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Size, age and firm growth in an infant industry: The computer hardware industry in India

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Abstract

In contrast to the existing studies on the relationship of firm growth with size and age of the firm, which typically focus on relatively mature industries in developed economies, this study analyses firm growth patterns for an infant industry in a developing economy. It is found that (a) age positively impacts growth, which is the opposite of the result in previous studies; (b) as in previous studies, current size negatively impacts growth but the magnitude is much higher; and (c) lagged size negatively impacts growth suggesting that fixed factors become a hindrance to growth in rapidly growing infant industries.

Keywords: Firm growth; Infant industry; Indian computer hardware

JEL classification: L77; L63

1. Introduction

Firm and industry growth is critical to the evolution of any economy, perhaps more critical to a developing rather than a developed economy. But very few papers in the existing (vast) theoretical and empirical literature on firm and industry growth address the experience of developing economies. Toward their general goal of leaping into the 21st century without lagging further behind the first-world countries, these countries not only continue to build the 'traditional' sectors such as steel, textiles and chemicals but also

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emphasize the development and growth of the so-called 'high-tech' industries such as electronics, computers and information technology (IT).

This paper presents an empirical analysis of such an industry, the computer hardware industry in India. Specifically, it examines the patterns of firm growth in the Indian computer hardware industry over 1983–1988. This period is known as the 'new era' for the Indian computer industry, because favorable government policies and a massive computerization drive by the public sector propelled the birth of indigenous firms.[1] It is one of the fastest growing industries within the manufacturing sector; while the manufacturing sector as a whole grew at 8% over this period, the average growth rate of computer firms in our data set (which includes almost the entire industry in each year) was 63% and there was an enormous variation in growth among the firms.

How does growth vary across firms in an infant industry? Do small firms grow faster than large firms? Do new firms grow faster than old firms? The relationship between growth and size has traditionally been a major issue in the theoretical as well as the empirical literature on firm growth. The older literature holds that growth (rate of change of size) is independent of size, i.e. Gibrat's law holds (see Hart and Prais, 1956; Simon and Bonini, 1958; Hymer and Pashigan 1962). Lucas' (1967) model of adjustment-costs with constant returns to scale provides a justification for such independence.

In contrast, subsequent studies, which took current size as the only basic explanatory variable, find a statistically significant relationship between growth and current size. But the signs have been mixed. For instance, Mansfield (1962) finds a negative relationship between growth and size using US data, whereas Singh and Whittington (1975), who use UK data, find a positive sign. In a more recent study, Hall (1987) confirms Mansfield's finding using US data. These studies have used data on firms from different industries with quite different technologies and perhaps different growth processes, which might explain the mixed nature of the results.

A handful of recent studies, using US and Canadian data, have related growth of plant or firm to current size as well as to current age in the presence of exit (see Evans, 1987a,b; Dunne, Roberts and Samuelson, 1989; Baldwin and Gorecki, 1990; Davis and Haltiwanger, 1992; Troske, 1992).[2]

[1] For more details see Section 2 of this paper and Chapter I, Table 1 of *A report on the evolution of IT industry in India* by the Manufacturer's Association for Information Technology (1991).

[2] In related work, Pakes and Ericson (1990) have used annual age and size data to distinguish whether data are consistent with active learning (firms actively invest to learn) or with passive learning (firms learn over time by virtue of just staying in business). This dilemma is irrelevant for the Indian computer industry because R&D expenditure by firms is almost non-existent. Only a few firms conduct R&D. The average R&D intensity for those who do, in recent years, is only 3% (see p. 39 of *A report on the evolution of IT industry in India*, Manufacturer's Association for Information Technology, 1991).

Age not only helps to examine the life-cycle behavior of firms, but also, if related to growth and significantly correlated with size (this correlation is 0.55 in our data), will be useful in obtaining unbiased estimates of the relationship between firm growth and size. However, most of the theoretical studies on firm growth do not have an explicit role for age with the exception of Jovanovic (1982). These recent empirical studies have been based on Jovanovic's model and conclude that growth, after accounting for sample selection bias due to exit, is negatively related to current size as well as age. Diminishing returns to scale or bounded efficiency is the rationale for the negative relationship between growth and current size, whereas diminishing returns to learning is the rationale for the inverse relationship of growth and age, since for older firms there is less scope for further efficiency gains from learning.

With the exception of Dunne, Roberts and Samuelson (DRS) who use data on manufacturing plants in the US, the earlier studies have related growth between period t and $t+1$ to current size at t, not to past size, thereby implicitly assuming that fixed factors are unimportant. This is also assumed in Jovanovic's model. Under this assumption, a firm's information on its efficiency at time t is fully reflected in its size (output) and age at t because current output is also the long-run optimal output given information at t. However, if fixed factors or adjustment costs of changing output are important – as may be expected in infant dynamic industries with rapidly changing demand – then current size at t may not fully adjust to the desired level at t. Hence current size and age may no longer be sufficient statistics for the unobserved efficiency of a firm. Lagged size may also become important in predicting growth. Hence DRS relate growth between period t and $t+1$ to size in t as well as to size in $t-1$ to test for the importance of fixed factors. However, they find fixed factors to be unimportant in affecting the growth rate. This is perhaps to be expected for mature industries in which demand does not change much from one year to the next.

Turning to the present study, the data set compiled consists of information on annual sales and the year of birth of computer hardware firms. Hence it allows us to examine the impact of current and lagged size, as measured by real sales,[3] and age on firm growth. Our main findings are the following.

(a) Current size has a strong negative impact on growth.
(b) Lagged size has a negative impact on growth.
(c) Age has a strong positive impact on growth.

[3] The measure of firm size has not been the same across all studies. Various measures including the value of assets of a firm, employment and sales have been used. Where data have been available for the various measures the results have generally been invariant to the measure of size (see Evans, 1987a, b; Hall, 1987; DRS, 1989). For this study, data on other measures of size are not available.

Besides the results obtained, the data set and the empirical analysis per se also possess some distinguishing features relative to the existing literature. First, as opposed to using data on firms from diverse industries, it uses data on firms with relatively similar technology and industry characteristics. This is important because different theories emphasize different factors determining firm dynamics – e.g. learning about innate efficiencies as in Jovanovic (1982), success in R&D as in Ericson and Pakes (1989), heterogeneity in productivity shocks as in Hopenhayn (1992), and Das and Das (1994), production flexibility as in Mills and Schuman (1985), learning about demand as in Jovanovic and Rob (1987) – and these factors can vary greatly across industries. A single model of firm dynamics is unlikely to be the most appropriate one for a heterogeneous group of industries such as a country's manufacturing sector. Also, the time taken for infant industries to reach maturity varies considerably across products (Klepper and Graddy, 1990, Table 1). This implies that the quantitative impact of a firm's age on its growth may vary widely across products, which in turn suggests that product-specific studies of such impacts may be desirable.

Second, previous studies of firm growth have implicitly assumed that all sources of heterogeneity among firms are fully reflected in the observed variables like size and age. We test and find that current size, lagged size and age do not account for all sources of heterogeneity among firms. Ignoring unobserved heterogeneity may lead to biased estimates. In the Indian computer hardware industry, unobserved firm-specific factors are important and may be in the form of product quality. Product quality is largely determined by the foreign firm who is the technological collaborator and by 'brand-effect'. These factors are likely to change slowly over time. Hausman's specification test favors the fixed-effect model over the random-effects model.

Third, in our data, mergers or acquisitions and exit are negligible (about 4% over the sample period). Therefore, unlike most previous studies, there is no confusion between internal growth and growth from mergers (see Evans, 1987a, p 660), and the effect of sample selection due to exit is likely to be unimportant. The advantage of the absence of the sample selection problem is that distributional assumptions on the probability of survival need not be made while evaluating the effect of size and age on the growth of surviving firms (Evans, 1987a,b; Hall, 1987). Further, sample selection bias, if any, is minimized by using an unbalanced panel that contains information on entrants, and exiters as long as they survived. The factors that affect growth of an existing firm are also likely to determine entry and exit choices of firms, so the results of this paper will be useful in modeling the entry and exit behavior of firms in future work.

The remainder of the paper is organized as follows. Section 2 provides further details about the data. Section 3 presents the estimation and test results. Concluding remarks are made in Section 4.

2. Nature of industry and data

To begin with, a few words on the Indian computer hardware industry are in order. Prior to 1984, the general governmental policy of heavy regulation towards the entire industrial sector harmed the computer industry. In particular, the Monopolies and Restrictive Trade Practices Act set limits on the capacity of companies and prevented them from achieving economies of scale and quality improvement by learning through mass production. Licenses for narrowly defined products were required from more than one government authority. Import of components and foreign investment was highly restricted. In 1982 there were only ten firms in the industry. In 1983 a massive computerization of the public sector began, leading to a sudden increase in the demand for computers, thereby triggering the entry of new firms. In 1984 and 1985 the new industrial policy withdrew limits on capacity and delicensed entry. Restrictions on imports were reduced and import of technology and foreign collaboration were permitted. Hence post-1983 is known as the 'new era' for the Indian computer industry.

Data for the Indian computer industry were compiled from various issues of a computer magazine, *Dataquest*, published by H.C. Gupta on behalf of Cyber Media (India) Ltd., New Delhi.[4] The magazine collects information on sales directly from the firms and ranks firms each year by their sales. Hence the sales data are expected to be quite reliable. The age of the firm is computed as the difference between the calendar year and the birth-year of firms reported in the magazine. Size in year t is measured as nominal sales in year t deflated by the CPI in year t. Growth in year t is given by the difference in the logarithms of size in $t+1$ and t.

The data include 206 observations on 51 firms over 1983–88. These firms make up almost the entire industry sales in every year. The panel of firms is unbalanced since many firms entered the industry after 1983. Exit is negligible, about 4% of the observations over the sample period. The likely reason for such little exit (failure) is that the industry was growing very rapidly, as seen in Table 1, over the sample period, which does not cover the 'shakeout' period.

In most studies of the relationship between growth, size and age, sample-selection bias arises because of the use of a balanced panel. The reason is that a balanced panel ignores data on firms that have been in operation only during a part of the sample period because of entry and exit (see Hall, p 584). Here, we include the data on any surviving firm be it an entrant or a slow-growing firm that exits later. Hence our panel is unbalanced. Table 1 presents patterns in the data on the evolution of size, age and growth distribution over the sample period, 1983–88.

It is interesting to note that mean size and age and variability in size (or

[4] This is not affiliated with *Database Inc.*, a company of the Dunn & Bradstreet Corp., US.

Table 1
Size, age and growth distributions over time

Period	No. of observations	Size[a]		Age (in years)		Growth	
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
1983–88	206	7.44	11.52	3.47	3.65	0.63	1.15
1983	18	5.0	7.4	2.6	3.8	0.69	1.10
1984	26	4.7	6.1	3.0	3.4	0.78	1.00
1985	34	5.6	7.5	3.0	3.5	1.00	1.60
1986	39	7.6	10.1	3.3	3.6	0.59	1.10
1987	48	7.7	10.9	3.5	3.7	0.47	1.15
1988	41	11.3	18.0	4.6	3.9	0.44	0.69

[a] Size is real sales measured in 100,000 rupees (base year = 1985).

concentration) and age are all increasing over time and the variability is at least as high as the mean for all the variables. However, growth distribution parameters fluctuate over time indicating that the growth process is non-stationary. Therefore, stationary growth models, as used by Simon and co-workers (e.g. Ijiri and Simon, 1977; Simon and Bonini, 1958) may not be appropriate. Table 2 shows how size and growth distributions change with age.

It is seen that, except for two years, the average size increases with age as

Table 2
How size and growth change with age

Age (in years)	No. of firms	Size		Growth	
		Mean	Std. dev.	Mean	Std. dev.
0	39	1.6	1.9	1.38	1.720
1	42	3.4	5.1	0.69	0.940
2	28	4.8	6.1	0.53	1.100
3	21	8.0	9.1	0.42	0.910
4	18	8.1	8.6	0.19	0.710
5	15	7.9	11.0	0.45	0.950
6	7	16.0	23.9	0.83	1.430
7	6	7.5	5.9	0.58	0.290
8	6	10.9	7.2	0.18	0.360
9	6	14.3	12.5	0.07	0.240
10	5	17.3	17.2	0.34	0.490
11	3	36.7	45.5	0.17	0.350
12	3	17.7	12.1	−0.10	0.090
13	2	22.6	5.2	0.21	0.150
14	2	27.7	9.7	0.17	0.001
15	1	40.3	0.0	−0.09	0.000
16	1	36.7	0.0	−0.30	0.000
17	1	25.7	0.0	0.71	0.000

expected. But interestingly, the variance is higher than the mean in most cases, as in Table 1 and increases until age six and then oscillates with age, suggesting that, in infant industries, the degree of heterogeneity among firms is large. Similarly, average growth and variability in growth oscillate with age, perhaps indicating the non-stationary nature of an infant industry.

3. Econometric analysis

3.1. Specification of the growth equation

Jovanovic's model implies that size at $t+1$ depends on size at t and age at t.[5] We do not specify this relationship, non-parametrically, as in DRS (1989), because we lack the very large number of observations required for reliable non-parametric estimation. Instead, we use the flexible functional form approach of Evans. Let S_t be the size at t and A_t the age at t. Then, in logarithmic form, size at $t+1$ may be written as a general function of S_t and A_t, as:

$$\ln S_{t+1} = \ln F(A_t, S_t) + u_t \tag{1}$$

where u_t is the disturbance. Using a second-order logarithmic expansion of $F(.)$,[6] Eq. (1) may be written as:

$$\ln S_{t+1} = a_0 + a_1 \ln S_t + a_2 \ln A_t + a_3(\ln S_t)(\ln A_t) + a_4(\ln S_t)^2 + a_5(\ln A_t)^2 + u_t\,. \tag{2}$$

Eq. (2) may be written in the form of the firm growth equation by subtracting $\ln S_t$ from both sides. Hence we have

$$\ln S_{t+1} - \ln S_t = a_0 + (a_1 - 1)\ln S_t + a_2 \ln A_t + a_3(\ln S_t)(\ln A_t) + a_4(\ln S_t)^2 + a_5(\ln A_t)^2 + u_t\,. \tag{3}$$

This is the form of the equation estimated by Evans. DRS however relate growth not only to S_t and A_t but also to S_{t-1} to allow for the impact of fixity

[5] Some studies such as those by Evans and DRS also examine the variability in growth rates of surviving plants across different size and age combinations. Jovanovic's model implies that holding size fixed the variance in the growth of surviving plants declines with age. This issue is not examined here because our data involves firms from a narrowly defined industry as compared to the earlier studies and the number of firms at each age is not large enough to group them into cells of different sizes and estimate the conditional variance reliably at each size and age combination.

[6] Similar to Evans (1987a, 1987b) we find a second-order logarithmic expansion in A_t and S_t to be the most satisfactory in terms of diagnostics although the qualitative results were similar across semilog and double-log specifications (first-order and second-order expansions).

of capital. Hence we generalize Evans' equation by adding $\ln S_{t-1}$ in Eq. (3). Therefore our estimated equation for firm i in year t has the form:

$$\ln S_{it+1} - \ln S_{it} = a_0 + (a_1 - 1)\ln S_{it} + a_2 \ln A_{it} + a_3(\ln S_{it})(\ln A_{it}) + a_4(\ln S_{it})^2 + a_5(\ln A_{it})^2 + a_6 \ln S_{it-1} + u_{it} \,. \tag{4}$$

Earlier studies by Evans, Hall, and DRS discuss the issue of estimating (4) in the presence of sample selection bias arising from exit. They distinguish between the latent growth equation given in (4) that is relevant for all firms and the growth equation relevant for survivors only. Since in our data exit is negligible we do not distinguish between latent growth and growth conditional on survival. They are taken to be the same.

Table 3 reports summary statistics for the variables used in the regression analysis.

3.2. *Ordinary least squares estimates*

If the size and age variables in Eq. (4) are sufficient statistics for the unobserved efficiency differences across firms, as suggested by Jovanovic's model of passive learning with no fixed costs, then OLS is the appropriate estimator of the parameters of the growth equation in (4). Hence we use OLS as our starting point and estimate (4) in the presence of time dummies that control for policy and the industry environment in each year.

Table 4 reports the OLS estimates of the growth equation. Results are similar to the existing studies relating growth to size and age, i.e. size and age are both negatively related to growth, and fixity of capital is not significant (see p 689–91 of DRS, 1989). The estimate of the constant term is ignored because it does not have a counterpart in the growth equation when additional unobserved heterogeneity is accounted for.

If current age and current and lagged size reflect all the heterogeneity among firms then the OLS residuals for each firm should be random. In other words, the deviations of growth of a firm from the regression line should be random over time in the absence of firm-specific factors other

Table 3
Summary statistics of the variables used in regression analysis

Variable	Minimum	Maximum	Mean	Std. deviation
$\ln S_t$	−2.76	4.49	1.15	1.36
$\ln A_t$ [a]	0	2.89	1.19	0.80
$\ln S_{t-1}$ [a]	0	3.89	1.24	1.06
$\ln S_{t+1} - \ln S_t$	−0.69	7.29	0.63	1.15

[a] Since age and lagged size is zero for entrants in a given year, age + 1 is used in place of age, and lagged size + 1 is used in place of lagged size.

Table 4
OLS estimates of the firm growth equation

Variable	Coefficient	Std. error	t-ratio
$\ln S$	−0.1619	0.1313	−1.233
$\ln A$	−1.0734	0.4252	−2.524
$(\ln S)(\ln A)$	−0.3979	0.1463	−2.720
$(\ln S)(\ln S)$	0.1642	0.0461	3.559
$(\ln A)(\ln A)$	0.5502	0.1956	2.813
$\ln S_{t-1}$	0.0634	0.2567	0.247
	$R^2 = 0.2336$		

than size and age. Otherwise the regression line will either over-predict growth (negative residuals) or under-predict growth (positive residuals) for most years. Hence the departure of the proportion of observations on a firm with residuals of the same sign from 0.5 may be taken as an indication of persistence after allowing for size and age. The pattern of residuals is presented in Table 5.

The clustering of frequency at 1.0 suggests that the OLS residuals of a firm are not random over time. There are perhaps two reasons: (1) Adjustment costs in changing output are very important in an infant industry as firms have to respond to a rapidly changing demand or information set and they cannot respond fast enough so that current size, one-period lagged size and age may not reflect all the information a firm has at that time. (2) Firms may have their own growth paths that differ due to unobserved factors not reflected in size or age. Examples of such factors for the Indian computer hardware industry are the product quality since it is a differentiated product industry, and firm-organization (e.g. whether a firm is multiplant or not).

Previous studies of growth used data on mature industries where changes in demand and the information set of a firm are likely to be small so that adjustment costs may not pose a problem and unobserved efficiency differences may be fully reflected in size and age. Since this is not likely to

Table 5
The pattern of OLS residuals of firms

Proportion of residuals of a firm with the same sign	Number of firms
0.50	11
0.60	7
0.67	12
0.75	3
0.80	1
0.83	3
1.00	14
	51

be true for infant industries we now turn to explore the presence of unobserved heterogeneity among firms in our data.

3.3. Unobserved heterogeneity

Unobserved heterogeneity is modeled by a firm-specific constant in Eq. (4) as:

$$\ln S_{it+1} - \ln S_{it} = a_i + (a_1 - 1)\ln S_{it} + a_2 \ln A_{it} + a_3(\ln S_{it})(\ln A_{it}) + a_4(\ln S_{it})^2 + a_5(\ln A_{it})^2 + a_6 \ln S_{it+1} + u_{it}\,. \quad (5)$$

The firm-specific constant in Eq. (5) captures the difference in growth processes among firms for given size and age configurations. Both random effects and fixed effects models are estimated. The former assumes that firm-specific factors are uncorrelated with size and age, which may not be reasonable. The latter allows for such a correlation. We let the data discriminate between the two, as discussed below. Random effects estimates and the fixed effects estimates are respectively presented in Table 6 and Table 7.

The random effects estimates are very close to the OLS estimates. However the fixed effects estimates show a marked difference. The signs of

Table 6
Random effects estimates of the firm growth equation

Variable	Coefficient	Std. error	t-ratio
$\ln S$	−0.1862	0.0949	−1.962
$\ln A$	−1.0864	0.3049	−3.563
$(\ln S)(\ln A)$	−0.3984	0.1057	−3.770
$(\ln S)(\ln S)$	0.1595	0.0334	4.777
$(\ln A)(\ln A)$	0.5583	0.1412	3.995
$\ln S_{t-1}$	0.0938	0.1826	0.514
	$R^2 = 0.2332$		

Table 7
Fixed effects estimates of the firm growth equation

Variable	Coefficient	Std. error	t-ratio
$\ln S$	−2.3805	0.2161	−11.014
$\ln A$	2.0215	0.4960	4.076
$(\ln S)(\ln A)$	0.8184	0.1802	4.541
$(\ln S)(\ln S)$	−0.0635	0.0522	−1.218
$(\ln A)(\ln A)$	−0.5506	0.3944	−1.396
$\ln S_{t-1}$	−0.9252	0.2469	3.747
	$R^2 = 0.7193$		

all coefficients except that of $\ln S_t$ have changed. The fit is also improved considerably with R^2 increasing more than three times.

Residual diagnostics are reported in Table 8. Because of the similarity of the random effects and the OLS estimates, it should be expected that the random effects residuals will have the same non-random pattern as the OLS residuals. This is confirmed in Table 8. The proportion of random effects residuals of a firm with the same sign are clustered at 1.00, like those from the OLS estimates, whereas the fixed effects residuals are not. The non-randomness of the random effects residuals implies that the estimator does not adequately capture the unobserved heterogeneity among firms. The randomness in the fixed effects residuals indicates that all the systematic variation in firm growth is adequately reflected by the fixed effects estimates.

At this point we conduct formal tests for model selection. First, the null hypothesis of no firm-specific effects is tested against the alternative that there are firm-specific effects that may be correlated with the regressors (especially size and age). The test statistic has an F-distribution with 50 numerator degrees of freedom (51 firm-specific constants minus 1) and 144 denominator degrees of freedom (206 observations minus 51 firm-specific constants minus 11 regressors). The p-value, reported in Table 9, is 0.000. Hence OLS is rejected in favor of the fixed-effects model.

Second, the null hypothesis that OLS is the right model is tested against the alternative that the random-effects model is the right one, by using a Lagrange multiplier test (see Greene, 1993, ch 16 for details). The LM test statistic has a Chi-square distribution with one degree of freedom. The p-value obtained is 0.8363. Hence the null cannot be rejected at the usual levels of significance.

Third, the null hypothesis that the random-effects model is true (i.e. the firm-specific effects are uncorrelated with the regressors) is tested against the alternative that the fixed-effects model is appropriate, by using Hausman's

Table 8
Pattern of random effects and fixed effects residuals of firms

Proportion of residuals of a firm with the same sign	Number of firms	
	Random effects	Fixed effects
0.50	10	21
0.60	7	6
0.67	10	19
0.75	3	2
0.80	1	2
0.83	3	0
1.00	17	1
	51	51

Table 9
Hypothesis test statistics

Hypothesis	Test statistic	p-value	Conclusion
(1) OLS versus fixed effects	4.982	0.0000	Reject OLS
(2) OLS versus random effects	0.043	0.8363	Accept OLS
(3) Random versus fixed effects	197.263	0.0000	Reject random effects

specification test. The test statistic has a Chi-square distribution with 11 (the number of regressors) degrees of freedom. The p-value obtained is 0.000. Hence the random effects model is rejected.

It is clear that the fixed effects model is decisively the best among the three. This implies that firm-specific factors are important and that they are correlated with the regressors. Age and size variables are not sufficient statistics for unobserved heterogeneity.

3.4. Discussion of results

We now discuss the results, which are based on the fixed effects estimates. All the coefficients in Table 7 are significant at 0.5% except those of squared size and squared age. Even though the latter are insignificant, the likelihood ratio test rejects the first-order expansion in favor of the second, indicating that the insignificance of the coefficients in Table 7 is perhaps due to multicollinearity. Lagged size has a significant negative impact on growth indicating that fixed factors are an important deterrent to growth. Since the growth equation is non-linear in age and size, further calculations are used to compute the partial derivative of growth with respect to a percentage change in size or age evaluated at the sample mean values of the regressors. These are reported in Table 10.

Table 10 indicates that at the sample mean a 1% increase in size leads to a 1.556% decrease in the expected firm growth rate and the negative impact holds over the entire sample evaluated at mean age. This implies that size is

Table 10
Effects of firm size and age on firm growth

Variable	Minimum	Maximum	Mean
Size	−0.02659	−0.00427	−0.01556
Age	−0.01555	0.04025	0.01654

negatively correlated over time[7] *holding age and lagged size constant.* It does not imply that a *given* firm will contract over time. It indicates how current size affects growth among firms of the same age and lagged size. A possible explanation of the strong negative impact is proposed below.

Age has a strong positive impact on growth. At the sample mean, a 1% increase in age leads to a 1.65% increase in the expected growth rate. The age effect evaluated at the mean size is positive for most of the sample. This may be due to various reasons. First, although firms in mature as well as infant industries keep learning about their own efficiencies over time and find their niches in the product market as they age, the returns to such learning may be increasing in an infant industry while it may be diminishing in a mature industry. Second, in an infant industry, learning or awareness by consumers about the existence of a new product may increase over the age of a firm producing the product and may have a positive impact on its growth. Third, a firm's reputation may be enhanced with age. The marginal returns from such reputation building is likely to be quite high in an infant industry leading to a positive impact of age on its growth.

The importance of fixity of capital and the strong learning effect together may explain why current size has such a strong negative impact on growth. Inflexibility in production by larger firms implies they cannot respond as fast as the small firms to new information in the market and this hampers their growth. Any positive effect of size on growth that may exist due to economies of scale *in the absence of adjustment costs* is outweighed by the negative impact when bigger firms, due to the fixity of capital, cannot respond quickly to what they learn. In an infant industry, production flexibility is likely to be a very important asset and hence size, by limiting flexibility, may hamper growth.[8]

3.5. Prediction of future sizes

Using the fixed-effects estimates, future sizes of firms and the industry beyond 1988 may be predicted, given the 1988 growth rate, the configuration of size and age variables in 1988, and the assumptions that the macro variables facing all the firms in the future remain close to their 1988 values and that there is no exit.

Let g_t denote the growth in t, defined as $\ln S_{t+1} - \ln S_t$. Note that knowing g_t is equivalent to knowing S_{t+1} for a given value of S_t. The expected change in the growth rate for firm i from t to $t+1$, denoted by cg_{it}, is obtained by

[7] Note that $\partial \ln S_{t+1} / \partial \ln S_t = 1 + \partial g_t / \partial \ln S_t$, where g_t is the growth of t.

[8] See Stigler (1939) and Mills and Schumann (1985) for the importance of production flexibility in a market where demand is not stable.

Table 11
Prediction of future size and its distribution

Year	Industry size	Average firm size	Std. dev. of firm size
1989	717.35	17.50	26.07
1990	972.64	23.72	33.78
1991	1026.72	25.04	38.64
1992	1162.84	28.36	47.03
1993	1734.50	42.30	73.66

taking the difference of the growth equation in (5) for $t+1$ and t as follows.

$$\begin{aligned} cg_{it} = g_{it+1} - g_{it} = & -2.3805(\ln S_{it+1} - \ln S_{it}) \\ & + 2.0215\,[\ln(A_{it}+1) - \ln A_{it}] \\ & + 0.8184\,(\ln S_{it+1}\ln(A_{it}+1) - \ln S_{it}\ln A_{it}] \\ & - 0.0635\,[(\ln S_{it+1})^2 - (\ln S_{it})^2] \\ & - 0.5506\,[(\ln(A_{it}+1))^2 - (\ln A_{it})^2] \\ & - 0.9252\,(\ln S_{it} - \ln S_{it-1})\,. \end{aligned} \tag{6}$$

The predicted growth of the i-th firm in $t+1$ is

$$g_{it+1} = cg_{it} + g_{it}\,, \tag{7}$$

and the predicted size for the i-th firm in $t+2$ is given by

$$S_{it+2} = \exp(\ln S_{it+1} + g_{it+1})\,. \tag{8}$$

Then the industry size in $t+2$ may be predicted as the sum of the sizes of the individual firms in $t+2$. The process may be continued to predict firm sizes and industry size for future years. For the year 1989 Table 11 presents the sizes observed in the data but after 1989 industry size and the distribution of firm sizes are predicted using the model above. As in Table 1, the pattern in the observed sizes over time continues in the predicted sizes. There is an increasing trend in the average as well as the variability of predicted sizes and the standard deviation exceeds the average in all the years.

4. Concluding remarks

Recent studies that relate firm growth to firm size and age have typically used data on American industries and found a negative relationship between growth and both size and age (see Evans and DRS) and that fixed factors are insignificant (as in DRS). Hall's study that relates size only to growth also found a negative relationship using data on large American manufacturing firms, whereas Singh and Whittington found a positive one using data on British manufacturing, construction, distribution and service industries. In general the results of these studies are applicable for mature industries in developed countries.

This paper presents a contrasting econometric analysis of an infant industry in a developing country, namely, the computer hardware industry in India. Allowing for more heterogeneity among firms than that reflected through size and age differences, it finds that current size as well as lagged size are negatively related to growth, and most strikingly, age has a strong positive impact on growth. The sign of the current size effect is consistent with other recent studies and need not be emphasized but it should be noted that the magnitude is very high. Unlike the result obtained by DRS, the negative impact of lagged size indicates that fixed factors are important for the Indian computer industry. In infant industries when market demand is increasing rapidly and calls for quick response by firms, fixed factors become a hindrance.

The strong positive effect of age on growth is perhaps the most striking result of this study. It contrasts with the previous studies that have used data on mature industries. It suggests that in infant industries learning by firms about their own efficiencies, learning by consumers about a new product and reputation building by firms may be very important.

Although the current study has been motivated in terms of infant industry growth in a developing country, the factors identified are applicable to developed countries as well when new product lines are introduced into the market.

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