Firm and Product Life Cycles and Firm Survival

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On average, roughly 5–10 percent of the firms in a given market leave that market over the span of a single year. At least so data for a broad range of industries in several economies tell us. What is it, other than random shocks, that determines the probability of survival for a firm in a given market?

We start by decomposing the forces that affect survival into industry and firm attributes. Industry attributes, we hypothesize, encompass variables that exert their influence both over time and across markets. The variables that operate over time are defined by the life cycle of the industry. Life cycles of the industry affect mainly the characteristics of demand and the rate and form of technical change. Variations across firms, we hypothesize, arise mainly from learning-by-doing, Darwinian survival of the fittest, and the obsolescence of initial endowments. These variables are linked to the life cycle of the firm. How these industry and firm life cycles define patterns of survival is the story we tell.

The literature on the effect of both firm and industry life cycles on firm survival has developed largely without taking the effect of one on the other into account (see John Sutton, 1997; Richard Caves, 1998). Doing so may confound the effects of the individual determinants and may cause erroneous conclusions to be drawn regarding the relationship between survival and the firm and industry variables.

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I. Determinants of Firm Survival: Analytical Framework

Our model explaining the probability of survival begins with the industry attributes and then specifies the relevant firm characteristics.

A. *Role of Industry Attributes*

The level of competition, the predictability of demand, and the rate and form of technical change all vary across industries and affect the probability of survival. We decompose industry attributes into two groups: (i) those that change for all products over time or, more specifically, over successive phases of a product's life cycle, and (ii) those that vary across industries through all or most of the life cycle.

1. *Life Cycle Phase.*—Product-life-cycle models and the empirical evidence supporting their existence are now well established in the literature. As a market evolves from infancy to maturity, systematic changes occur that affect the probability of survival. For example, in the early years, technological opportunities for innovation are often highest. As the product market matures, technological opportunities decline, and innovations increasingly shift to minor product refinements and to cost reduction. Further, a shift occurs from pure innovation to imitation. All these changes intensify competition. Moreover, the distribution of innovations between new and incumbent firms also changes over the life cycle with consequences for entry barriers and the probability of survival for new firms.

The phase of life cycle, ϕ_i, in this formulation, interacts with all other variables. From the standpoint of empirical estimation, therefore, it must either enter the estimating equation multiplicatively, or alternatively, it requires partitioning the data according to life-cycle phase.

2. *Cross-Sectional Variations in Industry Attributes.*—While the intensity of competition is presumed to be captured by life-cycle phase, and the latter is derivative from changes in technology, industries also vary (independently of life-cycle phase) in technological intensiveness. By technological intensiveness, we mean the employment of human skills associated with scientific development. An operational definition of the concept is given in the empirical section of the paper. We associate technological intensiveness with the rate of technical change.

Technical change leads to obsolescence. We define $\omega(T_i)$ as the obsolescence rate specific to the technology index (T) of industry i. The more technically intensive the industry, the higher is the rate of obsolescence of older technology, since new inputs, human and physical, interact with old inputs and the adaptability of old inputs declines as the rate of technical change rises. Interindustry variations in obsolescence rates should therefore have parallel adverse effects on survival rates of both new and incumbent firms.

Industries may also differ in the mobility of inputs. Fixed capital is less mobile than labor, with the result that differences in production functions with respect to capital intensiveness should lead to consequent variations in exit rates. Survival may also partly depend on volatility of market demand. The more volatile the demand, the greater is the likelihood of unfavorable surprises, and the lower the survival rate.

B. *Firm Attributes*

We start with the hypothesis that there are three key attributes of firms that explain variations in the probability of survival. These are learning-by-doing, differences in the quality of initial endowments, and changes in endowments as a result of net investments (new investments minus obsolescence). Both learning-by-doing and changes in endowments follow a predictable course over the firm's life cycle.

1. *Learning-by-Doing.*—Type-A learning by a firm relates to knowledge that leads to cost reductions, product improvements, and new market techniques. The stock of such learning, L_a, accumulates with increases in a firm's age, a, but increases at a decreasing rate. This is because the most important lessons are learned first, and there is a finite stock of information to be learned about a given technology. Accordingly,

$$L_a = a^{\ell} \qquad 0 < \ell < 1 \tag{1}$$

$$L'_a > 0 \qquad L''_a < 0.$$

Type-B learning consists of information that a firm accumulates about itself. It also increases with firm age. Firms enter with incomplete knowledge of the quality of their endowments and learn progressively as they produce. Initial investments will therefore be riskier than later ones. Accordingly, initial ventures are apt to be small, thereby producing an inverse association between survival rates and firm size. Another aspect of learning is the transfer of knowledge across product and industry boundaries via diversification. The stock of knowledge available to a diversifying firm at the time of entry into a product market may be viewed as its initial endowment.

2. *Endowments.*—How inherently suited the firm is for profitable production depends on the firm's initial endowments E_0. We assume that endowments initially have an asymmetric distribution with most new firms concentrated around the lower end of the endowment scale. Thus, the average level of endowments will be increasing over age cohorts due to the attrition of firms with lower levels of efficiency and endowments.

Firms also add to their endowments after entry by investments, for example, in R&D, which in turn yield uncertain outcomes. Since they add to their initial stock of endowments, at any age a, the firm has

$$\Delta E = E_a - E_{a-1} = r_a - \omega(T_i)E_{a-1} \tag{2}$$

$$r_a = \eta(E_{a-1}, L_{a-1}, \phi_i, \varepsilon) \tag{3}$$

$$\varepsilon \sim \mathcal{N}(0, \sigma^2)$$

where r_a is the increase in endowments attributable to new investment and depends on the preceding period's stock of endowments (E_{a-1}), accumulated learning by doing in the

previous period (L_{a-1}), phase of the product life cycle within which the firm is operating (ϕ_i), and a random shock (ε); η is a positive and nondecreasing function. Given the random shock ε, the role of initial endowments progressively diminishes in relevance, and this is reinforced by the obsolescence of such endowments.

In sum, endowments will generally rise over successive age cohorts for two reasons: (i) average endowments of surviving firms rise as less-efficient firms disappear with the resulting attrition of low endowment firms; (ii) there is net investment through most of the life of most firms. Obsolescence, however, gradually rises relative to new investment as firms age, and eventually, net investment in endowments (after obsolescence) generally turns negative. Accordingly, for most of the range of age cohorts, we expect:

$$\bar{E}'_a > 0 \qquad \bar{E}''_a \gtreqless 0 \tag{4}$$

where $\bar{E}_a$ is the mean level of endowments for a given age cohort.

C. *A Model of Survival*

We can now put together the several elements of a model of survival developed above:

$$S(a, i) = s(\phi_i)\psi(\mathbf{V}_{\mathrm{A}}, \mathbf{V}_{\mathrm{F}}, \mathbf{V}_{\mathrm{I}}) \tag{5}$$

where $S(a, i)$ is the probability of survival for a given age cohort a in industry i, $s(\phi_i)$ captures the effect of the life-cycle phase of the relevant industry, and ψ is the function that defines the relation of survival to three vectors of variables. $\mathbf{V}_{\mathrm{A}}$ is the vector of unobserved but age dependent variables, namely, the stock of endowments and learning-by-doing. We have shown how $\mathbf{V}_{\mathrm{A}}$ produces a survival path that is dependent on the firm's life cycle. $\mathbf{V}_{\mathrm{F}}$ is the vector of observed variables that relate to the attributes of the firm, and $\mathbf{V}_{\mathrm{I}}$ is a vector of observed industry variables defining cross-sectional, as distinct from phase-related, differences.

$\mathbf{V}_{\mathrm{F}}$ consists of firm size and diversification. We have already explained the relation of firm size as a consequence of incomplete type-B learning. As Caves (1998) discusses in his review of the literature on dispersion of entry size, less-confident entrants rationally start up small. We explain the role of diversification as reflecting organizational capital in the form of knowledge available for transfer from one market to another. The vector of industry variables, as previously noted, consists of an index to capture technology intensiveness and a measure for demand volatility. The key variable $\mathbf{V}_{\mathrm{I}}$, namely, the industry technology index, affects the rate of obsolescence of the firm's endowments and thereby the probability of survival over the firm's life cycle.

Most models predict hazard rates to decline monotonically with age. Our model differs in predicting a non-monotonic hazard rate, due to both phase-related and firm-specific attributes.

II. Empirical Methodology and Results

In our analysis below, we first examine patterns of firm survival within phases of the product life cycle. That is, all observations relate to the same phase of the relevant life cycle, even though the phases occur at different chronological time points for various products. Unlike previous studies, information on firm survival is not grouped by entry cohorts (i.e., by the life cycle segment in which a firm entered the market) but by "existence" phase. The latter is defined as the current product life-cycle segment in which survival or non-survival is observed. In this way, we attempt to standardize the observations on firm survival rates for the key phase-related industry attributes (e.g., intensity of competition, rate and form of technical change). The values of the implicit variables are thus relevant to the same time intervals as decisions to exit or remain in the industry.

Accordingly, the data are decomposed into five phases of the product life cycle, with phases delineated on the basis of gross entry rate per year. The phases, which vary in duration across products, are identified as follows: (1) initial low entry, (2) increasing entry rate, (3) decreasing though still high entry, (4) low entry, and (5) erratic pattern of gross entry that characterizes the span of maturity of the life cycle. Most product markets evolve through all five phases. Observations (i.e., hazard rates) are computed across products on the basis of the current phase

for each firm in each year of its existence. Hazard-rate cells are thus defined by both age and relevant life-cycle phase.

The analysis uses a non-balanced panel of 3,435 firms in 33 product markets. The historical data were drawn from the *Thomas Register of American Manufacturers* and consist of a complete inventory of all entering, surviving, and exiting firms for each product from its first commercial introduction to 1991.

The analysis in Section II-A focuses on how firm and industry life-cycle attributes affect the firm's probability of survival by applying the nonparametric technique of kernel estimation to the life-table-generated survival rates. In Section II-B, we examine the simultaneous effect of explanatory variables on the overall hazard-rate function by using the semi-parametric Cox proportional-hazards regression analysis, which allows for both censored observations and stratification of population groups. In conducting the multivariate analysis of the hazard-rate function, we accommodate the importance of the industry life cycle (time-dependent industry variables) by stratifying the data by the phases in which the firms exist and defining the dependent variable as the firm's span of survival within the phase. The empirical specification of equation (5) above is given by the hazard function for the ith firm in the jth phase and is expressed as

$$h_{ij}(t) = h_{j0}(t)\exp(\mathbf{x}_{ij}'\boldsymbol{\beta}) \tag{6}$$

where $h_{j0}(t)$ is the baseline hazard function for the jth phase, $\mathbf{x}_{ij}$ is a vector of explanatory variables for the ith firm, and $\boldsymbol{\beta}$ is the vector of unknown regression parameters to be estimated.

A. *The Time Path of Hazard Rates*

Figure 1 shows the estimated yearly hazard rates of firms. The hypothesis of homogeneity of hazard rates across phases is rejected at the 0.01 level. For all phases combined, the hazard rate declines from age 3 to age 7 and then remains relatively flat until about age 16. A much sharper pattern emerges, with far larger variations across age, when hazard rates are decomposed by phase of the firms' existence. Equally important, decomposition by phase appears clearly justified by the large differences in hazard rates across phases. As markets mature, they become more competitive and hazard rates rise. This is clearly reflected in the higher hazard rates for Phases 4 and 5 as compared with phases 2 and 3.

Moreover, the hazard rate curves become flatter as markets mature. This also accords with a priori expectations. With maturity, information is communicated more quickly, and reliance on learning-by-doing is reduced. Further, one does not need to depend as much on trial and error if one can hire skilled labor with experience. Markets for experienced labor develop progressively as industries mature. The effect of industry life-cycle phase on the rate at which obsolescence of firm endowments occurs is seen in the systematic shift of the critical point of the hazard rates across phases and is consistent with the hypothesized decline in the rate of technical change as industries mature. As technological opportunities for change decline, initial endowments obsolesce more slowly. Thus, the point at which hazard rates start rising is reached at ages 12–14 in phases 2 and 3, and at ages 19–21 in phases 4 and 5.

Turning to firm life-cycle effects, we now examine the pattern of hazard rates to ascertain whether it appears roughly consistent with the effects of learning-by-doing and change in the average stock of endowments as predicted in Section I-C. Since the two explanatory variables are unobserved, we cannot directly estimate the relevant parameters. Moreover, in the absence of information on exact functional forms, we cannot solve the problem via calibration. The technique we use is to see whether survival rates change with respect to age as predicted. More specifically, we examine changes in hazard rates over age cohorts after standardizing the data for all industry variables that systematically change with phase of the product life cycle.

We start with one aspect of what we have called type-B learning. Firms need time to learn about their own efficiency levels compared to those of their competitors. Given that exit is costly, it follows that hazard rates should initially rise as learning proceeds after entry. The learning effect is clearly evidenced in all phases of the product life cycle except phase 1.

In each phase, there is an interval of falling hazard rates with a negative second derivative.

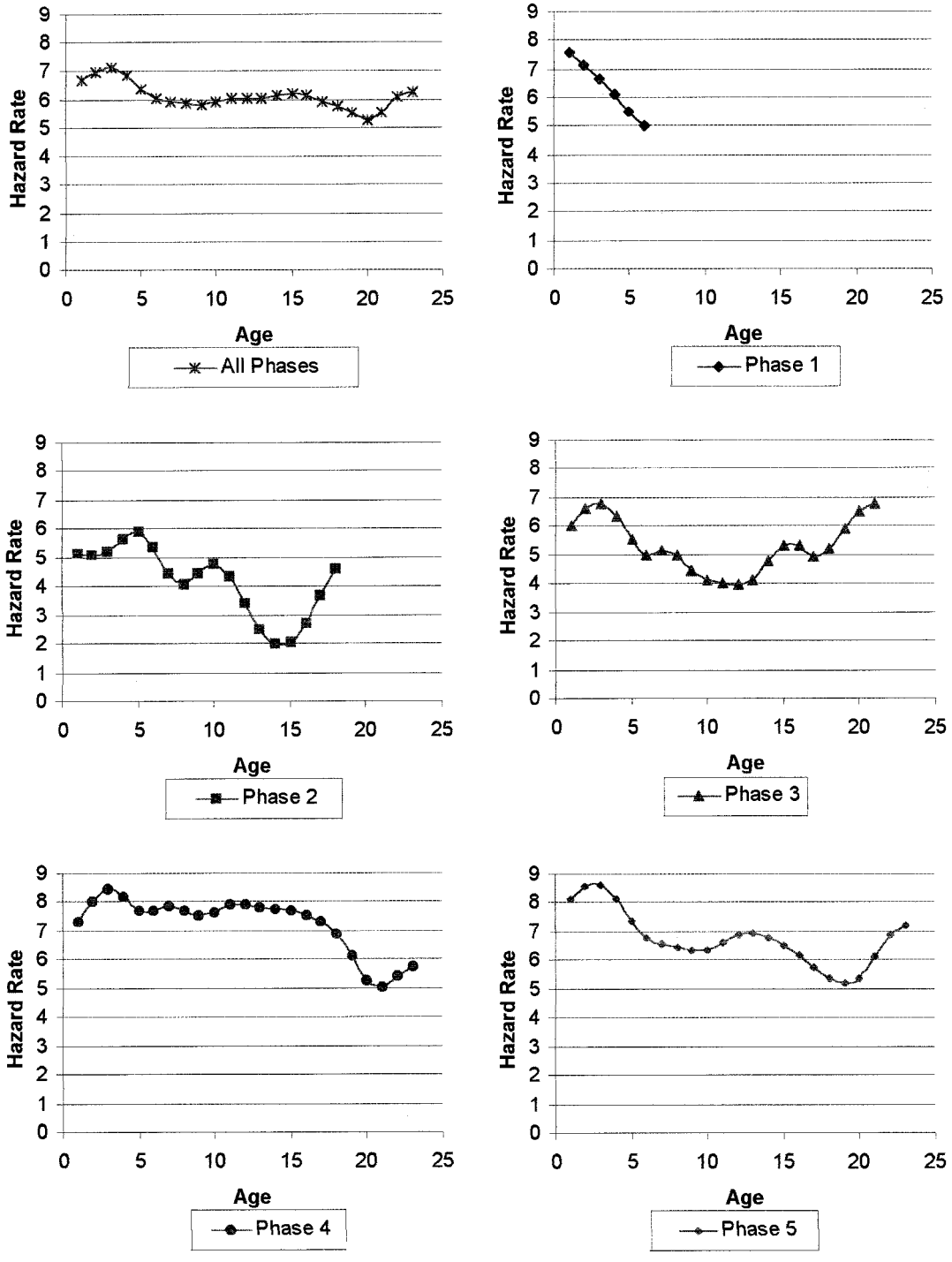

FIGURE 1. ESTIMATED HAZARD RATES, BY PHASE

In phase 1, the fall in hazard rates commences immediately and continues at least to age 6. In the remaining phases, it commences immediately following the interval in which the learning effect dominates the observed pattern. The decline continues to age 8 or 9 in phases 2, 4, and 5 and somewhat longer in phase 3. In sum, there is considerable consistency across phases in the duration of this decline in hazard rates. The observed pattern of declining hazard rates but at a diminishing rate accords with a priori analysis about the effects of learning-by-doing.

There is no clear-cut explanation in single-variate analysis for the second interval of falling hazard rates that begins at about age 10 in phase 2, age 12 in phase 4, and age 15 in phase 5. On the other hand, hazard rates eventually rise in all phases as firms age beyond some point, a phenomenon we attribute to obsolescence of initial endowments.

B. *Multivariate Analysis of Hazard Rates*

Our analysis of phase-specific hazard rates in the preceding section leads to conclusions generally consistent with the predicted pattern of learning-by-doing and with at least some hypotheses on changes in average endowments. However, it leaves, some observed results (e.g., the second acceleration of decline in hazard rates) without a definitive explanation. Confirmation is therefore needed from a more complete model. Accordingly, we proceed to test the following specification of equation (6):

$$(7)\quad \text{Hazard Rate} = f(\text{Technology Index, Producer or Consumer Goods, Capital–Labor Ratio, Size, Diversification, Age, [Age]}^2).$$

Age and $(\text{Age})^2$ capture learning-by-doing and changes in average stock of endowments of successive age cohorts. The remaining firm attributes are size as a proxy for type-B learning and diversification as a transfer mechanism for organizational capital.

TABLE 1—PROPORTIONAL HAZARDS REGRESSION

Variable	Parameter estimate	SE	Wald chi-square	*P*
Technological intensity	0.2078	0.0517	16.1083	0.0001
Consumer good	−0.0585	0.0436	1.8022	0.1794
Capital–labor ratio	−0.1558	0.0471	10.9091	0.0010
Size	0.1099	0.0430	6.5172	0.0107
Diversification	−0.1123	0.0430	6.8106	0.0091
Age	−0.0454	0.0063	51.5178	0.0001
$(\text{Age})^2$	0.0004	0.0002	4.3287	0.0375

Notes: The global null hypothesis of maximum-likelihood-estimated coefficients equaling 0 is strongly rejected at the 1-percent level. All variables except age and $(\text{age})^2$ are categorical (0, 1) with values of 1 for high technical intensity, consumer goods, high capital–labor ratios, small size, and diversified firms.

There are three industry variables in equation (7) unrelated to life-cycle phase. First, there is a technology index that predicts the rate of obsolescence of a firm's initial endowments. Second, the capital–labor ratio is an index of the mobility of inputs and serves as a measure of exit barriers. Third, volatility of demand should increase failure rates and, hence, exit rates. In the absence of data to measure volatility of demand, we use the distinction between producer and consumer goods as a proxy on the assumption that demand for producer goods is generally more volatile.

Table 1 shows the estimates. In general, they confirm the hypothesized relations. The relation between technology intensity and hazard rates is positive, while that between high capital–labor ratios and hazard rates is negative. The distinction between producer and consumer goods is not statistically significant. Small firm size has a positive relation to hazard rates, and diversification a negative one. The statistically significant coefficients for age and $(\text{age})^2$ are negative and positive, respectively. The low value of the coefficient for $(\text{age})^2$ is understandable given the evidence shown in the kernel estimates that the net effect of obsolescence of initial endowments manifests itself strongly only at the upper end of firm age. Our samples were truncated too early to capture a stronger effect for $(\text{age})^2$. Finally, higher hazard rates are associated with technology-intensive industries.

III. Conclusions

We have shown that firm survival is crucially dependent on both the product and the firm life cycles. With regard to the firm life cycle, there appear to be two spans of time over which hazard rates decline. The decline continues until the obsolescence of initial endowments finally raises hazard rates.

We have also shown that hazard-rate functions have different baselines across phases of the product life cycle, with higher rates occurring in the later phases due to market maturity and increased competitiveness. The effect of industry life-cycle phases is also seen in the systematic shift of the point at which obsolescence of endowments begins to take effect. In the early years of the product market, a higher rate of technical change leads to a rise in hazard rates at an earlier age. The relation of survival to age of the firm is not simply an empirically observed regularity, but follows an endogenously determined path predicted by the life cycle of the firm. The result that technology-intensive industries are associated with higher hazard rates is explained by the faster obsolescence of initial endowments in such industries.

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