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The two views of small firms in industry dynamics: a reconciliation

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Abstract

Recent empirical studies show that small firms are confronted with a lower likelihood of survival than their larger counterparts. An alternative view is that small firms can overcome inherent size disadvantages by occupying strategic niches. This paper offers empirical evidence in the context of product life-cycles suggesting that the relationship between firm size and the likelihood of survival is shaped by the stage of the industry life-cycle, and that both views of small firm survival relative to large firms are correct.

Keywords: Industry evolution; Life-cycle; Survival

JEL classification: L20; O30

1. Introduction

One of the more perplexing phenomena in economics is the persistence of an asymmetric firm-size distribution predominated not only by small enterprises, but firms which are sufficiently small to be considered sub-optimal in many, if not most, industries. Ijiri and Simon (1977) (p. 2) characterize this ‘‘regularity in social phenomena that is both striking and observable in a number of quite diverse distributions. It is a regularity in the size distribution of firms.’’ In fact, few other economic phenomena have persisted as consistently as the skewed asymmetric firm-size distribution. Not only is it almost identical across every manufacturing industry, but it has remained strikingly constant over time (at least since the Second World War) and even across developed industrialized nations (Acs and Audretsch, 1993). This has raised the question, ‘‘How are such small firms able to remain viable if so many of them are too small to have attained an optimal scale of output?’’

The economics literature has responded with two quite distinct views about the economic role played by such small firms. The first, and more traditional, view holds that small firms are able to compensate for inherent size disadvantages by occupying strategic niches (Caves and Porter, 1977; Porter, 1979). An important implication of this view is that small firms do not need to grow in order to survive. Rather, small firms can remain small and avoid being confronted by a greater likelihood of failure by occupying a strategic niche. By contrast, a new interpretation has emerged in the literature

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arguing that small firms play an important role because they tend to be new. This view argues that entrepreneurs start new firms to try out new ideas. Several models, including the theory of noisy selection (Jovanovic, 1982), suggest that those new startups discovering that they are viable will expand in order to become efficient, while those learning from market experience that their ideas are not viable will stagnate and ultimately exit from the market.

The purpose of this paper is to reconcile these two views about the role of small firms. We suggest that both views are in fact correct, but that each view tends to be specific to a particular phase of the industry life-cycle. What has emerged as a Stylized Result of the review of the literature of Geroski (1995) – that the likelihood of survival is greater for larger firms than for small firms – should hold in the formative stages of the life-cycle but not the mature stages. By contrast, the theory of strategic niches – which holds that firms can remain small and face no disadvantage with respect to the likelihood of survival – should hold in the mature phase of the life-cycle.

2. Survival over the life-cycle

The life-cycle of product markets has been widely studied, and certain theoretical and empirical regularities have been established about market structure and firm behavior across the different stages of the product market evolution.[1] This paper combines the five stages in the product life-cycle first described by Gort and Klepper (1982) into two stages, the formative years – when the entrants in the market are trying new ideas, and the mature period – when the product is standardized.

Models like Jovanovic's theory of noisy selection and evolution of firm size are clearly appropriate in the formative years of the product life-cycle, since the market is characterized by high uncertainty, and firms have much to learn about themselves and their constantly changing environment. In this scenario, size would matter, and the smaller size firms should face a lower probability of survival than their larger counterparts. On the other hand, small firms entering a mature market with standardized technology and well defined product design could do so to occupy strategic niches. In this case, size is not a disadvantage.

To examine whether the relationship between firm size and the likelihood of survival is invariant to the stage of the life-cycle, a firm-specific database consisting of longitudinal observations was compiled for 33 product markets from the *Thomas Register of American Manufacturers*.[2] The database identifies entry, exit and survival of firms within the formative and mature stages in the

[1] See Gort and Klepper (1982), Jovanovic and MacDonald (1994a), (1994b), and Agarwal (1998).

[2] See Agarwal (1998) and Agarwal and Gort (1996). The database includes a sub-set of 31 of the 46 products selected from the *Thomas Register* by Gort and Klepper (1982). While the study draws from the same pool of products as the Gort–Klepper study, the data are developed independently. Fifteen of the 46 products in the Gort–Klepper study could not be used for new data development for various reasons. Some products, like Nylon, Telemeter, Computers and Solar Batteries, had breaks in consistency either because the listing was missing in the *Thomas Register*, or due to substantial changes in definition of product over the years. Products like DDT and cryogenic tanks were omitted since they were discontinued over the years for which the analysis was extended (from 1973 to 1991). Other categories like streptomycin and penicillin were discarded in favor of a broader product group Antibiotics. Finally, a few products were not included in the analysis due to time limitations on the development of data. We included two new products which gained prominence over the last two decades – contact lenses and video cassette recorders – to maintain representativeness of the sample across military, consumer and producer goods.

Table 1
Small and large firm survival rates

	Small firms	Large firms
Formative years		
Number of firms	1356	791
Survival rates		
1 Year	93.26	95.56
5 Year	67.46	75.48
10 Year	50.59	55.65
15 Year	39.28	44.60
Tests of homogeneity across size: χ^2 (P-value)		
Wilcoxon	18.08 (0.0001)	
Log-rank	18.25 (0.0001)	
Likelihood ratio	20.11 (0.0001)	
Mature period		
Number of firms	891	393
Survival rates		
1 Year	92.00	94.52
5 Year	63.87	66.92
10 Year	44.58	42.25
15 Year	33.08	29.27
Tests of homogeneity across size: χ^2 (P-value)		
Wilcoxon	0.08 (0.78)	
Log-rank	0.79 (0.38)	
Likelihood ratio	0.20 (0.66)	

product life-cycle (see Appendix A for a description of the methodology used to distinguish between the stages). Firm size is measured as the asset size of the firm in the year it entered into the relevant market.[3]

Life-table analysis is used to calculate the survival and hazard rates. We wish to check if probability of survival differs across small and larger startups, and if this difference varies over the product life-cycle. Accordingly, we test if there are significant differences between survival rates of small and large startups for both the formative and the mature period.[4] Results from three tests of homogeneity across startup size are reported for each stage of the product life-cycle.[5] The survival rates are shown in Table 1.

[3]The *Thomas Register* lists the asset size of firms in categories ranging from less than 100,000 to greater than 250 million. Since the data spans a period of more than 80 years, the asset size boundaries for small firms are adjusted over time to account for inflation, and are available from the author on request.

[4]Earlier studies (Agarwal and Gort, 1996; Agarwal, 1997, 1998) have shown that survival rates differ significantly across the stages of the product life-cycle. The test statistics for differences of survival across stages are significant at the 99% level of confidence, and available on request.

[5]The likelihood ratio test assumes that the data for small and large startups are exponentially distributed, and tests that the scale parameters (based on startup size) are equal. There is no reason, however, to assume a particular underlying distribution. Accordingly, we also use the nonparametric tests of log-rank and Wilcoxon, that rely on $v'V^{-}v$ as the overall test statistic for homogeneity, where v is the rank vector of survival rates across small and large startups, and V^{-} is the generalized inverse of the estimated covariance matrix. See Lee (1992) for details.

Table 1 shows that survival rates are in general higher in the formative years of the product life-cycle for small and large startups alike.[6] Comparing small to large firms, though, the most important observation from this table is that for products in the formative stage of the life-cycle, 93% of the small startups survived 1 year, 67% survived 5 years, and about one-half survived one decade. By contrast, the survival rates of the larger firms in the formative-stage products were all higher – 96% for 1 year, 75% for 5 years and 56% for 10 years. The 15 year survival rate also reflects the advantage that size bestows on the long-run likelihood of survival. As reflected by all the test statistics, the hypothesis of homogeneity across small and large firms for the formative years is rejected at the 99% level of confidence. The evidence seems to support the stylized fact that the larger the firm startup size, the greater the probability of survival in an environment of uncertainty.

In the mature period though, there is no evidence of a positive relationship between size and survival. Indeed, the test statistics reveal no significant difference between the survival rates of large and small startup size firms. In fact, there is some evidence that the relationship is reversed in the mature life-cycle stage – the 10 and 15 year survival rate for small startups is higher than their larger counterparts. While 45% of the small firms survive a decade, and more than 33% survive 15 years, large firm survival rate is lower at 42 and 29%, respectively. This suggests that, in an environment with little uncertainty, and a standardized technology, small startup size firms are able to combat their size disadvantage by possibly occupying strategic niches.

To better understand the dynamic relation of size and survival, we now turn to hazard rates to look at the changing relationship of startup size and survival over the age of the firm. We use kernel estimation (Silverman, 1986) as a powerful nonparametric technique to identify regularities in hazard rate patterns without imposing a particular hazard rate structure as a result of parametric restrictions. Briefly, if the relationship between two variables is given by

$$Y_i = m(X_i) + \varepsilon_i, \tag{1}$$

where m is the unknown regression function, then

$$\hat{m}_\lambda(x) = \sum_{i=1}^{n} W(x,X_i;\lambda)y_i. \tag{2}$$

The kernel estimate of m has the form where $W(x,X_i;\lambda)$ is the weight sequence for kernal estimates that depends on the kernal function K_0 and the smoothing parameter or bandwidth λ. The weights are derived from a single function that is independent of the design:

$$W(x,X_i,\lambda) = \frac{K_0(x - X_i/\lambda)}{\sum_{i=1}^{n} K_0(x - X_i/\lambda)}. \tag{3}$$

Symmetric probability functions, typically a gaussian density function, can be used as kernel functions. Because there is no loss in efficiency across different kernel functions, the shape of the kernel is generally not crucial. The bandwidth, λ, however, influences the degree to which any

[6] One possible reason for the larger survival rates observed in the formative period could be that the products included in the analysis have proven to be successful. Survival rates of large and small firms alike would be lower if one were to consider the universe of all products – successful and nonsuccessful – that were introduced in the market.

Table 2
Hazard rates by size and stage of product life-cycle

Age	Formative stage		Mature stage	
	Small firm	Large firm	Small firm	Large firm
1	7.44	4.67	8.79	5.99
2	8.35	5.02	10.12	7.61
3	8.11	5.04	10.83	9.94
4	8.16	6.37	8.60	9.33
5	7.22	6.83	6.42	7.88
6	6.44	5.93	6.11	9.18
7	5.98	5.57	7.52	8.91
8	5.26	7.06	7.59	8.77
9	5.19	5.77	7.32	9.09
10	6.11	6.01	7.72	9.10
11	6.64	4.90	7.28	8.03
12	6.74	5.17	7.26	8.72
13	5.85	6.29	5.86	10.70
14	6.20	5.91	7.62	9.16
15	6.92	5.02	6.67	7.24

particular data point will exert on the functional shape. As λ increases in value the function has more smoothing; lower values of λ imply less smoothing. By minimizing the mean squared error (MSE), optimal values of λ can be determined.

The kernel estimated hazard rates are shown in Table 2 and Fig. 1. Hazard rates are seen to be higher in the mature period for both small and large startups alike. The initial increase in hazard rates is consistent with theories that indicate that firms need time to learn about their own efficiency levels and ability to survive. Small startups have a higher infant mortality rate in both the formative and

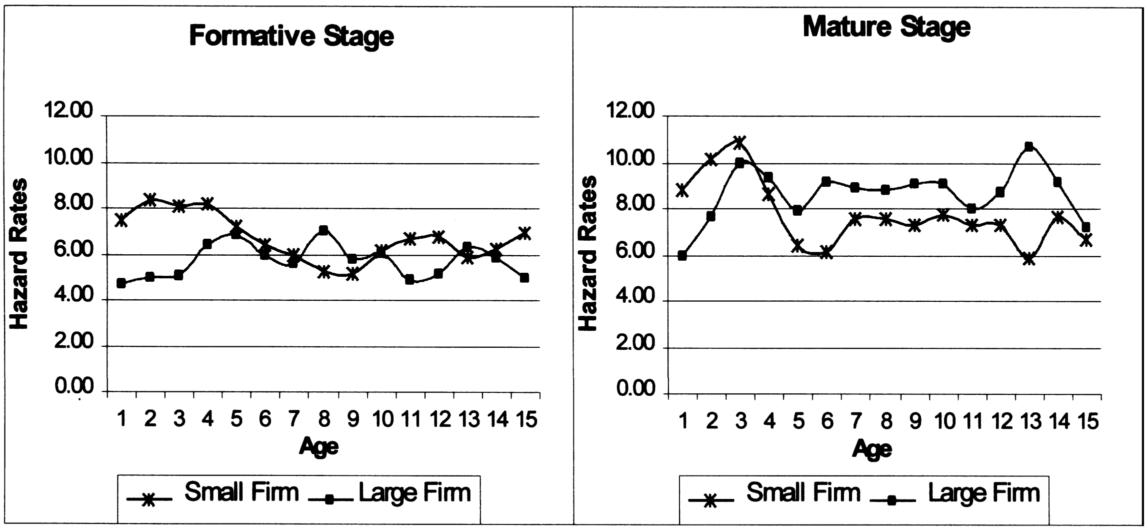

Fig. 1. Hazard rates by size and stage of product life-cycle.

mature stages of the product life-cycle. In the formative years, the hazard rates are higher for small firms till age eight, and continue slightly higher, on average, when compared to the larger startups, showing the advantage that size renders to continued survival. This is, however, not the case for small firms in the mature period. Immediately after the end of the Jovanovic effect at age three, the hazard rate function is smaller for small startups when compared to larger firms, indicating the possibility that these small startups may be occupying strategic niches that allows them to negate the disadvantage of size. A possible interpretation of the statistical evidence could thus be that since startups in the formative phase are still exploring the potential of a new technology, size matters in the probability of survival. In the mature stage, though, smaller startups may be targeting a market niche that is evident in a product market with standardized technology, and hence do not feel the adverse effects of their size.

3. Conclusions

Several influential surveys have recently claimed the emergence of a stylized fact showing that ‘‘firm size is correlated with the survival of entrants’’ (Geroski, 1995, p. 434). Consistent with such a stylized fact is the evolutionary view that entering firms represent the implementation of new ideas and, therefore, smaller firms are burdened with a lower likelihood of survival in an uncertain environment. We find this view consistent with the formative stages, where larger startups have significantly higher survival rates than their smaller counterparts. The finding of no significant differences in survival rates across startup size in the mature period (and that small firms may actually have a higher likelihood of survival at later ages) suggests that the strategic niche view of small firms may, in fact, be more applicable than the evolutionary view in such industries. This would suggest that the evolutionary and the strategic niche views of the role of small firms are correct, but for different stages of the life-cycle.

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Appendix A

Procedure to identify formative and mature stages

The procedure that we used to identify the formative and mature stages is the same as the generalization of the standard discriminant analysis used in Gort and Klepper (1982) to separate the five stages in the product life-cycle. To distinguish between the formative stage (positive net entry) and the mature period (negative net entry with ensuing period of approximately zero net entry), we first examined the data on annual net entry rates for each product. To determine the cut-off year for each product, we first partitioned the series into three categories – the first and third category contained the years where the net entry rate clearly reflected the formative and mature stages, respectively. The net entry rates of the T consecutive 'in-between' years of the second category were then labeled $x_1, x_2, \ldots, x_T$. The problem was then to choose an optimal dividing year j such that observations $x_1, x_2, \ldots, x_j$ are classified in the formative stage, and $x_{j+1}, x_{j+2}, \ldots, x_T$ are classified in the mature stage. This was accomplished using a three-step procedure:

(1) For each $j = 1,2, \ldots, T$, we computed

$$d_1(j) = \sum_{i=1}^{j} x_i / j, \quad d_2(j) = \sum_{i=j+1}^{T} x_i / (T - j). \tag{A.1}$$

(2) The choice of the dividing year was limited to those values of j for which

$$|d_1(j) - \mu_1| \leq |(\mu_1 - \mu_2)/2|, \quad |d_2(j) - \mu_2| \leq |(\mu_1 - \mu_2)/2|, \tag{A.2}$$

where μ_1 and μ_2 represent the mean rate of net entry in categories 1 and 2. If there were no values of j satisfying (2), then all observations were classified in the formative stage if $|d_1(T) - \mu_1| < |d_1(T) - \mu_2|$ and in the mature stage otherwise.

(3) If there were multiple values of j satisfying (2), then we selected the value of j from this set that maximized $|d_1(j) - d_2(j)|$.

Step 2 requires that the mean of the observations classified in each of the two stages is closer to the sample mean of the observations initially classified in those stages than in the alternative stage. Step 3 ensures that, among the classifications that would satisfy 2, the classification that is chosen maximizes the difference between the means of the points classified in the two alternative stages.

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