Knowledge resources, spinouts and exit through acquisition

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ABSTRACT

Research suggests that successful acquisitions begin with the selection of the 'right' target firm. Our study offers new insights for the literature on acquisitions by focusing on spinouts as a unique subset of target firms. Spinouts have increasingly been identified as attractive targets for acquisitions in high technology industries where the pace of innovation and new product development often involves large and highly uncertain investments. Spinouts are recognized for their unique resources that distinguish them from established firms and other new entrants into industries. This study adopts a resource perspective to examine the impact of the knowledge heritage and product strategies of spinouts from different knowledge contexts on the their potential to be acquired by firms in both the focal industry and downstream industries. Overall, our findings support our proposition that the knowledge heritage of spinout ventures represents an important resource that affects evaluations concerning acquisitions.

KEYWORDS: acquisitions, knowledge heritage, spinouts

1. INTRODUCTION

Acquisitions represent key elements in the technology strategies of firms in many sectors. Established firms may use acquisitions to obtain valuable resources, enhance market power, or reconfigure the strategic direction of their operations (Agarwal and Helfat, 2009; Graebner *et al*., 2010). Such acquisitions are not always targeted at large and established companies. Rather, in many high technology industries, firms may use the acquisition of new, entrepreneurial ventures as a complement to internal innovation (Dierickx and Cool, 1989). Small and dynamic start-ups are often better equipped than established firms to follow rapid and frequent changes in technology and to introduce truly novel innovations. One study of the semiconductor industry, for example, found that almost one in five of the start-ups that entered the industry between 1997 and 2007 was acquired by established firms by 2009 (Adams et al., 2016).

The extant literature on acquisitions provides important insights into the factors that may influence both the potential for an acquisition to occur and the potential for an acquisition to improve the innovation performance of the buyer firm post-acquisition (Ahuja and Katila, 2001; Yu *et al*., 2015; Sears and Hoetker, 2013; Kapoor and Lim, 2007; Karim and Mitchell, 2000; Kaul and Wu, 2016). At the root of this research is the question of the optimum balance between the resources of target and buyer firm. Much of the scholarship in this field, in fact, examines overlap in technological knowledge in terms of patent histories, patent numbers and patent citations to explain acquisition choices. Other studies examine the balance between the resources of acquirer and target firm in terms of the degree of similarity or complementarity with respect to product lines, R&D projects or production capabilities. In this study, we propose that, while such analyses may be appropriate for acquisitions regarding established firms, they may be less appropriate for examining acquisitions related to new ventures. Many new ventures start life without patents and may remain without proprietary technology for years. Similarly, new ventures tend to enter industries with small budgets for research and with narrow product lines that may not fully characterize their knowledge resources. Analyzing patents, research capabilities and product lines, therefore, may not provide a full picture of the resource attributes of new ventures or of how their resources may differ from those of established firms. Such analyses may therefore leave us without a clear understanding of how the specific characteristics of new entrants influence the choice of acquisition targets.

Our study seeks to address this gap by focusing on the acquisitions of spinouts as a specific form of new venture. We draw on the literature on entrepreneurship, industry dynamics and the 'resource-based' view of the firm to propose that the initial knowledge endowments of spinouts influence their potential value to buyer firms. Extant studies on spinouts suggest, in fact, that the knowledge context from which spinouts originate provide them with informational advantages that serve as a source of innovation and firm survival (Agarwal and Shah, 2014). We argue that these same advantages also influence their potential to be acquired. We distinguish between two types of spinouts based on the pre-entry industry experience of the founders: focal spinouts that enter the same industry in which the founders were previously employed and user-industry spinouts that enter the focal industry from a downstream industry (Helfat and Lieberman, 2002; Klepper, 2009; Adams *et al*., 2016). We then develop and test a set of hypotheses regarding how differences across the knowledge resources of these spinouts affect their attractiveness to different types of buyers in the context of the semiconductor industry between 1997 and 2014.

We find confirmation for our hypotheses that spinouts that originate from distinct knowledge contexts have a different potential to be acquired by buyers. Focal spinouts have a higher potential to be acquired by a wider range of buyer firms than user-industry spinouts.

These findings suggest that knowledge heritage clearly makes a difference in terms of the acquisition potential of different types of spinouts. Our results also suggest that, while user-industry spinouts may enter the focal industry, their value as potential acquisition targets remain linked to their pre-entry experience in a downstream industry and their ability to produce market specific products, rather than to the resources gained as a result of their newly acquired experience in the focal industry.

Our work contributes to the literature on technology acquisitions by narrowing the lens of analysis to focus specifically on the acquisitions of new entrepreneurial ventures. This shift in focus allows us to build on previous studies concerning the influence of knowledge resources on acquisition choice by exploring the effect of pre-entry experience and initial knowledge endowments on such decisions. Further, this study extends the literature on industry dynamics and the 'resource-based' view of the firm by suggesting that the organizational capabilities and resources that precede and precipitate entry by new ventures affect not only their survival in an industry (Helfat and Lieberman, 2002), but also their ability to exit through acquisition.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

2.1. Acquisitions and Knowledge Resources

Acquisitions represent a means to assimilate the knowledge and capabilities of a target firm (Ahuja and Katila, 2001; Capron and Mitchell, 1998; Puranam *et al*., 2006; King *et al*., 2008). Acquisitions have become increasingly important in high-technology industries given the speed of innovation and the investments required for R&D and continuous new product development in such contexts (Bower, 2001; Hagedoorn, 2002; King *et al*., 2008). Research suggests, however, that both the potential for acquisitions to occur (Villalonga and McGahan, 2005) and the post-acquisition performance of the acquirer (Larsson and Finkelstein 1999; Ahuja and Katila, 2001; Cloodt *et al*., 2006) depend from their outset on the selection of the right target firm.

What acquirers look for when assessing targets in high technology industries remains an open question in the literature (Larsson and Findelstein, 1999; Graebner *et al*., 2010). For some, greater levels of similarity between the two firms' knowledge resources makes it easier for the acquirer to absorb the new resources of the target firm (Cohen and Levinthal, 1990; Kogut and Zander, 1992) and to exploit acquired resources commercially through innovations. For others, greater complementarity in knowledge resources is more beneficial in opening opportunities for learning and exploration in new technological or product domains through acquisitions (Teece, 1986; Makri et al., 2010; King et al., 2008).

Empirical research on acquisitions in high technology industries has identified different indicators to assess the degree of relatedness between the knowledge resources of target and buyer firm and its effect of the success of acquisition choices. A first research stream focuses on technological knowledge as measured by patents and patent citations. Ahuja and Katila (2001) examine the degree of overlap in the patenting histories of buyer and target firms in the chemical industry. They find that greater overlap produces better post-acquisition results for the acquiring firm. They also find that the relative size of the knowledge base of the target firm impacts the degree of integration of new knowledge into the acquiring organization. Their findings are supported by similar studies conducted in other industry settings (Kapoor and Lim, 2007; Cloodt et al., 2006). Building on this work, Makri et al. (2010) find that both technological knowledge, as measured by patents, and complementary scientific knowledge, as measured by firms' participation in research communities and science disciplines, contribute to post-acquisition performance by stimulating higher quality and more novel inventions.

A second stream of empirical research examines relatedness between buyer and target firms in terms of the degree of relatedness in product lines. The assumption at the base of such analyses is that different product lines require different sets of resources. In their study of the medical industry, Karim and Mitchell (2000) suggest that firms may follow differential strategies choosing high overlap when seeking to enhance existing skills and low overlap when seeking to enter into new skill sets. A more recent analysis conducted on data from the pharmaceutical industry (Yu *et al*., 2015) also suggests that, when considering its own products, acquirers prefer resource complementarity (i.e. less overlap in product lines) when choosing a target firm.

A third research stream focuses on R&D, marketing, and manufacturing capabilities as important factors to consider in acquisitions. One study on the long-term stock returns following technology acquisitions (King *et al*., 2008) finds that the marketing resources of an acquirer firm and the technology resources of the target firm positively reinforce each other. This study also suggests that the interaction between the R&D expenditures of acquirer and target firm has a negative impact on post-acquisition financial performance. Still, another recent study (Yu *et al.*, 2015) suggests that, when it comes to their own R&D pipelines, acquirers are more likely to choose a target firm with resource similarity than complementarity. Finally, looking at the combination of production capabilities and geographic context, a recent study on the Chinese brewery industry finds that acquirers pursue targets with weaker capabilities in existing markets but that they are more willing to acquire targets with strong capabilities when entering new markets (Kaul and Wu, 2016).

These research streams provide important insights into the relationship between resource relatedness and acquisition choice in a range of different high technology industries. We argue, however, that the indicators used to examine knowledge and resource relatedness in these three research streams (i.e. patenting, product lines, R&D) may not be fully appropriate for examining relatedness between acquiring and target firm in the case of new ventures. New firms often enter industries without proprietary patents (Graham *et al*., 2009; Helmers and Rogers, 2011). This is especially true for spinout firms whose founders were previously employed in an incumbent firm. It may also take years for a new venture to build a patent history. Similarly, new ventures often enter an industry with a single or narrow product offering. Looking only at what they currently produce, therefore, might not provide a full picture of what these new ventures know (Brusoni *et al*., 2001). Finally, new ventures may not have production capacity at the time of entry and may have more limited resources and capabilities than established firms to invest in R&D and marketing (Helfat and Lieberman, 2002). The resources examined in extant studies, therefore, may provide only a partial assessment of the types of resources and capabilities possessed by new ventures or of their potential to patent and commercialize innovative products in the future. As a result, they may not be appropriate gauges for what drives the acquisition of such ventures. We therefore argue that the question of how the specific resource base of new ventures might affect their potential to be acquired is, as yet, underdeveloped both conceptually and empirically in extant research on acquisition choices.

To address this gap, we draw from two additional bodies of research related to knowledge resources. The first, rooted in evolutionary economics, suggests that technological knowledge is often tacit in nature and embedded in the personnel, routines and teams of an organization (Nelson and Winter, 1982; Kogut and Zander, 1992; Nonaka, 1994). Such arguments are relevant for acquisition research since evidence suggests that, although the tacit knowledge embodied in employees and teams is often difficult to identify and to measure, it represents a critical element in acquisition choices (Ernst and Vitt, 2000; Graebner, 2004; Ranft and Lord, 2002; Puranam *et al*., 2003; Kapoor and Lim, 2007). The second body of research is provided by scholarship in both strategy and entrepreneurship that suggests that entrepreneurial origin is an important source of both resources and capabilities in new ventures (Carroll *et al*., 1996; Shrader and Simon, 1997; McGrath and MacMillan, 2000; Klepper and Simons, 2000; Agarwal *et al*., 2004). The knowledge resources of new ventures, in fact, may be understood by looking the source of the knowledge and experience inherited by these firms through their founders. In the next section, we integrate these two bodies of research to create a foundation for theorizing about knowledge relatedness and new ventures and, more specifically, about spinouts as acquisition targets. We use the knowledge context from which founders originate to classify different types of spinouts; this classification provides an initial proxy to characterize the knowledge endowments from which spinouts benefit and to develop hypotheses concerning the value of such resource for different types of buyer firms.

2.2. A Typology of Spinouts based on Knowledge Endowment and Product Strategy

Scholarship on entrepreneurship, strategy and industry dynamics suggests that the pre-entry knowledge resources of new entrants, embodied in their founders, affects not only their entry strategy, but also their long-term performance and ability to survive (Bruderl *et al*., 1992; Klepper, 2001; Klepper and Simons 2000). Research also shows that the knowledge heritage of new entrants makes spinouts different from other start-ups in terms of their ability to recognize and exploit new sources of knowledge (Agarwal *et al*., 2004, Chatterji, 2009; Shane and Khurana, 2003). The growing literature on entrepreneurship and innovation shows, in fact, that the pre-entry resources and capabilities of spinouts may be drawn from different ‘knowledge contexts’ related to the origins of their founders (Agarwal and Shah 2014, Chatterjee and Wernerfelt 1991, Helfat and Lieberman 2002). Founders originating from distinct knowledge contexts benefit from different information advantages that underlie firm strategy and performance.

In a value-chain perspective, knowledge contexts may include not only the focal industry, but also downstream industries (Agarwal and Shah, 2014). New ventures created by the ex-employees of incumbent firms in the same industry are widely referred to as ‘spinouts’ or ‘focal spinouts’ (Agarwal *et al.*, 2004, Klepper and Sleeper, 2005; Adams *et al*., 2013). This category has received extensive attention by scholars seeking to understand how knowledge is passed from parent to spinout and what impact this knowledge has on entry and survival rates. By contrast, when the employees of downstream industries leave their prior employment to create new and independent firms in the focal industry they form what is referred to as ‘user-industry spinouts’ (Adams, *et al*., 2016). They are considered spinouts to the extent that they are entrepreneurial ventures founded by ex-employees of an incumbent firm (Agarwal *et al*. 2004, Klepper 2001). Their industry of origin, however, is not the focal industry, but a downstream, user industry. Such spinouts enter the focal industry with knowledge from the demand side about how the focal industry’s products are used and integrated by downstream firms in their final products.

Such distinctions are significant since focal spinouts and user-industry spinouts do not have the same likelihood to survive in all product categories. Recent research suggests, in fact, that the knowledge resources inherited by spinouts through their founders work both to define and constrain the product strategies of such new ventures (Helfat and Lieberman, 2002; Agarwal *et al*., 2004; Chatterji, 2009; Clarysse et al., 2011; Khessina and Carroll, 2008). A recent study of both focal spinouts and user-industry spinouts finds that user-industry spinouts are more likely to enter and survive in product categories that require market- or application-specific knowledge of downstream industry processes and products (referred to as market-specific products) (Adams *et al*., 2016). Focal spinouts, by contrast, enter market-specific categories as well as generic products (i.e. products that may be sold into multiple markets without the need for adaptation or customization). They are less likely to survive, however, in market-specific product categories.

Consistent with these findings, we develop a typology of spinouts based on both the knowledge context from which their founders originate and the product strategy with which they enter an industry. The following table presents four combinations of knowledge heritage and entry strategy: 1) focal spinouts that enter generic products; 2) user-industry spinouts that enter generic products; 3) focal spinouts that enter market-specific products; 4) user-industry spinouts that enter market-specific products (See Table 1). We then use this typology to compare and contrast the potential of different spinout types to be acquired.

Insert Table 1 about here

Acquisition choices, however, are not made solely on the basis of the resources possessed by target firms. Rather, as the literature on resource overlaps between target and buyer firms suggests, the value of such resources may change in relation to the resources possessed by the buyer firm (Ahuja and Katila, 2001; Karim and Mitchell, 2000; Sears and Hoetker, 2011; Yu *et al*. 2015; Capron and Shen, 2007). In this study, we therefore distinguish between two types of buyer firms in parallel with our typology of spinout firms: buyers from the focal industry and buyers from downstream, user industries. Further, like spinouts, acquirer firms in the focal industry may also be characterized by the type of product categories (generic vs. market-specific) in which they are active. As a result, we compare and contrast the potential for each of our spinout types to be acquired by three different kinds of buyer firms: firms in the focal industry focused on generic products, firms in the focal industry focused on market-specific products, and firms in downstream, user-industries[1].

2.3. The Value of Spinouts' Knowledge Endowments

Central to our thesis is the suggestion that historical antecedents matter in defining the knowledge resources of spinout firms (Helfat and Lieberman, 2002). Spinouts benefit from the pre-entry experience and knowledge embodied in their founders (Agarwal *et al*., 2004). Founders that originate from different knowledge contexts, therefore, bring different knowledge resources to their new ventures (Agarwal and, 2014). Moreover, consistent with evolutionary theory, the initial stock of knowledge inherited by spinouts is also likely to have long-terms effects in terms of both strategy (Huber, 1991; Winter, 1987) and further knowledge development (Cohen and Levinthal, 1990; Nelson and Winter, 1982; Kogut and Zander, 1992). As a result, spinouts from distinct knowledge contexts represent different targets for buyer firms.

Focal spinouts inherit technological, marketing and operational knowledge from parent firms in the focal industry through their founders. This inheritance includes tacit knowledge concerning both products and processes in the focal industry, and the technological and business environment surrounding the industry. Using the taxonomy proposed by Teece (1986), focal spinouts inherit core resources that are required to create a product in the focal industry. Studies also show that focal spinouts imitate core capabilities from their parent organizations and tend to compete in market segments that are close to those of their parents (Agarwal and Shah, 2014; Chatterji, 2009; Franco and Filson, 2006). By contrast, user-industry spinouts inherit knowledge through the pre-entry experience of

[1] No distinction is made for the product categories of user-industry buyer firms since they are not competing in the focal industry or within the same product categories of the focal industry as the spinouts they may potentially acquire.

their founders in a downstream firm in which the products of the focal industry are used or integrated into other final products (Adams *et al*., 2016). Their core technological knowledge is thus focused on the use of products from the focal industry rather than the development or production of such products (Chatterji and Fabrizio, 2014; von Hippel, 1988, 2005). Similarly, the marketing knowledge that user-industry spinouts inherit is focused on networks and channels in a particular downstream industry. While such knowledge may be relevant for entry into the focal industry, it is more limited in scope than the knowledge resources inherited by focal spinouts.

Given their different knowledge heritages, focal spinouts and user-industry do not have the same resources when operating in the same product categories. We begin by examining generic product categories. Focal spinouts in generic product categories have strong advantages in terms of core knowledge in the focal industry with respect to user-industry spinouts. They benefit from deep technological knowledge in focal product areas and marketing experience across multiple downstream industries. User-industry spinouts, by contrast, have no such inheritance from the focal industry. Their experience is limited to one downstream industry, and they lack both core technological knowledge in the focal industry and wider customer experience with other user industries. As a result, we suggest that the potential value of these two types of spinouts to different buyers will not be the same. Focal spinouts that produce generic products have a higher potential to be interesting targets for firms in the focal industry that seek to acquire either similar or complementary resources in the focal industry. They may be less interesting, however, to user buyers seeking to acquire knowledge resources in the focal industry. Their focus on generic products is less likely to be a good match for user industries that need upstream technologies and products to fit their specific application needs. Their heritage and focus on generic products may also make it difficult for user-industry buyers to absorb the technological knowledge possessed by focal spinouts. We therefore propose:

> HYPOTHESIS 1a (H1a): *Spinouts from the focal industry that produce generic products have a positive likelihood to be acquired by all types of firms in the focal industry.*
>
> HYPOTHESIS 1B (H1b): *Spinouts from the focal industry that produce generic products do not have a positive likelihood to be acquired by firms in user industries.*

By contrast, the resources offered by user-industry spinouts that produce generic products are not likely to be a good match for any specific type of buyer firm. They have little to offer firms in the focal industry given they do not inherit core technological knowledge from the focal industry. Similarly, by choosing to compete in generic product categories, it is not clear that they offer buyers from user industries any particular knowledge of downstream application areas or of downstream markets. We therefore propose:

> HYPOTHESIS 2 (H2): *Spinouts from user industries that produce generic products in the focal industry do not have a positive likelihood to be acquired by either firms in the focal industry or by firms in user industries.*

Applying the same logic to market-specific products, we propose that focal spinouts that compete in market-specific products offer different resources than user-industry spinouts in the same product category. Focal spinouts have technological knowledge resources in the focal industry. Given their focus on market-specific products, it is also likely that they also have knowledge regarding downstream markets and applications for their products. In this case, such resources are drawn from external contacts with customers, markets and industry experts. User-industry spinouts, by contrast, inherit direct and contextual experience in downstream markets directly through their founders. Their knowledge of technology and operations in the focal industry, however, is more limited to their post-entry experience in the focal industry.

Again, we suggest that such differences in knowledge resources make them different targets for potential buyer firms. Focal spinouts that produce market-specific products are more likely to have a wider market in terms of potential buyers. They possess the technological and operational knowledge that might be interesting to other firms in the focal industry and, by producing market-specific products, they demonstrate the capabilities necessary to develop solutions for downstream user-industries. User-industry spinouts active in market specific product categories will still be less interesting to buyer firms in the focal industry that produce generic products. Neither their technology knowledge nor their downstream knowledge is likely to be of interest to such buyers. User-industry spinouts that produce market-specific products may be interesting targets, however, for firms in the focal industry that produce market-specific products. Such targets offer a source of tacit knowledge that may defy articulation and may be 'sticky' to individuals who have been employed directly in downstream industry settings (von Hippel, 1994, 1998). Acquisition may therefore be the only way for firms in the focal industry to access such knowledge. User-industry spinouts that produce market-specific products are also likely to be interesting to firms in user industries seeking to acquire knowledge resources in the focal industry. Their technological knowledge may be less advanced, but more easily absorbed by a user firm. Their combined contextual experience in both a downstream industry context and in the focal industry with market-specific products also offers a close match with the resources most likely required by firms in user-industries. We therefore propose:

HYPOTHESIS 3 (H3): Spinouts from the focal industry that produce market-specific products have a positive likelihood to be acquired by buyer firms in both the focal industry and user-industries.

HYPOTHESIS 4a (H4a): Spinouts from user-industries that produce market-specific products do not have a positive likelihood to be acquired by buyer firms in the focal industry that produce generic products.

HYPOTHESIS 4b (H4b): Spinouts from user industries that produce market-specific products have a positive likelihood to be acquired by buyer firms in the focal industry that produce market-specific products and by buyer firms in user-industries.

3. EMPIRICAL CONTEXT: SEMICONDUCTOR INDUSTRY

The semiconductor industry offers a rich and highly dynamic environment in which to study the acquisitions of new ventures from different knowledge contexts over this period. High levels of technological change and entrepreneurship have characterized the evolution of the industry since its birth in the 1950s (Brittan and Freeman 1986, Holbrook et al. 2000). The early part of the industry's history was dominated by spinouts from the focal industry. The famous spinouts from Fairchild, the so-called Fairchildren, are cases in point. In more recent periods, however, entrepreneurship in semiconductors (Saxenian 1990) has also involved innovative start-ups from downstream, user-firms (Adams *et al.*, 2013; Fontana and Malerba, 2010). Additionally, developments in the industry lowered the barriers to entry in many product categories in semiconductors and opened up the range of potential entry strategies for new start-ups (Brown and Linden, 2009). Semiconductor devices became an increasingly strategic component in many user product categories. At the same time, users required more and more customization in chip design for their own systems and product lines. However, the application specific knowledge required for designing customized semiconductor devices was often tacit and too complex for users to transfer it easily to their suppliers (Glimstedt, *et al.*, 2010). Many user-firms had also gained access to the capabilities and technologies needed to design their own chips (Ernst, 2005a; Brown and Linden, 2009). As a result, new entrants from both the focal industry (semiconductors) and downstream user industries had valuable, yet distinctive, knowledge that could represent key assets in acquisition evaluations.

4. DATA AND ESTIMATION MODEL

4.1. Data

4.1.1. Data sources. To test our hypotheses we combine information from several sources. The sample of firms is taken from a comprehensive dataset of semiconductor start-ups that entered the industry between 1997 and 2007. This dataset was provided by *Semiconductor Times*, a magazine published monthly by *Pinestream Communications*, a private consultancy company specialized in the semiconductor industry. The magazine records new start-ups in the industry each month and provides a profile of each company, including a description of their product offerings and activities. We consider this source exhaustive and reliable and it has already been used in prior research (Adams et al., 2016).

The fate of the firms in terms of survival or exit was tracked until November 2014 and with the help of *Lexis-Nexis* we identified the firms that were acquired. Information on the characteristics of the acquisition deal such as deal type, purpose, size, and overall value (when available) was gathered from *Factset*. The main SIC and/or NAICS codes necessary for classifying the buyer firm were retrieved through *Orbis*. Our final dataset of acquired firms includes 395 (or 42.2%) of the 936 firms in the original dataset.

4.1.2. Variables. Variables and summary statistics are reported in Table 2. To test our hypotheses we need to identify the knowledge heritage and product entry strategy of acquired (i.e. the targets) firms, as well as information on the industry buyers and their product strategy.

[Insert Table 2 about here]

Consistent with the arguments developed in Adams et al. (2016) we have identified the knowledge heritage of the targets with their industry of origin and their product strategy with the type of product they enter under the assumption that given their young age and relative lack of resources, new entrants tend to focus their activity, at least initially, on just one product area.

Depending on their knowledge heritage, targets can be defined as: FOCAL SPINOUTS (186 or 47% of the sample) if they were founded by entrepreneurs whose last employment was in a semiconductor firm, USER-INDUSTRY SPINOUTS (108 or 27.4% of the sample) if they were founded by entrepreneurs who were previously employed in industries that use semiconductors as components in their final products, and OTHER DE-NOVO (101 or 25.6% of the sample). Depending on the product market they enter targets can operate in: GENERIC SEMICONDUCTORS (124 or 31.3% of the sample) if they produce devices used in a wide range of systems and designed without a specific application in mind, SPECIFIC SEMICONDUCTORS (199 or 50% of the sample) if they work on solutions tailored to specific users in specific submarkets (i.e. computing, communication, storage), OTHER SEMICONDUCTORS (72 or 18.7% of the sample) if they are active in other semiconductor areas such as customized ASIC design services and electronic design automation (EDA) tools.

Buyer firms were first coded on the basis of their industry of activity as identified by their primary SIC or NAICS code and then assigned to one of the following three macro-categories following the logic explained in Adams at el. (2013): SEMICONDUCTOR BUYER (211 or 53% of buyers) if they belong to SIC code 3674 (until year 1999) and NAICS code 33441 for the subsequent years; USER BUYER (120 or 30.3% of buyers) if they belong to the following downstream industries: industrial and commercial machinery (also including electric, gas, and sanitary services); computer and office equipment; electronic and other electrical equipment and components; telecommunications (also including communication services); automotive (also including transportation equipment); instrumentation (also including medical instruments); aerospace and defense;[2] OTHER BUYER (64 or 16.7% of buyers).

To test hypotheses H4a and H4b semiconductor buyers have also been assigned to one of the following categories according to their own product strategy: SEMICONDUCTOR GENERIC-BUYERS (77 or 36.6% of semiconductor buyers); SEMICONDUCTOR SPECIFIC-BUYERS (109 or 51.6% of semiconductor buyers); SEMICONDUCTOR OTHER-BUYERS (25 or 11.8% of semiconductor buyers).[3]

Our list of controls includes two sets of variables. The first set accounts for characteristics of the target firm and its founder. We control for the SIZE of the target firm as measured by the (logarithm of) total number of employees at the time of entry. Prior works have found that there are benefits from firm size as relatively larger start-ups generally experience higher survival rates. However, those that do not survive have a higher probability of being acquired, as if the quality of the acquired firm depends on of its human capital as proxied by its size. We also account for potential diminishing return to size of the target by including a squared-term in our specifications.

An additional measure of the quality of a venture is the innovative activity of the target firm and prior studies have highlighted that innovative firms (if they do not survive) have a higher probability of exiting by acquisition (Hsu and Ziedonis, 2013; Arora and Nandkumar, 2011; Cockburn and McGarvie 2011). In our study, we measure innovativeness

[2] See Table A1 in the Appendix for the list of corresponding SIC and NAICS codes for these industries.
[3] Information on the shares of revenues at the time of acquisition has been collected from IC Insights. We have identified as Semiconductor generic-buyers those firms whose highest share of revenues comes from areas such as: memories (DRAM, Flash, SRAM, and other) and processors (including microprocessors, microcontrollers, and DSP). We have identified as Semiconductor specific-buyers those firms whose highest share of revenues comes from chips that are targeted at specific application markets (i.e. communications, consumer products, computation and storage, industrial products). Other semiconductors buyers those firms whose highest share of revenues comes from customized ASIC design services and electronic design automation (EDA) tools.

in terms of patenting. Specifically, the variable PATENT is equal to one if, at entry, the start-up had filed at least one patent with the U.S. Patent and Trademark Office (USPTO), and zero otherwise. Finally, we control for the status of the target semiconductor firm. The variable FABLESS is equal to one if the firm has manufacturing facilities and zero otherwise.

Our controls for the characteristics of the founder(s) include: SERIAL ENTREPRENEUR which is equal to one if the founder, or a member of the founding team, has previously founded another firm and zero otherwise; FOUNDING TEAM which is equal to one if the target firm is founded by a team of employees, and zero otherwise; PHD which is equal to one if at least one member of the founding team possess a doctoral degree. Indeed, previous research (Roberts, 1991) suggests that diminishing returns to firm's performance are triggered by an excessive amount of higher education exposure.

The second set of controls includes the characteristics of the acquisition deal. In line with the prior literature on acquisitions (Puranam et al., 2003 we control for the size of the acquisition deal. FULL ACQUISITION is equal to one if the deal involved 100% of the target firm (370 cases or 93.6% of the total) and zero otherwise.

Finally, in each regression we control for fixed effects linked to time of entry and exit, location of the target, and characteristics of the buyer not related to its industry and/or product strategy.

4.2. Model specification

We conceptualize the acquisition as the outcome of a selection process in which a target firm can be chosen by different types of buyers. We model the outcome of the process using the following multinomial logit equation:

$$Pr(y_i = j) = \frac{e^{\beta'_j x_i}}{\sum_{k=0}^{n} e^{\beta'_k x_i}}$$

(1)

where j indicates the type of buyer and X_i is a vector of covariates capturing the characteristics of the target spinout i as well as the control variables described above. We estimate two versions of (1). In the first estimation the type of buyer is defined only on the basis of the industry it belongs to and j varies between 0 and 2 ($j = 0$ for Semiconductor buyers, $j = 1$ for User buyers, and $j = 2$ for Other industry buyers). In the second estimation, the type of buyer is defined on the basis of a combination between the industry it belongs to *and* its products strategy (if it is a buyer from the focal industry) and j varies between 0 and 4 ($j = 0$ for Semiconductor generic buyers, $j = 1$ for Semiconductor specific buyers, $j = 2$ for Semiconductor other buyer, $j = 3$ for User buyers, and $j = 4$ for Other industry buyers).

Table 3 reports instead the correlations coefficients. Coefficients in the correlation matrix do not seem to suggest that co-linearity is a problem in our data. This conclusion is supported by a mean value of the Variance Inflation Factor (VIF) of 2.64.

[Insert Table 3 about here]

5. RESULTS

We present the results from the first estimate in Table 4.

[Insert Table 4 about here]

Columns (1) and (2) report the regression coefficients for those start-ups that have been acquired by Semiconductor buyers and User buyers respectively. The reference category is Other buyers.

In column (1) the coefficient estimate of focal spinouts producing generic products is positive and significant indicating that these firms have a positive likelihood to be acquired by semiconductor buyers. This result supports H1a. Interestingly, the coefficient is also positive and significant in column (2) indicating that focal spinouts also have a positive likelihood to be acquired by user buyers. This evidence contrasts with our expectations as put forward in H1b. The coefficient estimates of user-industry spinouts producing generic products is never significant suggesting that these firms do not have a positive likelihood to be acquired by either firms in the focal industry or by firms in user industries. This result is in line with H2. Finally, the coefficient estimates of user-industry spinouts producing specific products is positive and significant both in column (1) and (2). These results are consistent with H3 as they indicate that spinouts from a focal industry that produce market-specific products have a positive likelihood to be acquired by buyer firms in both the focal industry and in user-industries. Concerning our control variables, we find a non-linear relationship between firm size and the probability of being acquired by both semiconductor and user buyers. None of the remaining control variables is significant instead. Though this result might seem surprising, it should not be taken as an indication that the characteristics of the founders (as measured by serial entrepreneur) or firm quality (as measure by patents) do not affect acquisition. Both of them are important drivers of acquisition, but they do not seem relevant to discriminate between type of buyer.

To test the remaining hypotheses we need to explicitly account for the product strategy of the buyer firms. We do this in Table 5 where we distinguish four types of buyers:

Semiconductor buyers producing generic products (column 3), Semiconductor buyers producing market specific products (column 4), Semiconductor buyers producing other products (column 5), and User buyers (column 6). As in the previous case, the reference category is Other buyers.

[Insert Table 5 about here]

Accounting for the product strategy of the buyer allows us to highlight similarities and important difference with respect to the prior analysis. On the one hand, the coefficient estimates of focal spinouts producing generic and specific products is still positive and significant in columns (3), (4) and in column (6) indicating that these firms have a positive likelihood to be acquired both by Semiconductor buyers and User buyers. On the other hand, the coefficient estimates for user-industry spinouts producing specific products are non significant in column (3) but positive and significant in columns (4) and (6). The former result suggests that spinouts from user industries that produce market-specific products do not have a positive likelihood to be acquired by buyer firms in the focal industry that produce generic products. This is consistent with H4a. The latter results indicate that spinouts from user industries that produce market-specific products have a positive likelihood to be acquired by buyer firms in the focal industry that produce market specific products and by buyer firms in user industries. Both results provide support for H4a and H4b respectively.

All in all, our empirical analysis has provided two sets of results. First, we have found evidence that the knowledge heritage of spinouts influences their probability to be acquired by different types of buyers. This is particularly important for spinouts from the focal industry that are acquired by both buyers in the focal industry and user buyers. Second, we found evidence that the product strategy of spinouts also plays a role particularly for the acquisition of spinouts that enter the focal industry from downstream industries. Indeed, only user-industry spinouts that produce market-specific products have a positive likelihood to be acquired, and their buyers are limited to firms that are active in market-specific product categories.

Additional analysis is conducted to check for possible biases in our results. Our analysis has considered the case of a firm (the target) that must choose among a set of potential buyers. It might be argued that the choice of the buyer is indeed consequential to the choice of being acquired as opposed to continue to exist as a separate entity. If this is the case, then failing to explicitly account for this possibility would introduce a sample selection bias in our results. To overcome this potential problem we re-estimate our model using a two-step procedure similar to Heckman (1979). Specifically, we first estimate a binary Logit model on the overall sample of 936 semiconductor firms. The dependent variable in this case is equal to one if the firm has been acquired and zero otherwise.[4] We then use the residuals from the first stage regression to compute inverse Mills' ratios that are added as covariates in the multinomial regression in the second stage. The results of the second stage estimations are reported in Tables 6 and 7.

[Insert Tables 6 and 7 about here]

A comparison between these results and our primary ones indicates that in the case of acquisitions by categories of buyers (see Table 6) the sign and the statistical significance of the coefficients capturing the interaction between firms' origin and product strategy is

[4] The specification used in the first stage of the estimation is similar to Model (2) from Table 6 in Adams et al. (2016). It includes as covariates the same variables employed in the second stage (Firm origin, Fabless, Serial entrepreneur, Founding team, Patent, Size (Logarithm) and Size sq (Logarithm)). In addition to these it includes also a dummy for venture capital support which is used as exclusion restriction. The estimated coefficient of this variable is positive and significant.

maintained for both semi buyer and user buyer. The magnitude of the estimated coefficients is slightly higher than in our baseline regressions. Also, when we account for the product strategy of buyers (see Table 7) the sign and the statistical significance of the coefficients is maintained. However in this case coefficients are lower than in the baseline regression. It can be noticed that the estimated coefficient of the inverse Mills' ratio is positive and statistically significant only in Model (7) in Table 6 indicating that sample selection bias is a potential problem only for semiconductor buyers. To check whether this result might be the consequence of unadjusted standard errors due to the fact that our estimation procedure deviates from the traditional (i.e. linear) two-stage model, we reran the estimation presented in Table 6 via bootstrapping. Results of these further regressions produced non-significant coefficients for the inverse Mills' ratio which suggest that selection bias is not a concern in our data.

5.1 Further explorative analysis

Further analyses are conducted to assess the sensitivity of our results to changes in the composition of the sample of buyer firms.[5] We start by observing that the distribution of buyers firms in our sample is rather skewed with the top 10 buyers in terms of number of acquired firms accounting for one fifth of the total acquisitions. Skewness is higher within the subsamples with the top five semiconductor buyers accounting for one third of the acquisitions made by semiconductor firms and the top five user buyers accounting for one fourth of the acquisitions made by users.

If results are driven by some characteristics of the buyers rather than by the knowledge heritage and/or product strategy of the target firms we would expect our findings to change depending on the presence or absence of the top buyers. To control for this

[5] Results of these estimations are non shown here for reason of space. They are available upon request from the authors.

possibility, we remove the top 5 semiconductor and user buyers and re-estimate our models for these sub-samples. Results are unchanged.[6]

In addition to this, we consider the possibility that our results might be explained by the overall value of the deals above and beyond the number of acquisitions themselves. If some types of buyers are more likely than other to pursue expensive deals, then our evidence that the knowledge heritage of spinouts as well as their product strategy influences their probability to be acquired by different types of buyers may change depending on the propensity of the buyer to pay. To explore this possibility we compute the mean deal value and split the sample in two subsets (equal or above and below the mean) and rerun our regressions on these subsamples. While the analysis of the subsample of 'below the mean' deals generally confirms our main results, the analysis of the subsample of 'equal or above the mean' deals reveal some interesting divergence from our main results. In particular, only firms that produce market-specific products have a positive likelihood to be acquired, and their buyers are limited to user firms or semiconductor firms that are active in market-specific product categories. This result departs from H1a as spinouts from the focal industry that produce generic products no longer have a positive likelihood to be acquired by all types of firms in the focal industry.

Finally we also explore whether the identity of the buyers rather than the number or the value of the acquisition may affect our results. Semiconductor leaders such as Intel or Broadcom are very active buyers as they pursue acquisitions of young start-ups to get rid of potential competitors. At the same time notable user buyers (i.e. Cisco Systems) pursue acquisition base growth strategies which span across a variety of industries both their own and upstream. To check whether the presence of these 'very active' buyers affects our results

[6] We have also removed both the top 5 semiconductor buyers and the top 5 user buyers at the same time. Again results did not change.

we remove them from the sample and rerun our regression. Results from these additional regressions are generally consistent with our main hypotheses.

6. DISCUSSION

Research suggests that successful acquisitions begin with the selection of the 'right' target firm (Graebner *et al*., 2010; Larsson and Finkelstein, 1999; Graebner, 2004). To date, studies on what constitutes the best target have focused on the balance of resources between buyer and target firm as measured by patents, R&D, product lines and marketing investments. This study proposes that such indicators may be appropriate for a full understanding of the resources possessed by new entrants and, in particular, spinouts. This study adopts a knowledge heritage perspective to examine the impact of the knowledge heritage and product strategies of spinouts from different knowledge contexts on the their potential to be acquired by firms both in the focal industry and in downstream industries. Overall, our findings support our proposition that the knowledge heritage of spinout ventures represents an important resource that affects evaluations concerning acquisitions. Spinouts whose founders originate from distinct knowledge contexts have a different potential to be acquired by specific types of buyer firms. Specifically, our results suggest that spinouts from the incumbent industry (i.e. focal spinouts) are likely targets for acquisitions by all types of buyers *independent* of their product strategy. The founders of such spinouts inherit critical technological, operations and market knowledge that is valued across buyer firms looking to acquire resources and capabilities in the focal industry. It is interesting to note that, in contrast to what we predicted in H1b, focal spinouts that produce generic products have a positive likelihood to be bought even by buyers in downstream, user industries. We had proposed that their focus on generic rather than market specific products would make them less likely targets for downstream, user firms seeking complementary resources in the focal industry. Yet our results suggest that value of acquiring core technological knowledge from the focal industry seems to compensate for the challenges for downstream firms to absorb such knowledge.

By contrast, spinouts from downstream industries that enter the focal industry are likely targets for acquisitions *depending* on their product strategy. Only user-industry spinouts that produce market-specific products have a positive likelihood to be acquired, and their buyers are limited to firms that are active in market-specific product categories. User-industry spinouts that enter the focal industry through generic product categories have a negative likelihood to be acquired by all types of buyer firms; the greater distance between their knowledge inheritance and their product strategy leaves them without clear resources to offer to potential buyer firms.

Our study offers new insights for the literature on acquisitions by focusing on spinouts as a unique subset of target firms. Spinouts have increasingly been identified as attractive targets for acquisitions in high technology industries where the pace of innovation and new product development often involves large and highly uncertain investments. Spinouts are recognized for their unique resources that distinguish them from established firms and other new entrants into industries (Helfat and Lieberman, 2002). Yet despite such recognition, extant studies make little mention of how the specific characteristics of spinouts might influence the potential and success of acquisitions involving such new ventures. Our work provides initial evidence that spinouts from distinct knowledge contexts differ in terms of their potential as acquisition targets for different types of acquiring firms.

More broadly, our findings suggest that research on acquisitions based on the relatedness of buyer and target firms' technological knowledge may need to look further at the knowledge resources that lie behind outcomes regarding what firms do (i.e. patents and

R&D activities) or what firms produce (i.e. product lines). Technological knowledge is often tacit in nature and embedded in the personnel, routines and teams of an organization (Nelson and Winter, 1982; Kogut and Zander, 1992; Nonaka, 1994). Focusing on spinouts and distinguishing them by their initial knowledge endowments provided a way to overcome such challenges in analyses of acquisition choices. Additional work will be needed to understand how this approach may be extended to enrich analyses of acquisitions for other types of firms. A possible model for such research is provided by a recent study on the growth of new ventures once they have entered an industry (Chen et al., 2012). Although the focus of this study is the impact of knowledge resources on the transition into incumbency of new entrants, it suggests that differences in the pre-entry knowledge and experience of diversifying and *de novo* firms influence both the path and success rate of such transitions. This research could be extended to examine how the initial knowledge endowments of diversifying and different types of *de novo* entrants may also influence their potential to exit by acquisition and to be targeted by different types of buyer firms.

Finally, this research contributes to the literature on industry dynamics and the 'resource-based' view of the firm. Consistent with evolutionary theory, this literature has produced a rich body of evidence to show that the pre-entry resources and capabilities of firms impact both their choice of market to enter, and the timing, mode and success of entry (Helfat and Lieberman, 2002). We build on this research to show that historical antecedents also impact choices concerning how new firms may exit an industry. For spinouts, knowledge heritage impacts the potential of firms to be acquired by different types of buyers. This finding is consistent with theories that suggest that the initial stock of knowledge inherited by spinouts have long-lasting effects on their strategies (Huber, 1991; Klepper, 2001; 2009). Just as analyses of the organizational capabilities and resources that precede and precipitate entry help us to understand how entry occurs (Helfat and Lieberman, 2002), they may also help us to understand the constraints and limits of strategies to exit by acquisition.

Several limitations of this study should be noted. First, given the data are drawn from a single industry, the generalizability of our findings are, of course, restricted. Future research will be needed to see if similar patterns emerge in other contexts. We suspect that similar patterns will emerge in other high technology industries that are characterized by submarkets related to heterogeneous demand segments and complex user applications such as lasers, software, and medical devices. Second, while we examine the potential for acquisition, we do not examine the success of acquisition choices made. Future work will need to explore how such choices may have affected both the innovative and commercial performance of acquirer firms. Third, our definition of user industries is wide and we are unable to match the specific industry of origin of user-industry spinouts (e.g. telecommunications, consumer electronics, automobile, etc.) with the industries of specific user buyers or with specific product segments. Since scholarship indicates that spinouts tend to enter product categories close to their industry of origin, further research is needed to see how this relationship might affect acquisition decisions.

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LIST OF TABLES

Table 1: A typology of spinouts and product entry strategy

		Knowledge heritage	
		Focal spinouts	**User-industry spinouts**
Product entry strategy	**Generic semiconductors**	1	2
	Market specific semiconductors	3	4

Table 2: Variables list and summary statistics

Variable	Type	#Observations	Mean	S.D.	Min	Max
Semi Buyer	Dummy	395	0.534	0.499	0	1
User Buyer	Dummy	395	0.304	0.460	0	1
Other Buyer	Dummy	395	0.162	0.369	0	1
Semi Generic Buyer	Dummy	395	0.195	0.397	0	1
Semi Specific Buyer	Dummy	395	0.276	0.448	0	1
Semi Other Buyer	Dummy	395	0.063	0.244	0	1
Focal spinout	Dummy	395	0.471	0.500	0	1
User-industry spinouts	Dummy	395	0.273	0.446	0	1
Other de novo	Dummy	395	0.256	0.437	0	1
Generic semi	Dummy	395	0.314	0.465	0	1
Specific semi	Dummy	395	0.504	0.501	0	1
Other semi	Dummy	395	0.182	0.387	0	1
Full acquisition	Dummy	395	0.937	0.244	0	1
Fabless	Dummy	395	0.476	0.500	0	1
PhD	Dummy	395	0.387	0.488	0	1
Serial entrepreneur	Dummy	395	0.253	0.435	0	1
Founding team	Dummy	395	0.587	0.493	0	1
Patent	Dummy	395	0.372	0.484	0	1
Size (Ln)	Continuous	395	3.227	1.000	0	4.564
Size sq (Ln)	Continuous	395	11.413	4.413	0	20.833
Exit year	Continuous	395	2006.37	4.156	1997	2014
Entry year	Continuous	395	2000.304	2.395	1997	2007

Table 3: Correlation coefficients

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1	1																					
2	-0.707	1																				
3	-0.471	-0.29	1																			
4	0.46	-0.325	-0.216	1																		
5	0.576	-0.408	-0.271	-0.304	1																	
6	0.243	-0.172	-0.114	-0.128	-0.16	1																
7	0.007	0.005	-0.016	-0.016	-0.026	0.088	1															
8	0.049	0.002	-0.069	0.014	0.091	-0.089	-0.579	1														
9	-0.058	-0.009	0.089	0.005	-0.063	-0.009	-0.553	-0.36	1													
10	0.074	0.004	-0.105	0.053	-0.064	0.183	0.127	-0.182	0.041	1												
11	0.098	0.05	-0.196	0.003	0.194	-0.158	-0.098	0.291	-0.184	-0.682	1											
12	-0.216	-0.069	0.38	-0.067	-0.174	-0.015	-0.025	-0.157	0.189	-0.319	-0.476	1										
13	0.07	0.013	-0.111	0.075	-0.002	0.025	-0.046	0.043	0.009	-0.003	0.033	-0.039	1									
14	0.138	0.01	-0.199	0.056	0.115	-0.019	0.045	0.075	-0.129	0.076	0.165	-0.306	0.081	1								
15	-0.081	0.006	0.102	-0.011	-0.119	0.071	-0.136	-0.091	0.249	0.033	-0.126	0.123	0.015	-0.019	1							
16	0.03	-0.005	-0.035	0.022	0.044	-0.056	0.046	-0.018	-0.034	0.07	-0.074	0.012	0.056	0.086	0.063	1						
17	0.063	-0.05	-0.022	0.049	0	0.049	-0.003	-0.063	0.067	-0.02	0.042	-0.03	0.057	0.047	0.17	0.086	1					
18	0.078	-0.064	-0.026	0.031	0.052	0.015	0.029	-0.026	-0.007	0.1	-0.074	-0.024	-0.101	-0.021	-0.064	-0.027	-0.004	1				
19	0.017	-0.019	0	0.043	-0.052	0.062	-0.002	0.072	-0.071	0.027	0.03	-0.071	-0.007	0.044	0.074	-0.091	0	-0.062	1			
20	0.061	-0.021	-0.056	0.052	-0.01	0.058	-0.01	0.088	-0.079	0.044	0.051	-0.119	-0.017	0.098	0.049	-0.055	0.022	-0.056	0.956	1		
21	-0.05	0.015	0.049	-0.066	-0.059	0.112	-0.018	-0.034	0.056	0	-0.045	0.058	0.014	-0.038	0.105	0.096	0.031	-0.076	-0.051	-0.037	1	
22	-0.049	0.022	0.039	-0.073	-0.024	0.063	0.105	-0.057	-0.062	0.053	-0.113	0.083	-0.015	-0.083	0.053	0.121	0.094	0.086	-0.177	-0.208	0.462	1

1: Semi buyer; 2: User buyer; 3: Other buyer; 4: Semi generic buyer; 5: Semi specific; 6: Semi other buyer; 7: Focal spinout; 8: User-industry spinout; 9: Other de novo; 10: Generic semi; 11: Specific semi; 12: Other semi; 13: Full acquisition; 14: Fabless; 15: PhD; 16: Serial entrepreneur; 17: Founding team; 18: Patent; 19: Size (Ln); 20: Size sq (Ln); 21: Exit year; 22: Entry year.

Table 4: Multinomial Logit regression – acquisition by categories of buyers

		(1)		(2)	
		Semi Buyer		User Buyer	
Variable	Interaction	Coefficient	S.E.	Coefficient	S.E.
Focal spinout	Generic Semi	2.311	[0.782]***	2.057	[0.796]**
	Specific Semi	1.789	[0.633]***	1.956	[0.668]***
	Other Semi	-1.051	[0.725]	-0.689	[0.676]
User-industry spinout	Generic Semi	1.478	[0.954]	1.206	[1.073]
	Specific Semi	1.336	[0.666]***	1.318	[0.711]*
	Other Semi	0.730	[1.080]	1.166	[1.069]
Other de novo	Generic Semi	0.732	[0.748]	1.122	[0.780]
	Specific Semi	2.325	[0.794]***	2.048	[0.842]**
	Other Semi	Ref.	Ref.	Ref.	Ref.
Fully acquired		1.342	[0.620]	0.994	[0.640]
Fabless		0.509	[0.385]	0.331	[0.414]
PhD		-0.526	[0.356]	-0.389	[0.392]
Serial entrepreneur		0.046	[0.418]	0.024	[0.435]
Founding team		-0.199	[0.413]	-0.562	[0.425]
Patent		0.290	[0.343]	0.118	[0.363]
Size (Ln)		-2.049	[0.803]**	-1.407	[0.811]*
Size sq (Ln)		0.460	[0.145]***	0.281	[0.149]*
Constant		1.009	[1.530]	0.879	[1.564]
# of observations		395			
Log-pseudolikelihood		-338.516			
Chisq		146.507***			
Pseudo Rsq		0.1359			

Standard errors adjusted for clustering at firm level in brackets. ***, **, * indicate significance at 1%, 5% and 10% level respectively. All specifications include a full vector of country, entry year and exit year dummies. Other Buyers is the omitted category.

Table 5: Multinomial Logit regression – acquisition by categories of buyers and product strategy

		(3)		(4)		(5)		(6)	
		Semi generic Buyer		Semi specific Buyer		Semi other Buyer		User buyer	
Variable	Interaction	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Focal spinouts	Generic Semi	1.735	[0.892]*	2.444	[0.957]**	3.127	[1.072]***	1.996	[0.792]**
	Specific Semi	1.685	[0.755]**	2.291	[0.845]***	0.171	[1.388]	1.966	[0.664]***
	Other Semi	-1.178	[0.947]	-1.241	[1.152]	-0.575	[1.060]	-0.713	[0.680]
User-industry spinouts	Generic Semi	1.738	[1.061]	1.493	[1.161]	-11.112	[1.169]***	1.180	[1.065]
	Specific Semi	0.758	[0.807]	2.035	[0.876]**	0.614	[1.010]	1.330	[0.710]*
	Other Semi	0.895	[1.260]	1.029	[1.276]	-11.152	[1.115]***	1.159	[1.059]
Other de novo	Generic Semi	0.617	[0.911]	0.856	[0.995]	1.031	[1.100]	1.106	[0.780]
	Specific Semi	2.026	[0.930]**	3.073	[1.024]***	0.808	[1.501]	2.068	[0.852]**
	Other Semi	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Fully acquired		1.966	[0.866]**	0.928	[0.720]	1.581	[1.027]	0.996	[0.644]
Fabless		0.478	[0.437]	0.625	[0.416]	0.041	[0.621]	0.333	[0.416]
PhD		-0.443	[0.405]	-0.774	[0.399]*	-0.114	[0.531]	-0.393	[0.391]
Serial entrepreneur		1.357	[0.492]	0.281	[0.455]	-0.691	[0.631]	0.045	[0.440]
Founding team		-0.147	[0.462]	-0.352	[0.463]	0.138	[0.542]	-0.595	[0.430]
Patent		0.440	[0.405]	0.201	[0.387]	0.292	[0.552]	0.020	[0.368]
Size (Ln)		-1.852	[0.938]**	-2.445	[0.872]***	-0.375	[1.118]	-1.479	[0.830]*
Size sq (Ln)		0.416	[0.170]**	0.538	[0.164]***	0.188	[0.237]	0.293	[0.151]*
Constant		-0.341	[1.848]	0.885	[1.730]	-5.654	[2.116]***	1.027	[1.606]
# of observations		395							
Log-pseudolikelihood		-499.454							
Chisq		3868.88***							
Pseudo Rsq		0.1601							

Standard errors adjusted for clustering at firm level in brackets. ***, **, * indicate significance at 1%, 5% and 10% level respectively. All specifications include a full vector of country, entry year and exit year dummies. Other Buyers is the omitted category.

Table 6: Robustness check - Multinomial Logit regression – acquisition by categories of buyers(second stage Heckman selection model)

		(7)		(8)	
		Semi Buyer		User Buyer	
Variable	Interaction	Coefficient	S.E.	Coefficient	S.E.
Focal spinout	Generic Semi	2.391	[0.789]***	2.001	[0.799]**
	Specific Semi	1.848	[0.648]***	1.925	[0.674]***
	Other Semi	-1.037	[0.731]	-0.718	[0.683]
User-industry spinout	Generic Semi	1.475	[0.954]	1.180	[1.071]
	Specific Semi	1.360	[0.670]***	1.304	[0.710]*
	Other Semi	0.853	[1.108]	1.122	[1.081]
Other de novo	Generic Semi	0.774	[0.748]	1.055	[0.779]
	Specific Semi	2.367	[0.792]***	2.000	[0.835]**
	Other Semi	Ref.	Ref.	Ref.	Ref.
Fully acquired		1.387	[0.627]**	0.963	[0.640]
Fabless		1.024	[0.482]**	0.242	[0.511]
PhD		-0.749	[0.371]**	-0.339	[0.399]
Serial entrepreneur		0.184	[0.427]	0.019	[0.444]
Founding team		0.626	[0.622]	-0.710	[0.649]
Patent		0.744	[0.414]*	-0.053	[0.426]
Size (Ln)		-2.932	[1.044]***	-1.230	[1.055]
Size sq (Ln)		0.697	[0.208]***	0.236	[0.209]
Inverse Mills' ratio		5.206	[2.541]**	-0.758	[2.699]
Constant		-2.922	[2.339]	1.479	[2.429]
# of observations		395			
Log-pseudolikelihood		-335.709			
Chisq		333.05***			
Pseudo Rsq		0.1431			

Standard errors adjusted for clustering at firm level in brackets. ***, **, * indicate significance at 1%, 5% and 10% level respectively. All specifications include a full vector of country, entry year and exit year dummies. Other Buyers is the omitted category

Table 7: Robustness check - Multinomial Logit regression – acquisition by categories of buyers and product strategy (second stage Heckman selection model)

		(9)		(10)		(11)		(12)	
		Semi generic Buyer		Semi specific Buyer		Semi other Buyer		User buyer	
Variable	Interaction	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Focal spinouts	Generic Semi	1.553	[0.807]*	2.027	[0.847]**	2.872	[1.007]***	1.791	[0.735]**
	Specific Semi	1.696	[0.722]**	2.212	[0.781]***	0.063	[1.332]	1.984	[0.657]***
	Other Semi	-0.981	[0.856]	-1.254	[1.077]	-0.503	[1.090]	-0.649	[0.685]
User-industry spinouts	Generic Semi	1.984	[1.043]*	1.466	[1.093]	-11.094	[1.116]***	1.337	[1.058]
	Specific Semi	0.760	[0.732]	1.865	[0.769]**	0.574	[0.969]	1.302	[0.668]*
	Other Semi	0.916	[1.175]	1.041	[1.177]	-11.321	[1.251]***	1.174	[1.047]
Other de novo	Generic Semi	0.703	[0.869]	0.736	[0.883]	0.885	[1.062]	1.156	[0.716]
	Specific Semi	1.999	[0.887]**	2.777	[0.968]***	0.867	[1.354]	1.994	[0.851]**
	Other Semi	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Fully acquired		1.746	[0.885]**	0.871	[0.770]	1.450	[1.104]	0.829	[0.678]
Fabless		0.550	[0.433]	0.732	[0.413]*	0.287	[0.647]	0.429	[0.410]
PhD		-0.405	[0.395]	-0.703	[0.382]*	0.073	[0.516]	-0.368	[0.373]
Serial entrepreneur		0.118	[0.460]	0.221	[0.423]	-0.921	[0.670]	-0.007	[0.412]
Founding team		-0.016	[0.455]	-0.147	[0.445]	0.214	[0.575]	-0.434	[0.415]
Patent		0.337	[0.377]	0.345	[0.365]	0.311	[0.559]	0.014	[0.346]
Size (Ln)		-1.707	[0.921]*	-2.283	[0.864]***	-0.836	[1.160]	-1.445	[0.837]*
Size sq (Ln)		0.372	[0.177]**	0.482	[0.168]***	0.253	[0.270]	0.274	[0.160]*
Inverse Mills' ratio		0.072	[0.844]	0.637	[0.831]	0.829	[1.224]	0.431	[0.706]
Constant		-0.803	[1.971]	0.068	[1.761]	-5.583	[2.267]***	0.599	[1.602]
# of observations		395							
Log-pseudolikelihood		-521.491							
Chisq		1766.38***							
Pseudo Rsq		0.1231							

Standard errors adjusted for clustering at firm level in brackets. ***, **, * indicate significance at 1%, 5% and 10% level respectively. All specifications include a full vector of country, entry year and exit year dummies. Other Buyers is the omitted category.

APPENDIX

Table A1: SIC CODES (used until year 1999)

SEMI	Semiconductors and related devices - SEMI	3674
USER INDUSTRES	Industrial and Commercial Machinery (also including Electric, Gas and Sanitary services) – ICM	3511, 3519, 3523, 3531, 3537, 3541, 3542, 3544, 3545, 3555, 3559, 3562, 3563, 3567, 3568, 3569, 3585, 3586, 3599, 4911, 4931, 4953
	Computer Equipment – CMP	3571, 3572, 3575, 3577, 3578, 3578, 3579
	Electronic and other electrical equipment and components – ELC	3612, 3613, 3621, 3625, 3629, 3632, 3634, 3635, 3641, 3643, 3645, 3646, 3647, 3651, 3652, 3671, 3672, 3675, 3676, 3677, 3678, 3679, 3691, 3694, 3695, 3699
	Telecommunication (also including Communication Services) – TLC	3661, 3663, 3669, 4812, 4813, 4822, 4833, 4841, 4899
	Automotive (also including Transportation Equipment)- ATM	3711, 3714, 3721, 3724, 3732, 3743, 3799
	Instrumentation (also including Medical Instruments) – INS	3812, 3821, 3822,3823, 3825, 3826, 3827, 3829, 3861, 3873, 3841, 3842, 3845, 3851
	Aerospace & Defense – DFN	9661, 3761, 3764, 3769, 3483, 3489

Table A1 (ctd.): NAICS and corresponding codes (used after year 1999)

SEMI	ICM	CMP	ELC	TLC	ATM	INS	DFN
33441	22111	33337	33341	33421	33611	32229	33641
	22112	33411	33361	33422	33612	32599	54171
	22121	33994	33399	33429	33621	33331	92711
	31499	54151	33431	51312	33631	33451	
	33221		33461	51321	33633	33911	
	33232		33511	51322	33634		
	33241		33512	51331	33635		
	33243		33519	51332	33639		
	33271		33521	51333	33699		
	33299		33522	51334			
	33311		33531	51339			
	33312		33591				
	33322		33593				
	33329		33599				
	33351		33632				
	33391		33999				
	33392		51222				
	33651						
	56221						
	56292						