ASOs, involving time-consuming and costly reorientation (Vohora et al., 2004). Because academic entrepreneurs typically lack market insights, market searching can be described as an ill-structured problem. It is for them very difficult to define clear criteria for assessing solutions (Jeppesen and Lakhani, 2010). When searching for market applications based on their technology, they typically have no crystallized view of target customers' preferences and needs, making it impossible for them to link their technology to specific applications and product features. To overcome this uncertainty, academic entrepreneurs must experiment in the market using techniques such as prototyping (McGarth, 2010). Unlike technology entrepreneurs that come from outside university, they typically do not have a tight network of customers to kick start with (Baker, Eesley and Miner, 2003) nor do they have specific experience in a market that would help them to upfront link the technology to the market in a structurally aligned way (Grégoire et al., 2010).

Engaging in iterative cycles of market testing is both time- and resource-intensive. The ASO must invest its limited resources in translating technological resources into products, as well as in assets and capabilities to manufacture, distribute and provide after-sales services (Fiedler and Welppe, 2010). As a result, it risks investing all its resources in a market segment that may prove to be unattractive. The irreversibility of investments downstream in the value chain makes this a risky option for ASOs.

Under such circumstances, entering into a market search alliance has several advantages. It helps to avoid sunk costs relating to complementary assets, and also provides access to the

partner's in-depth market knowledge (Gans et al., 2002). It further offers the ASO opportunities for discovery-based learning and in-market experimentation without the need to invest in costly customer competences (Danneels, 2008). In addition, ASOs' technological competences are regarded as fungible, meaning that they can create value for end-users in multiple market domains and therefore transcend the product in which the technology is embodied (Danneels, 2007). Market search alliances allow ASOs to leverage their technology across new potential markets. This increases their business opportunity set without the need for additional investments in downstream markets. Each additional market search alliance also accelerates discovery-based learning and in-market experimentation, thereby contributing to the creation of firm value (De Cock et al., 2018). A higher number of business opportunities also increases the growth options and thus firm value (Gruber et al., 2008). While market search alliances may not necessarily contribute to revenue and profit generation in the short-term (they may even require resource investments), engaging in such alliances increases the future growth potential of the ASO and thus the likelihood of a liquidity event. We therefore hypothesize:

H1: The number of market search alliances will have a positive influence on the likelihood of a liquidity event for a VC-backed ASO.

2.2 Technology search alliances

Technology searches are less challenging for ASOs than market searches, as they entail clearly identified goals and a clearer approach to problem solving. Here, the ASO starts with an identified market need and engages in a search process to develop a solution. It will optimize its technology to address the market need identified at the outset. This can be seen as a problem-solving activity in which the search space is clearly defined in terms of both the outcome (i.e., what the organization is looking for) and the locus of search (where the organization is looking for a solution). Since the opportunity space upon which an ASO is

founded is typically a technology developed at a research lab (Molner et al., 2019), the knowledge needed to solve the technological problem is within the ASO's knowledge space, it is highly likely to be able to solve the problem internally (Afuah and Tucci, 2012). This implies diminished added value from using alliance partners for this type of search.

In contrast to market searches, where both risk and rewards are shared, technology searches using alliances involve sharing only the value created through the integrated technology/product offering. Furthermore, IP issues are more pronounced in technology searches than in market searches (Arora and Nandkumar, 2011). This is especially the case for ASOs which have been shown to benefit from building a sound technology base before even thinking about customers (Molner et al., 2019). The difficulties of managing joint technology development, and of monitoring when inputs are hard to observe, may undermine the added value of alliances (Jeppesen and Lakhani, 2010). Because of their weak bargaining position, ASOs may cede their IP rights disproportionately to their technology alliance partners (Rothaermel and Deeds, 2004), who are more likely to appropriate most of the value of the partnership at the expense of the ASO (Alvarez and Barney, 2001). Even if it were possible to write contracts covering all contingencies, ASOs' limited financial resources would make it very difficult to enforce them. Under such circumstances, developing complementary technology in-house offers the highest value creation potential for ASOs.

ASOs are distinctive in often involving broad-based technologies, which provide scope for multiple products and greater growth (Clarysse et al., 2011). However, technology searches through alliances to address technological solutions for particular market needs are likely to narrow this broad base. This reduces the fungibility of the technology, thus decreasing the potential number of product applications that can be created by the ASO (Gambardella and McGahan, 2010), as well as diminishing the firm's ability to respond to technological changes by introducing new products (Kapoor and Adner, 2012). It further

delays the new product development process, thereby decelerating the ASO's early cash flow, visibility, legitimacy and market share, which leads to a less favorable resource-dependence position for the ASO (Schoonhoven et al., 1990). Each additional technology alliance increases the associated costs, thereby reducing firm value. We therefore hypothesize:

H2: The number of technology search alliances will have a negative influence on the likelihood of a liquidity event for a VC-backed ASO.

2.3 Prior experience and market and technology search alliances

Besides the type of alliances in which they engage, ASOs also differ with regard to the knowledge and expertise of the founding team. While founding teams in pure ASOs consist only of teams of researchers, hybrid ASOs also employ founders from outside the university, who may bring valuable commercial expertise (Fryges and Wright, 2014). Previous studies show that entrepreneurial teams' prior knowledge of technologies and industries influences their identification of business opportunities (see Grégoire et al., 2010; Gruber et al., 2013). Building on these insights, we now turn our attention to how the entrepreneurial team's prior technological and market experience may moderate these relationships in VC-backed ASOs.

In market search alliances, the ASO's technological resources are linked with the alliance partner's market knowledge to identify new business opportunities. Such alliances allow the ASO to exploit its fungible technological resources across multiple market domains. ASOs often face considerable market ambiguity, which implies that there are different markets in which the technology might be applied but none of these markets is easy to prioritize upfront. Recent literature has shown that accepting market ambiguity rather than focusing too early on a particular end user pays off (Molner et al., 2019). This requires them to have comprehensive insight into how the technology can be used to develop products and services for more distant markets (Gruber et al., 2013). In-depth knowledge of the technology allows rapid identification of its functionalities, strengths and weaknesses and allows to

broadcast the technology to search for partners (Afuah and Tucci, 2012). Consequently, a thorough understanding of the technology's attributes is vital to identifying potential applications enabled by the technology (McGrath and MacMillan, 2000). Technologically experienced teams also have the necessary absorptive capacity to use market-related inputs from the alliance partner in order to select product features that more effectively address customers' needs and preferences. In contrast, technologically inexperienced teams will find it more difficult to recognize how their technology can be used for a market opportunity proposed by an alliance partner. This means that the process of technology–market linking through market search alliances will be more productive for ASOs with technologically experienced teams than with teams lacking such experience.

Technology search alliances in contrast, link ASOs' market knowledge with alliance partners' technological knowledge. Some ASO teams may involve academics with commercial experience from involvement in previous entrepreneurial ventures (Mosey and Wright, 2007), or who have contacts through which to recruit members from outside academia with commercial experience (Rasmussen et al., 2011, 2016). Other ASOs are formed of mixed teams consisting of both founders with a purely academic background and founders with commercial/market experience (Fryges and Wright, 2014). ASO teams with members who have prior market experience are likely to have a better understanding of market dynamics and market needs and preferences, and will hence initially be in a better position to search for, negotiate and establish alliances. ASOs that score relatively low on the technology maturity scale (Molner et al., 2019) will still need to focus on their internal technology development. However, those that have more developed technologies to start-from could potentially focus on end users immediately. Such a focus might trigger the need for additional complementary technologies to address the market problem.

Technology search alliances are triggered by identification of a new need in the ASO's existing customer groups. However, the ASO's technology may be insufficient to develop an appropriate solution addressing that need, and it must therefore rely on an alliance partner with complementary technology. We expect a positive influence of the presence of prior market experience on the relationship between technology search alliances and the likelihood of liquidity events for VC-backed ASOs. This deeper market knowledge should enable the ASO to better articulate customer needs and preferences to the technology search alliance partner, which in turn should allow the alliance partner to make choices about specific product features more efficiently.

To conclude, levels of prior technological and prior market experience may play an important role in the effect of market and technology searches on the likelihood of liquidity events for VC-backed ASOs. Hence, we propose the following moderation hypotheses:

H3a: The positive effect of market search alliances on the likelihood of liquidity events for VC-backed ASOs will be stronger for SOs with greater prior technological experience.

H3b: The negative effect of technology search alliances on the likelihood of liquidity events for VC-backed ASOs will be weaker for SOs with greater prior market experience.

3. Data and method

3.1 Sample

We tested our hypotheses using a sample of VC-backed ASOs that had developed and commercialized technologies originating from British universities and had been founded between 1995 and 2010. We started with the population of ASOs listed on www.spinoutsuk.co.uk. This website provides an overview of all spin-offs emanating from UK universities, with information about their origin, activities, growth and status. The website distinguishes between spin-offs (based on university IP), start-ups (formed by

university staff and recent graduates, but not based on university IP) and others. From this list, we selected so-called spin-offs founded between 1995 and 2010 (Lockett and Wright, 2005). We set the lower bound of the firm's foundation year at 1995, since the period from the mid-1990s was characterized by professionalization of technology transfer offices (TTOs) in the UK as a result of government actions to stimulate entrepreneurial activity in universities and research institutes (Lockett et al., 2014). The upper bound was set at 2010 to allow sufficient time for the occurrence of alliances and exits. With these restrictions, we identified 1,097 spin-offs through www.spinoutsuk.co.uk, of which 265 had attracted VC funding. Our focus on VC-backed ASOs also justified using the realization of a successful exit as an indicator of performance and value capture, because these firms face "liquidity needs arising from the venture capital cycle, creating pressures to pursue exit opportunities" (Aggarwal and Hsu, 2014 p.872). Moreover, quality screening of VC involvement (Kortum and Lerner, 2000) provided our sample with a desirable level of homogeneity. We tracked the companies from the year of foundation until 2013, or the year of exit if earlier (including the exit events of IPO, acquisition, bankruptcy or dissolution). Therefore, left censoring was not an issue in our sample. However, there was right censoring because many firms were still active in 2013 and had not yet realized an exit.

3.2 Dependent variable

Our dependent variable records a liquidity event in terms of whether the VC-backed ASO was able to realize a successful exit. Following Arora and Nandkumar (2011), we define successful exit as an IPO or acquisition in which the price paid exceeded the total amount of VC received. Companies acquired at a price that did not cover the amount of VC raised were classified as failures, along with bankrupt and dissolved firms. As failure prevents the event of interest from occurring, it is important to track which companies failed

before they could realize a positive exit. Bankruptcies and dissolutions were tracked using information from Companies House provided by the British government.⁴

3.3 Independent variables and moderators

In this study, we distinguish four alliance types: pure explorative, market search, technology search and pure exploitative. Similarly to previous research (e.g., Rothermael and Deeds, 2004), we used a publicly available data source, Factiva, to track the alliances in which the ASOs engaged. VC-backed firms are typically well covered in the press; therefore, relying on public sources such as Factiva should not induce severe selection bias. For each company in the sample, a search was conducted using the query: “Company name” and “university of origin”⁵ and (“partner” or “license” or “cooperate” or “seller” or “distributor” or “collaborate” or “collaboration” or “cooperation” or “alliance” or “partnership”). The date range for the query was the year of foundation until the year of exit or 2013, whichever was earlier. Subsequently, press releases were screened and coded independently by two of the authors to categorize the alliances according to the alliance types presented in Figure 1. A total of 521 partnerships for 157 ASOs were coded, with between-coder agreement in 86.41% of cases (Cohen’s Kappa = 0.81). When different classifications were given, the two authors discussed the case until they reached agreement. The press releases were complemented with information from companies’ websites to assess markets that had already been identified by the ASOs. More specifically, we consulted the archived versions of the companies’ websites to determine the markets in which the ASOs were active. We considered an ASO to have competences in a certain market segment if its website indicated market presence in that particular segment. Illustrative examples of each type of alliance are available in Appendix 1.1. to demonstrate the coding process of the alliances.

⁴ Companies House is accessible at <https://www.gov.uk/get-information-about-a-company>.

⁵ We added university of origin to the query to increase the reliability and relevance of the search results.

Pure explorative alliances were coded as such if the objective was to develop an entirely new technology or product for which the company had no customer competences. In many of these alliances, the alliance partner was a university or public research institute, but partnerships with private companies could also be purely explorative. The pure explorative alliances variable reflects the total number of pure exploration alliances entered into by the ASO between the year of foundation and exit (or 2013).

Alliances were coded as *market search alliances* when the ASO's motive for entering the alliance was to exploit its technological competences in a market new to the ASO. In collaborating with a third party, an ASO explores a new potential market and gains access to market-related competences. Thus, to qualify as a market search alliance, the ASO should contribute technology-related competences, while the partner should bring market-related competences to a market new to the ASO. The market search alliances variable reflects the total number of market search alliances entered into by the ASO between the year of foundation and exit (or 2013).

An alliance was classified as a *technology search alliance* when the ASO sourced a new technology or product from an external party to address demand from the market it was currently serving. Thus, in contrast to market search alliances, in a technology search alliance, the partner contributes technology-related competences, while the ASO delivers market-related competences. The technology search alliances variable reflects the total number of technology search alliances entered into by the ASO between the year of foundation and exit (or 2013).

Finally, *pure exploitation alliances* were coded as such if the motive for the alliance was to exploit the ASO's technological competences in an existing market. The purpose of such alliances is to generate revenue streams from existing technologies and/or products through arm's-length agreements, as is typical of distribution agreements. The pure exploitation

alliances variable reflects the total number of pure exploitation alliances entered into by the ASO between the year of foundation and exit (or 2013).

We also created two variables for the founding team's level of prior experience to test for interaction effects. We distinguished between *prior market* and *prior technological experience*. Following, Fern et al. (2012), we constructed the team-level measures by considering the most experienced member in the team. We limited this to members of the founding team because these best characterized the group overall (Gruber et al., 2008). Two dummies were created to distinguish between experienced and less experienced teams. *Prior technological experience* was given a value of 1 if any team member had a PhD in the technological area of the ASO, and 0 otherwise. Similarly, *prior market experience* was coded as 1 if any of the founders had industrial experience in the targeted market applications. To track the founders' prior technology and market experience, archived web pages, LinkedIn and Crunchbase were consulted.

3.4 Control variables

Age. The age variable represents the number of calendar years between year of foundation and year of exit or 2013 (Ransbotham and Mitra, 2010).

Industry dummies. Because exit opportunities may differ across industries, we controlled for industry using two dummy variables, one for the ICT industry and one for the biotech and life science industry. These two sectors captured 79% of the ASOs in our sample (ICT = 24% and biotech and life science industry = 55%), and the remaining 21% of sample firms fell into the excluded category of "other industries." These industry classifications were obtained from the www.spinoutsuk.co.uk website.

VC rounds. The number of VC rounds was included as a control variable to indicate venture quality and performance (Nahata, 2008). This variable measures the cumulative number of VC rounds in which the ASO was involved in a given year. Together with *age*,

this variable captures the ASO's stage of development and indicates the maturity and growth options available to the firm.

Pre-financial crisis dummy. The financial crisis had severe consequences for financial markets. As a result, it became more difficult for a company to realize an IPO or trade sale. Therefore, we included a dummy that was set to 1 from the year 2008 onwards.

Patents at founding. We also used patent stock to control for ASO quality. Patents offer potential investors a valuable signal of the quality of the firm's technical capabilities (Hsu and Ziedonis, 2013). To determine the patent stock of the ASO, we consulted data provided by the European Patent Office. As this variable was highly skewed, we took the natural log of the ASO's total number of patents in a given year plus one.

University ranking. Previous research has demonstrated that a company's affiliations impact significantly on performance (Cattaneo et al., 2015; Reuer et al., 2012). At start-up, the university of origin was the most powerful affiliation for the companies in our sample. This affiliation might have an impact not only on the alliances that the ASO was able to form, but also on its likelihood of realizing a successful exit. Therefore, we added university ranking as a control variable to our model, as prestige is typically proxied by university rankings (Zahra et al., 2007). We used the Times Higher Education World University Ranking.

University spin-off experience. We controlled for the host university's experience of spinning off ventures, as more experienced universities might have developed more effective mechanisms to support ASOs than their less experienced counterparts (Lockett and Wright, 2005). This variable counts the number of ASOs created before the foundation of the focal ASO.

Prominence of the partner and Prominence of the investor. Finally, we included two control variables that capture the prominence of the alliance partners and investors.

Following Lavie (2007) and Reuer et al. (2012), we constructed a dummy variable equal to 1 when the alliance partner was publicly listed. Publicly-listed organizations play the role of public endorsers who are well-known and appreciated by outsiders. The control variable Prominence of the partner is equal to 1 when at least one of the ASO's alliance partners is prominent, and zero otherwise. Following Reuer et al. (2012), we identified an investor as prominent if the number of IPOs by its portfolio companies was above the median number of IPOs realized by all VCs during the period 1995–2013. The control variable Prominence of the investor is equal to 1 if at least one of the ASO's investor is prominent, and zero otherwise.

4. Results

Table 1 presents descriptive statistics and correlations for the sample of VC-backed ASOs with alliances. Table 2 provides an overview of how exiting companies differed from their active and failed counterparts. The average age of ASOs that realized successful exits was 7.90 years, while the age at failure was higher (mean of 9.68 years). The table further shows that the number of market search alliances was substantially higher among ASOs that were able to realize an IPO or trade sale (1.38) compared with failed ASOs (0.64) or those that were still active (0.97). A similar trend can be detected for pure exploitative alliances. Regarding technology search alliances, we see no substantial differences between active ASOs and those that realized an exit, with 0.92 and 1.00 alliances on average, respectively. However, failed ASOs seemed to engage more frequently in technology search alliances, with 1.64 alliances on average.

---INSERT TABLES 1 AND 2 HERE---

Following Arora and Nandkumar (2011), we estimated a competing risks model in which we considered two possible exit events: successful exit (IPO or trade sale) or failure. For our

purposes, a competing risks model was most appropriate. In essence, competing risks models are a generalization of binary exit models, but offer a number of important improvements over binary models such as traditional survival models. First, competing risks regressions take into account that failed companies are no longer able to realize a successful liquidity event (i.e., the exit event of interest in our model). Second, this type of regression model allows the covariates to influence each exit type separately. Third, competing risks models also take into account that the exit may not yet have occurred at the time of analysis (in our case 2013). Indeed, some VC-backed ASOs had not realized a liquidity event by the end of 2013 but were still operating independently.

Of the 265 VC-backed ASOs, 157 had alliances. As the chances of realizing a successful exit might be affected by unobserved factors that might also influence the formation of alliances, our findings were potentially subject to endogeneity. To address this problem, we performed a conventional Heckman two-stage approach (Heckman, 1979; Greene, 2012). In the first stage, we estimated a probit model to predict the likelihood of ASOs forming alliances, using the full sample of 265 VC-backed ASOs. As an instrument for the selection model, we used a dummy variable reflecting whether the founding team included faculty members of the university from which the company had been spun off. The inclusion of faculty members in the founding team may function as a quality signal, increasing the chances of entering into third-party collaborations. However, it is expected that the effect of this signal diminishes over time and is no longer valuable at the moment the firm is subjected to due diligence for an IPO or acquisition. Our statistical analysis confirms the suitability of this variable as a selection instrument⁶. Based on these results, an inverse Mills ratio was included in our models, using the sample of 157 VC-backed ASOs with alliances. Entering

⁶ The correlation matrix available in Appendix 1.2. together with the probit analysis available in Appendix 1.3. shows that having a faculty founders correlates significantly with the probability of entering into a partnership but not with the probability of an exit.

the inverse Mills ratio into the competing risks model predicting the probability of a successful exit did not change the sign and significance of the coefficients in our model.

The findings from our competing risks analysis, presented in Table 3, show the results of predicting successful exit probability. Based on this competing risks model estimation, we also estimated the Kaplan-Meier curves to plot the exit function over time (see Figure 2a and 2b). In particular, we estimated these functions to compare ASOs with and without technology search and market search alliances. Figure 2a shows that ASOs with market search alliances exhibit a higher probability of realizing a successful exit (although, as the confidence intervals overlap, these results are not significant). The picture of technology search alliances (see Figure 2b) is somewhat more ambiguous, as it seems to indicate that in the early years having no technology search alliances is beneficial, while over time this effect reverses and ASOs with technology search alliances have higher exit probabilities. Yet these Kaplan-Meier estimates show the influence only of categorical variables, and thus do not show the effect of the *number* of alliances. These effects are demonstrated in our competing risks analysis.

In our sequential analysis, Model 1 constitutes the base model, including only the control variables. We introduce our main independent variables in Model 2 of Table 3. Model 2 shows that, consistent with hypothesis 1, market search alliances have a positive effect on the likelihood of realizing a successful exit ($\beta = 0.23, p < 0.05$). Furthermore, consistent with hypothesis 2, Model 2 demonstrates that technology search alliances have a negative effect on the likelihood of realizing a successful exit ($\beta = -0.39, p < 0.01$).

Model 3 of Table 3 presents the results for interaction effects. Hypothesis 3a predicted that the positive effect of market search alliances on the likelihood of a liquidity event would be stronger for ASOs with greater prior technological experience. Although the coefficient of the interaction term is positive, it is not significant and thus hypothesis 3a is not supported.

Similarly, we expected that the presence of high levels of prior market experience would be beneficial and would weaken the negative effect of technology search on the likelihood of a liquidity event. As the coefficient for this interaction term is positive and significant ($\beta = 0.57, p < 0.05$), hypothesis 3b is supported.

To facilitate interpretation of the significant interaction effect, we replace the single interaction indicator (Market experience X Technology search alliance) with two separate indicators. The first refers to ASOs with technology search alliances and *low* market experience, while the second refers to ASOs with technology search alliances and *high* market experience. The advantage of representing the results in this way is that the total group effects are easier to interpret than in a classical interaction model (Christensen et al., 2013). Model 4 in Table 3 shows the results of a competing risks regression including these two indicators, and shows that the effect of technology search alliances is significantly negative for ASOs with low market experience ($\beta = -0.60, p < 0.01$), but is insignificant for those with high market experience. The negative impact of technology search alliances is thus cancelled out for firms with high market experience.

---INSERT TABLE 3 HERE---

4.1 Post hoc analysis⁷

As previous research indicates that technology firms are often acquired by their partner firms (Porrini, 2004), our results might have been driven by this effect. To check for this possibility, we ran a number of additional analyses. First, we constructed a dummy variable indicating whether one of the ASO's alliance partners was the acquirer. Including this variable did not change the significance of our results. Next, we excluded ASOs that had been acquired by one of their partners. Again, the results remained robust.

⁷ Results are available from the authors on request.

To further test the robustness of our findings, we added a number of additional control variables, such as patent stock to date (rather than at founding) and amount of VC, both as proxies for VC-backed ASOs' quality. Including these variables did not change the significance or direction of the hypothesized effects. Our results also remained robust when excluding ASOs with multiple alliances with the same partner, as well as when adding year fixed effects, and with a different operationalization of university ranking using the Academic Ranking of World Universities rather than the Times Higher Education ranking. Lastly, we also examined if the prominence of the partners influenced the results. When counting the number of prominent partners and VC investors instead of including a dummy variable, the results remain robust. Next, we only considered alliances with prominent partners in our count variables. Again we find confirmation of our previous results and observed a positive and significant effect of market search alliances and a negative and significant effect of technology search alliances on the likelihood of realizing an exit.

In addition to testing the effect on the probability of realizing a successful exit through an IPO or trade sale, we also tested the effect on the probability of failure. The results show that market search alliances reduce the probability of failure while technology search alliances increase the probability of failure. Therefore, these results provide further support for the value-reducing effect of technology search alliances and the value-adding role of market search alliances. Similar conclusions were drawn from running a multinomial regression distinguishing three types of exits (failure, IPO and trade sale).

Finally, we also ran a competing risks model on the complete sample to test the effect of the absence of alliances. In this model, we find a significant and negative effect of absence of partnerships on exit probability ($\beta = -0.80, p < 0.05$). Subsequently, we added two dummy variables for absence of market search alliances and absence of technology search alliances. Regarding the former, we find a negative and significant effect ($\beta = -0.65, p < 0.05$) on

successful exit probability, while a positive and significant effect is found for the latter ($\beta = 0.50, p < 0.05$). This provides further support for our conclusion that market search alliances create firm value, while technology search alliances reduce firm value.

5. Discussion

Researchers are increasingly seeking to gain a better understanding of liquidity events as a primary performance measure for entrepreneurial firms. We adopted a behavioral perspective to investigate how market and technological alliances as search mechanisms contribute to realizing liquidity events for VC-backed ASOs.

Our study makes several contributions. First, we show that behavioral theory, and more specifically the search and learning literatures, offer important but neglected theoretical insights into the likelihood of liquidity events in the context of VC-backed ASOs. We show that the use of external partners in market and technology search processes impacts on the ultimate goal of a VC-backed ASO, namely the liquidity event. Therefore, this paper complements the economic view of liquidity events, which focuses primarily on the role of alliance partners in decreasing information asymmetry, with a behavioral perspective that considers the functional use of such alliances. In doing so, our study highlights the importance of alliances as channels for searching for new markets. Whereas searches for new technologies have been widely covered in the literature, demand-side searches for new markets have received much less consideration (Sidhu et al., 2007).

Second, we further elaborate and extend the growing body of literature on exploitation–exploration alliances by building on the concept of competence leveraging (Danneels, 2002). Whereas previous studies have typically characterized alliances as a dichotomy between pure explorative and pure exploitative alliances (e.g. Rothermael and Deeds, 2004), we argue that between these two extremes is a hybrid type of alliance, in which firms engage in exploration

in one area (market or technology) while simultaneously exploiting another area (technology or market). As a result, we shed new light on how firms may achieve ambidexterity through alliances. Koza and Lewin (2000) have already observed that hybrid alliances involve upstream as well as downstream value chain functions. However, previous studies have considered knowledge exploration and exploitation as activities pursued simultaneously by both alliance partners. In differentiating between market and technology search alliances, we further refine the concept of hybrid alliances by taking account of the perspectives of both focal firm and alliance partner.

Our findings also contribute to scarce empirical work on the performance implications of exploration and exploitation (Lavie et al., 2011). We show that pure explorative alliances are not associated with increased chances of realizing a liquidity event, whereas pure exploitative alliances are significantly positively related to liquidity events. Because a liquidity event is typically a long-term performance measure for VC-backed firms, this finding seems to be at odds with the notion that exploitation provides returns in the short term while exploration is needed to achieve value creation in the long term (March, 1991). Indeed, previous empirical work indicates that pure explorative alliances contribute to long-term success (e.g., Afuh and Menguc, 2005). However, engaging in pure exploitative alliances provides young firms with opportunities to make more efficient use of their existing knowledge and capabilities (Yamakawa et al., 2011).

Finally, our study advances the literature on academic entrepreneurship by extending understanding of the expertise required to enable VC-backed ASOs to develop sufficiently to reach a liquidity event. While much research on the development of spin-offs has drawn attention to the human and social capital of the founding team internal to the spin-off, our findings extend this research by showing the importance of the external expertise inherent in alliance partners. We also extend the previous research finding that technology possessed by

spin-offs tends to involve quite broad platforms that may be far from the product market (Clarysse et al., 2011). While this research has observed that there may be significant value in spin-offs' technology, we contribute by showing that this alone seems insufficient to attract potential investors (acquirers or public investors). Rather, in order to be "exit ready", VC-backed ASOs seem to need to demonstrate to potential acquirers that there are clear routes to the product market for the technology. Especially ASOs are in need for market search whilst avoiding over-commitment in a certain market (Molner et al., 2019). Market search alliances allow them to do so by economizing on search costs and thus serve as an attractive alternative to approaches previously identified in the literature such as simultaneous experimentation (Andries et al. 2013) and technology broadcasting (Afuah and Tucci,2012). We show that the use of market search alliances indeed positively impacts liquidity events and as such is an important way of dealing with market ambiguity, thereby providing an important addition to this recent conversation on how to deal with market scoping.

5.1 Implications for practice and policy

In addition to these contributions to research, our findings have implications for managers of ASOs. In particular, we show that alliance type matters to VC-backed ASOs' realization of liquidity events. Our findings suggest that these firms should invest primarily in setting up market search rather than technology search alliances. The importance of using alliances to access customer competence specifically addresses Meyer and Utterback's (1995, p. 302) observation that "for technology-based firms, it is more difficult to learn about new markets than it is to learn about new technologies."

Our insights also have implications for TTOs. One of their main concerns is to develop external networks that are likely to be useful to the success of the spin-off ventures they create to commercialize IP from the lab. In particular, our results show that they should be

mindful of which firms might be the most appropriate alliance partners to help them eventually to realize capital gains.

Universities also develop links with VC firms as a source of both investment funds and expertise (Wright et al., 2006). Our findings suggest that universities should consider developing links with VC investors that are able to contribute their networking role to spin-off firms' success. VCs should direct their networking efforts towards market search and pure exploitation alliances.

Our finding regarding the importance of market experience in a spin-off's founding team has policy implications for the creation and development of such teams. While this clearly indicates that TTOs and founders need to foster the inclusion of team members with experience in the spin-off's market sector, it also implies that they need to develop mechanisms to identify and recruit such members, especially if they are to be drawn from outside the university. For example, TTOs' development of links with corporations that may be potential alliance partners may also provide a mechanism for identifying potential team members with market experience in the relevant sector.

The insight that ASOs benefit significantly from forming market search alliances has interesting policy implications. While market experimentation through alliances clearly helps ASOs to find an optimal technology market space and leads to a liquidity event, it could also imply that, after a trade sale, these companies stay rather small. So, on the one hand innovation policies rightfully should stimulate incumbents to set up experiments with ASOs to increase the value of the commercialized research, but on the other hand such experiments might lead to trade sales. If incumbents are then located in a different region or country, the net benefits for the local economy of the policy are limited. Whilst many ASOs aim to commercialize potentially disruptive technologies, most of them have no disruptive innovation strategy in Christensen's terms, i.e. focusing on end users in a niche market and

vertically integrate in that market. Instead, market search alliances with incumbents pay off more on the shorter term, but do not lead to the unicorns policy makers might desire.

5.2 Limitations and further research

Several limitations in our study open up areas for future research. First, we examined our hypotheses in the context of UK-based, VC-backed ASOs. This research design has benefits with respect to reducing environmental and ASO heterogeneity. However, the UK has a mature VC market (George and Nathusius, 2007) and a strong market for corporate control (OECD, 2004), which facilitate M&A activity. Also, ASOs are very diverse, and VC-backed ASOs are only a subset of the broader population. For example, Horta et al. (2015) point to necessity ASOs, while Mustar et al. (2008) identify prospector and lifestyle ASO. Future studies of different types of ventures beyond VC-backed ASOs, and of other countries with different institutional arrangements and VC market development would contribute to the generalizability of our findings. In addition, future studies might also adopt a more nuanced perspective on the performance of VC-backed ASOs. In this study, we employed an economic value-capturing perspective by considering a liquidity event to be successful only when the acquisition price covered the amount of VC invested in the ASO (Arora and Nandkumar, 2011). However, from a societal value-capturing perspective, the acquisition of a VC-backed ASO implies that the technology is transferred to the acquirer and may be developed into future products and services, regardless of the acquisition price. Consequently, “performance” may potentially be ambiguous, depending on whether one adopts an economic or societal perspective on value capture (Powell and Sandholtz, 2012).⁸ Moreover, research has shown that academic founders differ in their emphasis on commercial goals (Huyghe et al., 2016), and prioritizing non-commercial goals causes academic entrepreneurs to resort less to external sources of information (Hahn et al., 2018). While VC

⁸ We thank an anonymous reviewer for pushing our thinking on this point.

backing ensures a focus on commercial goals, more research is needed to understand how the tension between commercial and non-commercial goals affects external collaborations, and in turn the likelihood of liquidity events.

Second, future studies might examine how characteristics of the alliance partner may function as boundary conditions in market and technology search. Factors such as partner reputation may be important for contextualizing the alliance in terms of the likelihood of a liquidity event relationship. For example, working together with a reputable partner may strengthen the positive influence of market search but exacerbate the negative effect of technology search. Indeed, reputable partners may have beneficial access to downstream markets, which will enhance detailed information on customer needs and preferences. However, collaborating with such a partner in order to access technologies may be more complicated. Owing to a greater imbalance in bargaining power when collaborating with a reputed partner, discussions about IP issues may be more prevalent, and the risk of appropriation may be higher. We leave it to future empirical studies to incorporate such characteristics into their research design.

Third, future research might investigate why ASOs engage in technology search alliances even though they are, on average, detrimental to realizing a liquidity event. Previous research in the R&D alliance literature provides some guidance on the potential drivers of technology search alliance activity. For example, they offer the opportunity to pool complementary technological resources and thus expedite solution development (Powell et al., 1996). Furthermore, engaging with incumbent partners for technology search may enable ASOs to gain a foothold in a specific ecosystem (Adner and Kapoor, 2015). Future research might usefully examine when these factors tend to be more closely associated with reducing the likelihood of a liquidity event, and when they may contribute positively towards such an event.

Fourth, future research might explore the dynamics of alliances in more detail using qualitative research designs. While we take a static perspective, alliances are dynamic, since initial motivations and objectives and the structural arrangements under which the alliance partners cooperate may change over time (Mayer and Argyres, 2004). Scholars addressing alliance dynamics might consider employing configurational logic, since both strategy-related and structure-related characteristics of the alliance may change over time (Payne, 2006).⁹

Fifth, future research might also consider exploring the role of innovation brokers in facilitating ASOs' search for market and technology partners. Brokers are intermediaries who enable collaboration between organizations but are not involved in the innovation process (Winch and Courtney, 2007). Specifically, we suggest that future research might explore the role of generalist and specialist brokers in seeking market and technology search partners (Gianiodis et al., 2010).

Notwithstanding these limitations, our study provides novel insights into the role of different types of search alliance in helping VC-backed ASOs to realize a liquidity event. In summary, we hope that our insights will pave the way for more fine-grained analysis of the nature, role, sequencing and configuration of search alliances by ASOs and other high-tech firms.

References

- Adner, R., Kapoor R., 2015. Innovation ecosystems and the pace of substitution: re-examining technology S-curves. *Strateg. Manage. J.* 37 (4), 625–648.
<https://doi.org/10.1002/smj.2363>
- Ambos, T., Birkinshaw, J. 2010. How do new ventures evolve? *Organization Science?* 2(16), p. 1125-1140.

⁹ We thank an anonymous reviewer or pointing this out to us.

- Andries P, Debackere K, Van Looy B. 2013. Simultaneous experimentation as a learning strategy: business model development under uncertainty. *Strateg. Entrep. J.* 7(4): 288–310.
- Afuah, A., Tucci, C.L., 2012. Crowdsourcing as a solution to distant search. *Acad. Manage. Rev.* 37 (3), 355–375. <https://doi.org/10.5465/amr.2010.0146>
- Agarwal, R., Moeen, M. & S. Shah (2017). Athena’s Birth : Triggers ; Actors, and Actions Preceding Industry Inception, *Strateg. Entrep. J.* 11(28), 287-305.
- Aggarwal, V.A., Hsu, D.H., 2014. Entrepreneurial exits and innovation. *Manage. Sci.* 60 (4), 867–887. <https://doi.org/10.1287/mnsc.2013.1801>
- Aghion, P., Festré, A., 2017. Schumpeterian growth theory, Schumpeter, and growth policy design. *J. Evol. Econ.* 27 (1), 25–42. <https://doi.org/10.1007/s00191-016-0465-5>
- Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. *Econometrica* 60 (2), 323–351. <https://doi.org/10.2307/2951599>
- Alvarez, S.A., Barney, J.B., 2001. How entrepreneurial firms can benefit from alliances with large partners. *Acad. Manage. Exec.* 15 (1), 139–148. <https://doi.org/10.5465/AME.2001.4251563>
- Amabile, T.M., 1983. The social psychology of creativity: a componential conceptualization. *J. Pers. Soc. Psychol.* 45 (2), 357–377. <http://dx.doi.org/10.1037/0022-3514.45.2.357>
- Arora, A., Nandkumar A., 2011. Cash-out or flameout! Opportunity cost and entrepreneurial strategy: theory, and evidence from the information security industry. *Manage. Sci.* 57 (10), 1844–1860. <https://doi.org/10.1287/mnsc.1110.1381>
- Afuh, S., Menguc, B., 2005. Balancing exploration and exploitation: the moderating role of competitive intensity. *J. Bus. Res.* 58 (12), 1652–1661. <https://doi.org/10.1016/j.jbusres.2004.11.007>
- Baker, T., Miner, A. S., & Eesley, D. T. 2003. Improvising firms: bricolage, account giving and improvisational competencies in the founding process. *Research policy*, 32(2): 255-276.
- Bonardo, D., Paleari, S., Vismara, S., 2010. The M&A dynamics of European science-based entrepreneurial firms. *J. Technol. Transfer* 35, 141–180. <https://doi.org/10.1007/s10961-009-9109-3>
- Cattaneo, M., Meoli, M., Vismara, S., 2015. Financial regulation and IPOs: evidence from the history of the Italian stock market. *J. Corp. Financ.* 31, 116–131. <https://doi.org/10.1016/j.jcorpfin.2015.02.001>

- Christensen, H.B., Hail, L., Leuz, C., 2013. Mandatory IFRS reporting and changes in enforcement. *J. Account. Econ.* 56 (2-3), 147–177.
<https://doi.org/10.1016/j.jacceco.2013.10.007>
- Clarysse, B., Wright, M., Van de Velde, E., 2011. Entrepreneurial origin, technological knowledge and the growth of spin-off companies. *J. Manage. Stud.* 48 (6), 1420–1442.
<https://doi.org/10.1111/j.1467-6486.2010.00991.x>
- Colombo, M., Meoli, M., Vismara, S., 2019. Signaling in science-based IPOs: the combined effect of affiliation with prestigious universities, underwriters, and venture capitalists. *J. Bus. Venturing* 34 (1), 141–177. [https://doi.org/10.1016/S0883-9026\(02\)00100-3](https://doi.org/10.1016/S0883-9026(02)00100-3)
- Cyert, R.M., March, J.G., 1963. *A Behavioral Theory of the Firm*. Prentice Hall, Englewood Cliffs, NJ.
- Danneels, E., 2002. The dynamics of product innovation and firm competences. *Strateg. Manage. J.* 23 (12), 1095–1121. <https://doi.org/10.1002/smj.275>
- Danneels, E., 2007. The process of technology competence leveraging. *Strateg. Manage. J.* 28 (5), 511–533. <https://doi.org/10.1002/smj.598>
- Danneels, E., 2008. Organizational antecedents of second-order competences. *Strateg. Manage. J.* 28 (4), 519–543. <https://doi.org/10.1002/smj.684>
- De Cock, R., Bruneel, J., Bobelyn, A., 2018. Making the lean start-up method work: the role of prior market knowledge. *J. Small Bus. Manage.* <https://doi.org/10.1111/jsbm.12506>.
- Dunbar, K., 1998. Problem solving. In: Bechtel, W., Graham, G. (Eds.), *A Companion to Cognitive Science*. Blackwell, London 289–298.
- Fern, M.J., Cardinal, L.B., O’Neill, H.M., 2012. The genesis of strategy in new ventures: escaping the constraints of founder and team knowledge. *Strateg. Manage. J.* 33 (4), 427–447. <https://doi.org/10.1002/smj.1944>
- Fiedler, M., Welp, I.M., 2010. Antecedents of cooperative commercialisation strategies of nanotechnology firms. *Res. Policy* 39 (3), 400–410.
<https://doi.org/10.1016/j.respol.2010.01.003>
- Fryges, H., Wright, M., 2014. The origin of spin-offs: a typology of corporate and academic spin-offs. *Small Bus. Econ.* 43 (2), 245–259. <https://doi.org/10.1007/s11187-013-9535-3>
- Gambardella, A., McGahan, A., 2010. Business-model innovation, general purpose technologies, specialization and industry change. *Long Range Plann.* 43 (2-3), 262–271.
<https://doi.org/10.1016/j.lrp.2009.07.009>
- Gans, J., Hsu, D., Stern, S., 2002. When does start-up innovation spur the gale of creative destruction? *Rand J. Econ.* 33, 571–586. <https://doi.org/10.2307/3087475>

- George, G., Nathusius, E., 2007. European venture capital market: scaling beyond current boundaries. Research Collection, Lee Kong Chian School of Business, Singapore Management University.
- Gianiodis, P.T., Ellis, S.C., Secchi, E., 2010. Advancing a typology of open innovation. *Int. J. Innov. Manage.* 14 (4), 531–572. https://doi.org/10.1142/9781783262816_0003
- Greene, W.H., 2012. *Econometric Analysis*, 7th ed. Prentice Hall, Upper Saddle River, NJ.
- Grégoire, D., Barr, P., Shepherd, D., 2010. Cognitive processes of opportunity recognition: the role of structural alignment. *Organ. Sci.* 21 (2), 413–431. <https://doi.org/10.1287/orsc.1090.0462>
- Gruber, M., MacMillan, I.C., Thompson, J.D., 2008. Look before you leap: market opportunity identification in emerging technology firms. *Manage. Sci.* 54 (9), 1652–1665. <https://doi.org/10.1287/mnsc.1080.0877>
- Gruber, M., MacMillan, I.C., Thompson, J.D., 2013. Escaping the prior knowledge corridor: what shapes the number and variety of market opportunities identified before market entry of technology start-ups? *Organ. Sci.* 24 (1), 280–300. <https://doi.org/10.2307/23362113>
- Gulati, R. 1998. Alliances and networks. *Strateg. Manage. J.*, 19 (4), 293-317
- Hahn, D., Minola, T., Eddleston, K., 2018. How do scientists contribute to the performance of innovative startups? An imprinting perspective on open innovation. *J. Manage. Stud.* 56 (5), 895–928. <https://doi.org/10.1111/joms.12418>
- Hayek, F.A., 1945. The use of knowledge in society. *Am. Econ. Rev.* 35 (4), 519–530.
- Heckman, J., 1979. Sample selection bias as a specification error. *Econometrica* 47 (1), 153–161. <https://doi.org/10.2307/1912352>
- Hoehn-Weiss, M.N., Karim, S., 2014. Unpacking functional alliance portfolios: how signals of viability affect young firms' outcomes. *Strateg. Manage. J.* 35 (9), 1364–1385. <https://doi.org/10.1002/smj.2158>
- Horta, H., Meoli, M., Vismara, S., 2015. Skilled unemployment and the creation of academic spin-offs: a recession-push hypothesis. *J. Technol. Transfer* 41 (4), 798–817. <https://doi.org/10.1007/s10961-015-9405-z>
- Hsu, D., Ziedonis, R., 2013. Resources as dual sources of advantage: implications for valuing entrepreneurial-firm patents. *Strateg. Manage. J.* 34 (7), 761–781. <https://doi.org/10.1002/smj.2037>

- Huyghe, A., Knockaert, M., Obschonka, M. 2016. Unraveling the “passion orchestra” in academia. *J. Bus. Venturing* 31 (3), 344–364.
<https://doi.org/10.1016/j.jbusvent.2016.03.002>
- Jeppesen, L.B, Lakhani, K.R., 2010. Marginality and problem solving effectiveness in broadcast search. *Organ. Sci.* 21 (5), 1016–1033. <https://doi.org/10.1287/orsc.1090.0491>
- Kapoor, R., Adner, R., 2012. What firms make vs. what they know: how firms’ production and knowledge boundaries affect competitive advantage in the face of technological change. *Organ. Sci.* 23 (5), 1227–1248. <https://doi.org/10.1287/orsc.1110.0686>
- Katila, R., 2005. Innovative product portfolios by navigating markets and technology. Working paper, Stanford University, Stanford, CA.
- Knight, F.H., 1921. *Risk Uncertainty and Profit*. Martino Fine Books, Eastford, CT.
- Kortum, S., Lerner, J., 2000. Assessing the contribution of venture capital to innovation. *Rand J. Econ.* 31 (4), 674–692. <https://doi.org/10.2307/2696354>
- Koza, M.P., Lewin, A.Y., 2000. Managing partnerships and strategic alliances: raising the odds of success. *Eur. Manag. J.* 18 (2), 146–151. [https://doi.org/10.1016/S0263-2373\(99\)00086-9](https://doi.org/10.1016/S0263-2373(99)00086-9)
- Lavie, D., 2007. Alliance portfolios and firm performance: a study of value creation and appropriation in the US software industry. *Strateg. Manage. J.* 28 (12), 1187–1212.
<https://doi.org/10.1002/smj.637>
- Lavie, D., Kang, J., Rosenkopf, L., 2011. Balance within and across domains: the performance implications of exploration and exploitation in alliances. *Organ. Sci.* 22 (6), 1517–1538. <https://doi.org/10.1287/orsc.1100.0596>
- Lockett, A., Wright, M., 2005. Resources, capabilities, risk capital and the creation of university spin-out companies. *Res. Policy* 34 (7), 1043–1057.
<https://doi.org/10.1016/j.respol.2005.05.006>
- Lockett, A., Wright, M., Wild, A. 2014. The institutionalization of third stream activities in UK higher education: the role of discourse and metrics. *Brit. J. Manage.* 26 (1), 78–92.
<https://doi.org/10.1111/1467-8551.12069>
- Mankins, John C. (1995), "Technology Readiness Levels," National Aeronautics and Space Administration (NASA) (Ed.).
- March, J.G., 1991. Exploration and exploitation in organizational learning. *Organ. Sci.* 2 (1), 71–87. <http://dx.doi.org/10.1287/orsc.2.1.71>
- Mayer, K.J., Argyres, N.S., 2004. Learning to contract: evidence from the personal computer industry. *Organ. Sci.* 15 (4), 394–410. <https://doi.org/10.1287/orsc.1040.0074>

- McGrath, R.G., 2010. Business models: a discovery driven approach. *Long Range Plann.* 43 (2-3), 247–261. <https://doi.org/10.1016/j.lrp.2009.07.005>
- McGrath, R.G., MacMillan, I.C., 1995. Discovery driven planning. *Harvard Bus. Rev.* 73, 44–54.
- McGrath, R.G., MacMillan, I., 2000. *The Entrepreneurial Mindset: Strategies for Continuously Creating Opportunity in an Age of Uncertainty.* Harvard Business School Press, Boston, MA.
- Meoli, M., Paleari, S., Vismara, S., 2013. Completing the technology transfer process: M&As of science-based IPOs. *Small Bus. Econ.* 40 (2), 227–248. <https://doi.org/10.1007/s11187-012-9416-1>
- Meyer, M.H., Utterback, J.M., 1995. Product development cycle time and commercial success. *IEEE T. Eng. Manage.* 42 (4), 297–304. <https://doi.org/10.1109/17.482080>
- Moeen, M., 2017. Entry into nascent industries: disentangling a firm’s capability portfolio at the time of investment versus market entry. *Strateg. Manage. J.* 38 (10), 1986–2004. <https://doi.org/10.1002/smj.2642>
- Moeen, M., Agarwal, R., 2017. Incubation of an industry: heterogeneous knowledge bases and modes of value capture. *Strateg. Manage. J.* 38 (3), 566–587. <https://doi.org/10.1002/smj.2511>
- Molner, S., Prabhu, J.C. & M.S. Yadav. 2019. Lost in a Universe of Markets: Toward a Theory of Market Scoping for Early Stage Technologies, *Marketing Science*, 83(2): 37-61.
- Mosey, S., Wright, M., 2007. From human capital to social capital: a longitudinal study of technology-based academic entrepreneurs. *Entrep. Theory Pract.* 31 (6), 909–936. <https://doi.org/10.1111/j.1540-6520.2007.00203.x>
- Mustar, P., Eyquem, M., Colombo, M.G., Piva, E., 2006. Conceptualising the heterogeneity of research-based spin-offs: a multi-dimensional taxonomy, *Res. Policy* 35 (2), 289–308. <https://doi.org/10.1016/j.respol.2005.11.001>
- Mustar, P., Wright, M., Clarysse, B., 2008. University spin-off firms: lessons from ten years of experience in Europe. *Sci. Publ. Policy* 35 (2), 67–80. <https://doi.org/10.3152/030234208X282862>
- Nahata, R., 2008. Venture capital reputation and investment performance. *J. Financ. Econ.* 90 (2), 127–151. <https://doi.org/10.1016/j.jfineco.2007.11.008>
- Nelson, R.R., Winter, S.G., 1982. *An evolutionary theory of economic exchange.* Harvard University Press

- Nerkar, A., Roberts, P.W., 2004. Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. *Strateg. Manage. J.* 25 (8-9), 779–799. <https://doi.org/10.1002/smj.417>
- OECD, 2004. *The Theory of the Market for Corporate Control and the Current State of the Market for Corporate Control in China*. OECD, Paris.
- Payne, G.T., 2006. Examining configurations and firm performance in a suboptimal equifinality context. *Organ. Sci.* 17 (6), 756–770. <https://doi.org/10.1287/orsc.1060.0203>
- Porrini, P., 2004. Can a previous alliance between an acquirer and a target affect acquisition performance? *J. Manage.* 30 (4), 545–562. <https://doi.org/10.1016/j.jm.2004.02.003>
- Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. *Admin. Sci. Quart.* 41 (1), 116–145. <https://doi.org/10.2307/2393988>
- Powell, W.W., Sandholtz, K., 2012. Amphibious entrepreneurs and the emergence of organizational forms. *Strateg. Entrep. J.* 6 (2), 94–115. <https://doi.org/10.1002/sej.1129>
- Ransbotham, S., Mitra, S., 2010. Target age and the acquisition of innovation in high-technology industries. *Manage. Sci.* 56 (11), 2076–2093. <https://doi.org/10.1287/mnsc.1100.1223>
- Rasmussen, E., Mosey, S., Wright, M., 2011. The evolution of entrepreneurial competencies: a longitudinal study of university spin-off venture emergence. *J. Manage. Stud.* 48 (6), 1314–1345. <https://doi.org/10.1111/j.1467-6486.2010.00995.x>
- Rasmussen, E., Mosey, S., Wright, M., 2016. The transformation of network ties to develop entrepreneurial competencies for university spin-offs. *Entrep. Region. Dev.* 27 (7-8), 430–457. <https://doi.org/10.1080/08985626.2015.1070536>
- Reuer, J.J., Tong, T.W., Wu, C-W., 2012. A signaling theory of acquisition premiums: evidence from IPO targets. *Acad. Manage. J.* 55 (3), 667–683. <https://doi.org/10.5465/amj.2010.0259>
- Rothaermel, F.T., Deeds, D.L., 2004. Exploration and exploitation alliances in biotechnology: a system of new product development. *Strateg. Manage. J.* 25 (3), 201–221. <https://doi.org/10.1002/smj.376>
- Schoonhoven, C.B., Eisenhardt, K.M., Lyman, K., 1990. Speeding products to markets: waiting time to first product introductions in new firms. *Admin. Sci. Quart.* 35 (1), 177–207.
- Shane, S.A., 2000. Prior knowledge and the discovery of entrepreneurial opportunities. *Organ. Sci.* 11 (4), 448–469. <https://doi.org/10.1287/orsc.11.4.448.14602>

- Sidhu, J., Commandeur, H., Volberda, H., 2007. The multifaceted nature of exploration and exploitation: value of supply, demand and spatial search for innovation. *Organ. Sci.* 18 (1), 20–38. <https://doi.org/10.1287/orsc.1060.0212>
- Simon, H.A., 1973. The structure of ill structured problems. *Artif. Intell.* 4 (3-4), 181–201. [https://doi.org/10.1016/0004-3702\(73\)90011-8](https://doi.org/10.1016/0004-3702(73)90011-8)
- Vanaelst, I., Clarysse, B., Wright, M., Lockett, A., Moray, N., S’Jegers, R., 2006. Entrepreneurial team development in academic spin-outs: an examination of team heterogeneity. *Entrep. Theory Pract.* 30 (2), 249–272. <https://doi.org/10.1111/j.1540-6520.2006.00120.x>
- Vohora, A., Wright, M., Lockett, A. 2004. Critical junctures in spin-outs from universities. *Res. Policy* 33, 147–175. [https://doi.org/10.1016/S0048-7333\(03\)00107-0](https://doi.org/10.1016/S0048-7333(03)00107-0)
- Von Zedtwitz, M., Gassmann, O., 2002. Market versus technology drive in R&D internationalization: four different patterns of managing research and development. *Res. Policy* 31 (4), 569–588. [https://doi.org/10.1016/S0048-7333\(01\)00125-1](https://doi.org/10.1016/S0048-7333(01)00125-1)
- Winch, G.M., Courtney, R. 2007. The organization of innovation brokers: an international review. *Technol. Anal. Strateg.* 19 (6), 747–763. <https://doi.org/10.1080/09537320701711223>
- Wright, M., Clarysse, B., Mustar, P. & Lockett, A. 2007. *Academic Entrepreneurship in Europe*. Edward Elgar Publishers.
- Wright, M., Clarysse, B., Lockett, A., Knockaert M., 2008. Mid-range universities’ linkages with industry: knowledge types and the role of intermediaries. *Res. Policy* 37 (8), 1205–1223. <https://doi.org/10.1016/j.respol.2008.04.021>
- Wright, M.; Clarysse, B. 2020. Guidepost: Technology Entrepreneurship and Shaping Industries, *forthcoming Academy of Management Discoveries*, <https://doi.org/10.5465/amd.2019.0120>
- Wright, M., Fu, K., 2017. University spin-outs in the UK. In: Fini, R., Grimaldi, R. (Eds.), *Process Approach to Academic Entrepreneurship: Evidence from the Globe*. World Scientific, Singapore 165–186.
- Wright, M., Lockett, A., Clarysse, B., Binks, M., 2006. University spin-offs and venture capital. *Res. Policy* 35 (4), 481–501. <https://doi.org/10.1016/j.respol.2006.01.005>

- Wry T, Lounsbury M, Jennings PD (2014) Hybrid vigor: Securing venture capital by spanning categories in nanotechnology. *Academy of Management Journal*, 57(5): 1309–1333.
- Yamakawa, Y., Yang, H., Lin, Z.J., 2011. Exploration versus exploitation in alliance portfolio: performance implications of organizational, strategic, and environmental fit. *Res. Policy* 40 (2), 287–296. <https://doi.org/10.1016/j.respol.2010.10.006>
- Zahra, S.A., Van de Velde, E., Larraneta, B., 2007. Knowledge conversion capability and the performance of corporate and university spin-offs. *Ind. Corp. Change* 16 (4), 569–608. <https://doi.org/10.1093/icc/dtm018>
- Zhang, Y., Li, H., 2010. Innovation search of new ventures in a technology cluster: the role of ties with service intermediaries. *Strateg. Manage. J.* 31 (1), 88–109. <https://doi.org/10.1002/smj.806>
- Zhang, J., 2009. The performance of university spin-offs: an exploratory analysis using venture capital data. *J. Technol. Transfer* 34 (3), 255–285. <https://doi.org/10.1007/s10961-008-9088-9>

Tables

Table 1: Descriptive statistics and correlations (N = 157)

| | Mean | S.D. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | |
|--------------------------------|-------|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|--|
| Success exit | 0.25 | 0.43 | | | | | | | | | | | | | | | | | |
| Age | 9.28 | 3.47 | -0.23 | | | | | | | | | | | | | | | | |
| ICT dummy | 0.24 | 0.43 | -0.08 | 0.02 | | | | | | | | | | | | | | | |
| Biotech dummy | 0.55 | 0.5 | 0.10 | 0.10 | -0.63 | | | | | | | | | | | | | | |
| Pre-financial crisis | 0.14 | 0.35 | 0.57 | -0.38 | 0.07 | -0.01 | | | | | | | | | | | | | |
| VC rounds | 3.31 | 2.91 | 0.08 | 0.22 | 0.12 | -0.06 | 0.14 | | | | | | | | | | | | |
| Patents at founding | 10.55 | 18.19 | 0.00 | 0.06 | -0.07 | 0.03 | -0.02 | 0.28 | | | | | | | | | | | |
| University spin-off experience | 13.26 | 111.37 | -0.24 | -0.40 | -0.08 | -0.12 | -0.23 | 0.00 | 0.14 | | | | | | | | | | |
| University ranking | 98.36 | 13.76 | -0.23 | 0.00 | 0.11 | -0.13 | -0.16 | -0.26 | -0.22 | -0.27 | | | | | | | | | |
| Prominent VC | 0.58 | 0.48 | -0.02 | 0.05 | 0.09 | -0.19 | 0.08 | 0.29 | -0.03 | -0.11 | 0.08 | | | | | | | | |
| Prominent partners | 0.46 | 0.45 | 0.14 | 0.11 | 0.01 | 0.07 | 0.14 | 0.05 | 0.03 | -0.13 | -0.17 | 0.02 | | | | | | | |
| Pure explorative alliances | 0.33 | 0.50 | -0.12 | 0.07 | -0.04 | 0.08 | -0.07 | 0.08 | 0.15 | -0.01 | 0.07 | 0.03 | -0.09 | | | | | | |
| Pure exploitative alliances | 0.76 | 0.50 | 0.12 | 0.00 | 0.22 | -0.20 | 0.02 | 0.03 | 0.07 | -0.04 | 0.01 | 0.13 | 0.22 | -0.07 | | | | | |
| Technological experience | 0.71 | 0.66 | -0.06 | 0.02 | -0.17 | 0.03 | 0.01 | -0.02 | 0.04 | 0.03 | -0.15 | 0.00 | 0.00 | -0.08 | -0.20 | | | | |
| Market experience | 0.35 | 1.64 | 0.01 | -0.13 | 0.02 | -0.01 | 0.01 | 0.07 | 0.00 | 0.11 | 0.11 | 0.00 | -0.12 | 0.02 | 0.07 | -0.60 | | | |
| Market search alliances | 1.03 | 1.51 | 0.15 | 0.17 | 0.01 | 0.09 | 0.05 | 0.21 | 0.18 | -0.03 | -0.20 | -0.10 | 0.34 | -0.04 | 0.15 | 0.01 | -0.03 | | |
| Technology search alliances | 1.04 | 1.61 | 0.03 | 0.08 | 0.06 | 0.04 | 0.10 | 0.30 | 0.20 | 0.05 | -0.38 | 0.00 | 0.28 | -0.08 | 0.07 | -0.01 | 0.04 | 0.24 | |

Note: Correlations of 0.16 or higher are significant at $p \leq 0.05$, two-tailed tests.

Table 2: Descriptive statistics by exit type (N = 157)

| | Active companies | | Successful exit | | Failures | |
|--------------------------------|------------------|--------|-----------------|-------|----------|-------|
| | N = 96 | | N = 39 | | N = 22 | |
| Age | 9.75 | 3.33 | 7.90 | 3.55 | 9.68 | 3.41 |
| ICT dummy | 0.26 | 0.44 | 0.18 | 0.39 | 0.27 | 0.46 |
| Biotech dummy | 0.51 | 0.50 | 0.64 | 0.49 | 0.59 | 0.50 |
| Pre-financial crisis | 0.00 | 0.00 | 0.49 | 0.51 | 0.14 | 0.35 |
| VC rounds | 3.08 | 2.65 | 3.92 | 3.41 | 3.18 | 3.03 |
| Patents at founding | 10.19 | 16.71 | 13.49 | 24.48 | 6.95 | 8.95 |
| University ranking | 121.71 | 123.02 | 54.54 | 74.69 | 74.14 | 83.10 |
| University spin-off experience | 16.09 | 14.99 | 7.62 | 8.91 | 10.91 | 12.04 |
| Prominent VC | 0.57 | 0.50 | 0.56 | 0.50 | 0.63 | 0.49 |
| Prominent partners | 0.40 | 0.49 | 0.59 | 0.49 | 0.55 | 0.51 |
| Pure explorative alliances | 0.39 | 0.75 | 0.21 | 0.47 | 0.32 | 0.57 |
| Pure exploitative alliances | 0.64 | 1.40 | 1.15 | 2.24 | 0.64 | 1.26 |
| Technological experience | 0.73 | 0.45 | 0.67 | 0.48 | 0.73 | 0.46 |
| Market experience | 0.36 | 0.48 | 0.36 | 0.49 | 0.27 | 0.46 |
| Market search alliances | 0.97 | 1.46 | 1.38 | 1.82 | 0.64 | 1.00 |
| Technology search alliances | 0.92 | 1.66 | 1.00 | 1.40 | 1.64 | 1.71 |

Table 3: Competing risks analyses (N = 157)

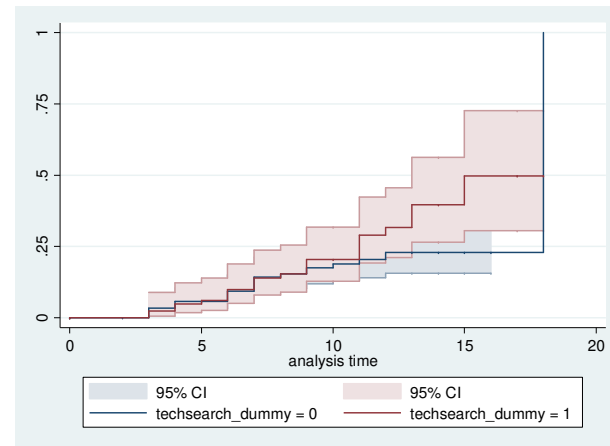
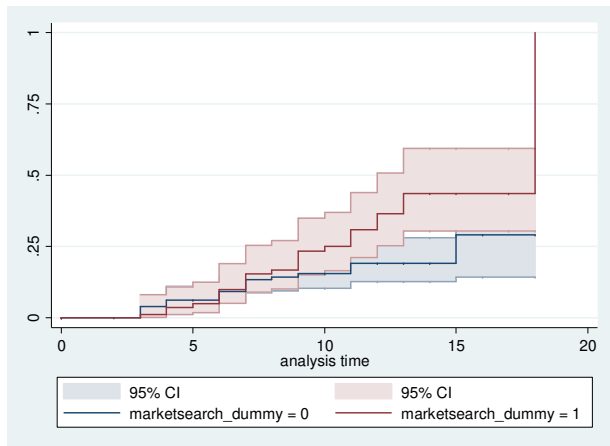
| | Model 1 | | | Model 2 | | | Model 3 | | | Model 4 | | |
|--|---------|--------|----|---------|--------|-----|---------|--------|-----|---------|--------|-----|
| Age | -0.37 | (0.12) | ** | -0.43 | (0.12) | *** | -0.45 | (0.12) | *** | -0.46 | (0.12) | *** |
| ICT dummy | -1.84 | (0.59) | ** | -1.60 | (0.65) | * | -1.73 | (0.69) | * | -1.74 | (0.69) | * |
| Biotech dummy | -0.54 | (0.51) | | -0.14 | (0.58) | | -0.19 | (0.60) | | -0.16 | (0.59) | |
| Pre-financial crisis | 1.23 | (0.72) | | 1.18 | (0.68) | | 1.46 | (0.81) | | 1.36 | (0.71) | |
| VC rounds | -0.10 | (0.31) | | -0.20 | (0.34) | | -0.08 | (0.36) | | -0.04 | (0.34) | |
| Patents at founding | 0.01 | (0.07) | | -0.02 | (0.09) | | -0.04 | (0.09) | | -0.06 | (0.09) | |
| University spin-off experience | -0.05 | (0.02) | * | -0.06 | (0.02) | ** | -0.06 | (0.02) | ** | -0.07 | (0.02) | ** |
| University ranking | -0.01 | (0.00) | ** | -0.01 | (0.00) | *** | -0.01 | (0.00) | ** | -0.01 | (0.00) | ** |
| Inverse Mills ratio | -0.45 | (1.01) | | -0.63 | (1.01) | | -0.20 | (0.94) | | -0.21 | (0.95) | |
| Prominent Partner | -0.12 | (0.38) | | -0.10 | (0.38) | | -0.23 | (0.38) | | -0.25 | (0.38) | |
| Prominent VC | -0.72 | (0.39) | | -0.62 | (0.40) | | -0.63 | (0.40) | | -0.64 | (0.40) | |
| Number of founders | -0.02 | (0.21) | | 0.09 | (0.22) | | 0.11 | (0.23) | | 0.10 | (0.21) | |
| Market experience | 0.05 | (0.56) | | 0.18 | (0.61) | | 0.44 | (0.60) | | 0.44 | (0.60) | |
| Technological experience | -0.79 | (0.56) | | -0.51 | (0.56) | | -0.61 | (0.53) | | -0.65 | (0.52) | |
| Pure explorative alliances | 0.02 | (0.20) | | -0.12 | (0.17) | | -0.10 | (0.15) | | -0.10 | (0.16) | |
| Pure exploitative alliances | 0.30 | (0.11) | ** | 0.31 | (0.12) | ** | 0.28 | (0.12) | * | 0.27 | (0.12) | * |
| Market search alliances | | | | 0.23 | (0.13) | * | 0.19 | (0.21) | | 0.29 | (0.12) | ** |
| Technology search alliances | | | | -0.39 | (0.15) | ** | -0.62 | (0.19) | *** | | | |
| Technology experience X Market search alliances | | | | | | | 0.15 | (0.28) | | | | |
| Market experience X Technology search alliances | | | | | | | 0.57 | (0.27) | * | | | |
| Low market experience X Technology search alliances | | | | | | | | | | -0.60 | (0.17) | *** |
| High market experience X Technology search alliances | | | | | | | | | | -0.04 | (0.21) | |
| Log pseudolikelihood | -132.85 | | | -128.33 | | | -126.29 | | | -126.43 | | |
| Wald chi square | 129.50 | | | 164.70 | | | 165.28 | | | 163.22 | | |
| Prob > Chi square | 0.00 | | | 0.00 | | | 0.00 | | | 0.00 | | |

Notes: Robust standard errors (standard degree-of-freedom adjustment); *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.05$, one-tailed significances for hypothesized relations and two-tailed tests for control variable effects.

Figure 1: Stylized categorization of alliances and technology-market linking

| | | Technology competence | |
|-------------------|----------|---------------------------------|---------------------------------|
| | | Existing | New |
| Market competence | Existing | (1): Pure exploitative alliance | (2): Technology search alliance |
| | New | (3): Market search alliance | (4): Pure explorative alliance |

Figure 2a, 2b: Kaplan-Meier exit function estimates by market search alliance dummy (2a) and by technology search alliance dummy (2b)



Appendices

Appendix 1.1. Illustrative examples of the different alliance types

| Alliance type | Example |
|----------------------------|---|
| Pure explorative alliance | <p>In 2006 E-Therapeutics set up a partnership with Brazilian company, Grupo TCI to establish a joint research facility to explore the potential therapeutic use of natural substances found in the Amazonian and Atlantic rain forests in Brazil. This partnership was clearly purely explorative, as both the potential drug candidates and the markets were unknown at the start of the partnership. The partnership was described in <i>Drug Week</i> via NewsRx.com (24/11/2006) as follows:</p> <p><i>At a time when the number of new drugs in the world's development pipeline has dwindled, the British company e-Therapeutics has formed a partnership with Brazilian company Grupo TCI to establish a joint research facility close to the Amazonian and Atlantic rain forests, to start testing substances from the millions of plants in the most diverse ecosystem on the planet.</i></p> |
| Market search alliance | <p>TeraView, a spin-off from the University of Cambridge, developed a technology platform for use in its chemical agent detection systems. In 2008, the company entered into an agreement with Goodrich to supply the products resulting from its technology platform to the US security market. The company stated that it expected “to evolve with its terahertz platform for use in product solutions outside of its core pharmaceutical market”. This statement indicates that this alliance enabled TeraView to explore a new market (the security market) by exploiting its existing technology. (Terror Response Technology Report, November 12, 2008.)</p> |
| Technology search alliance | <p>For instance, Acrobot, emanating from Imperial College London, entered into a deal with Alliance Medical in 2008. Both parties worked together to improve orthopedic surgery by offering an integrated process from CT scanning through to surgical navigation. The alliance</p> |

| | |
|-----------------------------------|--|
| | <p>thus combined technology from Acrobot with Alliance Medical’s advanced imaging techniques to better serve an existing market of Acrobot. The press commented on the partnership as follows:</p> <p><i>“Acrobot, a medical devices company specializing in computer assisted orthopedic surgical navigation, and Alliance Medical, part of the largest pan-European medical imaging company in Europe, supporting more than 400 hospitals and clinics in the UK, yesterday (1 December) announced they have entered into a partnership which will help improve surgical outcomes through the provision of advanced imaging techniques. The deal will see Acrobot and Alliance Medical collaborate to provide orthopedic surgeons with an integrated process from CT scanning through to navigated joint replacement that can influence clinical outcomes, making life easier for the surgeon and better for the patient.”</i></p> <p>(M2 Europharma, December 12, 2008.)</p> |
| <p>Pure exploitation alliance</p> | <p>Activiomics engaged in a strategic alliance with BioFocus. Commenting on the partnership, Activiomics’ CEO said: <i>“We are looking forward to making our platform even more widely available through exposure to BioFocus’s large and growing client base.”</i> As this partnership merely enlarged the ASO’s presence in an existing market, it was coded as a pure exploitation alliance.</p> <p>(“BioFocus Expands its Drug Discovery Offering with Proteomics Technology from Activiomics”, Business Wire, July 25, 2012.)</p> |
| <p>Example of ASO with all</p> | <p>A company called Paraytec exhibited all four alliance types, thus illustrating the differences between the various alliance types. Founded</p> |

| | |
|----------------|---|
| four alliances | <p>in 2005, it was active in medical imaging and originated from the University of York. The company aimed to extend the use of UV absorbance detection to a range of new biological and pharmaceutical imaging applications. In 2006, the company launched its first product, the ActiPix™ D100 UV Area Imaging Detector, targeting the pharmaceutical and biopharmaceutical market. In 2007, the company entered into an alliance with the University of Bradford to try to find a way to stop molecules from sticking together in pharmaceutical products. We classified this alliance as a pure explorative alliance, as both the technological solution and related market opportunities were unknown at the start of the collaboration. A year later, in 2008, Paraytek received a grant and entered into a collaboration with a number of parties to develop an instrument to monitor and quantify aggregation during biopharmaceutical processing. This time the objective was to develop an instrument that served a market that was already being served, i.e. biopharmaceutical companies, so it was coded as a technology search alliance. In 2011, Paraytek signed a distribution agreement with Distek regarding its ActiPix SDI300 system. As this agreement involved exploiting existing technology in a market that was already being served, it was classified as a pure exploitative alliance. Later in 2011, Paraytec signed a development and licensing agreement with Malvern Instruments. Central to the agreement was the ActiPix technology, which would be further developed, marketed and sold by Malvern, targeting not only biopharmaceutical applications (Paraytec's existing market), but also the food and personal care sectors. As these</p> |
|----------------|---|

| | |
|--|---|
| | markets were new to the ASO, we coded this as a market search alliance. |
|--|---|

Appendix 1.2: Descriptive statistics and correlations for full sample (N = 265)

| | | Mean | S.D. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|-----|-----------------------------------|----------------|----------------|-------|-------|-------|------|-------|-------|-------|-------|------|
| 1. | Partnership probability | 0.60 | 0.49 | | | | | | | | | |
| 2. | Exit probability | 0.19 | 0.39 | 0.19 | | | | | | | | |
| 3. | Failure probability | 0.19 | 0.39 | -0.15 | -0.24 | | | | | | | |
| 4. | University spin-off experience | 15.05 109.9 | 15.74 117.2 | -0.15 | -0.21 | -0.06 | | | | | | |
| 5. | University ranking | 4 | 4 | -0.13 | -0.18 | 0.04 | 0.32 | | | | | |
| 6. | Patents at founding | 0.91 | 2.00 | 0.01 | 0.17 | -0.05 | 0.0 | -0.15 | | | | |
| 7. | Number of founders | 2.04 | 0.98 | 0.01 | 0.02 | -0.10 | 0.1 | -0.06 | 0.14 | | | |
| 8. | Faculty founder | 0.59 | 0.49 | 0.16 | 0.06 | -0.09 | 0.10 | -0.07 | 0.01 | 0.13 | | |
| 9. | ICT dummy | 0.28 | 0.45 | -0.10 | -0.09 | 0.13 | 0.09 | 0.23 | -0.09 | -0.04 | -0.19 | |
| 10. | Biotech dummy | 0.52 | 0.50 | 0.06 | 0.12 | -0.04 | 0.08 | -0.24 | 0.05 | -0.04 | 0.08 | 0.65 |

Note: Correlations of 0.13 or higher are significant at $p < 0.05$, two-tailed tests.

Appendix 1.3: Probit regression results (N = 265)

| Probit partnership likelihood | | | |
|--------------------------------------|--------------|-----------|-----|
| | Coeff | SE | |
| University spin-off experience | -0.018 | 0.006 | *** |
| University ranking | -0.002 | 0.001 | *** |
| Patents at founding | -0.016 | 0.040 | |
| Number of founders | 0.027 | 0.086 | |
| Faculty founder | 0.366 | 0.166 | ** |
| ICT | -0.271 | 0.244 | |
| Biotech | -0.169 | 0.220 | |
| Constant | 0.666 | 0.325 | * |
| Log Likelihood | | - | |
| R ² | | 167.360 | |
| | | 0.064 | |

Notes: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$, one-tailed significances for hypothesized relations and two-tailed tests for control variable effects.