Technology Commercialization Strategy Dynamics and Entrepreneurial Performance: Evidence from the Speech Recognition Industry*

Matt Marx
MIT Sloan School of Management
100 Main Street
E62-478
Cambridge, MA 02142
mmarx@mit.edu

David H. Hsu
The Wharton School
University of Pennsylvania
2028 Steinberg-Dietrich Hall
Philadelphia, PA 19104
dhsu@wharton.upenn.edu

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Abstract: How do technology entrepreneurs formulate a commercialization strategy, and how do those choices impact performance? We present evidence from all entrants into the speech recognition industry, where a "greenfield" commercialization environment affords wide latitude in strategic choice. While the initial choice of commercialization strategy does not predict performance, subsequently "pivoting" to another strategy strongly increases the hazard of a liquidity event. Intra-industry spinoffs are particularly likely to pivot. Results are confirmed when we instrument for pivoting with the unanticipated 2001 demise of the industry's largest technology licensor following an accounting scandal. Our results extend the literature on commercialization strategies, both by examining the dynamics of strategy-making and their impact on ultimate outcomes. They also suggest a novel mechanism underlying the success of spinoffs and indicate a possible role for dynamic capabilities in small firms.

Keywords: Technology commercialization strategy; entrepreneurial performance; dynamics.

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1. Introduction

To say that entrepreneurship is risky is a truism. In a sample of over 22,000 venture capital (VC) funded startups founded between 1987 and 2008, 75% had a liquidation value of zero while 0.39% had an exit value of $500M or greater (Hall & Woodward, 2010). Furthermore, scholars have documented a "private equity premium puzzle" in which the returns to entrepreneurial investment are only comparable to the returns to public equity despite relative illiquidity and poor asset diversification associated with holding private equity (Moskowitz & Vissing-Jorgensen, 2002). Accordingly, a burgeoning literature explores mechanisms by which VCs and other investors can mitigate risk. In addition to assembling a diversified portfolio of firms, VCs might lower their risk by investing in founders with prior experience (Gompers, et al., 2010), concentrating their investments in specialized industries (Gompers, Kovner & Lerner, 2009), allocating capital in rounds of financing rather than via a lump sum (Gompers, 1995), and by crafting cash flow- and control-rights in their financing contracts (e.g., Admati & Pfleiderer, 1994; Kaplan & Stromberg, 2003).

Less often have scholars examined how entrepreneurs can reduce their risk. To be sure, the literature has explicitly or implicitly explored explanations for the private equity puzzle and the skewed distribution of entrepreneurial returns. Individuals more likely to become entrepreneurs are wealthier than average (Evans & Jovanovic, 1989; Hurst & Lusardi, 2004) or may realize a great deal of non-pecuniary benefits from their career choice (Hamilton, 2000) and so may be less sensitive to financial risk. Entrepreneurs may have a preference for skewness in returns, akin to purchasing a lottery ticket (Moskowitz & Vissing-Jorgensen, 2002). Entrepreneurs may be (overly) optimistic in their venture outlook (e.g., Bernardo & Welch, 2001). But even if entrepreneurs are wealthy, risk-loving, or overoptimistic, they engage in new ventures not simply as games of chance but with the intent to create and capture value.

Our goal is to inform the literature regarding an unexplored mechanism of mitigating entrepreneurial risk. To do so, we conceptualize entrepreneurship as a process of economic experimentation. Experiments are usually conducted to make a discovery or test a hypothesis, which might be an apt analogy for entrepreneurs developing new enterprises. A critical question is where the locus of experimentation lies—at the level of the firm, or within the firm itself. From the perspective of an investor, it may be natural to view each portfolio firm as an individual experiment: to be funded as long as prospects look good, otherwise to be shut down so as not to "throw good money after bad." Alternatively, a startup itself may experiment, for example by "pivoting" or reorienting its strategy in order to find a new means of commercializing a technology. Google, for example, was not always an advertising company but rather adopted an initial commercialization strategy of licensing its search technology to Yahoo, Lycos, and other web-portal incumbents. Only after a few years did the company pivot from this strategy of cooperating with incumbents to one of competing directly with those portals for end-users.

Entrepreneurial experimentation by pivoting strategies has been explored largely in the practitioner domain (McGrath & MacMillan, 1995; Mullins & Komisar, 2010) but rarely in the academic literature. The few studies that examine startup performance and strategic experimentation disagree as to the value of pivoting (Bhide, 2000; Murray & Tripsas, 2004; Gavetti & Rivkin, 2007; Kaplan, Sensoy & Stromberg 2009), perhaps in part because these scholars examine only companies that were ultimately successful. Ideally, one would want to observe the full population of entrants into an industry from its inception and track their commercialization strategies over time as well as ultimate outcomes—a challenging data collection task. The difficulty of studying strategic experimentation by startups has led Aldrich and Martinez (2001: 25) to claim that "the weakest point in the field of entrepreneurship is, perhaps the most important one for an evolutionary perspective…We understand strategic choices and environmental selection process, but we know far less about how they interact with each other over time."

We introduce a new, hand-collected dataset tracking all entrants into the automatic speech recognition (ASR) industry from its inception in 1952 through the end of 2010. ASR is an attractive industry for analysis because its commercialization environment does not predetermine commercialization strategy. Using these data, we are able to follow technology commercialization strategies for all entrants, both de alio and de novo, on a monthly basis until a liquidity event, failure, or right-censoring.

Consistent with the literature on intra-industry spinoffs, we find that experienced entrants outperform other types. Interestingly, considering the initial strategic choice does not provide additional explanatory power. But pivoting TCS predicts improved performance, weakly in terms of survival but more strongly in terms of liquidity events—a key aspiration for many entrepreneurs and common outcome measure in the entrepreneurship literature. The inclusion of the pivoting measure weakens somewhat the effect of experienced entrants. Moreover, we find that these effects are concentrated among the spinoff entrants; diversifying (de alio) entrants do not appear to benefit much from pivoting. The results moreover strengthen when we instrument for the possibly endogenous nature of pivoting with the unexpected 2001 demise of Lernout & Hauspie, the most prominent supplier of speech recognition technology at the time.

2. Related literatures and prior empirical work

A key role of entrepreneurs in society is to catalyze "economic experiments" (Rosenberg, 1992), both as the founders of new firms and among incumbents with whom they compete. Indeed, new ventures are often viewed the vehicles for bringing inventions to market when large firms are either unable or unwilling to do so (Henderson, 1993; Christensen, 1996). The literature on industry dynamics and technological lifecycles tends to depict each entrant as a single experiment with a unique combination of technology as well as business plan (Klepper, 1997; Anderson & Tushman, 1990). An important driver in the Jovanovic (1982) theory of industry evolution stems from entrepreneurs entering an industry to learn their own cost efficiency as they operate in the industry and exiting if found to be inefficient. This view is reinforced by the entrepreneurial finance literature: investors adopt a portfolio strategy given the low likelihood of an individual startup achieving a liquidity event and reserve their exit option by staging capital infusions (Gompers, 1995). In this across-firm view of entrepreneurial experimentation, "the white coat is not worn by the entrepreneur but rather by the venture capitalist" (Murray & Tripsas, 2004: 50).

But experimentation and learning can also take place inside a startup. An organization can remain in one industry but adapt or pivot its commercialization strategy as it learns about the ideal configuration of its capabilities given market opportunities. Certainly the impact of learning from experience and experimentation has been a frequent topic of inquiry (Levinthal & March, 1993; Brown & Eisenhardt, 1997; Argote, 1999) though primarily in the context of large firms facing environmental change. We contend that new ventures will also benefit from experimentation. While some may choose a winning strategy initially, many may need to evolve beyond the first business plan before achieving fit (Siggelkow, 2002).

We study pivots in the context of technology commercialization strategy (TCS) because enterprise design and development decisions importantly depend on TCS choices. For example, organizational scope investment decisions differ dramatically between a strategy to compete against industry incumbents or alternatively to cooperate with them, and so TCS can be regarded as a core element of organizational design. At least since Teece (1986), scholars have sought to understand the relationship between TCS and value capture by innovators. A recent literature focuses on how intellectual property protection and the accessibility of complementary assets may prescribe a "cooperative" strategy in which entrants seek to partner with industry incumbents or, alternatively, a strategy in which one competes directly with incumbents (Gans, Hsu & Stern 2002; Gans & Stern, 2003; Fosfuri, 2006).

This stream of research yields implications for how technology entrepreneurs should analyze their initial TCS choice based on features of their commercialization environment, but it leaves at least two issues unaddressed. First, as most models are static (though see Gans, 2010 and Wakeman, 2010 for exceptions[1]) little guidance is provided beyond the initial selection of TCS. The dynamics of pivoting technology strategy are empirically unaddressed, though such actions may have important organizational and performance consequences. Second, despite the normative implications of the TCS literature, its prescriptions have rarely been tested by tying particular strategic choices to ultimate outcomes for new entrants, including survival and/or liquidity events.

The latter gap is particularly salient given work by scholars of industrial evolution and entrepreneurship regarding the role of organizational heritage in explaining entrant performance. A robust finding in the literature on intra-industry spinoffs is that startups whose founders were previously employed in the same industry outperformed other entrants - including diversifying de alio firms, which arguably have access to superior resources. This finding has been replicated in several industries: autos and lasers (Klepper, 2002; Klepper & Sleeper, 2005); shipbuilding (Thompson, 2005); disk drives (Agarwal et al., 2004); medical devices (Chatterjee, 2007); and in a population-level dataset from Denmark (Dahl & Reichstein, 2007). Yet scholars disagree on the mechanism underlying the strong performance of experienced entrepreneurs: whether technical inheritance (Agarwal et al., 2004) or market knowledge (Chatterji, 2007). Perhaps one reason for the discord is that spinoff studies, although often referencing the type of technology the firm attempts to market, generally do not note the commercialization strategy by which that technology is brought to market. Even when scholars have tied heritage to strategy (Burton, Sorensen & Beckman, 2002), they have generally done so by focusing on the initial choice and without attention to the dynamics over time, including whether the firm eventually pivots.

Perhaps it is the literature on dynamic capabilities that has most vocally called for an examination of how firms change strategies over time (Teece, Pisano & Shuen, 1997; Eisenhardt & Martin, 2000; Winter, 2003), though empirical follow-up has been slow to occur other than through case studies and simulations (but see Tripsas, 1997). More relevant evidence is found in the population ecology literature, which generally maintains that core strategic change is not only difficult to undertake but also undermines performance (Hannan & Freeman, 1984). However, to the extent that these effects are increasing in size and age (Greve, 1999), it seems possible if not likely that younger, smaller firms including new entrants might more successfully engage in strategic change and experimentation.[2] Woo et al. (1990) do find

[1] These papers present different facets of the argument that commercialization experience in innovation and production (as compared to a technology out-licensing strategy) may be worth more dynamically than statically due to developing downstream commercialization capabilities.

[2] Hannan and Freeman themselves carve out small organizations as an exception to their theory of structural inertia (1977: 158): "*Some organizations are little more than extension of the wills of dominant*

frequent pivoting among a random sample of startups in the Panel Study of Entrepreneurial Dynamics, but they do not tie pivoting to outcomes. Studies involving data from the Stanford Project on Emerging Companies (SPEC)—see Baron and Hannan (2002) for an overview—assess the rate of organizational change in small firms and connect these to outcomes including survival. These studies tend to focus, however, on changes in the employment model of the firm (Baron, Hannan & Burton, 2001), leaving open the question of how changes in market commercialization strategy impact performance.

Only a few scholars have directly assessed the connection between entrepreneurial experimentation and performance. Murray and Tripsas (2004) provide a case study of an MIT licensee that succeeded only after shifting how it commercialized its technology, "purpose[fully] experiment[ing]" with multiple commercialization strategies in the biotechnology industry. Similarly, Gavetti and Rivkin (2007) relate how the success of internet portal Lycos was dependent on evolving from its initial strategy. Larger-sample studies have attempted to address the question by examining firms that were successful. Bhide (2000) claimed that over one-third of the Inc. 500 significantly altered their initial strategic concepts, exhibiting what he calls "opportunistic adaptation" as they stumbled upon strategic possibilities not obvious to them at founding. In stark contrast, Kaplan, Sensoy, and Stromberg (2009) find that only one of 49 venture-backed firms that completed an IPO substantially changed from the strategy laid out in their initial business plan. A higher, but still small subsection (7%) of the population of firms completing an IPO in 2004 evolved from their initial strategy.

The limits—and in some cases, conflicting conclusions— of these studies naturally leave open questions, including whether the rates of pivoting differ for successful vs. unsuccessful firms. Kaplan et al. (2009: 83) recommend studying firms that fail, that are acquired, and that survive but do not go public, acknowledging that such data are difficult to assemble. Indeed, a key challenge in assessing the impact of pivoting on performance is capturing the evolution of strategy for an unbiased sample of firms. In the following section, we describe our approach for doing so.

3. Empirical approach

An ideal experiment for assessing the dynamics of TCS and their implications for performance would have at least three characteristics. First, one would want to study an industry whose structure does not

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coalitions of individuals…Such organizations may change strategy and structure…almost as quickly as the individuals who control them. Except in exceptional cases, only relatively small organizations fit this description." That said, only rarely have ecologists explored that strategic change might affect organizational outcomes positively, and then in the case of industry incumbents (Haveman, 1992).

strongly favor a cooperative or competitive TCS but is "Greenfield" in the rubric of Gans and Stern (2003) – as we will elaborate on below. Otherwise, the implications of the process of changing might become conflated with the value of being in different strategic positions (Barnett & Carroll, 1995). Second, one would want to follow the full population of entrants from the inception of the industry, with detailed data regarding strategic choices and ultimate outcomes. Third, in order to account for the endogeneous nature of strategic decisions one would want some exogenous source of variation in incentives for a subset of firms to change their TCS. Otherwise, one might be concerned that pivoting is correlated with unobserved firm quality or the availability of resources to facilitate the process of shifting from one strategy to another.

3.1 Data

For our study, we use a new, hand-collected dataset of the automatic speech recognition (ASR) industry from its inception in 1952 through the end of 2010. The speech recognition industry is best categorized as "Greenfield" given the lack of critical complementary assets as well as the strength of intellectual property protection. Unlike in the automotive industry, for example, where inventors mostly partner with auto manufacturers to reach end consumers by adopting a cooperative TCS, roughly equal proportions of entrants choose cooperative or competitive commercialization strategies. Technology is strongly excludable, with ASR firms having filed more than 3,000 patents. Moreover, the speech recognition industry has not been subjected to regulation that constrain strategic choices. In sum, entrants into the ASR industry "enjoy freedom to evaluation competition and cooperation options in the absence of the risk of expropriation or the inability to overcome established firm market power" (Gans & Stern, 2003: 345). This stands in contrast to extant TCS studies, which have largely been in industries whose structures either favor a cooperative approach, such as biotechnology (e.g., Lerner & Merges, 1998) or in sectors in which entrant competition with incumbents is dominant, such as disk drives (e.g., Christensen, 1996).

Speech recognition technology converts spoken language into text by modeling the sound waves generated by the human vocal tract. It is a science-based industry whose technology was incubated for many years in corporate and university research labs before coming to market. The earliest recorded ASR research effort was in 1952, when scientists at AT&T Bell Laboratories built a machine that could recognize digits zero through nine when spoken in isolation. Similar projects sprang up shortly thereafter at nearby RCA Laboratories and Lincoln Laboratories in the U.S., as well as internationally at London's University College, Kyoto University, and NEC Laboratories. The early 1960s brought the entry of Texas Instruments and the founding of IBM's T.J. Watson Research Center, which included ASR in its research portfolio. The industry's first company dedicated exclusively to ASR was Threshold Technology, founded by Thomas Martin. In the summer of 1970, he abandoned RCA Labs to found the firm and achieved early prominence by signing up Federal Express as a customer. Threshold's early success combined with its initial public offering is said to have strongly influenced the Department of Defense Advanced Research Projects Agency (DARPA) decision to initiate public funding of basic ASR research (Juang & Rabiner, 2004). Since then, ASR has been used for myriad applications including radiology dictation, plush toys that respond to verbal commands, remote access to a personal computer, 411 directory assistance automation, control of household functions for the disabled, personal telephone assistants, and podcast transcription.

The data for our study comprise nearly sixty years since the inception of the ASR industry. The original archives consist of approximately 15,000 pages of seven monthly trade journals variously spanning the years 1981 through 2000 and, as well as a historical account of the industry from its inception in 1952 (Juang & Rabiner, 2004). While it is possible that some firms have been omitted from the newsletters or historical documents, even obscure companies were covered in detail.[3] These trade journals offer the ability to characterize entrepreneurs' backgrounds and choices "as it happened" from third-party accounts rather than relying on retrospective reconstruction of events. Moreover, they offer detail regarding the strategy formulation process unavailable from business registers or other traditional data sources.

The first author, along with research assistants, coded the monthly trade journals by hand, reading each article individually. We noted in each article the ASR firms mentioned, and coded them as "active" in that month. A firm was counted as having entered the industry as of its first mention in the trade journals. A firm was counted as having left the industry when a trade journal article noted that it either ceased operations in the ASR industry or was acquired by another company. For firms that were never noted to have left the industry, we checked current corporate websites to ensure that they were still operating in the ASR industry as of December 2010. For the few that were not, we attempted to determine their date of exit from web sources; when such information was not otherwise available, we backdated their exit date to their final mention in the trade journals. Patterns of entry and exit are depicted in Figure 1.

Figure 1 about here

[3] However, since the newsletters were published in the U.S., it is possible that they omitted some non-U.S. firms or under-reported the strategic change of non-U.S. firms. Three-quarters of firms covered in the trade journals were U.S.-based, but Canada, Germany, France, and the U.K. contained at least a dozen companies per country.

In addition to dates of operation, we collected data regarding organizational heritage and evolution as well as strategic choices. Organizational data included whether the company entered the industry by diversifying from another industry (de alio) or as a startup (de novo). For de novo startups, we recorded whether any of the founders had previously worked at another ASR firm.[4] We also noted whether the de novo companies were sponsored by their parent firms, either in part or as wholly-owned subsidiaries. A small number of wholly-owned subsidiaries were classified as de alio entrants, though labeling them instead as de novo did not substantially affect the results.

Regarding the evolution of the firm, we recorded data regarding funding, leadership transitions, and patent awards. Financing events included fundraising from venture capital (cross-checked with VentureXpert), government, banks, other firms, or the public markets. CEO transitions were also noted. Data on granted patents from the U.S. Patent & Trademark Office were merged based on application date.

Finally, and most unique to our study, we coded commercialization strategies undertaken by the firm. Firms that competed directly for end customers by offering products or services were classified as having adopted a "compete" strategy. For example, Dragon Systems sold shrink-wrapped software that enabled consumers to dictate onto their personal computers. Angel.com built custom solutions for Fortune 500 firms to automatically handle telephone customer service. Tellme Networks offered an advertising-supported 1-800 number for retrieving sports scores, stock quotes, etc. By contrast, ASR firms that cooperated with incumbents by licensing technology or development tools were classified as having a "cooperate" strategy. As examples, BBN licensed its "HARK" speech recognition algorithms and VoiceObjects supplied toolkits that companies like Angel.com used to build end-user applications.[5] The

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[4] For the most part, the trade journals described whether the founders had previously worked at other ASR firms. Where such information was not available, we consulted public sources on the internet including company websites and LinkedIn to determine the founders' prior work experience. In a few cases where said sources were uninformative, we contacted founders to ask if they had had prior experience in the ASR industry. We were able to characterize the heritage of all but 35 de novo firms (271 of the 651 ASR firms were de novo startups). Excluding these firms from the analysis did not substantially affect results.

[5] We depart from the extant commercialization-strategy literature in that we do not classify firms that were eventually acquired as having adopted a "cooperative TCS. At least in the speech recognition industry, an acquisition was typically viewed as an attractive liquidity event and favorable organizational outcome as opposed to a strategic tactic—a view we believe is common to many entrepreneurs. Moreover, of the ASR firms eventually acquired, more of them adopted a "compete" strategy as defined above as opposed to a "cooperate" strategy.

adoption of a particular TCS was coded as having taken place the month it was reported in the trade journal. Subsequent mention of the same TCS was noted for purposes of continuation. If both compete and cooperate strategies were mentioned initially, they were coded as such.

A "pivot" was coded as such only if an initial TCS was noted in the newsletters, followed by a subsequent mention of a different TCS. As an example of a "pivot", Nuance Communications was spun out of SRI International, initially embarking on a cooperative commercialization strategy involving technology licensing and the sale of development toolkits. But a December 2002 trade journal article described Nuance's pivot to a competitive TCS: "Nuance has in the past emphasized sales through partners…contribut[ing] 82% of Q3 revenues. Nuance will develop and sell *pre-packaged applications* directly, and has formed an applications group to develop the applications. Nuance will sell *directly to end-user customers.* [T]his may result in some sales that would otherwise go to partners" (Meisel 2002:23, emphasis in original).

3.2 Variables

The outcome variables were coded from the measures of leaving the industry and liquidity events. Ceasing operations in the ASR industry was coded as the firm having failed. A liquidity event resulted from being acquired or completing an IPO. Following an exit or acquisition, no further observations were recorded as the firm disappeared from the trade journals.

The key explanatory variable of pivoting was identified as a firm adopting a TCS other than its initial TCS. For example, if a firm had initially adopted a "cooperate" TCS but later adopted a "compete" TCS, the month of the latter adoption was coded as a pivot. If the firm only ever adopted a single TCS, or if it adopted both cooperate and compete initially, no pivot was ever recorded. A given firm could pivot at most once given our definition. The variable "already-pivoted" was set to 1 if the firm had previously pivoted and 0 otherwise.

Other explanatory variables include initial TCS and organizational heritage. A dummy is set to 1 if the first reported TCS was "compete" and 0 if it was "cooperate" (it is undefined for the 13 firms that adopted both compete and cooperate strategies initially). Regarding organizational heritage, the *de alio* dummy is set to 1 for diversifying entrants; all other entrants are *de novo*. The *spinoff* variable is set to 1 for de novo firms where at least one of the founders previously worked at an ASR firm. The omitted category for these two dummies is de novo firms where none of the founders previously worked at an ASR firm.

Control variables include the year that the firm entered the ASR industry, an indicator variable for whether the CEO had been replaced in the past year, an indicator for the firm having previously received venture-capital funding, and a count of granted patents that were previously applied for (logged). Finally, a measure of initial quality is a disjunction of three factors: (1) whether the firm had any patents at its inception,[6] (2) whether the firm received venture capital funding at the time it entered the industry, and (3) for spinoffs, whether their parent firm had experienced a liquidity event. Finally, two dummy variables indicate whether the year of the current firm-month observation is after the demise of Lernout & Hauspie (i.e., 2001 or later) and whether the firm in question was in operation at the time. Descriptive statistics and correlations are in Table 1.

Table 1 about here

3.3 Estimation strategy

Given that our longitudinal data are right-censored but not left-censored, we employ an event-history model. However, given that we have two absorbing states—failure and liquidity—simple survival models are insufficient. We thus estimate a discrete-time competing hazard model (such as has been used by Martin & Mitchell, 1998; King & Tucci, 2002; Boyd et al., 2005; Arora & Nandkumar, 2011) implemented with a multinomial logit where the base state is continuing as a going concern. As in those prior studies, we adopt a nested specification in which survival is first decided with some probability, and conditional on survival, ratios of failures and liquidity are modeled in a multinomial logit specification. All models were estimated using Stata 11.

4. Results

4.1 Baseline analyses

We begin by examining the distribution of cooperative versus competitive TCS among various types of entrants, focusing on the initial choice in Panel A of Table 2. Of all entrants, 40% started with a cooperative strategy, 58% started with a competitive strategy, and 2% started with both cooperative and

[6] Data merged from the USPTO indicate the date of application for patents that were ultimately granted. In some cases, application dates were earlier than the first mention of the firm’s entry in the trade journals; these were reclassified as having been applied for in the month that the firm entered the industry.

competitive simultaneously. This relatively even split between cooperative and competitive reinforces the notion that ASR is a "Greenfield" industry; moreover, this balance is fairly consistent across entrant types, although spinoffs more often started with a competitive strategy.

Panel B shows basic pivoting patterns among entrants. Only 10% of firms ever pivot, while most stick with their initial commercialization strategy. (As a point of comparison, Kaplan, et al. (2009) report in their study of the startup lifecycle that of firms completing an IPO in 2004, 7.5% change their lines of business between the initial business plan and the IPO prospectus.) However, pivoting rates vary considerably across entrant types. Spinoffs are more than twice as likely to pivot than either de alio entrants or non-spinoff de novos. Moreover, spinoffs pivot earlier: median time to pivot is just three years after entry as compared with more than four years for other entrant types.

The remaining panels of Table 2 relate TCS to ultimate outcomes. Without controlling for other factors, Panel C suggests that the initial choice of commercialization is associated with outcomes; those with a cooperative initial TCS appear more likely to fail but show no significant difference in terms of liquidity. Panel D shows that pivoting firms are much less likely to fail and much more likely to have a liquidity event. These univariate findings are statistically significant at the 1% level in unreported t-tests.

Table 2 about here

Table 3 presents discrete-time hazard regressions for organizational outcomes. Observations are firm-months, with standard errors clustered by firm. Model 1 examines control variables alone. Firms that entered the ASR industry later were no more or less likely to fail, but they were considerably more likely to achieve a liquidity event. Firms are more apt to fail in their early years. Interestingly, the initial quality of a firm—including whether it has any patents or venture capital at entry—appears to be negatively associated with liquidity events, but the subsequent accrual of patents appears to have no bearing on ultimate outcomes. Having subsequently raised venture capital however is a strong predictor of both survival and liquidity. CEO replacement is associated with higher variance in outcomes, though the evidence is weaker for survival. Moving on to organizational heritage, in the ASR industry de alio firms' most likely outcome is failure. Consistent with the spinoffs literature, de novo entrants whose founders had previously worked in the industry outperformed other types of entrants—they are somewhat less likely to fail, and have a 1.6x higher hazard of experiencing a liquidity event.

Table 3 about here

In Model 2 we add the indicators for initial TCS and subsequent pivoting. The control variables behave largely as in the previous model, although the coefficient on the spinoff indicator is less statistically significant. As noted above, studies of spinoffs and other entrants, although they often note technological shifts (Bayus & Agarwal, 2007), have generally not taken account of commercialization strategy. The weakening of the spinoff coefficient upon accounting for TCS suggests that commercialization decisions and not just technology inheritance or market knowledge contributes to the performance of spinoffs. Moreover, Model 2 indicates that it is not the initial strategic choice but rather the dynamics over time that are responsible. This is in contrast to the univariate results from Panel C of Table 2, which might lead one to conclude on first glance that adopting a competitive TCS strategy is advantageous. Controlling for covariates in Model 2 shows that the initial TCS does not influence ultimate outcomes.

Pivoting, on the other hand, is strongly associated with liquidity events: the relative risk of pivoting firms achieving liquidity events is 2.16. Pivoting does not seem to discourage failure, as might be the case if pivoting were merely an artifact of having survived longer and thus having more opportunities to change strategies. Model 3 moreover suggests that what makes the difference is not just having engaged in a "mixed-mode" strategy that employs both types of TCS from the start (Teece, 1986). Rather, the sequencing of the different commercialization strategies matters: an indicator for firms that simultaneously adopted both a cooperative TCS as well as a competitive one upon entry do not differ in performance. Model 4 suggests that while all types of firms experience greater liquidity after having pivoted, spinoffs that pivot are particularly unlikely to fail once they have pivoted (indeed, in this population only one spinoff that pivoted subsequently failed).

4.2 Directional analysis

So far we have analyzed pivoting without regard for whether the firm pivoted from cooperative to competitive TCS or vice versa. In this section, we consider the directionality of the pivot. From a frictionless standpoint, the value of cooperative and competitive TCS strategies should be equivalent. The reasoning is that an innovator will demand payments under a cooperative strategy that equals the net present value of the revenue stream the firm would have received with a competitive strategy. In practice, however, this may not be the case. Factors such as assembling tightly-held complementary assets (Teece, 1986), firm reputational capital, and more generally bargaining power differences under varied commercialization strategies likely introduce deviations from the frictionless benchmark. Moreover, the performance implications of pivots in certain directions may be more or less advantageous for different types of entrants depending on organizational heritage. For example, in moving from a competitive to a cooperative TCS, spinoff firms may hold an advantage as compared to other types of entrants because they have legitimacy in the industry (Burton et al., 2002) and industry knowledge while not facing potential channel conflict issues as might hold for de alio entrants. The combination of these forces might lower the transactions costs of pivoting to a cooperative strategy.

Panels A and B of Table 4 provide insight into the frequency of pivoting by direction and by type. Panel A examines entrants who began with a cooperative TCS. Of those, approximately 15% eventually pivoted to a competitive TCS, with spinoffs much more likely to make the change: more than 40% of spinoffs which began with a cooperative TCS pivoted to competitive. Likewise, spinoffs were the most frequently pivoting entrant type when starting with a competitive TCS. For firms starting with a competitive TCS, only 6% eventually pivoted.

Table 4 about here

Panels C and D explore outcomes for pivoting ASR firms. Panel C shows that firms starting with a cooperative TCS were much less likely to fail when they pivoted to a competitive TCS. For firms with an cooperative initial TCS, 38% of those who pivoted eventually experienced a liquidity event as compared to 19% of those that did not pivot. For firms that began with a competitive TCS, Panel D shows that pivoting was responsible for an even slightly greater improvement in liquidity events (40% vs. 16.5%).

Table 5 continues the analysis in a multivariate framework. Models 1 and 2 are restricted to firms that began with a cooperative TCS, as with Panels A and C of Table 4. Model 1 indicates that when splitting the sample in this way, there is no longer a discernible advantage for spinoffs. There is some evidence that firms pivoting from cooperating to competing have a higher hazard rate of liquidity events, but this is only significant at the 10% level. Model 2 adds interaction terms for de alio and spinoff entrants, indicating that spinoffs pivoting from cooperating to competing have a much lower hazard of failure.

Table 5 about here

Models 3 and 4 provide similar analysis for the subset of firms that began with a competitive TCS. Here, the evidence is stronger, indicating that firms pivoting from competing to cooperating have a 2.7 fold higher hazard of liquidity events. Adding interaction terms for de alio and spinoff entrants only strengthens that base result while also demonstrating that pivoting from competing to cooperating avoids failure by spinoffs.

4.3 Instrumental variables approach using the demise of Lernout & Hauspie

While the above results provide strong support for the notion that pivoting strengthened the performance of entrants into the ASR industry, despite the use of longitudinal data the results are susceptible to endogeneity. Pivoting is a choice, one that may be epiphenomenal with other qualities (such as superior managerial insight) that benefit firm performance in ways unrelated to the pivot (Greve, 1999). Although the above analysis controls for a number of quality-related factors including heritage, patenting, and venture capital, there may still be omitted variables at play which are impossible to capture in our archival dataset. In order to identify the impact of pivoting more carefully, we take advantage of a singular event in the ASR industry that may have exogenously raised the likelihood of pivoting for a subset of firms: the unanticipated demise of Lernout & Hauspie Speech Products (abbreviated "L&H"). The following section draws both on as-it-happened news articles (Echikson & Moon, 2000; Einstein, 2000; Maremont, Eiseinger, & Carreyou, 2000) as well as retrospective analysis (Buelens & Cools, 2006).

Jo Lernout and Pol Hauspie founded their eponymous company in 1987 and grew it rapidly via acquisition and with the support of the Flanders Valley Language Fund in Ieper, Belgium. L&H was a developer of core speech-recognition technologies, licensing them broadly as part of a cooperative commercialization strategy to companies including Analog Devices, Microsoft, and Motorola. By the mid-1990s, nearly one-third of firms pursuing a competitive TCS licensed core technology from L&H. The firm completed an IPO in 1995, quadrupled sales in 1996, and subsequently went on an acquisition spree including 18 companies (both inside and outside the ASR industry) during the next few years.

Some observers had questioned the rapid growth of Lernout & Hauspie's claimed revenue, including a *Wall Street Journal* article in 1999 suggesting possible fraud. However, this was difficult to prove since Belgium-based L&H's financials were less than transparent, as they were not subject to U.S. Securities and Exchange Commission (SEC) disclosure requirements. However, L&H's acquisition of U.S.-based Dictaphone in May 2000 triggered such disclosure and provided skeptics with visibility into the firm's financial operations. Investigators noted that sales in Korea and Singapore had jumped from less than $300,000 in 1998 to $143.2M in 1999, in large part from 30 startup companies that were thought to be have funded at least in part by L&H and half of whom shared the same address. When contacted by *Wall Street Journal* reporter Jesse Eisinger in August of 2000, several of the Korean customers claimed never to have done business with the company, and others claimed that their purchases were considerably smaller than L&H's statements had claimed.

As a result, in September 2000 the SEC launched a probe of L&H's financial statements. The investigation revealed that L&H hid R&D expenses by funding a separate company, Dictation Consortium NV, to perform R&D on its behalf. The scheme involved Dictation Consortium hiring L&H

employees to conduct both business planning and technical execution. L&H subsequently acquired Dictation Consortium and wrote off the expense as "goodwill" over seven years, much longer than the permissible amortization of R&D. As a result of the audit, L&H announced that it would restate earnings since 1998 due to "errors and irregularities." Jo Lernout and Pol Hauspie resigned as co-chairmen of the company, trading of the company's stock was suspended, and on November 29 the company filed for bankruptcy protection. The co-founders were arrested (eventually sentenced to five years in prison) amid an exodus of talent from the once-prominent ASR firm, whose assets were frozen and then later sold by court-appointed liquidators.

The unanticipated demise of Lernout & Hauspie in late 2000 provided an unexpected business opportunity as perhaps the most influential licensor of ASR technology crumbled. ASR firms that had been pursuing a competitive TCS would suddenly have had reason to consider pivoting to a cooperative TCS to fill the L&H void. Indeed, Table 6 presents a univariate difference-in-difference analysis of pivoting patterns of ASR firms that were active at the time of L&H's demise. Although it was quite rare with a competitive TCS to pivot to a cooperative TCS prior to the demise of L&H, it became more frequent thereafter. Although pivoting became more common for firms with both types of initial TCS, the shift was much more pronounced for those who had a competitive initial TCS. The relative risk of pivoting after the demise of L&H as compared to before was 4.7 times higher for firms with a competitive TCS as compared to those with a cooperative TCS. As such, it appears that the demise of L&H may have resulted in increased pivoting from competing to cooperating.

Table 6 about here

This trend is moreover visible in Table 7, where Model 1 replicates the simple difference-in-difference analysis of Table 6 in a regression framework. Model 2 adds controls from the prior analyses, which account for the higher rate of pivoting by all firms after the demise of Lernout & Hauspie but preserve the result that firms with an initial competitive TCS became more likely to pivot following the shock. As such, we believe that the demise of L&H provides a plausibly exogenous source of variation in pivoting. At the same time, the impact of L&H's demise on ultimate outcome is unclear. More than three-dozen firms entered the ASR industry with a cooperative TCS in the years shortly after the demise of L&H, providing competition for those who pivoted to a cooperative TCS. As such, it appears that the increase in pivoting from competing to cooperating following the demise of L&H satisfies the exclusion restriction for use as an instrumental variable.

Table 7 about here

Although methods for estimating instrumental variables with multiple unordered outcomes have been theoretically developed (Heckman, Urzua & Vytlacil, 2008), the ordered case as in our data (failure, going-concern, liquidity) remains unaddressed. Moreover, even the unordered case has not been implemented in standard statistical packages, leading us to consider multiple outcomes in separate models. Our resulting dependent variables (failure and liquidity) are both dichotomous, as is our explanatory variable of pivoting. Thus we adopt a bivariate probit model in the remaining models of Table 7, which report the second stage of bivariate probit regressions where the first stage resembles Model 2. (Because the L&H instrument relies on variation between firms with different types of initial TCS, we do not test directional pivoting here.) Model 3, like the models of Table 3, indicate no discernible effect of pivoting on survival. But of most interest here, the effect of pivoting on liquidity events is confirmed in Model 4 and with stronger statistical significance than in Table 3. In Model 5, we narrow the sample by excluding those firms that eventually failed, with consistent results. Model 6 bootstraps the regression (200 replications), yielding slightly larger standard errors on the pivoting coefficient, but the estimate is still significant at the 5% level. Standard errors are larger still in an unreported linear model, an alternative approximation recommended by Angrist & Pischke (2009:198-204), but the results are otherwise consistent.

5. Discussion and Conclusions

Using a dataset of the population of entrants into the worldwide speech recognition industry from 1952 through 2010, we find that entrepreneurial experimentation via technology strategy pivoting is responsible for a higher hazard rate of achieving a liquidity event. Furthermore, we find evidence that these results hold when examining both pivoting from a cooperating to competing commercialization strategy as well as pivots in the opposite direction. We address the endogeneity of pivoting with organizational performance by instrumenting for pivoting using the unexpected 2001 demise of Lernout & Hauspie, the most prominent supplier of speech recognition technology at the time, and find that our core results hold. The industry context we examine is advantageous not only because we are able to observe objective third party characterizations of technology commercialization strategy over time, but also because the speech recognition industry operates in a business environment in which no particular commercialization strategy is dominant.

This last point entails an important scope condition for our findings. By no means do we claim that entrants in every industry will benefit from pivoting their commercialization strategy. The structure of certain industries may dictate a winning TCS, for example a “market for ideas” environment (Gans &

Stern, 2003) where technology is excludable (like ASR) and incumbent complementary assets are essential (unlike ASR). Our results are best applied in contexts where entrants have wide latitude regarding their commercialization strategy. When technology commercialization contexts are fluid, as with ASR, choosing the right strategy up-front may be less important than putting processes in place to explicate assumptions and then adapt quickly when assumptions are proven wrong (McGrath & MacMillan, 1995). We should note, however, that we are unable to draw broad-based conclusions about all forms of business pivoting, and no doubt there are a myriad of ways in which one could define and operationalize the term. We study a specific, albeit important, form of technology commercialization strategy pivoting and ground our study in the prior literature in this domain.

These results add to the nascent literature on entrepreneurial experimentation, advancing the state of empirical research by examining the full population of entrants into an industry and following them over their life course using contemporaneous third-party accounts of commercialization strategies. The results lend support to the findings of early case studies that indicated a role for experimentation within new firms (Murray & Tripsas, 2004; Gavetti & Rivkin, 2007), as opposed to viewing each startup as a self-contained experiment. Moreover, our results suggest that pivoting is not limited to the very early days of a venture (Bhide, 2000; Kaplan et al., 2009) but is an ongoing phenomenon. We note that our findings may seem inconsistent with studies using the SPEC data, which conclude that changing employment models can be dangerous, while we find that changing commercialization strategy can be beneficially adaptive. Of course, commercialization strategy and employment models are different constructs; one may pivot the former without reworking the latter, but future research could investigate the interplay between the two.

More generally, our study draws on three literatures that heretofore have not been explicitly linked, and we believe that our results contribute to these same three domains: technology commercialization strategy, spinoffs and organizational heritage, and dynamic capabilities. We discuss each in turn.

This study extends work on technology commercialization in three important ways. Extant TCS literature shows how business environment and innovation factors such as the appropriability environment, stage of industry evolution, and the nature of complementary assets influence the initial selection of commercialization strategy (Gans & Stern, 2003). Our first contribution is to take the additional step of linking TCS choice to performance, a critical step in validating work to date. Secondly, we examine not only the impact of the initial TCS choice but the dynamics of commercialization strategy over time, a subject that has only begun to be touched on theoretically (Gans 2010; Wakeman 2010) and where little or no empirical work has been performed. Third, while existing TCS studies focus exclusively on the external environment, our study begins to look inside the firm for determinants of TCS, including the heritage of the founders (though see Eesley, Hsu & Roberts (2011) for an analysis of fit between strategy and founding team composition).

Our findings with regard to founders and organizational heritage also contribute to the literature on intra-industry spinoffs. While the literature on spinoffs has found that organizational heritage seems to matter in that intra-industry spinoffs tend to outperform other types of entrants (Helfat & Lieberman, 2002), there is no widespread agreement on the cause of this relationship. Our findings suggest that one reason spinoffs outperform other entrants is because they are more likely to pivot. We are unable to draw conclusions, however, regarding the relative importance of managerial recognition for the need to pivot which may be linked to organizational heritage as compared to the ability to conduct the pivot; future work could expand on this point.

Finally, although our study is not primarily motivated by the search for dynamic capabilities, these results may be of interest to those in that field. As has been suggested by past theoretical work, we find that pivoting is productively adaptive, but we use statistical methods rather than case studies or simulation methods, as has been the usual practice in that literature. Of course, we study new entrants as opposed to incumbents, which are typically the focus of the dynamic capabilities literature. This setting may, however, reveal one boundary condition—namely, the importance of a dynamically changing business environment. In our empirical setting, which can be characterized primarily as a business environment of incremental technical change, we find that TCS pivots can still be important in explaining organizational performance as organizations adapt in order to resolve the uncertainty posed by the to-them new environment.

To conclude, commercialization strategy pivots can be an important means by which organizations may conduct valuable entrepreneurial experiments. Since entrepreneurs typically face considerable financial risk as a result of being both illiquid and undiversified in their holdings, pivoting may be one of the few strategies available to help lower such risk, and so deserves further analytic consideration.

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Table 1: Descriptive statistics and correlations for *n*=49,738 firm-month observations.

	Variable	Mean	Std. Dev.	Min	Max	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)
1)	de alio	0.597	0.490	0	1	1.000												
2)	spinoff	0.140	0.348	0	1	-0.398	1.000											
3)	year of entry	1992.8	11.696	1952	2010	-0.260	0.013	1.000										
4)	active at demise of L&H	0.559	0.497	0	1	0.133	-0.044	-0.261	1.000									
5)	initial quality	0.359	0.480	0	1	0.064	0.073	0.023	0.209	1.000								
6)	initial TCS = compete	0.512	0.500	0	1	-0.097	0.015	0.440	0.000	0.037	1.000							
7)	months since entry (L)	3.848	1.232	0	6.562	0.113	0.016	-0.432	0.356	0.081	-0.182	1.000						
8)	already raised VC	0.350	0.477	0	1	-0.154	0.048	0.032	0.254	0.524	0.094	0.144	1.000					
9)	CEO replaced in past year	0.024	0.152	0	1	-0.114	0.050	-0.011	-0.010	-0.034	-0.038	0.047	0.117	1.000				
10)	patents to date (L)	0.561	1.168	0	5.793	0.146	-0.018	-0.253	0.144	0.258	-0.232	0.304	-0.090	0.032	1.000			
11)	already pivoted	0.084	0.278	0	1	-0.013	0.105	-0.070	0.122	-0.053	-0.139	0.231	0.017	0.106	0.307	1.000		
12)	exit	0.005	0.070	0	1	0.019	-0.017	0.003	-0.048	-0.025	0.001	-0.041	-0.032	0.007	-0.014	-0.015	1.000	
13)	liquidity	0.003	0.052	0	1	-0.020	0.015	0.013	-0.015	-0.005	0.001	0.000	0.015	0.022	-0.001	0.022	-0.004	1.000

Table 2: Univariate tabulations of entrant type, commercialization strategy, and outcomes. *n*=651 firms.

Panel A: Initial TCS and entrant type

		dealio	spinoff	other	Total
					Avg.
Cooperate		159	24	77	260
	%	*42.6*	*34.3*	*37.0*	*39.9*
Compete		210	44	124	378
	%	*56.3*	*62.86*	*59.6*	*58.06*
Both at first		4	2	7	13
	%	*1.07*	*2.86*	*3.37*	*2*
Total		373	70	208	651
	%	*100*	*100*	*100*	*100*

Panel B: Pivoting and entrant type

		dealio	spinoff	other	Total
					Avg.
did not pivot		343	54	189	586
	%	*92.0*	*77.1*	*90.9*	*90.0*
pivoted		30	16	19	65
	%	*8.0*	*22.9*	*9.1*	*10.0*
Total		373	70	208	651
	%	*100*	*100*	*100*	*100*
Median time to pivot		4.33	3.04	4.41	3.83

Panel C: Initial TCS and ultimate outcomes

		Cooperate	Compete	Both at first	Total
Going concern		84	182	5	271
	%	*32.3*	*48.2*	*38.5*	*41.6*
Failure		119	128	4	251
	%	*45.8*	*33.9*	*30.8*	*38.6*
Liquidity		57	68	4	129
	%	*21.9*	*18.0*	*30.8*	*19.8*
Total		260	378	13	651
	%	*100*	*100*	*100*	*100*

Panel D: Pivoting and ultimate outcomes

		did not pivot	pivoted	Total
Going concern		239	32	271
	%	*40.8*	*49.2*	*41.6*
Failure		243	8	251
	%	*41.5*	*12.3*	*38.6*
Liquidity		104	25	129
	%	*17.8*	*38.4*	*19.8*
Total		586	65	651
	%	*100*	*100*	*100*

Table 3: Multinomial logit discrete-time hazard models of firm outcomes. The base outcome is continuing as a going concern.

	(1)		(2)		(3)		(4)	
	failure	liquidity	failure	liquidity	failure	liquidity	failure	liquidity
year of entry	-0.0057	0.0331***	-0.0051	0.0331**	-0.0057	0.0326***	-0.0049	0.0333**
	(0.008)	(0.009)	(0.008)	(0.011)	(0.008)	(0.009)	(0.008)	(0.011)
months since entry (L)	-0.3497***	0.0436	-0.3444***	-0.0103	-0.3497***	0.0456	-0.3433***	-0.0075
	(0.034)	(0.102)	(0.034)	(0.104)	(0.034)	(0.103)	(0.034)	(0.105)
initial quality	-0.2278	-0.6237**	-0.2964	-0.5293*	-0.2284	-0.6365**	-0.2876	-0.5212*
	(0.241)	(0.216)	(0.242)	(0.230)	(0.242)	(0.216)	(0.243)	(0.233)
patents to date (L)	-0.1072	0.1255	-0.0547	0.0354	-0.1072	0.1260	-0.0571	0.0386
	(0.082)	(0.083)	(0.083)	(0.086)	(0.082)	(0.083)	(0.083)	(0.086)
already raised VC	-0.8082**	0.7336**	-0.7668**	0.6300**	-0.8077**	0.7472**	-0.7913**	0.6077*
	(0.256)	(0.228)	(0.254)	(0.241)	(0.256)	(0.230)	(0.258)	(0.253)
CEO replaced in past year	0.7882+	0.7137*	0.7833	0.6306+	0.7864+	0.6968*	0.7951	0.6286+
	(0.429)	(0.352)	(0.479)	(0.348)	(0.433)	(0.354)	(0.485)	(0.347)
de alio	0.6593***	-0.2635	0.6815***	-0.2410	0.6600***	-0.2496	0.7158***	-0.2006
	(0.177)	(0.213)	(0.183)	(0.221)	(0.177)	(0.214)	(0.187)	(0.233)
spinoff	-0.5425+	0.4824*	-0.5410	0.4287+	-0.5419+	0.4942*	-0.4324	0.4741+
	(0.313)	(0.224)	(0.329)	(0.224)	(0.315)	(0.223)	(0.329)	(0.268)
initial TCS = compete			-0.0069	-0.1520			-0.0118	-0.1577
			(0.161)	(0.207)			(0.161)	(0.208)
already pivoted			-0.6251	0.7835**			0.1925	0.9113**
			(0.425)	(0.255)			(0.760)	(0.330)
already pivoted * de alio							-0.8481	-0.2244
							(0.881)	(0.543)
already pivoted * spinoff							-13.4326***	-0.1572
							(0.690)	(0.467)
initial TCS is both compete & cooperate					0.0253	0.4969		
					(0.478)	(0.452)		
Constant	7.1418	-72.2609***	5.9077	-72.0871***	7.1761	-71.1996***	5.5094	-72.4862***
	(15.466)	(18.173)	(16.963)	(21.786)	(15.490)	(18.242)	(16.958)	(21.891)
Observations	49,717	49,717	48,883	48,883	49,717	49,717	48,883	48,883

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 4: Univariate tabulation of directional pivots. *n*=651 firms.

Panel A: firms with initial TCS = Cooperate

	dealio	spinoff	other	Total *Avg.*
TCS always = Cooperate	139	14	68	221
%	*87.4*	*58.3*	*88.3*	*85.0*
pivoted to Compete	20	10	9	39
%	*12.6*	*41.7*	*11.7*	*15.0*
Total	159	24	77	260
%	*100.0*	*100.0*	*100.0*	*100.0*

Panel B: firms with initial TCS = Compete

	dealio	spinoff	other	Total *Avg.*
TCS always = Compete	201	38	114	353
%	*95.7*	*86.4*	*91.9*	*93.4*
pivoted to Cooperate	9	6	10	25
%	*4.3*	*13.6*	*8.1*	*6.6*
Total	210	44	124	378
%	*100.0*	*100.0*	*100.0*	*100.0*

Panel C: firms with initial TCS = Cooperate

	TCS always = Cooperate	pivoted to Compete	Total *Avg.*
going concern	64	19	83
%	*29.0*	*48.7*	*31.9*
failure	115	5	120
%	*52.0*	*12.8*	*46.2*
liquidity	42	15	57
%	*19.0*	*38.5*	*21.9*
Total	221	39	260
%	*100.0*	*100.0*	*100.0*

Panel D: firms with initial TCS = Compete

	TCS always = Compete	pivoted to Cooperate	Total *Avg.*
going concern	170	12	182
%	*48.2*	*48.0*	*48.2*
failure	125	3	128
%	*35.4*	*12.0*	*33.9*
liquidity	58	10	68
%	*16.4*	*40.0*	*18.0*
Total	353	25	378
%	*100.0*	*100.0*	*100.0*

Table 5: Directional analysis of pivot using multinomial logit discrete-time hazard models. The base outcome is the firm as a going concern.

	(1)		(2)		(3)		(4)	
	failure	liquidity	failure	liquidity	failure	liquidity	failure	liquidity
year of entry	0.0100	0.0610***	0.0103	0.0636***	-0.0604***	-0.0184	-0.0605***	-0.0161
	(0.009)	(0.013)	(0.009)	(0.014)	(0.014)	(0.020)	(0.014)	(0.020)
months since entry (L)	0.3236**	0.2383	-0.3222***	0.2466	-0.3489***	-0.1566	-0.3472***	-0.1575
	(0.053)	(0.171)	(0.052)	(0.169)	(0.048)	(0.124)	(0.048)	(0.125)
initial quality	-0.2356	-0.7893*	-0.2238	-0.8037*	-0.4747	-0.3403	-0.4448	-0.3298
	(0.316)	(0.347)	(0.314)	(0.367)	(0.420)	(0.343)	(0.433)	(0.343)
patents to date (L)	-0.0234	-0.0114	-0.0301	-0.0105	-0.1086	0.1184	-0.1150	0.0631
	(0.097)	(0.116)	(0.099)	(0.126)	(0.180)	(0.138)	(0.182)	(0.143)
already raised VC	-1.0949**	1.0279*	-1.1496**	1.0024*	-0.7660+	0.2287	-0.8031+	0.2625
	(0.377)	(0.427)	(0.382)	(0.446)	(0.419)	(0.304)	(0.440)	(0.320)
CEO replaced in past year	0.9163	0.9263*	0.9354	0.9390*	0.7876	-0.5859	0.7959	-0.5376
	(0.684)	(0.395)	(0.716)	(0.400)	(0.688)	(1.063)	(0.690)	(1.061)
de alio	0.5808*	0.1706	0.6285*	0.2712	0.7135**	-0.5628*	0.7381**	-0.5496+
	(0.275)	(0.382)	(0.286)	(0.409)	(0.248)	(0.275)	(0.251)	(0.295)
spinoff	-0.5648	0.4687	-0.3865	0.1297	-0.6284	0.3602	-0.5923	0.5501
	(0.483)	(0.325)	(0.479)	(0.469)	(0.438)	(0.336)	(0.442)	(0.342)
already pivoted cooperate->compete	-0.6772	0.5315+	0.3326	0.4861				
	(0.531)	(0.318)	(1.101)	(0.491)				
already pivoted cooperate->compete * de alio			-0.9556	-0.5407				
			(1.191)	(0.742)				
already pivoted cooperate->compete * spinoff			-13.5970***	0.7264				
			(0.885)	(0.631)				
already pivoted compete->cooperate					-0.5612	0.9949*	0.2519	1.3148**
					(0.748)	(0.423)	(1.096)	(0.453)
already pivoted compete->cooperate * de alio							-1.1467	0.1482
							(1.560)	(0.831)
already pivoted compete->cooperate * spinoff							11.9565**	-1.5711
							(1.235)	(1.236)
Constant	-24.0054	128.9118**	-24.7102	134.1670**	16.4824**	31.5599	16.5483**	26.8192
	(18.253)	(26.651)	(18.280)	(28.734)	(28.427)	(40.041)	(28.543)	(40.624)
only for initial TCS = cooperate	yes	yes	yes	yes	no	no	no	no
only for initial TCS = compete	no	no	no	no	yes	yes	yes	yes
Observations	23,730	23,730	23,730	23,730	25,153	25,153	25,153	25,153

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 6: Univariate difference-in-difference table of pivoting before and after the demise of Lernout & Hauspie. Dependent variable is whether the firm had already pivoted. N=28,107 firm-month observations for firms that were active at the time of Lernout & Hauspie**'s demise.**

	pre-demise	post-demise	difference	odds ratio	relative risk
initial TCS = cooperate	*9.83%*	*23.64%*	13.82%	2.8412	2.406
initial TCS = compete	*0.49%*	*6.77%*	6.28%	14.6274	13.705
	9.33%	16.87%		-4.1484	4.6965

Table 7: Instrumental variable regressions of pivoting on ultimate outcomes.

	(1) pivot	(2) pivot	(3) failure	(4) liquidity	(5) liquidity	(6) liquidity
year of entry		0.0560+	0.0398**	0.0240**	0.0225**	0.0235**
		(0.0326)	(0.0136)	(0.0075)	(0.0074)	(0.009)
months since entry (L)		1.0996***	0.0063	0.0789	0.0515	0.0779
		(0.2960)	(0.0327)	(0.0520)	(0.0507)	(0.068)
initial quality		-1.0498*	-0.0875	-0.0086	0.0057	-0.0031
		(0.5311)	(0.1296)	(0.1159)	(0.1174)	(0.133)
patents to date (L)		0.6384***	0.0356	-0.0401	-0.0434	-0.0451
		(0.1563)	(0.0592)	(0.0470)	(0.0521)	(0.058)
already raised VC		0.1579	-0.1545	0.1238	0.1158	0.1213
		(0.4426)	(0.1168)	(0.1152)	(0.1143)	(0.126)
CEO replaced in past year		1.1450*	0.2801	0.0136	0.0452	-0.0188
		(0.4565)	(0.2238)	(0.1983)	(0.2069)	(0.591)
de alio		-1.0187*	0.1200	-0.0952	-0.0968	-0.0972
		(0.4279)	(0.1258)	(0.1118)	(0.1139)	(0.121)
spinoff		0.9564	-0.0808	0.0016	-0.0164	0.0037
		(0.5899)	(0.2116)	(0.1395)	(0.1422)	(0.161)
initial TCS = compete	-3.0890***	-2.6223***	0.1434	-0.0071	0.0160	-0.0018
	(0.7136)	(0.7789)	(0.1244)	(0.1103)	(0.1093)	(0.129)
after demise of L&H	1.0442**	-0.0997				
	(0.3832)	(0.5998)				
after demise of L&H * initial TCS = compete	1.6387*	1.5420*				
	(0.6467)	(0.7112)				
already pivoted			-0.1340	1.1659**	1.1405**	1.2336*
			(0.4806)	(0.3837)	(0.3894)	(0.613)
Constant	-2.2165***	-118.0678+	-82.4297**	-51.0518***	-47.9657**	-50.1442**
	(0.3314)	(65.4000)	(27.1143)	(15.0135)	(14.7120)	(18.132)
rho			0.0596	-0.5640**	-0.5632**	-0.5766
			(0.269)	(0.189)	(0.191)	(0.383)
Exclude firms that eventually exited?	no	no	no	no	yes	no
Block-bootstrap?	no	no	no	no	no	yes
	28,414	28,107	28,107	28,107	24,577	28,107

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Figure 1: ASR firm entry and exit since the inception of the industry in 1952. The connected blue line is the overall industry density (i.e. number of active firms).