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THE ADOPTION OF RADICAL MANUFACTURING TECHNOLOGIES AND FIRM SURVIVAL

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The emergence of dramatically innovative, or radical, new manufacturing technologies can force pivotal and life-threatening decisions for industry competitors. These technologies can represent a huge cost for adopting firms, but may also offer the chance to achieve competitive advantage through superior manufacturing. While prior research has considered a range of production process decisions (e.g., JIT, mass customization) and outcomes for end-product technologies, little attention has been given to adoption decisions relative to core manufacturing technologies. This study examines an industry's adoption of major manufacturing technologies over several decades and demonstrates that two groups of contingencies related to adoption (e.g., timing and cumulative effects) have a significant impact on firm performance. Based on a sample of over 1,000 firms, the results provide insights into the effects of adoption timing and 'manufacturing technology bundles' on firm survival. We also find that adoption of manufacturing technologies prior to the inflection point of the estimated Bass diffusion curve for each technology leads to significant reduction in firm mortality. Thus, we are able to demonstrate the ability of the Bass model to predict the survival outcomes of firms facing manufacturing technology adoption decisions. The strategic implications of these pivotal decisions are considered.

INTRODUCTION

Modern industries are regularly threatened by shakeouts that impact all companies in the market. While these shakeouts can be catastrophic for some firms, they may also be viewed as opportunities for those firms with the proper foresight to gain a dominant position among a reduced competitive set. One common precipitator of an industry shakeout is a shift in the core technologies driving manufacturing processes.

Manufacturing *processes*, which might be described as the arrangement and application of production technologies, have been a focus of management and scholarly thinking for over a century. The process issues covered have ranged from general management philosophies, such as the Japanese belief in *kaizen*, or continuous, gradual improvement (Modarress, Ansari, and Lockwood, 2005), to more specific process approaches under various headings such as mass production, just-in-time manufacturing, lean manufacturing, flexible manufacturing, mass customization, agile manufacturing, rapid manufacturing, and prefabrication (Cooper and Edgett, 2005; Goldman, Nagel, and Preiss, 1995; Hounshell, 1984; Waurzyniak, 2007). Process management practices have also been central features of various quality-related initiatives

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such as total quality management (TQM), the International Organization for Standardization's Series 9000 program (ISO 9000), and Six Sigma programs (Benner and Tushman, 2002; 2003). The consequences of adopting many of these process approaches have been well studied in the literature.

Beyond this consideration of the manufacturing process and the application of technology, there is a knowledge gap related to the consequences of adopting the core manufacturing technologies themselves. Core manufacturing technologies have to do with the fundamental science and raw materials applied to create the end product. In the most pure example, different core technologies may be applied to produce the same end product. For example, electric arc furnace mills compete with so-called 'integrated mills' using fundamentally different technologies to produce the same output—molten steel. Of course, many technologies promise varying benefits to the firm, either in the form of production efficiencies or higher quality or performance of the end product. We adopt industry convention and define 'manufacturing technologies' as, *the 'master tools' of industry that magnify the efforts of individual workers and enable production of all manufactured goods, with production tools including machine tools and other related equipment, their accessories, and tooling.*[1]

In recent years, advanced manufacturing technologies have had a very positive effect on workforce productivity. Computers and information technology have been shown to account for less than half of the productivity growth in the durable goods sector in recent years, with the remainder largely accounted for by manufacturing technology improvements. During the 1980s and 1990s, multifactor productivity growth for the durable goods manufacturing sector far surpassed that for nondurable goods, highlighting these manufacturing advances (AMT, 2000).

Machine tooling advances have received a great deal of attention among manufacturing technologies, likely due to their importance across a wide swath of industries and their direct effect on manufacturing costs. Machine tools have also become increasingly combined with information technologies to enhance manufacturing efficiency. The change from manual control of the machine tool's movements to numeric and computer controls has fostered many creative new applications. McDonnell Douglas, for example, changed the manufacturing process for landing gear bulkheads of the C-17 aircraft to take advantage of high-speed machining. Using the new process, bulkheads are made with two parts rather than 72, and require only 35 fasteners to hold them together, rather than 1,720 under the previous method. Machining is now completed 15 times faster, generating dramatic cost savings (Krar and Gill, 2003 : 1–2).

Most past work on technology innovation and adoption has been focused at the consumer-product level. Often, a distinction has been made between incremental enhancements and more drastic (or 'radical') changes, largely as seen through the eyes of the consumer (Sood and Tellis, 2005). This study proposes that this same dichotomy can be applied in considering emerging manufacturing technologies. For example, the development of 'five-axis' machine tools allowed for significantly quicker and more flexible cutting and grinding operations than previous 'three-axis' machines. In recent years, parallel kinematic machines (PKMs) have emerged as 'a quantum step in machine tool development' and a threat to supplant five-axis tools due to their superior setup time and resulting surface quality (Wiens, 2000: 1). Other enhancements in manufacturing technologies are more incremental, in the spirit of the Japanese *kaizen* philosophy of continuous improvement.

Extending the product technology-based perspectives on innovation, we define 'radical manufacturing technologies' as, manufacturing tools and technologies that have the potential to redefine an industry through the disruption of existing competitive advantages, reducing the leverage of established firms and creating opportunities for the entry of new competitors (Henderson and Clark, 1990). We should highlight the notion of *potential* in this definition. Radical manufacturing technologies may represent discontinuous innovation and quantum change in the way things are produced, but only implementation and competitive reaction can ultimately determine whether they are financially superior to existing technologies (Dess and Beard, 1984; Henderson and Clark,1990). The choices firms make when faced with the opportunity to adopt such technologies and the consequences of those decisions are the focus of study here.

[1] www.amtonline.org (The Association for Manufacturing Technology)

This study makes several contributions to the literature. First, we extend past work on production *processes* (e.g., Benner and Tushman, 2002; 2003) to focus instead on the core manufacturing *technologies* used in production, an area that has received much less attention in the strategy literature. Second, we apply the distinction made in the innovation literature between incremental and radical change to the setting of manufacturing technologies, helping to develop a deeper theoretical understanding of this domain. Third, we expand our knowledge of the central premise that adoption of these radical technologies is conducive to firm survival by considering two groups of contingent factors that deepen our understanding of these phenomena: adoption timing and cumulative adoption effects. Fourth, we demonstrate the usefulness of the Bass model (Bass, 1969) to predict the survival outcomes of firms. While we describe the Bass model in detail later, we note here that although it has gained widespread acceptance for predicting the sales growth of product categories (Bass, Krishnan, and Jain, 1994), this represents the first attempt to use it for predicting firm survival. Finally, we demonstrate that our results hold even when we extend our model to control for the possibility that firms may choose to make their adoption decisions based on industry- and firm-specific characteristics that they think might impact their survival, thereby making their adoption decision endogenous and self-selected.

To examine the effects of these issues, this study considers firm survival, the ultimate measure of success for any firm. We evaluate the effects on survival of various adoption and timing of adoption decisions by a panel of firms in a mature industry over an exceptionally long time frame. These data are particularly appropriate since radical manufacturing technologies may take some time to diffuse through a population, and their effects on performance are not easily or accurately identified in cross-sectional analyses. The data were also comprehensive in that we were able to study the industry over the course of all the major technologies that arose during its modern history. However, it is important to note that not all of these technologies were equally successful, a fact that we assess with the help of diffusion models. In all, this study provides several theoretical, empirical, and practical insights into the nature of radical manufacturing technology adoption and its influence on firm survival.

THEORY AND HYPOTHESES

In this research, we focus on various contingencies surrounding the link between radical manufacturing technology adoption and firm survival. Research on organizational technology adoption has grown gradually over the past decades, though this work has generally focused on the technologies implanted into end products rather than on the manufacturing technologies used to produce them. Much of this work has focused on factors influencing the technology adoption decision (e.g., Gatignon and Robertson, 1989; Robertson and Gatignon, 1986). On a broader scope, another stream of research has considered industry-wide technology diffusion. This research, often driven by the foundational work of Bass (1969), is of interest here. Various studies have examined marketing mix and firm-specific variables and their influence on diffusion rates (e.g., Horsky and Simon, 1983; Lilien, Rao, and Kalish, 1981; Sinha and Chandrashekaran, 1992). However, these studies have explored only factors surrounding the decision whether or not to adopt without considering the organizational performance consequences of the adoption decision. Despite this breadth of work on product technology adoption, little is known of whether these models can be extended to the domain of core manufacturing technologies. Given the importance of industrial processes for national productivity and the quality and price of consumer goods, this is a knowledge gap that needs to be addressed.

The economics literature provides a good deal of insight into issues surrounding the diffusion of technology and innovation. A range of studies have linked technology to firm performance, as measured through wages, firm productivity, growth, and other factors (López-Acevedo, 2002). Doms, Dunne, and Roberts (1995) examined the impact of some advanced manufacturing technologies on firm performance. They found strong evidence that firms adopting a range of manufacturing technologies such as CAD/CAM systems, robotics, and computer networks exhibited superior performance. Across a range of technologies and performance measures, López-Acevedo (2002) found consistent relationships between manufacturing technology adoption and performance. Research in this field has consistently demonstrated that in simple correlational work, important adop-

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ted technologies are almost always positively related to firm performance.

The ultimate mark of poor firm performance is failure. Shakeouts, or *en masse* firm failures due to industry competitive pressures, are a ubiquitous stage in most models of industry evolution (e.g., Jovanovic and MacDonald, 1994b; Klepper, 1996). At the firm level, we take the perspective of Mitchell (1994) and define failure as the exit of a company from the relevant product market, whether the business is dissolved or sold to another company. Firm survival is the avoidance of an exit from the product market. Combined, this literature frames the central premise of this research, that the adoption of radical manufacturing technologies has a generally positive effect on the chances of firm survival.

However, this simple link between adoption and survival is too unequivocal to be of use from a theoretical or practical perspective. As in most strategy phenomena, it is likely that contingencies exist that influence the value of the adoption decision. Missing from much of the literature on manufacturing technology adoption is a clear consideration of two potentially contingent general factors: the timing of the adoption decision and the aggregate effects of adopting various 'bundles' of available manufacturing technologies. Next, we develop multiple theoretical perspectives for considering these contingencies, adding a more robust contribution to the research stream.

Adoption timing and survival

While radical manufacturing technologies often promise benefits to adopters, research suggests that the *timing* of this adoption is of great importance. A synthesis of several studies in this area suggests that Schumpeterian (Schumpeter, 1934) invention (a new discovery) leads to firm level innovation, or the application of that breakthrough to some commercial purpose (Jovanovic and MacDonald, 1994a). Adoption can vary widely, however, as some firms may not learn of the emerging technology as quickly as others (Rogers, 1995) and still others may follow a *vintage capital model* in which they knowingly cling to less than state-of-the-art technology given the synergies that exist with other firm assets (Chari and Hopenhayn, 1991). Most firms will ultimately be classified as imitators, as they adopt the technologies used by market pioneers.

As the impact of the emerging technology crystallizes, its status as either a competence-destroyer or competence-enhancer emerges. Competence-destroying manufacturing innovations represent a fundamentally new way of making a given product, whereas competence-enhancers produce incremental improvements in existing technologies (Tushman and Anderson, 1986). The successful adoption and implementation of an important new manufacturing technology leads firms to ultimately increase sales and/or profits, followed by declining profit margins for non-adopters and, ultimately, a shakeout among competitors (Gort and Klepper, 1982; Jovanovic and MacDonald, 1994b; Klepper and Simons, 2000). A clear observation from this view of competitive dynamics is that even being late to adopt an ultimately dominant or 'radical' manufacturing technology may have disastrous consequences for a firm's long-term viability.

Another perspective providing support for the survival advantages of earlier adoption is provided by Karshenas and Stoneman (1993) in their discussion of rank effects. In this view, potential adopting firms have different inherent characteristics that result in varying potential returns from the adoption of a new technology. Based on this theory, firms with the most to gain from a technology are likely to adopt it earlier. This view on varying potential returns combines with the assumption that technology acquisition costs will decline over time to suggest that firms with high potential returns will adopt first, but firms with lower potential returns will adopt at some point, once acquisition costs fall below expected benefits.

This range of perspectives supports the view that new technologies will experience a diffusion process, with performance and survival advantages for earlier adopters. Therefore:

> *Hypothesis 1: The early adoption of radical manufacturing technologies will increase the likelihood of firm survival.*

Beyond considering just the extent to which 'earlier is better' in manufacturing technology adoption, research on technology diffusion has suggested some more sophisticated perspectives on the interplay between timing and adoption of important technologies. For example, Klepper (1996) suggests that the performance implications of radical process technology adoption are driven

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more by firm size than by timing. In this view, innovations are largely intended to lower a firm's average cost of production. Therefore, the incentive to adopt is greater for firms with a larger base of production (Schmookler, 1966). Of course, one could make a counterpoint here that larger firms are more inertial and, therefore, less apt to engage in radical innovation (Hannan and Freeman, 1989).

The Bass (1969) model is among the most widely referenced models of technology diffusion across several disciplines (e.g., Bemmaor and Lee, 2002; Schmidt and Druehl, 2005; Teck-Hua, Savin, and Terwiesch, 2002). It has been applied to areas as diverse as the diffusion of educational ideas (Lawton and Lawton, 1979) and the adoption of cocoa-spray chemicals by Nigerian farmers (Akinola, 1986). Briefly, in the Bass model, the initial diffusion is generated as a result of the rate of acceptance of the product by the early adopters or innovators. Following the early purchases by innovators, the growth rate accelerates due to word-of-mouth effects that lead to adoption by the imitators. The cumulative number of adoptions takes the shape of an 'S'-function, hinging on a 'point of inflection' after which the product sales growth begins to decelerate. The diffusion process described above can be summarized as: $dN(t)/dt = [p + q/m\ N(t)][m - N(t)]$ where, $N(t) =$ cumulative number adopters till t, $m =$ maximum potential, $p =$ coefficient of innovation and $q =$ coefficient of imitation. Thus, if $F(t) = N(t)/m =$ fraction of potential adopters who adopt by t, then $dF(t)/dt = [p + qF(t)](1 - F(t))$.

In the case of radical manufacturing technology adoption, the basic tenets of the Bass model are reinforced by insights into order effects and stock effects (Karshenas and Stoneman, 1993). Research on order effects suggests that when faced with the industry-wide potential for technology adoption, higher-order (i.e., earlier) adopters will achieve a greater rate of return than lower-order adopters, for reasons including the acquisition of pioneering advantages (Ireland and Stoneman, 1985). In the case of manufacturing technologies, these advantages might include the negotiation of long-term sales contracts based on lower prices allowed by the new technology. Stock effects build on this view by adding the important insight that the potential benefit to a marginal adopter decreases as the number of previous adopters increases, establishing a point below which adoption for a given firm is not profitable (Karshenas and Stoneman, 1993; Reinganum, 1981). One of the reasons for the phenomenon is the likely reduction in manufacturing costs, subsequent price reduction, and shift of market share to adopters, reducing market opportunities for the marginal adopter. Firms making poor adoption decisions and acquiring new technology below this pivotal point will face detrimental performance consequences.

Given these theoretical views and past empirical support for the Bass model in a wide array of adoption situations, we expect it can provide more specific timing guidance regarding the adoption of radical manufacturing technologies:

Hypothesis 2: Adopting radical manufacturing technologies prior to the point of maximum penetration (per the Bass diffusion model) will increase the likelihood of firm survival.

Cumulative technology adoption

A second group of contingent factors considers the effects of cumulative technology adoption, or 'bundling.' Colombo and Mosconi (1995) highlight the limitations of the research tradition of considering technology adoption issues in isolation. They demonstrate the influence of cumulative learning effects and complementarity issues across adopted technologies and their influence on firm success. Research suggests that a pattern of proactive technology adoption should result in enhanced chances for firm survival. For example, a history of successful manufacturing technology adoption may erect a competitive advantage over non-adopters, the duration of which can range from very short-lived (for highly imitable technologies) to more enduring (Jovanovic and MacDonald, 1994b; Klepper, 1996). Since most manufacturing technologies are relatively available on the open market and *any* particular competitive advantage is difficult to defend, indefinite sustainability of advantage from an adoption is not likely (Porter 1985). A more realistic approach for most firms is to not seek a single enduring advantage, but rather a consistent series of discrete advantages with varying terms of success (Datar *et al.*, 1997). We refer to this technology strategy as the 'adoption magnitude effect.'

The absorptive capacity literature also supports the view that a cumulative benefit exists from adopting greater numbers of radical manufacturing technologies. Firms that have been successful technology adopters in the past are geared toward more aggressive technology adoption going forward (Cohen and Levinthal, 1990; Lenox and King, 2004). That is, technology adoption can become a firm capability that positively influences firm performance and survival. From different perspectives, this theory base suggests:

Hypothesis 3: Adopting greater numbers of radical manufacturing technologies (the adoption magnitude effect) will increase the likelihood of firm survival.

Beyond any benefits from sheer numbers of radical process technology adoptions, there may be particular advantages to certain combinations of technologies due to complementarity with past adoptions, learning curve advantages, or other factors (Colombo and Mosconi, 1995). Adopting powerful combinations of emerging manufacturing technologies can leverage the 'technology gap' a firm possesses over its more laggard competitors (Castellacci, 2002). According to technology gap theory, the successful adoption and use of new technologies requires investments in many areas including capabilities, capital equipment, and infrastructure. Those not making these investments risk falling increasingly behind technology leaders (Verspagen, 1991). Challenging combinations of adopted technologies may pose a particularly daunting obstacle for non-adopters, enhancing the survival chances of adopters.

Beede and Young (1996) found enormous diversity in adoption patterns, suggesting fundamental differences in managerial philosophies and strategies toward technology within the same industry. They also found significant differences in the effects of various technology combinations on performance. They clearly demonstrate the need to consider technology bundles in assessing adoption scenarios.

The most powerful way to leverage this phenomenon is through the identification and adoption of *synergistic* technology bundles. That is, while individual technologies may each have a discrete value-added effect on the firm, certain technology combinations may exhibit an amplifying benefit effect. In a more complex form, technology ladders may exist in which new technologies build upon in-use technologies to produce firm advantage (Beede and Young, 1996; Song, 2002). We expect that evidence of technology bundles and/or ladders will exist over the modern lifespan of a manufacturing industry:

Hypothesis 4: Over an industry's lifespan, certain technology bundles or ladders will emerge, the adoption of which will positively influence the likelihood of firm survival.

DATA AND ANALYSIS

Our objective in this research is to consider contingent factors on the central premise that the decision to adopt major manufacturing technologies influences firm survival. We consider the contingent effects of adoption timing, both in an absolute sense and as it relates to the Bass model of technology diffusion. Another contingency group considers the effects of cumulative adoption through general aggregate effects and specific technology bundles. The findings show that the *whether* and *when* (Mitchell, 1989) of the adoption decision are both critical in determining firm survival.

Data

The ideal dataset to investigate the impact of manufacturing technology diffusion on performance would contain the complete life history of the population of potential adopters, the characteristics of well-defined and relevant technologies, and the availability of data for a sufficiently long period beginning with the first appearance of these major technologies. Such ideal datasets are scarce, not least due to the major hurdles involved in obtaining disaggregated data on technology adoption. Our data, which meet most of these requirements, are based on manufacturing technology adoption surveys of firms in the United Kingdom metal working and engineering industry in 1981 and 1986.[2] The 1981 surveys generated 1,127 usable responses with a response rate of 40 percent. A follow-up survey in 1986 achieved a response rate of over 95 percent of surviving firms. The disadvantages of limited generalizability are more than offset by the availability of detailed information

[2] The authors are grateful to the Warwick Business School Research Bureau and Professor Paul Stoneman of the Warwick Business School for providing the data used in this study.

that is only possible in the context of a single industry. The surveys provide data on:

(a) the establishment date of each firm, including firms that were established prior to 1900 (representing 10% of the sample);
(b) the closure date, if the event had occurred between 1981 and 1986;
(c) demographic variables such as firm size measured by number of employees (EMP) and onsite research and development resources (R&D); and
(d) the date of first adoption of four technologies that had a major impact on the evolution of this industry.

These four technologies were: coated carbide tools and tips (CCT), numerically controlled machine tools (NC), computerized numerically controlled machine tools (CNC) and microprocessors for production (MIC). The adoption statistics for these technologies are as follows: (1) 28.7 percent of the firms adopted NCs, of which 98.17 percent had adopted prior to 1981; (2) 42.7 percent adopted CNCs, of which 53.9 percent had adopted prior to 1981; (3) 37.5 percent adopted CCTs, of which 69.14 percent had adopted prior to 1981; and (4) 25.7 percent adopted MICs, of which 17.48 percent had adopted prior to 1981. Finally, 36.6 percent had not adopted any one of these four technologies by 1986.

A discussion of key industry technologies

The choice of which process technologies to study was central and critical in order to test our framework. A review of numerous industry sources corroborated that the four manufacturing technologies chosen were pivotal in the evolution of the industry (or 'radical' as we have defined the term). Carbide tools and tips (CCT) were extensions of the work of Frederick Taylor in the late-nineteenth century. He experimented with various metal alloys that dramatically extended the cutting life of machine tools. These metals had the further advantage of performing even better under the high heat conditions common in a production environment. Carbide-coated instruments became the dominant choice for industrial cutting operations by the early part of the twentieth century (Holt, 1965).

Numerically-controlled machine tools (NC) were early forms of computer programs used to perform industrial milling and other operations that had previously relied almost exclusively on operator skill. Thus, this technology improved operational flexibility and speed and reduced costs (Arnold, 2001). As observed by Arnold concerning the broad machine tool industry,

> *Through this one invention [NCs] the industry was thrust into the age of digital electronic machine-tool controls, and opportunities were created for a variety of new products and business models in the marketplace. Some companies were able to transform their businesses, many not (* Arnold, 2001: 2).

His data show that the adoption of early-form numerical control systems began in the early 1950s and continued until the proliferation of the personal computer in the early 1980s. Clearly, NC systems represented a 'radical' technology. Not only did they cause the redesign of many production machines, but they spurred the consolidation of functions and the development of more multi-functional, flexible machines.

Computerized numerically controlled machine tools (CNC) and microprocessors for production (MIC) represented advances in the development of more automated and refined production processes. CNC systems offered dramatically greater operational flexibility, in part because they coincided with the development of more intuitive operating software. This led to faster retooling and more flexible production. These systems began to enter the industry in the late 1970s. MIC systems are a more recent invention and offer another dramatic step forward in the sophistication of production processes in this industry. The benefits from these processes have been directly linked to better and faster machining and to powerful strategic advantages such as lead time reduction, quality improvement, flexibility improvement, and better inventory management (Bessant, 1991; 1995). Despite the widespread belief of their importance for this industry, these technologies had very different levels of success, as verified by the Bass model, the results of which are presented later.

The structure of these data allowed us to investigate whether the adoption of these different manufacturing technologies had an impact on firm survival. However, despite the advantages offered by the data, we wish to recognize the possibility of attrition bias in our results. Since the survey was started in 1980, firms that ceased to exist prior to 1980 (but had adopted the technologies in question

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between 1950, the date the first of the four technologies appeared in the market, and 1980) would not be included in the surveys. The severity of this bias will depend upon the number of such firms in the population, but we were unable to determine this figure due to the lack of secondary data on firms that exited the industry prior to 1980. Were this information available, we could have adjusted the sample likelihood by weighting the different observations by the selection probabilities in order to counteract the attrition bias. However, this attrition bias may be mitigated by jointly considering the following factors:

(a) while CCTs and NCs were introduced prior to the 1950s, two of the technologies under consideration were first introduced in 1968 (CNCs) and 1972 (MICs). Thus, any analysis that is restricted to the latter two technologies would not be impacted by any exit from the industry prior to 1968, the earliest time of introduction for these two technologies; and
(b) the post–World War II period in Britain from 1950–1973 has been characterized as the period of the 'long boom' (Booth, 2003). It was one of significant growth in this industry, and it was not until the mid-1980s that the industry suffered a decline.

Consequently, we ran our analysis of the impact of diffusion on firm survival based on these two technologies alone and found that our substantive results were virtually identical to those found with all four technologies in the sample. Since both these technologies were introduced during the long boom period, it is unlikely that a large number of adopting firms exited the industry during this period, thereby greatly alleviating any concerns over attrition bias.

Model and estimation

We use a hazard modeling framework to investigate the impact of technology diffusion on firm survival. Since hazard models have been used extensively and in a wide variety of contexts (such as technology diffusion, services, and consumer brands) in the innovation and strategy literatures (e.g., Bolton, 1998; Chintagunta and Haldar, 1998; Mitchell, 1989; Sinha and Chandrashekaran, 1992), we provide a cursory overview of the model specifications and then proceed to the results of estimating the hazard models.

The duration time for firm i, can be viewed as a random variable having some probability density $f(t)$ and a cumulative distribution function $F(t)$. In characterizing the time to mortality, it is convenient to consider the *hazard rate* $h(t) \equiv f(t)/(1 - F(t))$, which is the conditional probability of the event of interest (mortality.) A class of duration models called Accelerated Failure Time models, follow the parameterization:

$$\ln(t_j) = \mathrm{x}_j \beta_x + \varepsilon_j$$

The word 'accelerated' is used in describing these models because, rather than assuming a specific distribution for failure time itself, a distribution is instead assumed for $\tau_j = \exp(-\mathrm{x}_j \beta_x) t_j$ and $\exp(-\mathrm{x}_j \beta_x)$ is called the acceleration parameter. Thus, based on the acceleration parameter we can determine whether time passes at the normal rate or is accelerated or decelerated as a result of the occurrence of the event of interest. This model may be re-parameterized as $\ln(t_j) = \mathrm{x}_j \beta_x + \ln(\tau_j)$, where the distribution of $\ln(\tau_j)$ may now be specified. For example, in a log-normal model, τ_j follows a log-normal distribution, which implies that $\ln(\tau_j)$ follows a normal distribution. In this research, we use the generalized gamma model that has the advantage of flexibility and includes both the log-normal and Weibull models as special cases. This allows us to perform specification tests in order to select the most appropriate model for the data at hand.

These models greatly facilitate the interpretation of the estimated model parameters. For example, a one-unit increase in x_1 increases the expected value of $\ln(t)$ by β. For a subject predicted to fail at $t = 1$, this one unit increase would delay the predicted time of failure to $\exp\{\ln(1) + \beta\}$. For a subject predicted to fail at $t = 2$, this one-unit increase would delay the predicted time of failure to $\exp\{\ln(2) + \beta\}$. That is, the marginal effect of x_1 accelerates. For larger t, we expect a longer delay in failure due to a one-unit increase in x_1. An important consideration in duration analysis is to model unobserved heterogeneity in individual firm characteristics since the failure to do so can seriously bias parameter estimates. We follow the traditional approach of modeling this as $h(t|x_t) = h_0(t).\phi(x_t, \beta).\ \Psi(\theta)$, where β_{x} indicates the effect of covariates on the hazard rate, and

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h_0(t) is the baseline hazard function. The baseline captures the longitudinal effects associated with the duration dynamics, while $\phi(x_t, \beta)$, adjusts $h_0(t)$ up or down proportionately to reflect the effect of the measured covariates and the $\Psi(\theta)$ represents the functional form for unobserved firm characteristics (Lancaster, 1979, 1990).

In the event that there is little or no theoretical guidance for selecting among parametric approaches, the Proportional Hazard model proposed by Cox (1975) provides an appealing alternative to the foregoing approach. Since this model does not rely on parametric assumptions for the underlying hazard distribution, it is often taken as a reference model for assessing the results for sensitivity to the distributional assumptions made in the parametric model. Like the accelerated hazard mode, this parameterization also lends itself to a simple interpretation for the parameter estimates: as the value of a covariate increases by one unit, the hazard rate (mortality, in our case) changes by $\{\exp(\beta) - 1\} \times 100$ percent.

Results

An important issue in estimation is the specification of the functional form for $\phi(x_t, \beta)$ and the unobserved heterogeneity component $\Psi(\theta)$. Our model estimation proceeded as follows. First, we estimated the Proportional Hazard (PH) model using the partial likelihood procedure suggested by Cox (1975). We then tested different functional forms for the effects of the covariates, including the generalized gamma model and found (based on fitting the latter) that the log-normal hazard best characterized the data at hand. Finally, we fit the log-normal model with a gamma distribution representing the compounding factor for unobserved heterogeneity. This is the most general approach generally taken in order to model unobserved heterogeneity in household purchases and is a good representation of our data. This is particularly important in our analysis due to the paucity of control variables to adequately characterize the firms in our sample.

Prior to discussing the results, it is important to discuss an important control variable in our analysis. It seems reasonable to assume that firms born after 1968 (the year that CNCs were first introduced to the market) may have had little incentive to adopt both NCs and CNCs, or at the very least may have had a different incentive structure in terms of the order of adopting these technologies.[3] Consequently, in analyzing the impact of the timing and magnitude of adoption, we attempted to control for this effect by creating an indicator variable to denote whether a firm was born prior to 1968. However, including this did not have any appreciable impact on the technology parameters and in the interest of parsimony we do not report the results from estimating this model.

Adoption likelihood and survival

Tables 1–2 contain the results of estimating the PH and generalized gamma models, with and without unobserved heterogeneity. Figure 1 offers a range of descriptive statistics on the data. We first consider the impact of adopting a given technology, either alone or in combination with other manufacturing technologies. The indicator NC_AD in Table 1 indicates that a firm adopted numerically controlled machine tools, regardless of what other technologies it may also have adopted. Thus, the first column in Table 1 indicates that the adoption of computerized machine tools (CNC) decreases the mortality rate by $(1 - 0.375) = 62.50$ percent, the adoption of CCT by 54 percent and the adoption of MIC by 60 percent (compared to firms that did not adopt the technologies in question). It is interesting to note that the impact of the incremental technology (NC) is non-significant. However, we elaborate on this result later by pointing out that this technology does indeed have some impact, albeit under two specific conditions: (a) if it is combined with more radical technologies, i.e., when firms upgrade their technology portfolio; and (b) if it is adopted by a certain critical time in its diffusion path.

From the first column we also conclude that firm size and resources did not impact firm survival, once we control for the impact of technology. The lack of support for the Size variable is interesting as it has been one of the most consistently shown factors influencing firm technology adoption (Colombo and Mosconi, 1995; Sinha and Noble, 2005) and survival (Hannan and

[3] In talking to industry experts, we discovered that for many firms, CNCs represented a major leap in technological expertise such that it was not just an issue of acquiring the new technology, but also of finding the appropriate manpower. In addition, it was possible for firms to adopt CNCs first and then follow it up with NCs for specific tasks. Consequently, it is not inconsistent for firms to adopt these technologies in a different order.

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Table 1. Adoption likelihood and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
NC_AD	1.021 (0.163)	0.952 (0.0936)	0.9545 (0.094)
CNC_AD	0.375 (0.063)***	1.698 (0.163)***	1.686 (0.1612)***
CCT_AD	0.456 (0.071)***	1.492 (0.1336)***	1.479 (0.1289)***
MIC_AD	0.3998 (0.085)***	1.643 (0.1753)***	1.634 (0.1719)***
EMP	0.9995 (0.000)	1.0004 (0.0001)**	1.0004 (0.0001)**
R&D	0.948 (0.115)	0.9956 (0.073)	0.9904 (0.0717)
k		0.0895 (0.1948)	
σ		0.783 (0.050)	0.8008 (0.0326)
Log-likelihood	−1757.37	−596.29	−596.39

*** $p < 0.0001$, ** $p < 0.01$

Note 1: The variables indicate impact of adopting a given technology, either alone or in combination with other technologies

Note 2: For the Cox proportional hazard model, the coefficients represent $\exp(\beta)$ while for the accelerated hazard models (the other two columns), the coefficients represent $\exp[\ln(t) + \beta]$. For example, the PH model estimates that the adoption of CNCs (either alone or in combination with others) lowers the mortality rate by $(1 - 0.375 = 62.5\%)$, while the generalized gamma model states that the adoption of CNCs will increase the expected time to mortality to 1.69 years for those firms that are expected to exit in year one. Similarly, for firms expected to die in year five, the expected time to mortality would increase to $\exp[\ln(5) + 0.529] = 8.49$ years as a result of adopting CNCs. The other coefficients are interpreted in a similar manner.

Table 2. Adoption of specific technologies and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
NC	0.9794 (0.262)	1.031 (0.1967)	1.025 (0.1928)
CNC	0.217 (0.0896)***	1.958 (0.3536)***	2.00 (0.3621)***
CCT	0.3691 (0.1017)***	1.815 (0.2793)***	1.82 (0.2747)***
MIC	0.4733 (0.1814)**	1.467 (0.2842)**	1.476 (0.282)**
EMP	0.998 (0.0003)***	1.001 (0.0001)***	1.00 (0.0001)***
R&D	1.24 (0.1513)	0.8682 (0.0628)	0.8682 (0.063)
k		−0.1085 (0.1816)	
σ		0.8558 (0.052)	0.8322 (0.034)
Log- likelihood	−1802.03	−640.21	−640.32

*** $p < 0.0001$

** $p < 0.01$

Note: The variables indicate impact of adopting a given technology in isolation, i.e., NC is an indicator of whether or not the firm adopted NCs to the exclusion of all other technologies. From the PH model we can ascertain that the sole adoption of CNCs lowered the mortality likelihood by 79%. The gamma hazard model tells us that for firms expected to die in period one, the sole adoption of CNCs increases the expected time to 1.96 years.

Freeman, 1977; Klepper and Simons, 2000). One argument for this finding contends that larger firms have a better inherent buffer to withstand unexpected environmental shocks (Hannan and Freeman, 1989). On further analysis, the result here should be interpreted with some caution. While a few firms in the sample had over 5,000 employees, 95 percent of the firms studied had fewer than 900 employees and 75 percent had fewer than 200 employees (mean $= 214.72$, s.d. $= 409.19$). The lack of significant effect for firm size here is likely an artifact of the preponderance of small firms in the sample and the consequent lack of sufficient variance in the size variable.

The second and third columns of Table 1 present the results of the accelerated time hazard model, with and without the impact of unobserved heterogeneity. First note from the second column that the distributional parameter for the generalized gamma model (k) is not significantly different from zero and essentially reduces this to the log-normal model. The results closely parallel the results in the first column, thereby attesting to the robustness of the results. We find that for firms

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	Ceased	NC	CNC	MIC	CCT	NCINN	CNCINN	CCTINN	MICINN	T1	T2	T3	T4	Size	R&D
Mean Standard deviation	0.27 [0.44]	0..025 [0.157]	0.073 [0.259]	0.05 [0.23]	0.07 [0.27]	0.153 [0.36]	0.24 [0.43]	0.149 [0.357]	0.184 [0.388]	0.23 [0.419]	0.173 [0.378]	0.16 [0.37]	0.073 [0..26]	214.77 [409.19]	1.34 [0.478]
Ceased	1.000														
Probability of adoption															
NC	**0.0963**	1.000													
CNC	**-0.1236**	-0.0450	1.000												
MIC	**-0.0859**	-0.0391	**-0.0681**	1.000											
CCT	**-0.0630**	-0.0453	**-0.0791**	**-0.0686**	1.000										
Timing of adoption (prior to t*)															
NCINN	-0.0274	**0.0753**	**-0.1191**	**-0.1032**	**-0.1199**	1.000									
CNCINN	**-0.0914**	**-0.0915**	0.0257	**-0.1383**	**-0.1606**	**0.4617**	1.000								
CCTINN	-0.0556	**-0.0673**	**-0.1174**	**-0.101**	**0.1425**	**0.2989**	**0.2841**	1.000							
MICINN	**-0.1531**	**-0.0764**	**-0.1333**	**0.309**	**-0.1341**	**0.1718**	**0.1719**	**0.0872**	1.000						
Magnitude of adoption															
T1 (any one technology)	**-0.1269**	**0.2961**	**0.5165**	**0.4478**	**0.5199**	**-0.1769**	**-0.1940**	**-0.0648**	-0.0257	1.000					
T2 (any two technologies)	**-0.1008**	**-0.0734**	**-0.1280**	**-0.111**	**-0.1289**	0.0506	**0.1386**	0.0423	0.0405	**-0.2479**	1.000				
T3 (any three technologies)	**-0.1229**	**-0.0704**	**-0.1228**	**-0.1064**	**-0.1236**	**0.2559**	**0.3997**	**0.2560**	**0.1767**	**-0.2377**	**-0.2001**	1.000			
T4 (any four technologies)	**-0.1392**	-0.0450	**-0.0786**	**-0.0681**	**-0.0791**	**0.4483**	**0.3477**	**0.2710**	**0.4022**	**-0.1521**	**-0.1280**	**-0.1228**	1.000		
Other covariates															
Size	**-0.1061**	-0.0202	**-0.0681**	-0.0263	**-0.0757**	**0.4696**	**0.3967**	**0.2980**	**0.3025**	**-0.1114**	-0.035	**0.20**	**0.4518**	1.000	
R&D	0.0541	0.0175	0.0101	-0.0093	0.0580	**-0.1775**	**-0.1826**	**-0.1034**	**-0.1353**	0.0439	**-0.067**	**-0.143**	**-0.1203**	-0.1636	1.000

* Coefficients in **bold**: $p < 0.05$

Figure 1. Descriptive statistics

expected to fail in period one, the effect of CNC adoption is to delay the expected failure time to 1.69 years. This parameter estimate also suggests that for firms expected to fail in year five, the adoption of CNC would delay the expected failure time to 8.49 years. Clearly, the adoption of this radical technology has a major impact on the survival of firms. Continuing down the second column we find very similar results for both CCT and MIC. Finally, in the third column we note that heterogeneity due to unobserved factors is not a concern for these data and that the parameter estimates from Table 2 are entirely unaffected (we do not report the heterogeneity parameter because it was estimated to be not significantly different from zero). Given the potentially biasing impact of unobserved variables on the estimated hazard rate, this finding is encouraging and attests to the robustness of our results.

Table 2 further examines the impact of adoption on survival by focusing on the impact of *each technology in isolation*. While earlier we reported the impact of adopting each of the four technologies regardless of what other technology was adopted, in Table 2 we report the impact of adopting each technology when it was the only technology adopted by a firm. Once again, all three models provide very similar and consistent results. As expected, NCs do not have an effect, while the others do have a major impact on survival. However, it is interesting to note that both CNCs and CCTs had a more powerful impact when adopted in isolation (relative to their impact reported in Table 1.) For example, focusing on the results in the second column, we find that the adoption of CNC in isolation of any other technology increases the expected time to failure to 1.958 years for those firms that were expected to fail in period one. In the case of CCTs, the corresponding effect is 1.815 years and in both these cases the effect is stronger here than in the previous case where they may have been adopted either alone or in combination with other technologies. For MICs on the other hand, while the impact is significant, it is less than the effect reported earlier in Table 1, suggesting thereby that this technology has a complementary impact. Nevertheless, the substantive conclusion from these results is that the adoption of radical technologies has a significant general impact on reducing firm mortality and lends strong support to the basic premise of this study. In addition, we gain the insight that for some radical manufacturing technologies, adopting in isolation has an even more powerful impact than if they are adopted along with other technologies.

Adoption timing and survival

To examine if early adoption of major technologies was a major determinant of survival, we calculated

Table 3. Adoption timing and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
NC_t	0.9962 (0.0112)	1.006 (0.0068)	1.004 (.006)
CNC_t	0.9647 (0.0197)*	1.018 (0.0116)*	1.019 (.011)*
CCT_t	0.9586 (0.0121)***	1.022 (0.0073)***	1.023 (.007)***
MIC_t	0.9338 (0.0333)*	1.036 (0.0175)*	1.0367 (.018)*
EMP	0.9988 (0.0003)***	1.0006 (0.0001)***	1.0006 (.0001)***
R&D	1.084 (0.1325)	0.9076 (0.0658)	.918 (.066)
k		−0.3325 (0.2405)	
σ		0.8945 (0.0547)	.8303 (.0338)
Log- likelihood	−1808.46	−642.86	−643.86

*** $p < 0.0001$
** $p < 0.01$
* $p < 0.05$
Note: The variables indicate the time elapsed since first adoption of the respective technology.

the number of years elapsed since each technology was first adopted. Table 3 demonstrates that the timing of adoption of radical innovations has a significant impact on survival. Consistent with the results regarding the likelihood of adoption of NCs, hastening their adoption had no impact on the hazard. Given the relatively strong impact of the adoption of CNCs, it is interesting to note that the timing of adoption of CNCs had only a moderate impact on firm mortality, reducing the estimated hazard by about four percent. Similar results were found for CCTs and MICs, with corresponding reduction in the mortality rates of five percent and seven percent respectively. This result suggests that for certain technologies it may be a case of 'better late than never.' Therefore, we found support for Hypothesis 1. Further, these results were unaffected by the potential of unobserved heterogeneity, as the results in the third column are identical to those in the second column.

Unfortunately, it is not clear *ex ante* which particular technologies will have the greatest impact on future survival, so that a firm with limited resources is unable to determine with certainty which technologies warrant proactive investment. However, it may be possible to answer this critical question if there is a general relationship between the diffusion path of a given technology and firm mortality. Consequently, we now report the impact of adopting prior to the inflection point estimated by fitting the Bass model to each technology.

Bass model inflection and survival

As reported above, we investigated whether the Bass model could be used as mechanism for predicting the mortality of firms. We calibrated the Bass model for each of the four technologies and calculated the inflection point t^* (point where the penetration is maximized) of the diffusion curve for each technology. It is important to note that our data included adoption data from the inception of each technology. These results are contained in Table 6, from which one can ascertain that CNCs were the most rapidly diffusing technology and their growth peaked after approximately 12 years. Based on these results, we were able to determine whether or not a firm adopted each technology prior to t^*, the point of maximum penetration, and then relate each of these variables to the mortality rates based on the hazard model, the results of which are contained in Table 4A. From the latter, it is evident that adopting prior to t^* has a critical effect on increasing survival likelihood, regardless of the technology in question. Firms adopting NCs prior to the point of inflection based on the NC diffusion curve reduced their mortality likelihoods by 26 percent. Another way of stating this (from the accelerated hazard models in the second and third columns) is that firms that were expected to fail in year one would now delay their expected failure timing to about 1.3 years. Similarly, firms adopting CNCs prior to t^* increased their expected failure time to about 1.21 years, that is, they were less likely to perish.

It is interesting to note that CNCs were the fastest to diffuse (t^* of 12.3 years) and had the largest coefficient of imitation ($q = 0.39$). This suggests that contagion effects were a major factor in determining the diffusion of this technology. This is instructive in light of the earlier finding

Table 4A. Adoption *prior* to Bass inflection point and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
NC_t	0.737 (0.143)*	1.327 (0.155)**	1.292 (0.151)**
CNC_t	0.675 (0.115)**	1.209 (0.121)*	1.227 (0.124)*
CCT_t	0.635 (0.121)***	1.352 (0.151)***	1.364 (0.154)***
MIC_t	0.397 (0.082)***	1.728 (0.186)***	1.751 (0.195)***
k		−0.44 (0.25)	
σ		0.91 (0.05)***	0.83 (0.03)***
Log- likelihood	−1813.21	−646.56	−648.06

*** $p < 0.0001$
** $p < 0.01$
* $p < 0.05$
Note: Variables in Table 4A indicate whether or not the firm adopted the technology prior to t^*, the inflection point for the Bass diffusion curve. Variables in Table 4B indicate adoption after t^*.

Table 4B. Adoption *after* the Bass inflection point and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
NC_t	1.35 (0.264)	0.753 (0.087) ***	0.77 (0.09) ***
CNC_t	1.48 (0.254)**	0.826 (0.083) ***	0.81 (0.08) ***
CCT_t	1.57 (0.297)***	0.739 (0.082) ***	0.73 (0.08) ***
MIC_t	2.51 (0.52)***	0.578 (0.062) ***	0.57 (0.06) ***
k		−0.44 (0.25)	
σ		0.95 (0.05) ***	0.86 (0.03) ***
Log- likelihood	−1824.18	−661.3	−662.89

*** $p < 0.0001$
** $p < 0.01$
* $p < 0.05$

that the decision to adopt CNCs matters, but the timing of adoption was only a moderate determinant of firm survival. It may be that the benefits of this particular technology were easily observable and communicated via word of mouth. Innovative firms adopted this technology and stood to gain even by being late adopters, while non-adopters of this rapidly diffusing technology lost out.

The results for CCTs and MICs are similar, though it appears that adopting prior to t^* has the strongest impact for the latter, increasing the expected time of failure by about 73 percent for firms that would be expected to fail in the first period (from the second column). These results therefore suggest the interesting possibility of using the Bass model as a predictor of mortality among firms, and provide strong support for Hypothesis 2. While the results are preliminary and cannot be generalized beyond the sample at hand, future studies across different industries may shed further light on this subject. It is important to note that, once again, our results are unaffected when we model unobserved heterogeneity (results in the third column). Interestingly, we found that the respective effects on survival of early adoption (prior to t^*) and late adoption (after t^*) are not symmetric. As shown in Table 4B, where we look at the impact of adopting after t^*, late adoption of CNCs increases the likelihood of mortality by 48 percent; in contrast, early adoption reduces mortality by 34.5 percent. Similarly, late adoption of CCTs increases mortality by 57 percent; while the early adoption of the same technology reduces mortality by only 36.5 percent. Finally, and most remarkably, while the early adoption of MICs reduces mortality by almost 60 percent, later adoption increases mortality by 151 percent. These results clearly suggest that the deleterious effects of delaying adoption exceed the beneficial impact of early adoption.

Table 5. Technology bundles and survival (standard errors in parentheses)

Variables	Cox PH model	Gamma hazard model	Hazard model with unobserved heterogeneity
T1	0.249 (0.043)***	2.194 (0.2064)***	2.189 (0.2041)***
T2	0.2551 (0.0494)***	2.182 (0.2274)***	2.178 (0.2256)***
T3	0.2053 (0.0481)***	2.404 (0.29)***	2.399 (0.2864)***
T4	0.0644 (0.035)***	3.731 (0.8361)***	3.701 (0.8096)***
EMP	0.9995 (0.0002)	1.000 (0.0001)	1.000 (0.0001)
R&D	0.9597 (0.1165)	0.9858 (0.0704)	0.9838 (0.695)
k		0.0391 (0.1781)	
σ		0.7719 (0.0469)	0.7795 (0.0315)
Log- likelihood	−1753.42	−590.08	−590.10

*** $p < 0.0001$
** $p < 0.01$
Note: Variables T1–T4 indicate the number of technologies adopted: T1 represents any one technology, T2 any two, and so on. Adopting all four technologies had the greatest impact on survival: it reduced the likelihood of mortality by 94% or alternatively, for firms that were predicted to die in year one, the adoption of all four technologies increased the predicted time to 3.7 years.

Adoption magnitude and survival

Finally, we turn to the issue of adoption magnitude and mortality. In this context, magnitude refers to the variety of technologies in the manufacturing technology portfolio of each firm and is captured by whether a firm had adopted any one kind of technology (NC or CNC or CCT or MIC, referred to as T1 in Table 4), any two (NC and CNC or NC and MIC etc. referred to as T2), any three (T3), or any four (T4). From the first column in Table 5 it is clear that, while there is not much difference between T1 and T2, adopting any three or all four technologies had the greatest impact on mortality (reduced by 80% for T3 and 94% for T4). The combination of *any two* technologies reduced mortality by 75 percent, as did the adoption of any one technology, on average. Consequently, the best-equipped firms were the most likely to survive, providing significant support for Hypothesis 3.

Technology bundles and survival

What about the adoption of specific bundles of technology? We investigated all possible combinations of bundling these four technologies (six bundles of two technologies, four bundles of three technologies and one bundle of all four technologies, which corresponds exactly to T4 from the discussion above.) This approach might be considered a search for underlying 'technology ladders' without an *a priori* assumed hierarchy (Song, 2002). In order to conserve space, instead of reporting the results for all these 11 combinations, we limit our discussion to the three models that yielded significant results. First, the combination of CNC and CCT lowered the mortality likelihood by 67 percent (in contrast to 75% for *any two* technologies reported earlier). In terms of T3, the only combination that seemed to matter was CNC+CCT+MIC: adoption of all three of these technologies lowered the hazard rate by 68 percent. Interestingly, the impact of microprocessors (MIC) on firm survival appears to be limited to cases where firms have also adopted the other two radical technologies in question (CNCs and CCTs). This is consistent with, and sheds further light on, the earlier finding that the impact of MICs appears only in combination with some other technology. Finally, firms that adopted all four technologies were best positioned to survive, lowering their risk of mortality by 78 percent. It is important to note that these results are not sensitive to the functional form of the model specification. The results in the second and third columns have the same interpretation as before and are consistent with the results in the first column These findings support both Hypothesis 3 and Hypothesis 4, illustrating the importance of cumulative technology adoption in this industry setting.

At this stage it is important to consider whether these results might differ across firms that do not compete directly against each other.[4] It is important to consider this because if most of the firms are small job shops with low return while some compete in high-end work, then these conclusions

[4] We are grateful to an anonymous reviewer for raising this issue.

Table 6. Bass model parameters

Parameters	NC	CNC	CCT	MP
m	353	521	522	469
p	0.005	0.003	0.001	0.007
q	0.22	0.393	0.206	0.295
t*	18.6	12.3	25.7	28.1

Here, m is the market potential, p is the coefficient of innovation, q is the coefficient of imitation, and t* reflects the time to inflection.

may not hold. For example, consider a small job shop that makes mold for sundry toy manufacturers as one type of player in this industry. At the same time, consider another firm that is a supplier of piston rings to a major automobile manufacturer. It is possible that adding microprocessors may benefit the larger firms because it helps deliver on customer-valued attributes (turnaround time and reliability, for example). However, the same technology may not be cost-effective for the smaller firm who makes molds for occasional orders as its buyer is cost conscious. So, adopting this technology may indeed increase the survival chances for the larger manufacturer but may decrease the survival chances of smaller firm if it cannot sell to auto manufacturers due to lack of other capabilities.

Consequently, in addition to the results reported above, we estimated a variety of different models across different firm variables such as size and R&D. In fact, we followed two different estimation strategies to check for systematic differences across firms:

(a) In the first case, we allowed our firm-specific covariates to impact the shape of the hazard such that it was possible for firms with different values for the covariates to have different hazards. In order to conserve space, we do not report all the results here. Suffice it to say that there is no difference in the impact of size across the two groups. For example, for small firms the impact (i.e., coefficient with std. error in parentheses) of an overall adoption indicator is 2.21 (0.24), $p = 0.000$, while for large firms it is 2.59 (0.27), $p = 0.000$. This similarity holds across all the different indicators of technology adoption used in the study and also survives the different transformations for size and R&D described above.

(b) We also stratified the sample into groups based on whether or not small firms conducted their own R&D. Once again, there were no differences across these groups, with the impact of adoption on small firms with on-site R&D being 2.60 (0.41), $p = 0.000$ versus 2.55 (0.2), $p = 0.000$ for the rest. Thus, we are confident that our results are invariant across the different firm groups that could be considered in the dataset.

ADOPTION AS ENDOGENOUS

Thus far, our analysis has provided strong evidence that the adoption of radical manufacturing technologies lowers firm mortality. We also found evidence of firm-specific characteristics (observed and unobserved) that impact survival. Now, it is quite possible that some of these firms may themselves be aware of the impact of these observed, firm-specific characteristics (such as size and R&D in our example) and unobserved characteristics (such as managerial ability, attitudes towards risk and innovativeness) on their odds of survival. If so, perhaps firms that consider themselves to be at above-average mortality risks respond to this private knowledge by adopting technologies earlier and at an enhanced rate. The result will be that technology adoption will now be associated with firms with above-average mortality risks and, left unattended, this 'adverse selection' will underestimate the beneficial impact of adoption.

If this is true, the adoption decision must be treated as endogenous since we are taking into consideration the possibility that different adoption strategies are not being randomly selected by firms, but are instead based on both observable and unobservable firm and industry characteristics and *chosen* by firms in response to these characteristics. Consequently, it is important to address this potential endogeneity in the adoption decision (technically, adoption is no longer independent of the error term in the hazard model since unobserved variables such as managerial ability or 'innovativeness' may be expected to affect both the decision to adopt technology and firm survival) and investigate whether the earlier conclusions regarding the impact of technology on firm survival were an artifact of treating adoption as exogenous. This argument may be formalized based on the sample

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selection or self-selection models proposed initially by Heckman (1979).

Let Adoption* represent a latent variable that indicates the threshold for adoption, such that we observe the adoption of radical technology if this threshold is exceeded. Thus, the latent variable Adoption* represents the difference between the expected benefits of adoption versus non-adoption. Formally, letting ω denote firm and industry characteristics that are relevant for the adoption decision,

$$\text{Adoption}_i^* = \gamma\ \omega_i + u_i,\ \text{such that} \tag{1}$$

$$\text{Adoption} = 1,\ \text{if Adoption}^* > 0 \text{ and}$$

$$\text{Adoption} = 0,\ \text{otherwise} \tag{2}$$

Regarding the firm mortality model, using the log-normal form we have:

$$\log(t) = \beta X_i + \delta \text{Adoption}_i + \varepsilon_i \tag{3}$$

where, t is the time to death, X represents the exogenous predictors of mortality and Adoption is treated as endogenous for the reasons outlined earlier. Basically, the implication of this is that the error terms in these two equations are correlated. The standard treatment in selection models (Heckman, 1979) is to assume that ε and u have a bivariate normal distribution with correlation ρ.

Our concern is that a regression of the hazard model outlined above, without taking into account the potential endogeneity of the adoption decision, will lead to biased estimates of δ.

To see this, consider the fact that firms are now being conceived as setting their own adoption agenda and so their expected performance is *conditional* on their adoption decision. Following the econometric treatment outlined in Maddala (1983) and Greene (1990), we have

$$\begin{aligned} E(\text{t}|\text{Adoption} = 1) &= \beta X_i + \delta \\ &\quad + \text{E}(\varepsilon_i | Adoption = 1) \\ &= \beta X_i + \delta \\ &\quad + \text{E}(\varepsilon_i | u_i > -\gamma\omega_i) \\ &= \beta X_i + \delta + \rho\sigma_\varepsilon \left[\frac{f(\gamma\omega_i)}{F(\gamma\omega_i)}\right] \end{aligned} \tag{4}$$

where, f(.) and F(.) represent the density and cumulative distribution function of a standard normal distribution. The last term in the equation above reflects the selectivity bias: the expected value of the error term, *conditional on adoption* is non-zero.

Similarly,

$$\begin{aligned} E(\text{t}|\text{Adoption} = 0) &= \beta X_i \\ &\quad + \text{E}(\varepsilon_i | Adoption = 0) \\ &= \beta X_i + \text{E}(\varepsilon_i | u_i \leq -\gamma\omega_i) \\ &= \beta X_i + \rho\sigma_\varepsilon \left[\frac{-f(\gamma\omega_i)}{1 - F(\gamma\omega_i)}\right] \end{aligned} \tag{5}$$

Consequently, the expected difference in survival as a result of the adoption decision is:

$$\begin{aligned} &\text{E}(\text{t}|\text{Adoption} = 1) - \text{E}(\text{t}|\text{Adoption} = 0) \\ &= \delta + \rho \times \sigma_\varepsilon \left[\frac{f(\gamma\omega_i)}{F(\gamma\omega_i)[1 - F(\gamma\omega_i)]}\right] \end{aligned} \tag{6}$$

Equation 6 therefore gives us both the differential effect of adoption versus non-adoption (on expected survival time) as well as the impact of self-selection when evaluating the impact of technology adoption on firm survival. Clearly, unless the second term is zero, the estimated coefficient δ will fail to reflect the true impact of adoption on survival. Heckman (1979) has shown that failure to account for this term will result in the adoption parameter to be biased in the direction of correlation coefficient ρ and the estimated standard error will be biased downward, thereby artificially inflating the significance of technology adoption. Sample selection models control for this effect by taking this into consideration, and the model can be specified as:

$$\begin{aligned} \log(t) &= \beta'\chi + \delta \text{Adoption} \\ &\quad + \lambda H + \nu, \text{ where} \\ \text{H} &= \left[\frac{f(\gamma'\omega_i)}{F(\gamma'\omega_i)}\right], \text{ if Adoption} = 1, \\ \text{H} &= \left[\frac{-f(\gamma'\omega_i)}{1 - F(\gamma'\omega_i)}\right], \text{ if Adoption} = 0 \\ &\text{and } \lambda = \rho\sigma_\varepsilon \end{aligned} \tag{7}$$

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Table 7. Adoption and survival with adoption as endogenous (standard errors in parentheses)

Variables	Model with selectivity correction	Gamma hazard model
ADOPT	0.437 (0.171)***	0.816 (0.074)***
EMP	0.037 (0.005)***	0.051 (0.121)***
R&D	−0.016 (0.051)	1.352 (0.151)
Rho	−0.289 (0.164)	—
σ	0.617 (0.021)***	0.779 (0.031)***
λ	−0.178 (0.106)	—
Log- likelihood	−1628.16	−593.56

*** $p < 0.0001$
** $p < 0.01$
Note: ADOPT is an indicator of whether or not a firm adopted any technology.

In order to assess the impact of treating adoption as endogenous, we created a variable called AD to reflect whether a firm had adopted any one of the four technologies in question.[5] Table 7 reflects the results of the log-normal model, with and without the sample selection correction.

We notice that the estimated coefficient for the selectivity bias parameter (λ) is not significant and consistent with this, the Likelihood Ratio test fails to reject the hypothesis that ρ is zero (χ^2, 1 d.f. = 2.77.) We may conclude that selection bias is not a concern for these data, thereby suggesting that the decision to adopt technologies is not made with its possible impact on survival in mind. This is ironic given the strong impact of adoption on survival that was demonstrated earlier and underscores the importance of these findings for the purpose of marketing radical technologies. While these results are preliminary and need to be replicated using data from a cross section of industries, they do suggest that making explicit the link between adoption (likelihood and timing) and survival could be an effective marketing tool. However, the main point is that the fundamental conclusion that radical innovations are significant predictors of firm survival withstand the additional scrutiny of treating adoption as a self selected variable and add to the robustness of the findings.

[5] We estimated models with all the different adoption combinations considered in the original model specifications reported earlier. The results and substantive conclusions remain unchanged and we report the results of the summary adoption decision in the interest of parsimony.

DISCUSSION AND CONCLUSIONS

Increasingly, business success has its roots in technological innovations in manufacturing processes. We have extended prior work by using a robust dataset and methodology to consider the consequences of the adoption decision on the organization's likelihood of survival. This study offered several advantages over previous work, including our consideration of a set of the major technologies introduced to an industry over the course of its modern existence, an exhaustive sampling approach, consideration of several important contingent factors in this relationship, and our demonstration of the Bass model to predict survival during industry shakeouts. We also modeled the *timing* of adoption in contrast to the majority of prior studies that treat adoption as a 'yes/no' variable, and in doing so we made the additional contribution of modeling the potential endogeneity of adoption. Drawing together related theories largely from the field of economics, we developed and tested several hypotheses surrounding these manufacturing technology adoption and survival phenomena.

Our results generally showed strong support for the research hypotheses. Adoption of 'radical' manufacturing technologies (i.e., those that changed competitive dynamics in the industry) was a significant predictor of survival. Bundles of adopted technologies and a comprehensive technology set were associated with increasingly high likelihoods of firm survival. In all scenarios, earlier adoption (i.e., adoption prior to the Bass inflection point as well as earlier relative to other firms) had a more powerful positive influence on survival likelihood than later adoption.

An unexpected but intriguing pattern also emerged in these results. As noted previously, the penalties for late adoption (in the form of reduced survival chances) were consistently stronger than the survival advantages from early adoption. This finding, though somewhat serendipitous, has important implications for several streams within the technology adoption literature. First, a large portion of the technology adoption literature has looked solely at the firm outcomes associated with the adoption of a radical innovation without regard for the timing issue (e.g., Sorescu, Chandy, and Prabhu, 2003). The results here highlight the significance of adoption *timing* for firm survival. Another body of work in this general stream examines the evolution of technology markets, often identifying

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overall shapes and stages in the adoption curve (e.g., Sood and Tellis, 2005). The application of the Bass model in this study reveals an interesting adoption-survival relationship, highlighting the particularly dire consequences of late radical manufacturing technology adoption. Therefore, these results present a more complex and meaningful view of adoption phenomena and effectively provide some integration between the adoption-performance and technology evolution streams. In particular, the asymmetry between the benefits of early adoption and the detrimental effects of late adoption highlights the need to consider the performance and survival consequences for late adopters of radical manufacturing technologies, an area that has not yet received focused research attention.

One limitation that should be noted here is that the technologies studied, while not always widely adopted, did ultimately have a strong influence on individual firm survival. The ability to identify these important competence-enhancing or competence-destroying technologies is an advantage of such a long-term dataset. However, numerous other technologies likely emerged in this industry over its existence, many of which may have appeared quite promising at the time. Firms that adopted technologies that eventually failed to deliver their expected benefits incurred a cost. It seems likely that a pattern of these sorts of poor adoption decisions would have a negative effect on the chances for firm survival. While quite an interesting phenomenon, the dataset used here does not capture these failed technologies and, thus, this issue must be left to future research.

This issue also highlights the critical importance of a *managerial technology vision* in developing a technology strategy and managing firm survival. The firms that could identify and successfully adopt industry-changing manufacturing technologies at an early stage relative to the competition had a greatly enhanced chance for survival. However, for every CNC or NC technology, there were numerous emerging technologies for management to ponder. In practice there are real penalties associated with adopting the wrong innovations. Beyond financial costs, these would include disruptions in manufacturing processes without future compensating gains and managerial distraction. Thus, sifting through emerging manufacturing technologies in search of pivotal innovations should be a fundamental task of senior management.

Another worthwhile area for future research would be the deeper exploration of general technology types to determine whether the findings uncovered here would be replicated in significantly different technology settings. The technologies explored here related to production processes that would generally influence operational costs and efficiency more than the nature of the end product received by consumers. However, other types of technologies need to be studied further, such as those that change fundamental product architecture (Anderson and Tushman, 1990).

Finally, while organizational survival is the ultimate and, arguably, most important gauge of success, much may be learned by examining other performance measures. The ultimate survival or failure of any organization is determined by a host of factors, both within and sometimes outside the firm's control. Examining more traditional short-term performance measures (e.g., profitability, return on equity, etc.) may allow more subtle and immediate relationships between manufacturing technology adoption issues and performance to be exposed.

Survival is the ultimate test to be passed by any firm. This study showed powerfully that making the proper manufacturing technology adoption decisions is literally a life-or-death decision for the firm. As manufacturing technology is increasingly a basis for firm competitiveness, it is important that we better explore and understand the consequences of these critical adoption decisions.

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