NBER WORKING PAPER SERIES

DYNAMIC COMMERCIALIZATION STRATEGIES FOR DISRUPTIVE TECHNOLOGIES: EVIDENCE FROM THE SPEECH RECOGNITION INDUSTRY

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Working Paper 19764
http://www.nber.org/papers/w19764

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2013

We thank Ronnie Chatterji, Jason Davis, Chuck Eesley, April Franco, Thomas Hellmann, Ramana Nanda, Henry Sauermann, Scott Stern, and Ezra Zuckerman, as well as audience members at the Atlanta Competitive Advantage Conference, the BYU-Utah Winter Strategy Conference, Carnegie Mellon, University of Chicago, the Duke Strategy Conference, Georgia Tech, Harvard Business School, the HBS-MIT Strategy Conference, INFORMS, London Business School, Stanford, University of Toronto, and Wharton for helpful comments. We acknowledge funding from the Wharton Mack Institute for Innovation Management and the MIT Sloan Roberts E-Center Fund. We thank Greg Hum, Jacalyn Martelli, Lydia Volaitis, and Tianyu Wang for research assistance and are especially indebted to Walt Tetschner of ASRNews and Bill Meisel of TMA Associates for help obtaining archival materials. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w19764.ack

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NBER Working Paper No. 19764
December 2013
JEL No. O32

ABSTRACT

When startup innovation involves a potentially disruptive technology – initially lagging in the predominant performance metric, but with a potentially favorable trajectory of improvement – incumbents may be wary of engaging in cooperative commercialization with the startup. While the prevailing theory of disruptive innovation suggests that this will lead to (exclusively) competitive commercialization and the eventual replacement of incumbents, we consider a dynamic strategy involving product market entry before switching to a cooperative commercialization strategy. Empirical evidence from the automated speech recognition industry from 1952-2010 confirms the main prediction of the model.

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1 Introduction

Entrepreneurs seeking to commercialize their technical innovations often rely on cooperative strategies, such as technology licensing, with other organizations. They do so both to access the skills or assets they may not possess and to minimize competitive effects. Given that the decision to cooperate with incumbents is not unilateral, the incumbent must see some advantage in accessing the technology from the innovator. If the incumbent is unsure about the value of the technology, cooperation may be initially infeasible. Thus the entrant may find it necessary to compete in the product market, at least until the incumbent becomes convinced regarding the value of the technology.

Consider the case of Qualcomm’s code-division multiple access (CDMA) technology for handling cellular communications. CDMA took the controversial approach of handling multiple calls on the same frequency simultaneously and managing the interference as opposed to sequentially as in TDMA (time-division multiple access). Although CDMA promised to be more efficient than TDMA, there were many skeptics including a Stanford University professor who declared that the frequency-sharing approach would “violate the laws of physics” (Brodsky 2008: 199) and accused Qualcomm of faking its first demonstration. Qualcomm temporarily abandoned licensing and began manufacturing both base stations and handsets in order to prove the value of CDMA technology. It retained these complementary businesses for several years before selling the former to Ericsson and the latter to Kyocera. In personal communication, Qualcomm co-founder Andrew Viterbi (2012) recounted:

> *[F]or this large and complex opportunity it was essential to produce the infrastructure as well as the handsets…it was necessary to convince the carriers that CDMA was indeed a workable technology which had a major advantage over alternates: GSM, U.S. and Japanese TDMA standards. All of this took a lot of effort, several successful demonstrations, some luck and about three or four years; there were many skeptics.”*

Qualcomm’s strategy of temporarily entering the product market and subsequently switching to the preferred licensing model serves as an example of how firms can demonstrate the value of their technology to would-be partners.

One category of innovations that may be particularly difficult to commercialize in a cooperative setup are “disruptive” technologies. Disruptive technologies exhibit an initially worse performance profile on the dimension valued by mainstream consumers (Christensen, 1997), so the gains to trade with incumbents required for cooperative commercialization may not exist. If deployed, however, they may exhibit a favorable trajectory of improvement. Under such a circumstance, the commercialization partner may have little financial incentive early on to develop the innovation in-house or access it via contractual means, as combining it with their existing activities is costly. However, should a potentially disruptive technology prove to be valuable, these incentives may change. Thus, in contrast to the main predictions of existing analyses that find incumbent firm market leadership routinely replaced in the face of disruptive innovation by entrepreneurs, cooperative commercialization—which preserves incumbent market leadership—may still be a long-term outcome.

We theoretically and empirically explore a two-stage commercialization strategy in which a start-up entrant temporarily enters the product market in order to establish the value of its technology. Ultimately, the entrant may switch to a strategy of cooperating with incumbents once uncertainty of the disruptive technology is resolved and/or the incumbent's costs of integrating the new technology declines. This dynamic technology commercialization strategy (TCS) extends extant frameworks linking the environmental, organizational, and competitive factors to an entrant's initial choice of TCS (Teece, 1986; Gans and Stern, 2003). Such work characterizes TCS as a one-time, static decision to cooperate with incumbents via licensing or to compete against them in the product market.

Perhaps one reason commercialization strategy has not been explored dynamically is the difficulty of obtaining longitudinal data regarding TCS adoption and evolution. We introduce a 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 TCS analysis because its commercialization environment leaves open a variety of possible commercialization strategies. The data allow us to follow technology commercialization strategies on an annual basis, including when firms change from their initial TCS. Furthermore, our long time horizon of observing industry entrants allows us to study the relationship between innovation characteristics (e.g., disruptive technology status) and their commercialization strategies.

Our analysis reveals that ASR entrants who introduce disruptive technologies are more likely to adopt a two-stage commercialization strategy in which they initially compete with incumbents but later cooperate with them. This result calls into question the notion that disruptive technologies necessarily result in the demise of incumbents, such as in the disk-drive industry (Christensen, 1997). Although the initially unattractive nature of disruptive technologies does entail first stage entrant/incumbent competition, cooperation may ultimately ensue in commercialization environments where it is supported.

2 Related Literature

Tushman and Anderson (1986) classify innovation into two types according to organizational effect. Competence-destroying innovations are those that require new organizational skills to successfully commercialize, whereas competence-enhancing innovations build on existing organizational know-how. Across a variety of industrial settings, researchers have found that competence-destroying innovations are more likely to be initiated by new entrants, whereas industry incumbents tend to originate competence-enhancing discontinuities (Tushman and Anderson, 1986; Christensen and Bower, 1996). This pattern reflects the behavior of established firms, which are typically eager to invest and support innovations that sustain and extend rates of improvement along the dimensions demanded by their mainstream consumers. These incumbents have little financial incentive to develop or acquire innovations that are competence-destroying given the organization's structure of complementary assets and skills.

Entrants are more likely to originate competence-destroying innovations because they do not fear product cannibalization and typically do not have vested positions in a pre-existing complementary asset infrastructure. This ordinarily favors a competitive commercialization strategy. Using the predominant static TCS framework (Teece, 1986; Gans and Stern, 2003), the lower the cost of product market entry, including the costs of assembling the requisite downstream complementary assets for commercialization, the more attractive is a competitive commercialization strategy. This is especially true if the appropriability regime is weak so that the entrant's exposure to disclosure risks when bargaining over deal terms with industry incumbents is high. Moreover, the incumbent may have no motivation to incorporate the entrant's innovation if it represents a permanent threat to the incumbent's existing business.

In a seminal line of research, Christensen and coauthors describe a class of "disruptive technologies" whose competence-enhancing/destroying attributes become clear only in the long run. Disruptive technologies typically underperform existing technologies along performance dimensions of interest to existing customers and/or appear useful primarily in niche markets too small to be of interest to incumbents. For example, Christensen and Bower (1996) show that the lower capacity, slow access speed, and high cost of 5.25-inch disk drives compared to existing 8-inch drives led to their rejection by minicomputer OEMs. By contrast, "sustaining" technologies would improve capacity, access speed, etc.; the 5.25 drive was "disruptive" to the path of continuous improvement in that it performed worse in those respects. Of course, smaller drives later took over the market as their performance among traditional metrics improved and their use cases became better understood.

Even in situations where cooperatively commercializing a disruptive innovation might be preferable from the entrepreneur's perspective, the incumbent may be hesitant to do so because utilizing it harms existing profits. This means that an entrant may be better placed to test the efficacy and market potential of such technologies by taking the products to market themselves. If such a test is successful, a disruptive technology that appeared irrelevant initially may later be attractive to incumbents looking to preserve their market position. Thus, for such technologies we may see entrepreneurs switch their commercialization strategy. That is, competition may precede cooperative commercialization strategies (e.g., licensing or acquisition), as was the case with Qualcomm.

Arora, Fosfuri, and Gambardella (2001: 430) allude to this possibility in a footnote: "…[s]ometimes self-production is a necessary condition for successful licensing. For instance, self-production could help assess the true value of the technology or could help identify potential bottlenecks in technology transfer." We build on this idea, noting that potentially disruptive innovations introduce frictions for technology transfer. In such settings, product-market integration may indeed be a precondition for licensing. Unable to secure cooperative commercialization partners early on, the innovator competes against incumbents in the product market. The innovator later switches to its preferred strategy of cooperating once incumbents have been convinced that the technology has value.

One of the main claims of Christensen (1997) is that disruptive innovation is often associated with replacing incumbent firm market leadership despite (initial) technical underperformance in the predominant performance dimension. However, an entrant strategy of initially competing followed by later cooperating would suggest that in some cases of disruptive technology, incumbent market leadership might still be preserved. Bower and Christensen (1995), in discussing managing disruptive technological change, do consider an incumbent acquisition strategy (though not a technology in-licensing one). While the authors acknowledge and give examples of how such acquisitions have helped preserve incumbent market leadership, they point to both the innovator's possible reluctance in pursuing a cooperative strategy as well as the difficulty of successfully executing acquisitions as challenges of this strategy. The end result is the predominant conclusion in the existing literature that disruptive innovation overturns incumbent market leadership. We now explore how an innovator's commercialization strategy of initial cooperation followed by later cooperation might temper this view.

3 Model

In this section, we provide a formal model of disruptive technologies and commercialization strategy choice. While formal models of disruptive technologies have been provided in the literature (e.g., Adner, 2002; Adner and Zemsky, 2005), these models have focused on the structure of consumer demand that may give rise to entrant advantages. Those models have not considered the key choice between cooperative and competitive commercialization that is the focus of our study here.

3.1 Model Set-Up

There are two periods, 1 and 2, where an entrant with a new technology can choose to commercialize by either competing with an incumbent or cooperating (via licensing or acquisition) with that incumbent. Significantly, the entrant can exercise this choice in each period and thus, may compete or cooperate in both periods or choose one path and switch to another. In period 2, uncertainty regarding the value of the new technology is resolved and with it the trajectory of costs associated with the incumbent choosing to integrate the technology. There is a common discount factor of δ between the two periods. In notation, suppose that an incumbent earns profits $V(i)$ where $i = 0$ (with the status quo product) and $i = 1$ (with a product that incorporates a new technology). There is uncertainty over the value of $V(1)$. With probability p, $V(1)$ is $v + V(0)$ and with probability $1-p$, $V(1) = V(0)$.

It is assumed that, to integrate the new technology prior to the resolution of uncertainty, the incumbent must sink costs, C_I. Having sunk such costs, the uncertainty of $V(1)$ is resolved. Thus, if the incumbent sinks integration costs, its expected profit is $pv - C_I + V(0)$ while if it does not, its expected profit is $V(0)$. In this model, C_I is a measure of the difficulty an incumbent would have integrating a new technology. As noted earlier, disruptive technologies are defined by worse performance on the dimensions valued by mainstream customers even if they both perform better for niche consumers and have a strong trajectory of improvement compared to existing technologies. Such technologies are naturally harder for incumbents, with an existing set of customers, to integrate into their products. This is also related to the limited capacity of innovations a single firm can likely commercialize at once (Cassiman and Ueda, 2006). For example, the technical characteristics of existing products may make integrating the new technology by picking the best of both worlds impossible. Thus, C_I would represent the degradation in product performance for existing consumers caused by integration. Even if the new technology can be employed by the incumbent in a new product, C_I may be high because launching new products may lead to a loss in corporate focus and brand confusion. Thus, C_I is a parameter that varies and is related to the disruptiveness of the new technology. However, we assume that as more is learned about the new technology, the costs of incumbent integration fall. Thus, in period 2, those costs can fall to sC_I ($s < 1$). This captures the notion that disruptive technologies can improve in their appeal to more consumers over time.

New technologies are assumed to come from entrants. An entrant with a new technology can earn revenue $\underline{v}$ (with certainty) and a share, a (< 1), of $V(1)$-$V(0)$ if they independently enter the market *and* the technology is not integrated with the incumbent. The entry costs the entrant, C_E (assumed to be less than $\underline{v} + av$ but greater than $\underline{v}$).[1] Such entry, if it is sustained, leads to the incumbent's status quo profit, $V(0)$, being reduced to $bV(0)$ where $b < 1$. This only occurs if $V(1) > V(0)$, otherwise, the entrant can earn at most $\underline{v}$. Thus, competitive entry involves two impacts on the industry. First, the entrant must sink entry costs to build duplicative product market assets of the kind emphasized by Teece (1986). Second, entry potentially results in a competitive effect and dissipates incumbent market power rents (Gans and Stern,

[1] Thus, entry can be justified if the incumbent does not integrate the new technology and not otherwise. This assumption simplifies the cases examined in what follows and relaxing it would not appreciably change the results below. Importantly, if entry costs are sunk, the entrant will continue in the industry and earn $\underline{v}$. Note that, unlike C_I, C_E does not fall as more about the technology is learned. This assumption seems conservative as there are reasons to suppose that for new entrants, entry can grow more difficult over time as uncertainty is resolved (see Foster, 1986).

2000). By contrast, if an entrant engages in cooperative commercialization with an incumbent, the incumbent can maintain its profits but still must sink costs, C_I, in integration. This is a novel assumption for the model presented here, and distinguishes our contribution from the past literature on commercialization choices (Chatterji and Fabrizio, 2013).

This can be most clearly seen if we consider commercialization choice as a 'once-off' decision that is taken initially prior to uncertainty being resolved. Under cooperative commercialization, the entrant licenses the technology to the incumbent. As the incumbent integrates the technology, the entrant can earn at most $\underline{v}$ by entering and so does not do so. Thus, the total surplus accruing to the incumbent and entrant is:

$$\underbrace{(1+\delta)(pv+V(0)-t)-C_I}_{\text{Incumbent's profit under Coop}}+(1+\delta)t$$

where t is the license fee paid by the incumbent to the entrant. By contrast, the entrant engages in competition, total surplus becomes:

$$\begin{array}{ll} \overbrace{(1+\delta)(\underline{v}+pav)-C_E}^{\text{Start-up Profit under Comp}}+\overbrace{(1+\delta)(pbV(0)+(1-p)V(0))}^{\text{Incumbent Profit under Comp}} & \text{if} \quad (1+\delta)(\underline{v}+pav)\geq C_E \\ (1+\delta)V(0) & \quad\quad\; (1+\delta)(\underline{v}+pav)<C_E \end{array}$$

Thus, the total gains from cooperation relative to competition are $(1+\delta)\big(p(1-a)v+p(1-b)V(0)-\underline{v}\big)-C_I+C_E$ (if entry is credible) and $(1+\delta)pv-C_I$ (otherwise). Thus, a higher C_I reduces the probability that cooperative commercialization occurs (Gans and Stern, 2003).[2]

3.2 *Multiple Commercialization Choice Rounds*

Here we want to model a situation where the initial commercialization choice might be re-evaluated and reversed following the resolution of uncertainty. Thus, we assume there are two periods. In period 1, the start-up chooses whether to compete or cooperate with the incumbent. At the end of that period, uncertainty concerning $V(1)$ is resolved. In period 2, the start-up, regardless of whether it chose to license or not in period 1, chooses again whether to cooperate or compete from that point on.

Working backwards, consider the entrant's decision in period 2. First, if there has been competition in period 1 and the new technology is valuable, the total surplus from cooperation in period 2 is $\underline{v}+v+V(0)-sC_I$ while the total surplus from competition is $\underline{v}+av+bV(0)$ (as entry costs have already been incurred). Thus, cooperation will be chosen if $(1-a)v+(1-b)V(0)>sC_I$ (that is, if

[2] Throughout this model we focus on total surplus and how commercialization choice impacts that. As Gans and Stern (2000) and Gans (2012) demonstrate, this is what determines whether cooperative commercialization takes place or not. We could have used the Nash bargaining solution at each point commercialization strategy is chosen, but have chosen not to in order to economize on notation.

preservation of monopoly rents exceeds the costs of integrating the technology). Note that, if the new technology is not valuable, the gains from licensing in period 2 are $(1-b)V(0)-sC_I$.

Second, if there has been cooperation in period 1 and the new technology is valuable, the total surplus from cooperation in period 2 is $v+V(0)$ (as integration costs have already been sunk) while the total surplus from competition is $\underline{v}+av+bV(0)-C_E$. Thus, cooperation will be chosen if $(1-a)v+(1-b)V(0)+C_E \geq \underline{v}$. However, as $\underline{v}<C_E$ this implies that cooperation, if chosen initially, will continue if the technology is valuable. If the new technology is not valuable, there are no further gains to entry and hence, the entrant effectively exits at this point.[3]

Given this, we can now consider the period 1 commercialization choice. The total expected surplus from cooperation initially is:

$$(1+\delta)V(0)+(1+\delta)pv-C_I \qquad (1)$$

and the total expected surplus from initial competition is:

$$\begin{cases} (1+\delta)\underline{v}+p(av+bV(0))+p\delta(v+V(0)-sC_I)+(1-p)\delta V(0)-C_E & (1-b)V(0)>sC_I \\ (1+\delta)\underline{v}+p(av+bV(0))+p\delta(v+V(0)-sC_I)+(1-p)\delta bV(0)-C_E \quad \text{if} & (1-a)v+(1-b)V(0)>sC_I\geq(1-b)V(0) \\ (1+\delta)\underline{v}+p(1+\delta)(av+bV(0))+(1-p)\delta bV(0)-C_E & (1-a)v+(1-b)V(0)\leq sC_I \end{cases} \qquad (2)$$

Given this, Figure 1 depicts the equilibrium outcomes in (C_E, C_I) space. Note that, if C_E is high relative to C_I, then cooperation is chosen initially. In this model, that also implies that cooperation continues following the resolution of uncertainty. By contrast, if C_I is high relative to C_E, then competition is chosen initially. Here, however, two factors may cause a change in commercialization strategy. First, if uncertainty is resolved in favor of a valuable technology, the gains from trade to cooperation rise and so a switch to cooperation could occur. Second, even in the absence of a favorable state on technology value, a switch could arise as the use of the technology in competition may improve the trajectory of performance for the new technology and reduce the integration costs (i.e., s could be low). In this case, a switch occurs because integration costs following competition are lower.

As noted earlier, disruptive technologies are characterized by (a) high costs of integration with the incumbent's technology initially and (b) a trajectory of rapid performance improvement on traditional

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[3] Conceptually, the model thus far considers licensing as the mode of cooperative commercialization. The assumption here was that the incumbent would not be able to license a technology and then not use it. That it may not want to use it would be driven by the existence of C_I but for the entrant, this would mean that licensing would not reveal the technology's value and hence, would potentially harm future returns. That said, if an incumbent were to acquire the entrant, then it would be a more plausible outcome that the technology might be shelved. However, from the entrant's perspective, it is reasonable to suppose that acquisition, should it occur, would not be reversible and would be observationally an exit from the perspective of empirical analysis. Here, because cooperation persists when chosen, the model's conclusions apply equally to acquisitions and licenses as modes of cooperative commercialization and will be treated as such in the empirical tests that follow. For a perspective on where licensing and acquisition may differ in observational outcomes see Gans (2012).

performance metrics. The former characteristic was captured by C_I and the second was captured in our model by s. The model demonstrates that as C_I gets higher and s gets lower (consistent with a technology being more disruptive), the set of parameters that supports an equilibrium commercialization strategy involving competing initially and then switching to cooperation becomes larger. Thus, we have the following hypothesis:

H1: Disruptive technologies will be associated with a higher level of competition initially, followed by a switch to cooperation (either licensing, acquisition or both).

Intuitively, disruptive technologies are hard for incumbents to integrate especially during the phase when their value is still being established. Instead, when C_I is high relative to C_E, entrants are more efficient in conducting the necessary market experiments to establish the technology's value and also set it on a path to potentially higher performance on traditional metrics. If that latter path does not arise, competition will continue in the long-term. But if the technology is valuable, this will represent a greater threat to incumbent rents and if the improvement path is rapid, lower costs to ex-post integration of the technology into existing products. Thus, following the resolution of uncertainty and the realization of performance gains, there will be an incentive for the entrant to cooperate with the incumbent ex-post. It is this latter change in commercialization incentives that we believe has been neglected in the prior theory of the impact of disruptive technologies and that is, in fact, an important part of commercialization of those technologies.

4 Data

We test the prediction of this model using a new, hand-collected dataset of the automatic speech recognition (ASR) industry from its inception in 1952 through the end of 2010. ASR 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 the 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. The early 1960s brought the entry of Texas Instruments and the founding of IBM's T.J. Watson Research Center, which invested in ASR. The industry's first company dedicated exclusively to ASR was Threshold Technology, spun out of RCA Labs. Threshold's early success is said to have strongly influenced the Department of Defense Advanced Research Projects Agency (DARPA) decision to initiate public funding of basic ASR research. Since then, ASR has been used for myriad applications including radiology dictation, plush toys that respond to voice, remote access to personal computers, 411 directory assistance automation, personal telephone assistants, and podcast transcription.

ASR is an attractive industry for this study for at least two reasons. First, it represents a commercialization environment where cooperating with incumbents does not strongly dominate competing in the product market or vice versa. Technology is strongly excludable, with ASR firms having filed more than 3,000 patents. While complementary assets are often needed to bring innovations to market, including custom application development, many ASR entrants integrated into those assets Qualcomm-style in order to compete in the product market. This stands in contrast to other industries, such as automotive or biotechnology, where complementary assets such as clinical trials are so expensive and difficult for a startup to undertake that new entrants can hardly hope to “go it alone” (Baum, Calabrese, and Silverman, 2000). And there is little risk that the algorithms can be expropriated when included as part of an end-user product.

Second, ASR is an industry where considerable uncertainty surrounds the value of new innovations. At first glance this might seem surprising, as the performance of an algorithm ought to be verifiable. Indeed, many ASR companies have published performance claims for many years. As early as September 1981 Interstate Electronics Corporation claimed 85% accuracy for its speech recognition technology. One month later, competitor Weitek claimed 90% accuracy and the month after that, IBM claimed 91% accuracy. By February of the following year, Votan claimed 99% accuracy, matched that summer by Interstate Electronics and soon after by Verbex, NEC America, Dragon Systems, Kurzweil, Integrated Wave, General Instrument, and others. Such claims made it difficult for potential licensees to discriminate among technology suppliers, as reflected by the National Bureau of Standards’ observation regarding “the present untenable situation of nearly all vendors claiming 99% accuracy” (Creitz, 1982). The National Research Council echoed these concerns, lamenting that “there are no established/uniform procedures for the design, comparison, and evaluation of speech recognition” (Creitz, 1984).

Additionally, some ASR entrants employed disruptive technologies. Before describing these, it is worth noting that numerous sustaining technologies have been used in the industry. Early use of Linear Predictive Coding were widely replaced by Hidden Markov Models following Lawrence Rabiner’s 1983 discovery (Juang and Rabiner, 2004), which enabled more flexible searching and larger vocabulary sizes than previously. Extensive corpora of speakers saying various words and phrases are captured and used to train systems to improve accuracy. These and other “sustaining” innovations were generally aimed at increasing performance among existing performance criteria such as accuracy and vocabulary size. However, other ASR innovations could instead be regarded as potentially disruptive. Such innovations may not perform as well on traditional metrics and thus may be less attractive to potential cooperation partners who may regard their value as suspect. Three such innovations are listed below:

1) *Software-only*. ASR involves intensive audio signal processing, so early systems generally required algorithms to run on specialized DSP chips or standalone processing units. For example, Speech Systems Inc.'s 1988 MEDTRANS radiology dictation system tethered dedicated hardware to a Sun Microsystems workstation, which provided the user interface. While the move to software promised both cost reduction and convenience as dedicated hardware was eliminated, these came at the expense of performance tradeoffs in vocabulary size and (likely) accuracy. Consequently, many firms were reluctant to abandon hardware acceleration.
2) *Word-spotting*. Speech recognizers generally operate by attempting to decode all words spoken by the user, as is necessary in a dictation program. For some applications, however, it is less important to understand everything the user said and more important to capture a few key commands. As an example, some automated telephone call routing systems are designed to pick out the words "operator" and "collect call" while ignoring whatever else the user happened to say. Word-spotting promised to be advantageous for a niche set of applications, but the so-called "garbage models" required to filter out unwanted speech could be unreliable. Moreover, only a small number of keywords could generally be handled by such systems.
3) *Grammar-free recognition.* Historically, speech recognition systems were configured to recognize from a set of words or phrases called a "recognition grammar." The internal phonetic lattices generated by a statistical "Hidden Markov Model" search are pruned by comparing them against the set of allowed word sequences within the grammar. In grammar-free recognition, the results are not strictly filtered by a set of allowable phrases; the user may, in a sense, "say anything." Of course, the system may not recognize unusual or nonsensical utterances, but if the acoustic evidence is strong enough, it may override the prior word-sequence probabilities in the bigram/trigram models.

In the analysis section, we present evidence suggesting that these technologies indeed were disruptive in that they underperformed existing technologies initially but gradually improved over time.

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 several monthly trade journals variously spanning the years 1981 through 2010, as well as a historical account of the industry from its inception in 1952.[4] While it is possible that some firms have been omitted from the newsletters or historical documents, even obscure companies were covered in detail. 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 that is unavailable from business registers or other traditional data sources.

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[4] Few firms were active in the 1970s and earlier, and results are robust to omitting pre-1981 data.

The first author, along with research assistants, read and coded the monthly trade journals by hand. 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 coded 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 public 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 2.

Figure 2 about here

4.1 Technology Commercialization Strategies (TCS) Variables

Perhaps most unique to our study, we coded commercialization strategies undertaken by the firm. The adoption of a particular TCS was coded as having taken place the month it was reported in the trade journal. 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 software enabling consumers to dictate onto their personal computers. Tellme Networks offered an advertising-supported 1-800 number for retrieving sports scores, stock quotes, etc. on its voice platform. Firms were categorized as adopting a Compete strategy if, using information from the trade journals, they sold end-user products, built custom solutions, or provided an advertising-supported service. By contrast, ASR firms that licensed technology or development tools were classified as having a “Cooperate” strategy. As examples, BBN licensed its ASR technology and VoiceObjects supplied toolkits that companies used to build end-user applications. If both compete and cooperate strategies were mentioned at entry, the firm was coded as having started with them simultaneously as a “mixed mode” (Teece, 1986).

A shift of commercialization strategy from Compete to Cooperate or vice versa was coded as such only if an initial TCS was noted in the newsletters, followed by a subsequent mention of a different TCS. The variable *switched TCS* was set to 1 for a given firm-year observation if the firm had previously changed from its initial TCS, and 0 otherwise. Sub-categorizations of this variable were also noted for firms switching from Cooperate→Compete and vice versa. As an example of a switch from a Cooperate to a Compete strategy, Nuance Communications initially embarked on a cooperative commercialization strategy involving technology licensing and the sale of development toolkits. But a December 2002 trade journal article described Nuance’s switch 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*" (Meisel 2002, emphasis ours).

As an example of switching from Compete→Cooperate, Vlingo Corporation began by integrating its speech recognition technology into a downloadable application for smartphones, only later entering into OEM licensing agreements with device manufacturers. Vlingo was among the early adopters of grammar-free speech recognition for cellular phones, which was a bold move that met with skepticism regarding its feasibility. Vlingo began demoing its grammar-free speech recognition for phones in early 2005, fully five years before the entrant Siri released its iPhone application. At the time, most ASR technologies for mobile phones were embedded into the handset, offering limited functionality such as dialing phone numbers by voice. Vlingo offered to dictate text messages and perform freeform internet searches, taking advantage of recently introduced, but not yet widely available 3G data networks. Michael Phillips, co-founder of Vlingo, recalled his firm's reasons for adopting a dynamic commercialization strategy: "Having the consumer product greatly strengthened our ability to get the OEM deals – prove the technology works, and to be the safe choice for the OEMs because they know that consumers will like it. Even if you are losing money on the direct to consumer [product] that is OK because you will make it up on the OEM [licensing deals]. We cut back on the consumer effort – the pressure meant we needed to divert the resources." (Phillips, 2013).

In analyzing switches from one TCS to another, one must decide how to classify firms that started with a Compete strategy and then were acquired. The literature on commercialization strategy generally treats acquisitions as examples of a Cooperate strategy, as the firm ceases to compete against others either in the product or licensing market (e.g., Gans, Hsu, and Stern, 2002). Moreover, the decision to align oneself through acquisition is an irreversible strategic decision. Accordingly, our default analysis treats companies that started with a Compete strategy and then were acquired (or adopted a licensing strategy) as having switched to a Cooperate strategy. We also provide robustness tests for our main findings by not considering acquisitions as instances of cooperation.

In models where acquisitions are treated as cooperation, we count only "attractive" acquisitions, as opposed to the purchase of a company (or its assets) at a "fire sale" price resulting in little or no financial gain for shareholders. Following Arora and Nandkumar (2011), we classify an acquisition as attractive if it meets the following criteria. First, for venture capital-backed ventures, the acquisition price must exceed the invested capital. Second, for non-VC-backed ventures (or VC-backed ventures where the acquisition price was not available), either evidence from press releases and news stories that the founder or CEO of the focal firm joined the acquirer or an upward sales and/or headcount growth trend must exist. We implemented these criteria by retrieving acquisition values from SDC, Zephyr, and other public sources, by reviewing press materials associated with the acquisition and by assessing headcount and sales trends using data from Dun & Bradstreet (Walls, 2010). Using this method to determine whether sales and headcount grew or shrank in the year prior to the acquisition, approximately one-quarter of acquisitions were classified as unattractive.

4.2 Adopting Possibly-Disruptive Technologies Variable

Our theory proposes initial competition followed by eventual cooperation as a means of mitigating uncertainty regarding the commercial value of a technology. As described above, we exploit firms' adoption of potentially-disruptive ASR technologies as a measure of increased uncertainty regarding commercialization value. As described above, these are 1) *software-only*, 2) *word-spotting*, and 3) *grammar-free* (introduced in 1990, 1992, and 2001 respectively). We flag a firm as a "pioneer" if it adopts any of these technologies within three years of its initial introduction into the market, (results are robust to a two- or four-year window). For example, Logica Cambridge (UK) introduced word-spotting in April 1992. Logica Cambridge and other firms adopting speaker adaptation by April 1995 are marked as having adopted this potentially-disruptive technology. We reason that such technologies, which typically deliver poorer performance along existing dimensions, will be perceived as having particularly uncertain commercialization value when they are first introduced.

In firm-level analyses, we use a non-time-varying indicator of whether the firm ever adopted a potentially disruptive technology. Longitudinal analyses at the firm-month level instead use a time-varying variable, set to 1 only in the year the firm adopted the potentially disruptive technology. Results also hold when coding the variable as 1 in the year of adoption, and "decaying" thereafter by setting the value in subsequent years to 1/n where n is the number of years since adoption.

4.3 Control Variables

In addition to dates of operation, we collected data regarding organizational heritage as well as strategic choices. Organizational data included whether the company was a *de alio* or *de novo* entrant, and is motivated by the literature suggesting that organizational heritage implies different beginning knowledge, even if firms are founded at the same time (e.g., Helfat and Lieberman, 2002). For de novo startups, we recorded whether any of the founders had previously worked at another ASR firm (these firms are coded as spinoff firms, following the convention in the literature). For most firms, the trade journals contained information allowing us to code these organizational heritage variables; where such information was not available, we consulted public sources including company websites to determine the founders' prior work experience. In a small number of cases where these sources proved uninformative, we contacted founders to ask whether they had had prior experience in the ASR industry. We were able to characterize the heritage of all but 35 de novo firms (results are similar whether we exclude these unclassifiable de novo firms, assume that they were spinoffs, or assume that they were not). We also noted whether the de novo companies were sponsored by their parent firms, either in part or as wholly-owned subsidiaries (classified as de alio). We also recorded funding, leadership transitions, and patents. (Note: all results are robust to the use of patent citations instead of patents alone.) Financing sources included venture capital (cross-checked with VentureXpert), government, banks, other firms, or the public markets (i.e., IPOs). To round out the organizational variables, CEO transitions were noted, and data on granted patents were merged based on application date.

Interim performance variables are derived from Dun & Bradstreet, which were available only for U.S. firms after 1989. ASR firm names were matched manually for relevant establishments, with a success rate of 91.8%. D&B records annual sales as well as headcount, both of which we use in raw form.

5 Results

5.1 Summary Statistics and Trends

A total of 651 ASR firms are observed in the trade journals. We exclude 55 publicly traded firms from our analysis, as these are less likely than private firms to be acquired. We also drop 17 (private) professional services firms that did not enter the industry with an innovation. Descriptive statistics and correlations for the remaining 579 ASR firms are in Table 1. Firm-level observations are in Panel A; Panel B contains firm-year observations. (Although the trade journals were issued monthly, we collapsed observations to the firm-year level for analysis; models using firm-month observations yield consistent results.) Dun & Bradstreet data is available for 379 of the 579 firms, reducing the number of observations in models utilizing D&B-based variables. Slightly more than half of ASR firms are de alio firms while one tenth are intra-industry spinoffs. One quarter of firms have an ASR-related patent; a slightly higher percentage raised venture capital. The CEO was replaced in 12% of firms.

Table 1 about here

Regarding technological commercialization strategies, 60% started by competing in the product market vs. 38% starting with cooperation. (Two percent of firms were recorded as starting with a hybrid strategy of simultaneously cooperating and competing.) This relatively even split between the two types of commercialization strategy reinforces our claim that ASR firms are not subject to the sort of environmental pressures that strongly direct the choice of commercialization strategy as in other industries such as biotechnology. Panel A of Figure 3 plots the density of ASR firms by entry mode, with overall ASR firm density for reference. While cooperation dominates early on, this trend reverses sharply by the mid-1990s. Panel B refines this view, restricting the graph only to new entrants (given the small number of entrants per year, observations are grouped into five-year intervals). As in the full density plot of Panel A, Panel B shows that a competitive TCS dominates later on among new entrants. It would, thus, be difficult to conclude that switching commercialization strategies from Compete→Cooperate can be explained by an industry trend toward a cooperative TCS.

Figure 3 about here

Twenty percent of firms either pioneered or were early adopters of one of the disruptive ASR technologies described above. The corresponding time-varying variable is nonzero for 3% of observations. We note that no ASR firm was an early adopter of more than one of these potentially disruptive technologies, which should not be surprising given that such innovations underperform on traditional metrics such as accuracy and vocabulary size. However, several firms eventually adopted multiple of these innovations. For example, Voice Control Systems was an early adopter of word-spotting but did not adopt a software-only approach until several years after its introduction.

5.2 Disruptive vs. Sustaining Technologies: Initial Tradeoffs and Eventual Trajectories

Here we offer evidence that the technologies we listed as potentially disruptive did in fact underperform sustaining technologies on the common dimensions of merit in the ASR industry, vocabulary size (Christensen and Bower, 1996). As argued above, although recognition accuracy is a key performance measure, even as of the early days of the industry most ASR firms had begun to claim 99% accuracy, rendering this an uninformative measure. We instead explore another metric where there exists considerable heterogeneity across firms: vocabulary size. Vocabulary size refers to the number of words or phrases a particular ASR technology is capable of recognizing. For example, some early ASR technologies were designed to distinguish between the vocabulary set of “yes” and “no”—the vocabulary size is two. By contrast, a technology capable of recognizing U.S. city and state pairs (e.g., “Orlando, Florida”) would have a vocabulary size of tens of thousands. Although not every firm published claims regarding vocabulary-size metrics, we were able to locate vocabulary-size data at entry for 455 of the 579 firms (78.6%) in the trade journals. Considerable heterogeneity of vocabulary size exists, ranging from two words (i.e., “yes” and “no”) to well over a million. Mean vocabulary size for all firms, as coded from the trade journals, is 12,426 with a standard deviation of 26,288.

Vocabulary sizes at entry are indeed smaller for firms adopting potentially-disruptive ASR technologies. Difference-of-means tests in Panel A of Table 2 show that firms adopting disruptive technologies have vocabulary sizes approximately half as large as firms that utilize only sustaining technologies. These differences are statistically significant whether examining all firms or winsorizing the top and bottom 1% (the latter carried over to our multivariate analysis). We consider additional covariates in Panel B of Table 2 again winsorizing although results do not depend on dropping any observations. Column 1 reconfirms the connection between disruption and lower vocabulary sizes as shown in Panel A, while Column 2 controls for various factors including year, organizational heritage, patenting, and venture capital. The magnitude of the negative correlation between disruption and vocabulary size strengthens both in economic and statistical significance when adding covariates. This correlation is also recovered in Column 3, which controls for sales, even though doing so reduces the analysis set to those firms for which we have Dun & Bradstreet data.

Table 2 about here

The initially identifiable characteristic of disruptive technologies is that they suffer along traditional performance characteristics, as illustrated with the lower vocabulary size of ASR systems incorporating word-spotting, software-only, or grammar-free technologies. At first, these tradeoffs make incumbents reluctant to develop internally or in-license disruptive technologies, as uncertainty surrounds their commercial value. What makes the technologies attractive licensing or acquisition candidates later is the threat they pose once uncertainty has been resolved and the value of disruptive technologies has been demonstrated in the marketplace. While we were able to retrieve vocabulary size at entry for nearly four out of five ASR firms at the time of entry, longitudinal vocabulary-size data was not reliably available for more than a handful of firms. As an alternative approach, we analyze the financial performance of disruptors vs. firms that employed only sustaining technologies.

Figure 4 plots these dynamics. The y-axis represents annual sales per employee, calculated from the Dun & Bradstreet data, and represents the closest possible calculation of organizational efficiency or profitability using these data. The x-axis is the number of years since entry. It is visible in Figure 4 that those using disruptive technologies start out with comparatively low sales per employee around the time of entry. Eventually, however, these firms become roughly as profitable as those depending entirely on sustaining technologies, and eventually surpass them. Thus it appears that disruptive ASR technologies, though they initially trade off performance, indeed improve over time.

Figure 4 about here

5.3 Disruptive Technology Adoption and Commercialization Strategy

Table 3 shows the distribution of technology commercialization strategies for firms adopting sustaining vs. disruptive technologies. 461 ASR firms relied solely on sustaining technologies, while 118 or approximately one-fifth of firms were early adopters of disruptive technology. Two patterns are visible. First, early adopters of disruptive technologies are much less likely to cooperate with incumbents. Only 21.2% of disruptors fixed on a Cooperate strategy (and never switched) compared to 36% of those relying on sustaining technologies, whereas the reverse pattern obtained for Compete strategies. As is visible in the rightmost column of Table 3, these differences are statistically significant at conventional levels.

Second, firms that adopt disruptive technologies are more likely to switch from a Compete→Cooperate TCS. 12.7% of disruptors undertake this dynamic commercialization strategy vs.

7.8% of non-disruptors, differences again significant at the 5% level. Note that the percentage of firms adopting a Cooperate→Compete strategy is not meaningfully different between the two types of firms.

Table 3 about here

In Table 4, we revisit the analysis of Table 3 in a multivariate context using a multinomial logit specification while still keeping the firm as the unit of analysis. The baseline outcome is adopting a (permanent) Cooperate commercialization strategy. Each model has multiple columns, each corresponding to another of the commercialization strategies. The coefficients in each column of a given model are associated with the selection of that column's commercialization strategy relative to the baseline. For example, the first column in Model (1) examines the likelihood of adopting a (permanent) Compete commercialization strategy relative to the baseline of Cooperate. The positive and statistically-significant coefficient on adopting a disruptive technology is consistent with Table 3.

Model 2 of Table 4 refines the analysis by adding several firm-level covariates. Firms entering later are considerably more likely to adopt a (permanent) Compete strategy, as shown by the positive and significant coefficient on year of entry in the column for the Compete strategy. This trend is consistent with the patterns in Figure 2, which show that Compete strategies become more dominant over time (both in the full population, and among new entrants). Intra-industry spinoffs are considerably more likely to shift TCS, whether from Cooperate→Compete or Compete→Cooperate. Changing from Cooperate→Compete is strongly associated with having replaced the CEO, while Compete→Cooperate switches are more common among VC-backed ventures.

Net of these covariates, the association between a (permanent) Compete strategy and adopting disruptive technology in Model 2 is somewhat weaker, with statistical significance at the 10% level. However, the strategy of switching from Compete→Cooperate is still strongly associated with firms that adopted disruptive technologies. The odds ratio of temporarily integrating as compared to pursuing a permanent Cooperation strategy, are about two and a half times higher ($e^{0.7813}$=2.4) for firms adopting disruptive technologies. This result is robust in Model 3 to accounting for the firm's maximum annual sales, which reduces the number of observations considerably but maintains the economic and statistical significance of the coefficient on disruptive technology in the column for the Compete→Cooperate commercialization strategy.

Table 4 about here

In Table 5, we shift the unit of analysis to firm-year observations. Our explanatory variable of adopting disruptive technology is now set to 1 only in the year of adoption; similarly, other firm-level covariates from Panel A of Table 2 are replaced with time-varying variables from Panel B of Table 2. Given our longitudinal, right-censored data, we use a Cox hazard model where the failure event is defined as a firm changing its commercialization strategy. Switching can occur either from Compete→Cooperate or Cooperate→Compete, which we examine in separate sets of models. Models 1-3 of Table 5 examine the subset of firms that started with a Compete commercialization strategy, while Models 4-6 restrict analysis to firms that started with Cooperate.

Given that the sample in Models 1-3 is firms starting with Compete, the dependent variable is, therefore, restricted to transitions from Compete→Cooperate. Model 1 shows a strong correlation between adopting disruptive technology and switching from Compete→Cooperate without introducing any control variables. Firms that started with a Compete commercialization strategy are about four times as likely ($e^{1.38}$=3.97) to shift from Compete→Cooperate when they adopt a disruptive ASR technology. This result is also recovered when adding covariates in Model 2, which accounts for the higher propensity of firms to switch from Compete→Cooperate when they are intra-industry spinoffs, once they have raised venture capital, or once the CEO has been replaced. Model 3 introduces controls for sales performance, which reduces the number of observations but strengthens the statistical significance of the result.

In the remaining models of Table 5, we rule out the possibility that disruptive technology is not especially connected with switching from competition to cooperation but rather is associated with dynamic commercialization strategies in either direction. Models 4-6 analyze the subset of ASR firms that started with a Cooperate commercialization strategy, so the dependent variable is switching from Cooperate→Compete. Model 4 evidences no connection between adopting disruptive technology and shifting from Cooperate→Compete. Adding control variables in Models 5 and 6 shows that transitioning from Cooperate→Compete does appear to be connected to patenting, replacing the CEO, and (depending on the specification) raising venture capital. No correlation with adopting disruptive technology is found, though. Thus we can conclude that firms adopting disruptive technologies are more likely to adopt a dynamic strategy of competing initially and cooperating later.

Table 5 about here

5.4 Robustness

In Table 6, we assess the robustness of the longitudinal analysis of Table 5. Instead of building up each analysis from the explanatory variable alone, each pair of models in Table 6 reports the analysis for ASR firms that start with a Compete or Cooperate strategy, respectively. Models 1-4 revisit the choice of a three-year window following the initial introduction of a disruptive technology in order to identify early adopters of that disruptive technology. In Models 1 and 2, we identify as disruptors firms that adopted a disruptive technology within two years of its original introduction to the market. As expected, the coefficient on adopting disruptive technology is positive and statistically significant in Model 1 (firms starting with a Compete TCS) but not in Model 2 (starting with a Cooperate TCS), indicative that disruptors are more likely to switch from Compete to Cooperate. Likewise, in Models 3 and 4 we see that results are robust to identifying adopters of a disruptive technology within four years of its original introduction. A five-year window works as well; however, restricting analysis only to the original pioneers of each of the three disruptive technologies does not yield reliable estimates because only three firms are labeled as disruptive. We moreover note that the firm-level analyses of technology commercialization strategy choice in Table 4, and the vocabulary-size analysis of Table 2, are both robust to these alternate windows.

Table 6 about here

Models 5 and 6, instead of labeling only the firm-year disruption observation as 1 in the year of adoption, account for the possibility that it may take some time for a disruptive technology to prove its worth. In a sense, such technologies may be most disruptive when initially adopted and less so over time. The disruptive-adoption variable is still set to 1 in the year of adoption; subsequent years are however set to 1/n where n is the number of years since adoption (e.g., in the third year after adopting the disruptive technology, this variable is set to 1/3). Magnitudes and statistical significance of the relevant coefficients in Models 5 and 6 resemble those of prior models.

The final two models of Table 6 confirm that our results are not an artifact of acquisition patterns alone. We argued earlier for considering a firm that started with a Compete strategy but that then accepted an attractive acquisition offer as having switched to Cooperate, as acquisitions have often been treated as cooperative strategies in prior literature. Given that acquisitions might alternatively be seen as outcomes and sources of liquidity, in Models 7 and 8 we no longer consider entering into an acquisition as a move from Compete to Cooperate. Here, the switch to a cooperative commercialization strategy includes only those firms that begin to license out their technology while remaining an independent firm. If anything, the magnitude of the correlation between adopting disruptive technologies and switching from Compete to Cooperate is stronger in this model.

6 Discussion and Conclusions

Using a dataset of the population of entrants into the worldwide speech recognition industry from 1952 through 2010, we find evidence consistent with a theory of entrepreneurial strategy in which commercializing disruptive technologies starts by competing with incumbents followed by a switch to cooperating with them.[5] Note that our results are not necessarily causal, as commercialization strategy is an endogenous decision. Our goal has been to show the association between disruptive innovation and

[5] The dynamic strategy of initial competition followed by later cooperation differs from prior assessments of changing commercialization strategy as a generally beneficial trial and error process of experimentation by which naïve entrants learn about the industry and the best match with their capabilities (Bhide, 2000; Murray and Tripsas, 2004; Gavetti and Rivkin, 2007).

entrepreneurial use of a dynamic commercialization strategy where the disruptor competes initially and later cooperates. 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 and where there is within-industry variation in the introduction of disruptive innovations.

From that standpoint, the leading case example of disruptive innovations in the hard disk drive industry overturning incumbent firm market leadership (Christensen, 1997) may reflect two distinct forces.[6] First, industry incumbents may be reluctant to develop and/or acquire the potentially disruptive technology, as the Christensen line of research has emphasized. A second force, however, emerges from the business environment within which hard disk drive innovators operate (Gans and Stern, 2003): an environment in which appropriability conditions are relatively weak (mechanical innovations are notoriously susceptible to backward engineering, for example) at the same time that the relative costs of assembling the requisite organizational complementary assets to enter the product market are low (the competitive supply of contract manufacturers may be available to hard disk drive innovators, so vertical integration may not even be necessary). The combination of these business environment forces, both of which favor a compete strategy, may conflate the “attacker’s advantage” nature of disruptive technologies (Christensen and Rosenbloom, 1995).

At the other end of the spectrum, in industries such as drug development, there is rarely replacement of incumbent firm market leadership despite waves of radical innovation in techniques of drug discovery over the past 40 years by biotechnology firms. The business environment explanation for this pattern would be that the appropriability regime for biochemical innovations is well-known to be strong (so innovators have some protection against expropriation threats when negotiating deal terms with industry incumbents) at the same time that the cost of acquiring the specialized downstream complementary assets is very high (in domains such as navigating the regulatory environment, sales channels, and even manufacturing). Certainly we cannot claim in a single-industry study to have mapped the full set of commercialization-environment contingencies; rather, we see this study serving as a counterexample to the generally-accepted notion that incumbents generally succumb in the face of disruptive technologies. One critical implication of our study for practitioners is that in certain commercialization environments, an incumbent facing disruption may in fact pursue a wait-and-see strategy (eventually cooperating with the disruptor). An important next step would be to examine the

[6] Christensen (1997) also finds the same effect of disruptions in the mechanical excavator and steel mini-mill cases as he finds in hard disk drives. We believe these other industry settings also exhibit similar commercialization environment characteristics as what we discuss in this paragraph for disk drives.

market leadership consequences of disruptive innovations in other business environments, including those where cooperative commercialization is strongly favored.

In mixed business environments as in speech recognition, in which the appropriability regime is strong (favoring a cooperative strategy) at the same time that the relative cost of complementary asset acquisition is modest (favoring a competitive strategy), the innovator's preferred commercialization strategy may not be as straightforward (Gans and Stern, 2003). Therefore, having studied the technology commercialization strategies of disruptive innovators in such settings may allow us to minimize the role of the business environment in independently shaping commercialization strategies. This discussion also allows us to speculate about the generalizability of this strategy, which may be most important in mixed commercialization environments in which the entrant with a potentially-disruptive innovation is torn between a cooperative and competitive strategy.

Our work also makes two contributions beyond disruptive technologies. First, it may be that non-disruptors who wish to cooperate with incumbents will find it advantageous to engage in an initial period of competition when it is difficult to establish the value of their technology or when they lack reputation or other status markers which can help to attract the attention of desirable commercialization partners. While prior work has suggested that asymmetric-information problems can be handled contractually by specifying a low up-front licensing fee (Gallini and Wright, 1990), the integration-cost parameter in our model captures the fact that not all risks can be handled through pricing. Second, while the extant literature on technology commercialization takes a static, one-time view of the strategic choice (Gans and Stern, 2003), we believe this to be the first paper to empirically show conditions under which a dynamic commercialization strategy can be efficient.

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Table 1: Descriptive statistics and correlations

Panel A: Firm-level observations. Public and consulting firms are excluded.

	Variable	Obs	Mean	Std. Dev.	Min	Max	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)
1)	year of entry	579	1997.73	7.63	1970	2010	1.00										
2)	de alio	579	0.55	0.50	0	1	-0.17	1.00									
3)	spinoff	579	0.12	0.32	0	1	0.13	-0.44	1.00								
4)	total patents (L)	579	0.25	0.72	0	5.31	-0.29	-0.10	0.07	1.00							
5)	ever raised VC	579	0.28	0.45	0	1	-0.18	-0.10	0.10	0.18	1.00						
6)	ever replaced CEO	579	0.12	0.32	0	1	-0.18	-0.23	0.05	0.40	0.23	1.00					
7)	maximum annual sales (L)	379	14.80	2.01	9.02	21.7	-0.21	0.24	-0.09	0.29	0.15	0.10	1.00				
8)	initial TCS: compete	579	0.60	0.49	0	1	0.31	0.05	0.02	-0.18	-0.03	-0.17	0.00	1.00			
9)	initial TCS: compete+cooperate	579	0.02	0.14	0	1	0.09	-0.11	0.02	-0.03	0.00	0.06	-0.08	-0.24	1.00		
10)	firm ever switched TCS	579	0.19	0.40	0	1	-0.22	-0.14	0.14	0.31	0.25	0.31	0.14	-0.20	0.04	1.00	
11)	firm ever adopted disruptive technology	579	0.20	0.40	0	1	0.10	-0.05	0.02	0.00	0.04	0.04	-0.02	0.05	0.04	0.08	1.00

Panel B: Firm-year observations for 579 privately-held, non-consulting firms.

	Variable	Obs	Mean	Std. Dev.	Min	Max	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)
1)	year of entry	3987	1994.80	8.97	1970	2010	1.00											
2)	de alio	3987	0.55	0.50	0	1	-0.23	1.00										
3)	spinoff	3987	0.13	0.34	0	1	0.11	-0.47	1.00									
4)	patents to date (L)	3987	0.37	0.86	0	5.31	-0.32	-0.03	-0.01	1.00								
5)	already raised VC	3987	0.38	0.48	0	1	-0.16	-0.09	0.05	0.05	1.00							
6)	previously replaced CEO	3987	0.09	0.29	0	1	-0.19	-0.17	0.07	0.27	0.16	1.00						
7)	# of firms w/compete TCS	3987	127.55	71.60	0	214	0.58	-0.14	0.10	0.01	-0.02	0.05	1.00					
8)	sales (L)	2592	14.62	1.92	7.65	21.7	-0.29	0.26	-0.12	0.30	0.03	0.10	-0.05	1.00				
9)	initial TCS: compete	3987	0.55	0.50	0	1	0.35	0.03	0.01	-0.25	-0.02	-0.13	0.22	-0.14	1.00			
10)	initial TCS: compete+cooperate	3987	0.02	0.13	0	1	0.10	-0.09	-0.01	-0.06	-0.01	0.05	0.04	-0.08	-0.20	1.00		
11)	already switched TCS	3987	0.11	0.32	0	1	-0.15	-0.09	0.11	0.32	0.07	0.28	0.09	0.13	-0.16	-0.01	1.00	
12)	firm adopted disruptive technology in this year	3987	0.03	0.17	0	1	0.08	-0.02	0.00	-0.05	-0.05	-0.04	-0.02	-0.04	0.03	0.02	0.00	1.00

Table 2: Comparison of vocabulary size for firms adopting sustaining vs. disruptive technologies

Panel A: Difference-of-means tests

	observations	Sustaining	Disruptive	*p* <
all firms	455	15673.1	6761.2	0.003
windsorized	433	12897.5	7462.6	0.048

Note: the winsorized test drops observations above the 99th percentile or below the 1st percentile.

Panel B: Negative binomial regressions of vocabulary size at entry, one observation per firm

	(1)	(2)	(3)
adopted disruptive technology	-0.5471**	-0.6858***	-0.7084***
	(0.177)	(0.164)	(0.211)
year of entry		0.0925***	0.0752*
		(0.025)	(0.030)
de alio entrant		-0.0384	-0.2064
		(0.190)	(0.242)
spinoff		0.2560	0.5218+
		(0.248)	(0.316)
total # patents (L)		0.6983***	0.5537**
		(0.150)	(0.181)
ever raised VC		0.3296	0.3070
		(0.253)	(0.255)
ever replaced CEO		-0.6004*	-0.6489*
		(0.271)	(0.307)
maximum annual sales (L)			0.1480*
			(0.059)
Constant	9.4648***	-175.7335***	-143.3958*
	(0.118)	(50.862)	(60.641)
Observations	433	433	287

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

Note: The sample is limited to 455 firms (of the 579 non-public, non-consulting firms) for which vocabulary-size data could be found in the ASR trade journals. All columns drop observations above the 99th percentile or below the 1st percentile, resulting in 433 firms. Results are robust to not winsorizing. The number of observations is further reduced when controlling for maximum annual sales, available only for U.S.-based firms.

Table 3: Distribution of commercialization strategies, by firm-level adoption of disruptive technology

	Firms adopting only sustaining technologies		Firms adopting disruptive technologies		difference of means
Cooperate	166	36.0%	25	21.2%	0.002
Compete	227	49.2%	69	58.5%	0.038
both at first	8	1.7%	4	3.4%	0.261
Cooperate->Compete	24	5.2%	5	4.2%	0.668
Compete->Cooperate	36	7.8%	15	12.7%	0.048
	461	100.0%	118	100.0%	

Note: The sample is limited to 579 non-public, non-consulting firms. The first two classifications indicate that the firm adopted a Cooperate or Compete strategy initially and never switched. The third classification indicates that the firm adopted both a Cooperate and Compete strategy initially. The last two classifications indicate that the firm adopted either a Cooperate or Compete strategy and then at some point switched to the other strategy. The final column reports p-values of a *t* test of different means.

Table 4: Multinomial logistic regressions of technology commercialization strategy

	(1)			(2)			(3)		
outcomes	Compete	Cooperate Compete	Compete-> Cooperate	Compete	Cooperate-> Compete	Compete-> Cooperate	Compete	Cooperate-> Compete	Compete-> Cooperate
ever adopted disruptive technology	0.6962**	0.2776	1.0116**	0.4626+	0.1666	0.7813*	0.0700	0.3468	0.8682*
	(0.255)	(0.535)	(0.375)	(0.267)	(0.608)	(0.395)	(0.324)	(0.654)	(0.430)
year of entry				0.1135***	0.0206	0.0404+	0.1469***	0.0016	0.0255
				(0.016)	(0.027)	(0.024)	(0.024)	(0.036)	(0.031)
de alio entrant				0.4250+	0.8015	-0.4666	0.5870+	0.4841	-0.8280+
				(0.226)	(0.558)	(0.394)	(0.315)	(0.723)	(0.490)
spinoff				0.0874	1.7685**	1.0176*	0.0634	1.4336+	0.8508
				(0.379)	(0.644)	(0.466)	(0.479)	(0.799)	(0.561)
total # patents (L)				-0.1532	0.5110*	0.1903	-0.2421	0.5815*	0.0174
				(0.184)	(0.203)	(0.220)	(0.239)	(0.276)	(0.271)
ever raised VC				0.3425	0.2657	1.0019**	0.2545	0.1745	0.5616
				(0.243)	(0.482)	(0.354)	(0.299)	(0.558)	(0.410)
ever replaced CEO				-0.4213	2.2963***	0.3797	-0.4006	1.7417**	0.2527
				(0.398)	(0.544)	(0.488)	(0.478)	(0.647)	(0.553)
maximum annual sales (L)							0.0649	0.1059	0.1708
							(0.070)	(0.157)	(0.115)
Constant	0.3190**	-1.8871***	-1.5224***	-226.6185***	-44.8572	-82.5994+	-294.0497***	-8.0586	-54.6555
	(0.102)	(0.215)	(0.184)	(31.274)	(54.500)	(47.422)	(47.849)	(72.073)	(61.213)
Observations	579			579			379		

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

Note: The sample is limited to 579 non-public, non-consulting firms. Coefficients for the “both at first” outcome from Table 3 are not shown in order to conserve space. Given that only 2% of firms adopted such a strategy, most coefficients for the “both at first” outcome are not statistically significant except in the model without covariates, in which the coefficient on ever adopting disruptive technology is positive and significant at the 10% level. In models with covariates, however, the disruptive coefficient for the “both at first” outcome loses significance. Results are little changed in an unreported model that omits the “both at first” outcome.

Table 5: Cox event-history models for correlates of changing commercialization strategies

	initial TCS = Compete			initial TCS = Cooperate		
	(1)	(2)	(3)	(4)	(5)	(6)
adopted disruptive technology	1.3807*	1.3712*	1.8623**	0.5502	0.5000	0.4648
	(0.586)	(0.568)	(0.660)	(0.977)	(0.965)	(1.030)
year of entry		0.0021	-0.1883		0.1687*	-0.0064
		(0.083)	(0.168)		(0.081)	(0.134)
de alio entrant		-0.3990	-0.6849		0.3119	0.1574
		(0.380)	(0.453)		(0.335)	(0.437)
spinoff		0.8712*	0.5348		0.6818+	0.5373
		(0.426)	(0.478)		(0.358)	(0.444)
patents to date (L)		0.1136	0.1260		0.3562**	0.4297**
		(0.186)	(0.223)		(0.137)	(0.157)
already raised VC		0.6995*	0.4557		0.9859**	0.6013+
		(0.337)	(0.364)		(0.313)	(0.308)
CEO previously replaced		1.3000**	1.1095*		1.0467**	1.0169**
		(0.420)	(0.452)		(0.342)	(0.350)
# firms w/compete TCS		-0.0038	0.0108		-0.0133	0.0052
		(0.009)	(0.016)		(0.009)	(0.013)
annual sales (L)			-0.1082			0.2032+
			(0.140)			(0.120)
Observations	1,717	1,717	1,221	1,340	1,340	760

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

Note: The sample is limited to 579 non-public, non-consulting firms. Models 1 through 3 are limited to firms starting with a Compete strategy, so failure reflects switching from a Compete strategy to Cooperate, where Cooperate includes entering into an acquisition. Models 4 through 6 instead examine firms that started with a Cooperate strategy, so failure reflects switching to a Compete strategy.

Table 6: Robustness tests for Cox event-history models

Cooperationg TCS includes acquisitions	yes		yes		yes		no	
Disruption adoption window	2 years		4 years		3 years		3 years	
Disruption considered in initial TCS	year of adoption		year of adoption		1/n where n is years since adoption		year of adoption	
	Compete	Cooperate	Compete	Cooperate	Compete	Cooperate	Compete	Cooperate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
adopted disruptive technology	1.4058*	0.6811	1.7218**	0.3588	1.6906*	0.3072	2.6952**	1.4831
	(0.714)	(1.033)	(0.652)	(1.009)	(0.700)	(1.023)	(0.942)	(1.208)
year of entry	-0.1836	-0.0051	-0.1864	-0.0068	-0.1933	-0.0065	-0.3121	-0.0042
	(0.168)	(0.135)	(0.168)	(0.134)	(0.173)	(0.134)	(0.298)	(0.172)
de alio entrant	-0.6695	0.1618	-0.6996	0.1544	-0.6764	0.1594	-0.8382	-0.3772
	(0.448)	(0.436)	(0.458)	(0.437)	(0.442)	(0.437)	(0.829)	(0.658)
spinoff	0.5214	0.5493	0.5344	0.5331	0.5623	0.5377	0.5447	1.1692*
	(0.478)	(0.445)	(0.476)	(0.445)	(0.484)	(0.441)	(0.827)	(0.528)
patents to date (L)	0.1416	0.4285**	0.1189	0.4294**	0.1421	0.4321**	0.4971	0.0014
	(0.220)	(0.157)	(0.228)	(0.157)	(0.221)	(0.157)	(0.419)	(0.016)
already raised VC	0.4473	0.5920+	0.4412	0.6003+	0.4810	0.6084*	0.1682	-0.0948
	(0.361)	(0.307)	(0.364)	(0.308)	(0.366)	(0.310)	(0.708)	(0.365)
CEO previously replaced	1.0952*	1.0225**	1.1051*	1.0143**	1.1675*	1.0133**	1.1908	0.5721**
	(0.448)	(0.351)	(0.452)	(0.350)	(0.453)	(0.351)	(0.971)	(0.192)
# firms w/compete TCS	0.0102	0.0050	0.0108	0.0053	0.0111	0.0052	0.0181	1.0138*
	(0.016)	(0.013)	(0.016)	(0.013)	(0.016)	(0.013)	(0.026)	(0.464)
annual sales (L)	-0.1010	0.2035+	-0.1071	0.2034+	-0.1106	0.2035+	-0.4250*	0.2303
	(0.139)	(0.120)	(0.140)	(0.120)	(0.141)	(0.121)	(0.199)	(0.208)
Observations	1,221	760	1,221	760	1,221	760	1,274	808

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

Note: The sample is limited to 579 non-public, non-consulting firms.

Figure 1: Equilibrium Commercialization Strategies

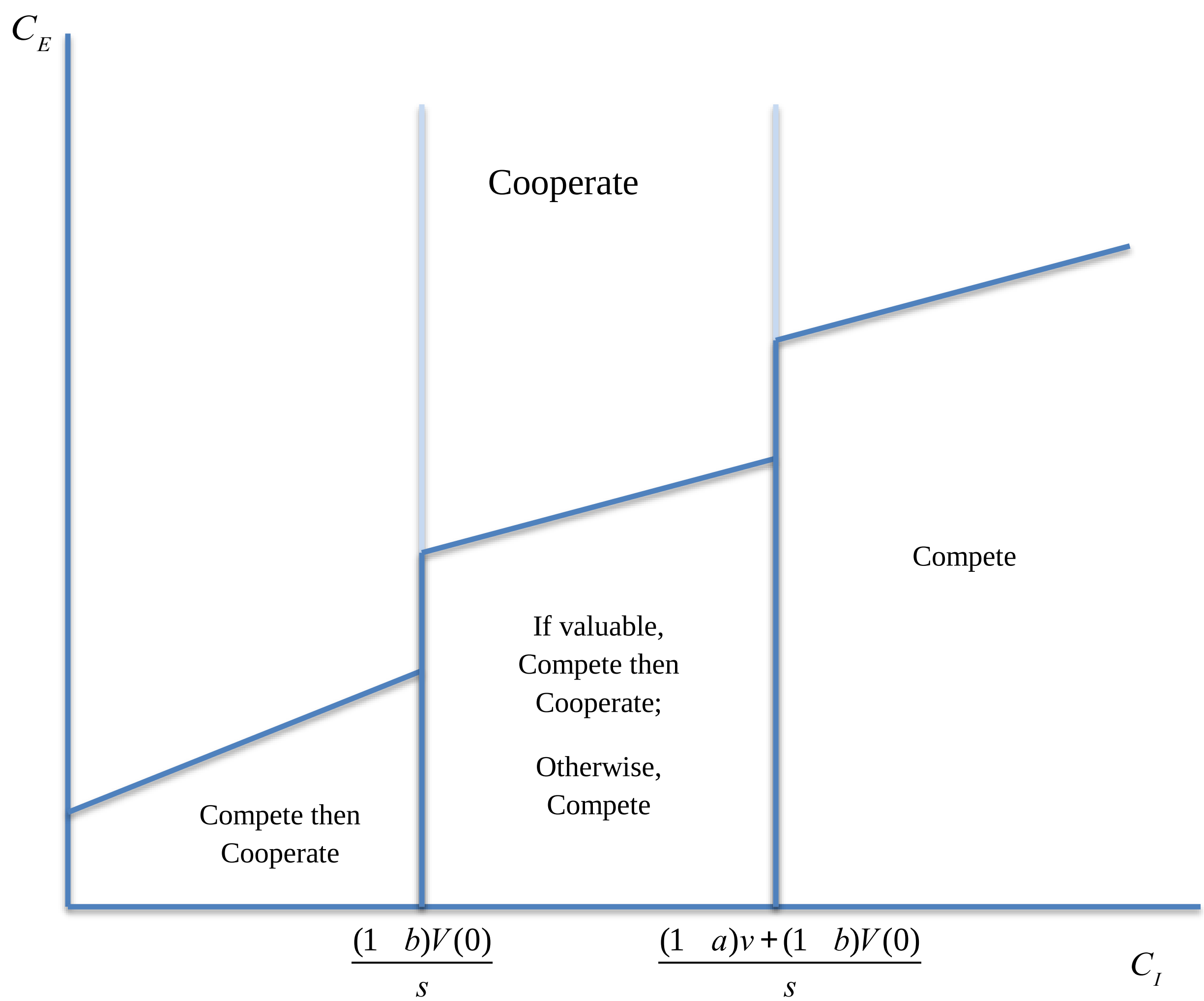


Figure 2: ASR firm entry and exit since the inception of the industry in 1952. The connected blue line is the overall industry density (i.e. number of active firms).

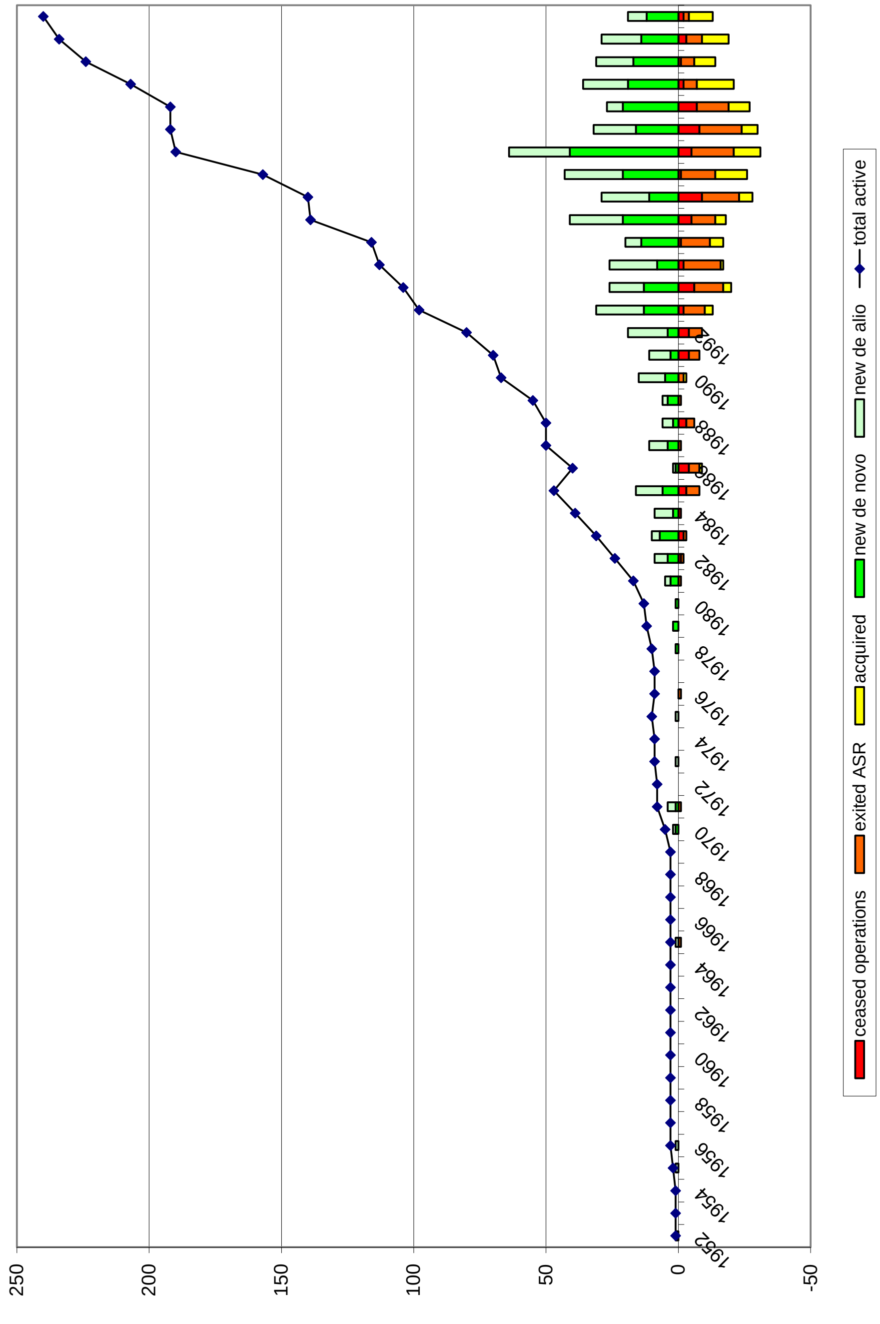
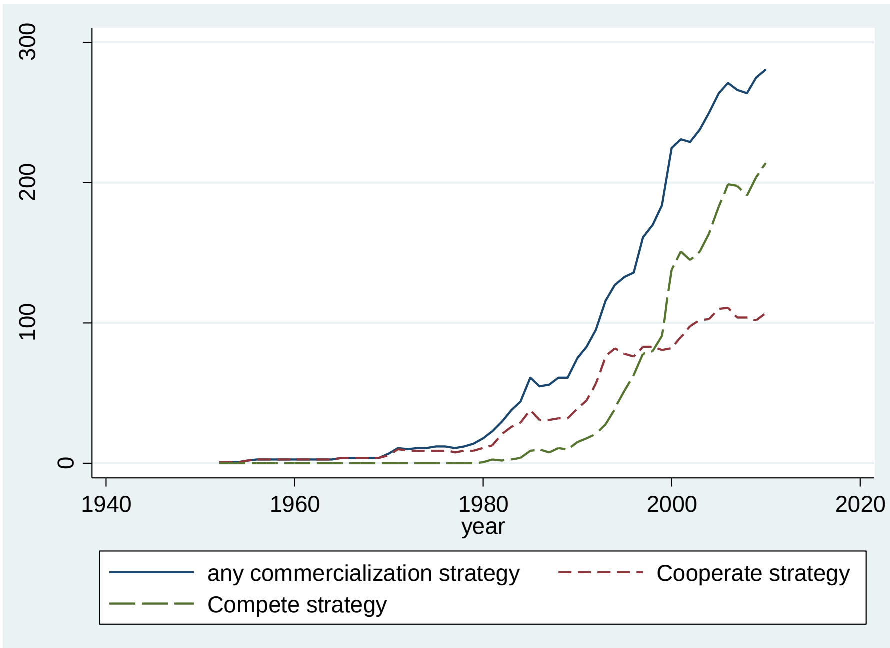


Figure 3: Commercialization strategy density

Panel A: All active ASR firms, by year



Panel B: New ASR entrants, by five-year intervals

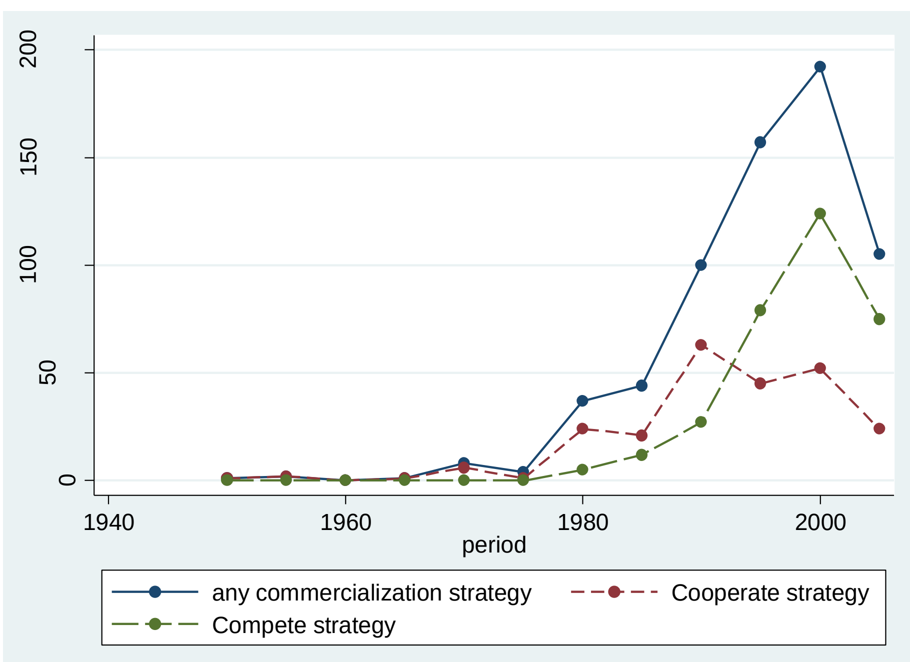
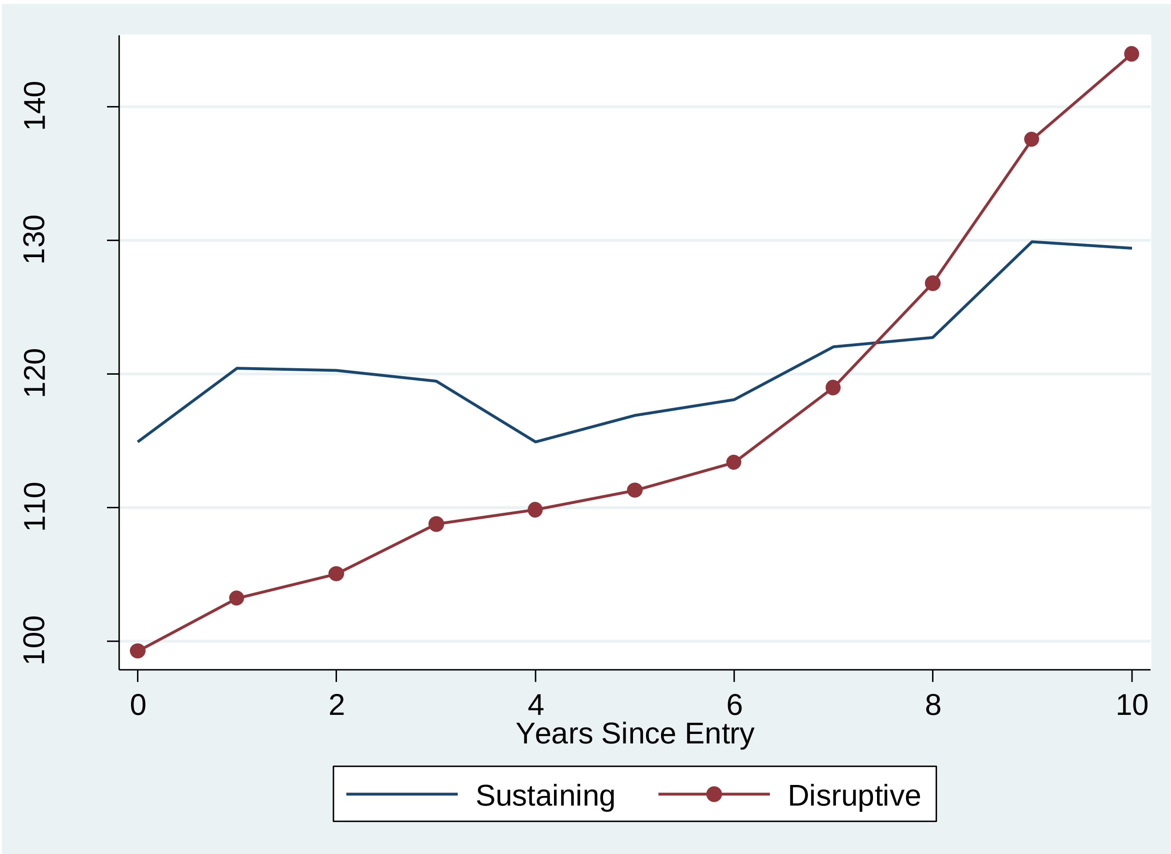


Figure 4: Sales per employee since entry for firms adopting sustaining vs. disruptive technologies



Note: Sample is limited to non-public, non-consulting firms that spent more than two years in the industry (*n*=291). Short-lived firms are omitted to avoid overreliance on sample attrition. Each data point is the three-year rolling average of sales per employee for that group of ASR firms; non-rolling-average plots look similar but have more year-to-year fluctuations.

8 Appendix: Dataset Construction

In chronicling the history of speech recognition and its commercialization it was not possible to rely purely on public sources such as SEC filings. Instead, we turned to a series of trade journals covering the industry from early commercialization attempts. As these publications were sent only to subscribers, we are deeply indebted to two individuals for making their archives available. William Meisel, president of TMAA Associates and publisher of *Speech Recognition Update*, *Telephone Strategy Update*, and *Speech Strategy News*, graciously made the complete set of his electronic archives available for all three newsletters. Walt Tetschner, publisher of *ASRNews*, likewise made his electronic archives available and also allowed us to borrow his personal, non-electronic archives of *VoiceNews* (William Creitz, editor), *Voice Processing Newsletter* (ed. Karl Kozarsky), and *Voice Technology News* (ed. Mark Mikolas).

Meisel's newsletters, along with *ASRNews*, focused specifically on ASR whereas the other newsletters reported on the voice industry more generally. Related voice technologies include text-to-speech generation (TTS), speaker verification (SV), and the digital recording and encoding technologies common to all of these. As such, these trade journals chronicle the development of several industries including interactive voice response systems (IVR, e.g. "for banking, press one…"), learning aids such as Speak 'n Spell, and even voice mail. Given the core speech-coding technology shared between all of these, several firms participated in two or more areas. For example, InterVoice began by building IVR systems and later added speech recognition. By contrast, Centigram started out in 1977 developing both TTS and ASR algorithms but abandoned the latter in 1982, citing "poor market conditions." Several ASR companies added SV to their offerings. While an examination of several voice technologies could be enabled by these archival sources, we have focused more narrowly on ASR alone.

We started with *VoiceNews* since it was the only trade journal that reached back to the beginning of the 1980s. Although *VoiceNews* was published through the late 1990s, it did not focus exclusively on ASR and, more detrimentally, was unavailable to us in 1986 and 1990, with only partial availability from 1987 through 1989. We thus folded in *Voice Processing Newsletter* as it became available in 1984, though it was not available in 1988 and 1992. As it was a fairly brief newsletter, we also summarized *Voice Technology News* in 1989 and 1990 in order to provide more detail until we could switch to the more specialized *ASRNews* in the summer of 1990 (*Voice Technology News* was summarized through the end of 1990 to provide some overlap). In 1993, *Speech Recognition Update* commenced publication. This as well as *ASRNews* continue through today and provide a nicely matched set as the editor of SRU is a former ASR company founder and perhaps a bit of a "cheerleader" for the industry whereas the editor of *ASRNews* is rather critical of the industry and leads off each issue with a column titled "The Emperor is Naked!". The two combined provide a balanced view of events within the industry.

Trade journal availability for each year is summarized in Figure A1. Coverage is present for every year since 1981, and since 1984 multiple journals cover each year except for 1986 and 1992. In addition to the trade journals described above, information on the history of ASR technology development—as opposed to commercialization—is borrowed from "Automatic Speech Recognition – A Brief History of the Technology Development" by B. H. Jung of the Georgia Institute of Technology and Lawrence R. Rabiner of Rutgers University and the University of California at Santa Barbara.

The trade journals were coded as follows. For each (monthly) issue of each trade journal, key details from each story were summarized, including information beyond what is used in the analyses in the present paper. The data coded included the following fields:

- Name of firm
- Firm founder(s) and previous employment
- Product introductions / withdrawals
- Intended market for products
- Price increases/reductions
- Claimed accuracy, vocabulary size, speaker (in)dependence
- Hiring of new CEO
- Stated commercialization strategy
- Acquisitions, liquidations, IPOs, industry exits
- Funding events, including venture capital, government, and other sources
- Lawsuits
- Financial reports
- Patent awards
- Licensing deals

The coding task above was distributed among the first author and multiple research assistants. Each RA was asked to code a year's worth of newsletter data previously coded in order to calibrate accuracy. Coded fields were then sorted by firm and date in Excel, which was exported to Stata for analysis.

Figure A1: ASR trade journal availability per year. All available issues were coded.