Version: December 27, 2002

Are Small Firms Really Less Productive? An Analysis of Productivity Differentials and Firm Dynamics

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Abstract
Small and medium-sized establishments (SMEs) account for a large proportion of industrial employment and production in almost all countries. Moreover, the recent literature emphasizes the role SMEs play in nurturing entrepreneurship and generating new products and processes. Although SMEs could be a source of new ideas and innovations, there are substantial productivity differences between small and large establishments. In this paper, we analyze three sources of productivity differentials: technical efficiency, returns to scale, and technical change. Our analysis on the creation, survival, and growth of new establishments in Turkish manufacturing industries in the period 1987-97 shows that all these three factors play a very important role in determining the survival probability and growth prospects of new establishments.

JEL Codes: L11, L25, D24

Acknowledgments: Earlier versions of this paper were presented at the 9th Annual Conference of Economic Research Forum (ERF), Al-Sharjah, UAE, October 26-28, 2002, and the workshop on The Post-entry Performance of Firms: Technology, Growth, and Survival, Bologna, November 22-23, 2002. I would like to thank the discussants and participants at those meetings and Prof. Cem Somel of METU for their helpful comments.

1. Introduction

The process of industrialization has been associated with large-scale factory production since the early days of the Industrial Revolution. The emergence and dominance of large corporations, first in the US, then in European countries in the late 19th Century, is thought to be the natural outcome of this process, and small and medium-sized establishments (SMEs) have been perceived as a transitory and fading institution of the economic development process. In fact, there seems to be a strong correlation between the income level of countries and the scale of the establishments where the majority of the labor force is employed. In low- and middle-income countries, SMEs are the dominant source of employment. As the income per capita rises, the predominance of small establishments declines. In high-income counties, most of the labor is employed in large-scale establishments (LSEs).

After the major economic crises in the 1970s, the perception of SMEs started to change. SMEs have proved that they could be quite successful in competing against LSEs in a rapidly changing uncertain environment, and are essential in nurturing an innovative milieu where the flow of new products and processes continuously re-shape competitive conditions (for a classical account of small firm innovativeness, see Acs and Audretsch, 1990). Moreover, the increase in employment (and output) share of SMEs in major developed economies in the 1980s showed that they are a vital form of industrial organization.

Although SMEs have been re-discovered by researchers as a dynamic agent of economic growth, and various SME-support programs have been adopted all around the world, the available evidence strongly indicates that there are substantial and persistent productivity differences between small and large enterprises independent of sector and country-specific factors. The productivity differential narrows down by economic development but its does not vanish completely even in the developed countries (Snodgrass and Biggs, 1995: 67).

The apparent contradiction between persistent productivity differentials and the emphasis on the role of small firm dynamism has generated an increasing number of studies on the evolution of firms and industrial productivity. Although research on these topics has a long tradition that dates even back to the classical economists, the availability of panel data on firms/establishments in the last couple of decades has provided a new impetus for a large number of creative studies. Most of these studies are influenced to a large extent by the path-breaking theoretical analyses, among others, of Nelson and Winter (1978 and 1982), Jovanovic (1982), Hopenhayn (1992), and Ericson and Pakes (1995), who emphasize the importance of uncertainty, learning, and selection processes. These theories are based on the Schumpeterian notion that markets are in motion, with new firms continuously entering the industry and forcing others to exit out of the industry. New firms become aware of their actual "productivity" only after observing their performance in the industry, and exit if they figure that their performance is lower than a certain threshold level. Those firms that discover they are more productive than the threshold level survive and grow. A snapshot of this process reveals a positive correlation between productivity and size, i.e., productivity differentials even if small firms are not intrinsically less productive.

The empirical work on the dynamics of firms has provided a great deal of "stylized facts" which are observed in many countries and/or sectors (for comprehensive surveys, see Geroski, 1995; Sutton, 1997; Caves, 1998, Tybout, 2000). One of the strongest findings about the entry process is the "stylized fact" that entrants start small: entrants are usually smaller than incumbents. This phenomenon is usually explained by two factors. First, as emphasized in learning models and real options theory, the entry process is surrounded with uncertainty: entrepreneurs may not exactly know how well they will perform in the market. It may be rational to start out small to limit sunk commitments even if it imposes a cost penalty, and to invest more after gathering information on the (potential) performance. Second, entrants may start out small because of (capital) market imperfections. Even a confident entrepreneur may start out with a small firm if asymmetric information and capital market imperfections make it difficult to raise capital (the liquidity constraint).

Another stylized fact is about post-entry performance: Most new entrants never overcome the competitive pressures. Entrants suffer from a high mortality rate, and there seems to be a strong positive correlation between entry size and the survival probability. However, new firms that survive achieve growth rates higher than the incumbents do. As a result, the growth rate is negatively correlated with the age and size of the establishment (for a small sub-set of studies, see Evans, 1987a and 1987b; Dunne *et al*., 1989; Audretsch, 1995; Mata, Portugal and Guimarães, 1995; Hart and Oulton, 1996; Audretsch, Santarelli and Vivarelli, 1999).

Although the concept of "productivity" plays an important role in understanding firm dynamics, it is simply defined by a cost parameter in most of the theoretical studies, and measured usually as labor productivity (value added per employee or hour worked) in empirical studies without any specific focus on its sources. This paper contributes to the existing literature by focusing on the dynamics of three sources of productivity: economies of scale, technical efficiency, and technical change. The novel feature of our study is to measure these three factors at the establishment level, and to keep track of their evolution over the life of entrants. In contrast to some earlier empirical work, we do not consider entrants as a homogenous group: entrants are classified into two groups, "small" and "large" on the basis of relative entry size, and the persistence of performance differentials is also analyzed.

The aim of this paper is then two-fold: i) to investigate the sources of productivity differentials, and ii) to understand if differences between small and large establishments tend to vanish as a result of selection and learning processes. In this context, we also estimate hazard functions for entrants to test the effects of various establishment- and industry-specific factors on survival probabilities, to see if active and passive learning processes play a significant role. A detailed analysis of productivity differentials and their sources is essential for designing *efficient* SME-support policies, because policies that encourage the survival of unproductive firms and restrict learning and experimentation processes may impose a heavy welfare loss on society. SME-support policies that target specific aspects that induce SMEs to be more productive and/or to grow faster would enhance social welfare.

The rest of the paper is organized as follows: Section 2 presents a simple framework for exit decisions. Basic concepts, estimation model, and data sources are explained in Section 3. Stochastic production frontier estimation results and a descriptive analysis of firm dynamics are presented in Section 4. Survival functions are estimated in Section 5, and major findings are summarized in Section 6.

2. The framework

Our framework is based on two strands of the literature: models of industry evolution, and stochastic production frontier approach. We first summarize the entry and exit decision of a firm here, then define the concepts of technical efficiency, returns to scale, and technical change at the establishment level in the following section.

The firm is assumed to choose its output, q, so as to maximize expected profits.

$$\max_{q_t} \pi_t^e = p_t^e q_t - c(q_t, \theta_t^e)$$

where subscript t denotes time, and superscript e denotes expected value. p is the product price, q the output level, and $c(q, \theta)$ is the cost function that is increasing in q, and decreasing in θ, the productivity parameter. Here we assume that the firm decides on its output level at time t before it observes its actual productivity level.

The optimum output level is denoted by $q^*(p^e|\theta^e)$ and the corresponding profit function can be written as $\pi^*(p^e, \theta^e)$.

Let V be the opportunity cost of being in the industry, i.e., the expected present value of the firm's assets in an alternative activity. It is defined by

$$V = (1 - s)A$$

where A is the value of assets, and s the degree of asset specificity ($0 < s < 1$). We assume that asset specificity is increasing in the value of fixed assets (machinery and equipment), K. If $(1 - s) < A(\partial s/\partial K)$, then $\partial V/\partial K < 0$. It other words, we assume that capital intensive firms have lower opportunity costs because they are less flexible in moving their assets towards other activities.

The value of continuing the operation, v_t, is given by the following recursive condition:

$$v_t(p^e{}_t, \theta^e{}_t) = \pi_t^*(p^e{}_t, \theta^e{}_t) + r \max \{V, v_{t+1}(p^e{}_{t+1}, \theta^e{}_{t+1})\}$$

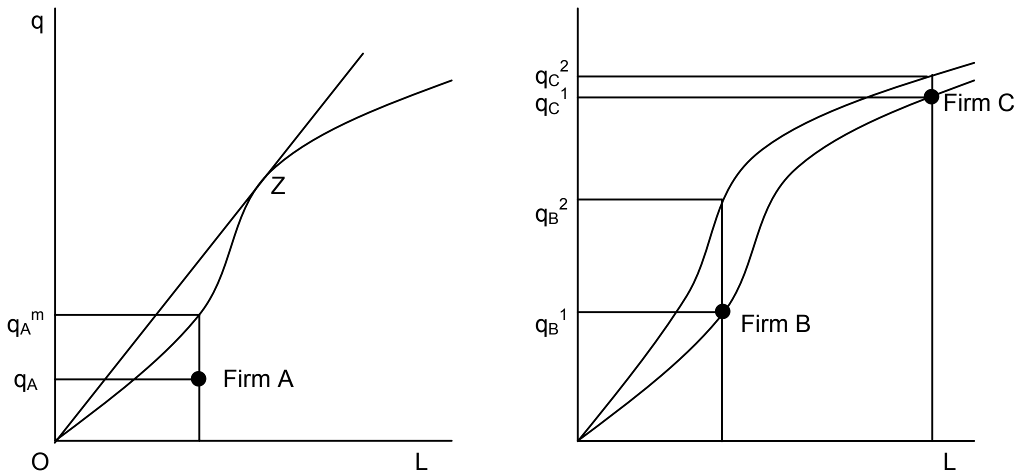
where r is the discount factor. The firm will exit from the market if the value of continuing the operation is less than the opportunity cost, $v_t < V$.

There are three variables that affect the exit decision (and entry decision at time 0) of a firm: expected productivity, expected prices, and the opportunity cost of the operation.

"Productivity" can be decomposed to three components: technical efficiency, economies of scale, and technological level. Changes in these variables, i.e., learning and technical change, will then govern the future (expected) values of the productivity parameter in the exit decision problem.

The concept and measurement of *technical efficiency* was made operational by Farrell (1957) who also discussed in detail the factors that lead to inefficiency in production. Technical efficiency refers to the ratio between actual output and the maximum output the firm could produce with the set of inputs and technology it uses (the q_A/q_A^m ratio for firm A with one input in Figure 1).[1] (For recent comprehensive surveys, see Kalirajan and Shand, 1999; and Kumbhakar and Lovell, 2000). There are various arguments on the impact of firm size on efficiency. On the one hand, it is claimed that large firms could be more efficient in production because they could use more specialized inputs, coordinate their resources better, etc. On the other hand, it is emphasized that small firms could be more efficient because they have flexible, non-hierarchical structures, and do not usually suffer from the so-called agency problem.

Figure 1. Technical efficiency, returns to scale, and biased technical change



[1] This is indeed an output-oriented definition. Efficiency could also be defined in terms of inputs (input-oriented), and these two definitions could lead to different values. Data envelopment analysis and stochastic production frontier estimation are two widely used methods to estimate the maximum output, i.e., the production frontier.

Empirical studies on the relationship between establishment size and efficiency have not generated unambiguous results, although they suggest that, in many sectors, large establishments tend to be more efficient that small establishments (see, for example, Caves and Barton, 1990: 115-130; for studies on Turkey, see Taymaz and Saatçi, 1997, and Taymaz, 1997).

Economies of scale in production have been a popular topic of both theoretical and empirical research. Although constant returns to scale are assumed in many theoretical models for the sake of analytical tractability and the existence of a unique equilibrium, there are numerous historical/empirical studies that have shown that variable returns are the norm in many sectors (for example, see Pratten, 1971; Chandler, 1990). Therefore, the main issue is how small establishments compete in spite of disadvantages due to economies of scale (Pratten, 1991: 93-104; Audretsch, 1999).

Figure 1 depicts a variable returns to scale production function with one input, L. There are increasing returns to scale up to point Z, constant returns to scale at point Z, and decreasing returns to scale thereafter. A firm achieves maximum productivity when there are constant returns to scale (point Z).[2] Thus, small and large establishments could be relatively less productive depending on their position on the production frontier. If it is assumed that there are no decreasing returns to scale beyond point Z, or if large firms could avoid lower productivity of large-scale production by multi-plant operations, then variable returns to scale would lead to productivity differentials between small and large establishments.

[2] However, given the set of input and output prices, the firm would prefer to operate at a larger scale (to the right of point Z) where marginal cost is higher than the average cost. Caves and Barton (1990: 10-11) use the concept of "scale inefficiency" to refer to the case where production is carried out at scales either too small or too large to minimize costs of production.

Finally, *technical change* is another important, but often neglected, factor in explaining productivity differentials. [3] In most of the empirical studies, production functions estimated are in quite restricted form that does not allow for biased technical change. However, if technical change is biased, then small and large establishments that use inputs in different proportions may experience different rates of technical change.

Figure 1 depicts the effects of biased technical change with one input. If technical change is neutral, than there will be a parallel shift in the production function, i.e., the same rate of technical change for all establishments. If technical change is biased, then establishments operating at different scales will benefit from technical change at different rates. For example, in Figure 1, the rate of technical change for the small establishment, B, is much higher than the rate of technical change for the large establishment, C, even if these two establishments operate on the same production frontier.[4] Since small and large establishments tend to use inputs in different proportions, biased technical change could be an important factor in explaining productivity dynamics.

To summarize, the expected productivity level at time *t* in the exit decision problem is assumed to be a function of technical efficiency and returns to scale at time *t-1* (λ_{t-1} and μ_{t-1}, respectively), and expected changes in these variables, and the expected rate of technical change.

$$\theta_t^e = \theta(\lambda_{t-1}, \mu_{t-1}, \Delta\lambda_{t-1}, \Delta\mu_{t-1}, \delta_{t-1})$$

where $\Delta\lambda_{t-1}$ is the average rate of change in technical efficiency from entry time till the present time, $\Delta\mu_{t-1}$ the average rate of change in the returns to scale parameter, and δ_{t-1} the average rate of technical change in the same time period. Thus, we expect that levels and

[3] There are some recent studies that estimate total factor productivity growth rates by establishment size (see for example, Awe, 2002; Urata and Kawai, 2002). These studies, however, could not differentiate the effects of economies of scale and technical change because of the assumptions imposed.

[4] For example, the logarithmic rate of technical change for establishment B is equal to $ln(q_B^2/q_B^1)$ whereas it is equal to $ln(q_C^2/q_C^1)$ for establishment C.

changes in technical efficiency, returns to scale, and technology affect survival probabilities.

3. Estimation of stochastic production frontiers and data sources

In estimating technical efficiency, returns to scale and the rate of technical change at the establishment level, we use translog specification for production frontiers because the translog function is a second-order approximation to any arbitrary function. The translog stochastic production frontier is defined by:

$$\ln y_{ft} = \alpha_0 + \sum_i \alpha_i \ln x_{ift} + \alpha_T t + \beta_{TT} t^2 + \sum_i \beta_{Ti} t \ln x_{ift} + \tfrac{1}{2}\sum_i \sum_j \beta_{ij} \ln x_{ift} \ln x_{ift} + \varepsilon_{ft} - v_{ft}$$

where the subscripts f and t indicate plant and time; y is the output; x_i is a vector of inputs. The subscripts i and j index inputs (i,j = K, capital; L, labor; E, energy; R, raw materials). The ε-random errors are assumed to be independently and identically distributed as $N(0,\sigma^2_\varepsilon)$ and independent of the v-terms which designate plant-specific technical inefficiency in production.

The technical efficiency of a plant is specified as the ratio of its actual output to the potential output. Then, the technical efficiency of production for the f-th firm at time t is defined by:

$$TE_{ft} = e^{-v_{ft}}$$

Technical efficiency lies in the interval 0 to 1, where the upper bound indicates full efficiency.

The inclusion of time as a variable in the production frontier allows for the shifts of the frontier over time, which are interpreted as technical change. In this model, technical change is input i-using (or input i-augmenting) if β_{Ti} is positive. Technical change is neutral if all β_{Ti}s (β_{TL}, β_{TR}, β_{TE}, and β_{TK}) are equal to zero.

The rate of technical change, δ, is then defined by:

$$\delta_{ft} = \partial \ln y_{ft} / \partial t = \alpha_T + 2\beta_{TT} t + \sum_i \beta_{Ti} \ln x_{ift}$$

The elasticity of output with respect to the i^th input is defined by:

$$\eta_{ift} = \partial \ln y_{ft} / \partial \ln x_{ift} = \alpha_i + \sum_j \beta_{ij} \ln x_{jft} + \beta_{Ti} t$$

The returns to scale, κ_{ft}, is the sum of output elasticities:

$$\kappa_{ft} = \sum_i \eta_{ift}$$

Note that both the rate of technical change and returns to scale are defined at the establishment level because their values depend on the levels of inputs. Therefore, this method allows us to compare technical efficiency, returns to scale and rate of technical change at the establishment level.

Following Battese and Coelli (1995), the technical inefficiency effects, v_{ft}, are assumed to be independently distributed, such that v_{ft} is defined by the truncation of the normal distribution with mean μ_{ft} and variance σ^2_v. This mean inefficiency term is assumed to be a linear function of some plant-specific factors:

$$\mu_{ft} = \delta_0 + \sum_{k=1}^{m} \delta_k z_{kft} + u_{ft}$$

where u-random errors are assumed to be independently and identically distributed as $N(0, \sigma^2_u)$ and z's are the following plant-specific factors that influence technical efficiency:

The stochastic production frontiers for all ISIC 4-digit manufacturing industries in Turkey are estimated separately by using the panel data of all private establishments employing more than 25 people and all state-owned establishments in the years 1987 to

1997.[5] The data source is the *Annual Survey of Manufacturing Industry* conducted by the State Institute of Statistics.

The output is measured by total output (sales + increases in output stocks) at constant 1987 prices. Depreciation allowances at 1987 prices are used as a proxy for capital (K). The labor input (L) is measured as the total number of hours worked in production. Energy (E) is measured as the value of fuel and electricity consumption at 1987 prices. The raw materials input (R) is measured as the expenditure on inputs (raw materials, supplementary materials, etc.) at constant 1987 prices.

The estimation method requires joint estimation of a stochastic production frontier and a model for technical efficiency. The following variables are used as explanatory variables in the efficiency effects model.

The *Size* variable is utilized to detect the relationship between the size of the plant and its technical efficiency level, and measured in terms of the log number of personnel employed. *Region*, the variable capturing the effects of agglomeration and urbanization externalities, is defined by the proportion of the output of the region in which the plant is located relative to the total output. *Owned* and *Joint* are dummy variables taking the value of 1 if the plant is individually owned or a stock company, respectively. These ownership variables are used to test the influence of the legal status of companies on technical efficiency. *Overtime* is defined by the proportion of the number of hours worked in the first shift to total number of hours worked, which depicts the effects of shift-work on technical efficiency. *S-input* and *S-output* variables are used to test the impact of subcontracting relations. *S-input* (*S-output*) variable is measured as the proportion of inputs (outputs) subcontracted to (by) other firms. The effects of product characteristics and strategic behavior on technical efficiency are tested by the advertisement intensity, *Advertising*,

[5] There are 86 ISIC (Revision 2) 4-digit manufacturing industries. The following industries were excluded from the analysis because of the lack of a sufficient number of observations: 3232, 3542, 3845, 3849, 3853, 3903 and 3909.

which is measured by the proportion of advertisement expenditures in total costs. *Private* and *Foreign* are defined as the shares held by private national and foreign agents, respectively. *Technology* is a dummy variable that takes the value of 1 if the firm transferred any foreign technology. *Wage,* the average wage level, is included as it may reflect the quality of the labor employed. Further, the women, technical, and administrative personnel shares are other control variables utilized to detect the impact of the skill composition of production workers.

4. Competition and Productivity Dynamics: A Descriptive Analysis

The Frontier 4.1 program developed by Coelli (1994) is used to obtain joint estimates of the parameters of stochastic production frontier and efficiency effects models for 79 sectors at the ISIC 4-digit level. For each sector, average rates of technical change, returns to scale, and technical efficiency are calculated at the sectoral (geometric) means of inputs. Table 1 presents the findings summarized at the ISIC 2-digit level.

The results show that the average rate of technical change in the period of 1987 to 1997 is quite high for engineering industries (4.5%). At the 4-digit industry level, the structural metal products (7.4%), engines and turbines (7.1%), special industry machinery (9.7%), office, computing and accounting machinery (8.2%) achieve the highest rate of technical progress in the engineering industries. The glass and cement (2.2%), basic metal (1.2%), wood products (1.0%), and chemicals (0.9%) industries have a mediocre performance. The traditional industries like food, textiles, and paper and printing have quite low, even negative, rates of technical change.

At the ISIC 4-digit level, capital-using technical change is observed in 12 industries at the average input use, and labor-using technical change is observed in 13 industries (capital-saving in only one industry). There is a noticeable bias towards raw material inputsaving change in 26 industries. Raw materials-using technical change is observed in only 3 industries. There is no clear pattern for energy input (energy-using in 6 industries, and energy-saving in 8 industries).

The average values of the returns to scale parameters at the 2-digit level indicate that in most of the industries there are mild decreasing returns to scale. The lowest returns to scale are observed in the basic metal (0.91) and textile (0.92) industries.

Establishment size is found to be one of the main determinants of efficiency. In about a third of the sectors, establishment size has a positive impact on efficiency, and in about half of the sectors, it does not have a statistically significant impact on efficiency. In a small group of industries, establishment size has indeed a negative impact on efficiency. The analysis of establishment-level efficiency estimates reveals that some small establishments are as efficient as large plants even in those industries where size is a significant determinant of efficiency.

Among the efficiency effects variables, the most significant variable is the wage rate. Those establishments that pay relatively high wages are associated with a high technical efficiency level in most of the industries. The agglomeration and urbanization effects captured by the region variable have a positive association with technical efficiency in 14 industries.

Estimated values of technical efficiency, returns to scale, and rate of technical change are shown in Table 2. Establishments are classified into two groups, “small” and “large” to make comparisons on the basis of size differences. “Small” (“large”) is defined as an establishment that employs less (more) than the (geometric) mean of the industry at the ISIC 4-digit level. All performance variables are measured relative to all other establishments operating in the same industry to eliminate industry-specific effects. Therefore, “relative size” means the difference between the (log) size of the establishment and the industry mean, and it gives the percentage difference between establishment size and industry mean. “Relative efficiency”, “relative returns to scale” and “relative rate of technical change” are defined as the difference between the establishment’s value and the average value of all establishments in the industry.

There are 12788 establishments in the database for the period 1987-1997, and 8191 of these are new establishments (entrants). There are, on average, 4.6 observations per establishment (4.0 for small, and 5.8 for large establishments).

The stylized fact on entrant size is valid for Turkish manufacturing industries as well: entrants are 40% smaller than incumbents, and the exit rate is quite high for small entrants. Only 41.6% of small establishments survive until age 5 whereas the 5-year survival rate is 51.2% for large establishments.[6] However, there are significant differences in growth rates. Small establishments grow 3.9% per year, whereas large establishments shrink 1.9% per year.

Figure 2a shows changes in the mean size of all cohorts of entrants. New establishments start small but grow quite rapidly, and those that survive 5-6 years reach the average size in the industry. The increase in the mean size of entrants is caused by two factors: exit of smaller entrants, and rapid growth of survivors. Figure 2b depicts changes in the mean size of non-survivors by survival duration. As shown clearly in Figure 2b, there is a strong correlation between survival duration and entry size. (ANOVA analysis indicates that the relationship is statistically significant at the 1% level.) Those establishments that survive longer were (relatively) larger establishments at the time of entry. Moreover, non-survivors do not exhibit any growth (except the first year), tend to stagnate, and even shrink before they finally exit. Survivors, on the other hand, achieve quite high growth rates, and eliminate size disadvantages in 5-6 years.

[6] Log-rank test rejects the equality of survivor functions of small and large establishments at the 1% level.

The data show that entrants are less efficient than incumbents, and the efficiency differential is wider for small entrants. Small establishments are 3.3 percentage points less efficient that an average establishment in the same industry, whereas large establishments are 5.3 percentage points more efficient.[7] However, the mean efficiency of entrants tends to increase over time (see Figure 3a). Those establishments that tend to exit earlier have a lower efficiency level at the time of entry. In other words, as in accordance with the learning models of firm dynamics (see, for example, Jovanovich, 1982), bad performers realize earlier that they would not be competitive in the market. Moreover, non-survivors are those establishments that are not able to improve their efficiency irrespective of the initial level (Figure 3b). Survivors achieve rapid increase in their efficiency, and become as efficient as others in 4-5 years (Figure 3c). It seems that there is not any difference between entry size and learning performance (efficiency improvements): large entrants are more efficient that small entrants, and they tend to learn as fast as small entrants (Figure 3d).

As may be expected, the relative returns to scale value are positive for small and negative for large establishments, i.e., returns to scale are much higher for small than large establishments. Since entrants start small, scale disadvantages are also important for small entrants. Figure 4a shows that relative returns to scale are higher for entrants (5.6 percentage points), but as entrants grow, the difference declines. Relative returns to scale at entry are significantly correlated with the survival duration for non-survivors. For example, those establishments that survive only one year had a scale disadvantage of about 8 percentage points at entry year, whereas those that survived 9 years had indeed a 2-3

[7] Unles otherwise stated, all differences between small and large establishments are statistically significant at the 5% level.

percentage points advantage (Figure 4b). Non-survivors are not able to overcome scale disadvantages. Survivors tend to reduce scale disadvantages quite rapidly (Figure 4c).[8]

Although efficiency and returns to scale indicators show that small establishments are in a disadvantageous position, technical change seems to favor small size. The difference between rates of technical change in small and large establishments is about 0.15 percentage point per year (Table 2). Entry-time rates of technical change are even higher for small establishments. An average small entrant achieves 0.22 percentage point higher rate of technical change than incumbents do.

The decomposition of technical change reveals very interesting differences between small and large establishments: raw materials-augmenting technical change favors small establishments, whereas capital and especially labor-augmenting technical change favors large establishments (see Table 2). Raw materials-augmenting change contributes a 0.5 percentage point to relative productivity increases in small establishments every year, whereas its contribution reaches almost one percentage point for small entrants at the time of entry. However, this advantage tends to vanish over time as a result of growth and changes in the combinations of inputs of survivors (see Figures 5a, 5b, and 5c).

Although small entrants are less efficient, they tend to grow fast and improve on their efficiency and scale disadvantages. But do they reduce their disadvantages against large entrants? We compare small and large entrants to test if the entry size has a persistent impact on performance. Table 3 presents the data and test statistics on small and large establishments that survived at least five years.[9] Small entrants tend to increase their relative size thanks to high growth rates, whereas large entrants grow almost at the same rate as incumbents do. As a result, the size differential contracts. The ANOVA analysis

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[8] Nguyen and Reznek (1991) and Nguyen and Lee (2002) found no difference between small and large establishments in the US data. Although the method used is not exactly the same, their findings may indicate that there may be country-specific differences between small and larges establishments.

[9] In Table 3, entrants are classified according to their entry size.

indicates that small and large entrants have different growth rates. As small entrants get larger, they also eliminate their disadvantages arising from operating at sub-optimal scales.

Small entrants enter the market with low technical efficiency but survivors improve their efficiency gradually. However, large entrants who are more efficient than small entrants at the time of entry also improve their efficiency almost at the same rate. Therefore, small entrants are not able to narrow down the efficiency differential that remains around 7-8 percentage points. Therefore, entry-time size differences seem to have persistent efficiency effects.

Small entrants have an advantage in achieving somewhat higher rates of technical change for about two years after entry, and this advantage disappears as the establishment gets 5-6 years old. Large entrants do not enjoy this advantage, and stay behind small entrants. Thus, the technical change differential stays at the same level even 9 years after entry.

Our analysis of firm dynamics shows that economies of scale are one of the major sources of productivity differentials between entrants and incumbents, and between small and large establishments. Surviving entrants grow faster and ease scale disadvantages. However, efficiency differentials between small and large entrants are persistent.

5. Selection and Learning Processes: A Survival Analysis

In this section, we analyze the effects of learning and competition on the survival of entrants. Our focus is on the role technical efficiency, returns to scale and technical change play in exit decisions. The framework summarized in Section 2 suggests that all these variables, as well as changes in these variables determine the exit decision.

The econometric analysis of survival is based on the estimation of the hazard function that defines the probability of exit in a certain time period as a function of a set of time-varying covariates:

$$h(t;X_t) = \lim_{dt \to 0} \frac{p(t \le T \le t + dt \mid T \ge t, X_{t+dt})}{dt}$$

where *h(.)* is the hazard function, *p(.)* the probability function, and X_t is the covariate path of *X* up to *t*. A functional form has to be assumed for the hazard function, *h(t)*, in the empirical implementation of the model. The Cox proportional hazards model is used frequently in empirical studies. The Cox model assumes a proportional hazard function that is defined by

$$h(t) = h_0(t)e^{X_t\beta}$$

where $h_0(t)$ is the baseline hazard function, *X* is a vector of explanatory variables, and β is a corresponding vector of regression coefficients. The β parameters are estimated by the maximization of the partial likelihood function that does not require the specification of $h_0(t)$.

The dependent variable is the time of exit. The exit time of those plants that survived until the end of 1997 is not observed (the longitudinal data for the period 1987 to 1997 were used in the analysis). Thus the distribution of the dependent variable is censored at year 1997.

In the estimation of the Cox proportional hazard function, we use two sets of explanatory variables. The first set includes establishment-specific variables. The second set includes data about the characteristics of the industry defined at the 4-digit ISIC level in which the establishment operates. This specification allows us to infer the establishment- and sector-specific characteristics that determine the survival process.

Establishment-specific factors include technical efficiency level and the degree of returns to scale at time *t-1* (*releff* and *relrts*).[10] The average annual rate of technical change (*relrtc*), and the average annual changes in technical efficiency (*greff*) and the degree of returns to scale (*grrts*) achieved since the time of entry are also included to test the effects of (active) learning on survival.

The framework summarized in Section 2 suggests that the opportunity cost of being in the industry has a negative impact on survival probability. We use capital intensity relative to the industry mean (*rellk*) as a proxy for this factor, because capital-intensive establishments could not be flexible enough to move into other activities. In other words, capital-intensive establishments may tend to be more likely to continue their operations in the same industry.

Establishment size in terms of the number of employees (*relsize*), and the annual average growth rate (*grsize*) are also included into the model because almost all empirical studies on this topic have found that size is one of the most important determinants of survival probability. The size variable may have a significant impact on the exit decision because it could be related to the expected prices. A large establishment can control to some extent the product price to enhance its profits. Therefore, large establishments tend to survive longer. The growth rate of the establishment will have the same effect on expectations.

There are, of course, some industry-level variables that are important in setting the product price. The first one is the size distribution of establishments in the industry (*lldev*). If establishments in the industry are of equal size, competition would be fierce, and the product price, and, hence, the value of continuing the operation will be lower. In other words, the probability of survival will be positively correlated with the size distribution of

[10] Since the effect of returns to scale depends on how far the establishment is located from the "optimum" point, we use the absolute value of the difference between the degrees of returns to scale of the establishment and of the industry in the Cox model.

establishments. Another important dimension of the market structure is, of course, the number of establishments in the industry (*lnest*). If there are many firms in the market, the market will be more competitive that leads to higher probability of exit.

Finally, we use some additional industry-level variables to capture industry-specific differences in the innovative environment, concurring with Audretsch (1991 and 1999) that the effects of "technological regimes" on post-entry performance may be important. We use the proportion of innovative establishments (*inno*), the proportion of innovative large establishments (*lseinno*), and the proportion of innovative small establishments (*smeinno*) to test if survival probabilities are affected by "technological regimes". The innovation data was collected for the first time in Turkey by the State Institute of Statistics (SIS) in 1998.[11] The survey covers the innovation activities of establishments in the period 1995-97. We calculated proportions of innovative establishments for all ISIC 3-digit industries for the period 1995-97. Since the innovation data are not available for all years, we also use the average rates of technical change for all ISIC 4-digit industries for each year, and use this variable (*sectrtc*) in the estimation of the Cox proportional hazards model.

Cox hazards function estimation results are summarized in Table 4. The table presents "hazard ratio" estimates that indicate the effects of variables on the baseline hazard (exit) probability. If the hazard ratio is equal to one, the variable under consideration does not have any effect on the exit probability. A hazard ratio larger (smaller) than one indicates that the variable increases (decreases) the hazard probability.

In the first model in Table 4, three productivity variables (efficiency, returns to scale, rate of technical change) and the current size are included. Estimation results indicate that more efficient and large establishments are more likely to survive, whereas establishments with scale disadvantages are more likely to exit. It is interesting that

[11] The survey adopted a questionnaire compatible with the *Community Innovation Survey* of the EU, and the concept of innovation as defined by the *Oslo Manual*.

establishments that achieve relatively faster technical change are also more likely to exit. However, this variable (*relrtc*) becomes insignificant when the sectoral innovation variables are added into the model.

In the second model, growth rates, size differentiation, and capital intensity variables are included. The technical efficiency variable now becomes insignificant and all new variables have expected effects on hazard probability. It is interesting that, although the growth rates of returns to scale and size variables (*grrts* and *grsize*) are highly correlated, both of them have significant coefficients.

Sectoral innovativeness variables (*inno*, *lseinno*, and *smeinno*) are included in Models 3 and 4. All these variables are statistically significant. Establishments have higher survival probabilities in industries populated with innovative establishments. Moreover, the coefficient of the small establishment innovativeness variable is smaller than the coefficient of the large establishment innovativeness variable. In other words, small firm innovativeness has a stronger impact on the survival probability.[12] Finally, when the (log) number of establishments and sectoral rate of technical change variables are included, large establishment innovativeness becomes insignificant. Sectoral rate of technical change variable has also insignificant coefficient when it is included into the model with innovation variables. The number of establishments has the expected positive impact on the hazard rate.

Our findings support both active and passive learning models: those establishments that perform worse tend to exit earlier, whereas improvements in performance make establishments to stay longer. In this process, establishment size and returns to scale where the establishment operates are both important determinants of survival, even if they are highly correlated. The survival dynamics are also shaped by innovativeness of the industry

[12] In order to explore if sectoral innovativeness has a different impact on small and large establishments, we also included size-sectoral innovativeness interaction terms into the model, but these interaction variables all had insignificant coefficients.

in which the establishment operates. Entrants are more likely to survive in industries populated, especially by small, innovative establishments. The likelihood of survival confronting entrants is generally lower in “mature”, less dynamic industries.

6. Conclusions

The analysis of productivity dynamics at the establishment level reveals that

a) New firms usually start small,
b) New firms, on average, are less efficient and enter at sub-optimal scale, but achieve somewhat higher rate of technical change,
c) There is a positive correlation between entry size and entry level of efficiency,
d) Those establishments that have lower efficiency level and sub-optimal scale are more likely to exit, and
e) Those establishments that increase their efficiency and/or scale after entry are more likely to survive.

To summarize, the empirical evidence shows that the productivity differential between SMEs and LSEs can be explained by the dynamics of entry, learning, selection, and exit processes. Thus, our analysis lends support to passive learning, active learning, and scale theories of productivity differentials. In other words, a large number of establishments are founded on the basis of optimistic expectations about the firm’s profit potential. The competition process selects which firms are not efficient enough to survive (passive learning). Therefore, a large proportion of firms exit within a few years after their entry, and a small number of establishments are able to improve their efficiency and survive longer (active learning). Surviving establishments tend to increase their scale and reduce their cost disadvantages that arise due to increasing returns to scale at sub-optimal levels, but they find it difficult to overcome efficiency differentials.

This process, described by Schumpeter as the process of "creative destruction", is a wasteful process. The Schumpeterian economists suggest that although this process has certain costs, experimentation and selection are necessary to create an environment where new ideas can flourish and be tested.

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Table 1. Technical change, returns to scale, and technical efficiency in Turkish manufacturing industries, 1987-97

Sector	Rate of technical change	Returns to scale	Technical efficiency
31 Food and Tobacco	-0.019	0.948	0.718
32 Textile	0.003	0.921	0.738
33 Wood Products	0.010	0.952	0.721
34 Paper and Printing	-0.009	1.022	0.831
35 Chemicals	0.009	0.945	0.705
36 Glass and Cement	0.022	0.955	0.601
37 Basic Metal	0.012	0.914	0.656
38 Engineering	0.045	0.981	0.722
39 Other Manufacturing	-0.073	1.010	0.400

Note: Mean values of ISIC 4-digit industries

Table 2. Descriptive statistics (mean values, 1987-97)

Label	Variable	All establishments			Entrants (entry values)		
		All	Small	Large	All	Small	Large
Establishment-level variables							
releff	Relative efficiency	0.000	-0.033	0.053	-0.037	-0.056	0.025
relrts	Relative returns to scale	0.000	0.055	-0.090	0.056	0.094	-0.070
relrtc	Relative rate of technical change (pp)	0.000	0.055	-0.089	0.187	0.222	0.069
	Capital bias	0.000	-0.148	0.240	-0.108	-0.193	0.174
	Labour bias	0.000	-0.303	0.489	-0.238	-0.433	0.405
	Energy bias	0.000	0.023	-0.037	-0.040	-0.068	0.049
	Raw materials bias	0.000	0.483	-0.780	0.573	0.915	-0.560
relsize	Relative size	0.000	-0.503	0.812	-0.395	-0.733	0.723
grsize	Growth rate of size	0.019	0.039	-0.014			
greff	Growth rate of efficiency	0.002	0.002	0.002			
grrts	Growth rate of RTS	-0.002	-0.003	0.000			
5year	5-year survival rate	0.439	0.416	0.512			
rellk	Relative capital stock	0.000	-0.660	1.067	-0.462	-0.873	0.896
rts	Returns to scale	0.905	0.961	0.816	0.960	0.999	0.830
Sector-level variables							
lseinno	LSE innovation rate	0.398	0.396	0.402	0.389	0.386	0.398
smeinno	SME innovation rate	0.209	0.207	0.212	0.195	0.195	0.195
İnno	Innovation rate	0.252	0.251	0.255	0.241	0.240	0.242
sectrtc	Sectoral rate of technical change (pp)	0.053	-0.036	0.197	0.032	-0.030	0.236
lldev	Standard deviation of (log) size	0.937	0.934	0.941	0.919	0.923	0.906
lnest	Number of establishments (log)	4.877	4.920	4.806	4.999	5.015	4.946
nobs	Number of observations	58554	36163	22391	8191	6291	1900
nest	Number of establishments	12788	8943	3845	8191	6291	1900

Note: SMEs are defined as establishments smaller than the (geometric) mean establishment at the ISIC 4-digit level.

LSEs are larger than the mean establishment. Size is defined by the number of employees. pp means "percentage point".

Sources: SIS, *Annual Survey of Manufacturing Industries.* Innovation data from SIS*, Technological InnovationSurvey, 1995-97.*

Table 3. Post-entry performance and entry size
(Plants survived at least 5 years)

Age	Relative size			Relative returns to scale			Relative efficiency			Relative rate of tech change (pp)		
	Small	Large	Differ.	Small	Large	Differ.	Small	Large	Differ.	Small	Large	Differ.
0	-0.731	0.776	1.508	0.073	-0.094	0.167	-0.051	0.028	0.079	0.202	-0.172	-0.373
1	-0.529	0.778	1.307	0.052	-0.097	0.148	-0.038	0.046	0.085	0.066	-0.198	-0.265
2	-0.418	0.760	1.178	0.040	-0.097	0.136	-0.036	0.044	0.080	0.018	-0.215	-0.233
3	-0.343	0.736	1.079	0.028	-0.101	0.129	-0.029	0.059	0.087	0.034	-0.244	-0.278
4	-0.273	0.687	0.960	0.023	-0.100	0.123	-0.026	0.070	0.096	-0.034	-0.543	-0.509
5	-0.237	0.706	0.943	0.016	-0.099	0.115	-0.018	0.064	0.082	-0.001	-0.520	-0.519
6	-0.229	0.689	0.918	0.016	-0.100	0.116	-0.015	0.068	0.083	-0.009	-0.465	-0.456
7	-0.221	0.727	0.948	0.008	-0.102	0.110	-0.010	0.082	0.093	-0.037	-0.381	-0.344
8	-0.186	0.753	0.939	0.008	-0.096	0.103	-0.008	0.078	0.086	-0.003	-0.405	-0.402
9	-0.180	0.773	0.953	0.013	-0.112	0.124	-0.001	0.070	0.070	-0.067	-0.331	-0.264
Anova results (F-statistic/d.o.f.)												
Age (9)		4.77 **			5.90 **			11.16 **			2.65 **	
Size (1)		1965.26 **			1532.47 **			747.18 **			80.91 **	
Age*Size (9)		7.76 **			3.84 **			0.48			0.72	

** means statistically significant at the 5% level

Table 4. Cox hazards function estimation results

Variables	Hazard ratio	Std. Err.	Hazard ratio	Std. Err.	Hazard ratio	Std. Err.	Hazard ratio	Std. Err.	Hazard ratio	Std. Err.
releff	0.783	0.091 **	1.077	0.140	1.041	0.137	1.030	0.137	1.027	0.137
relrts	3.572	0.444 **	2.179	0.307 **	2.113	0.298 **	2.096	0.297 **	2.068	0.297 **
relsize	0.779	0.016 **	0.917	0.023 **	0.922	0.023 **	0.923	0.023 **	0.922	0.023 **
relrtc	5.251	4.257 **	4.001	3.251 *	3.209	2.629	2.893	2.379	2.898	2.423
greff			0.419	0.222 *	0.430	0.230	0.436	0.233	0.431	0.232
grrts			6.582	5.081 **	6.557	5.022 **	6.595	5.043 **	6.897	5.297 **
grsize			0.530	0.068 **	0.513	0.066 **	0.508	0.065 **	0.501	0.065 **
lldev			0.694	0.053 **	0.759	0.059 **	0.777	0.062 **	0.742	0.062 **
rellk			0.865	0.009 **	0.865	0.009 **	0.865	0.009 **	0.865	0.009 **
inno					0.529	0.062 **				
lseinno							0.825	0.073 **	0.886	0.083
smeinno							0.564	0.079 **	0.624	0.092 **
lnest									1.036	0.019 **
sectrtc									0.758	0.250
# obs	23069		23067		23067		23023		23023	
# estab.	6874		6873		6873		6860		6860	
# exits	3764		3763		3763		3755		3755	
Log-likelihood	-30962		-30843		-30830		-30754		-30751	
Wald test	315.8 **		557.6 **		576.5 **		578.8 **		577.7 **	

** (*) means statistically significant at the 5% (10%) level.

Figure 2a. Relative size, cohorts of entrants

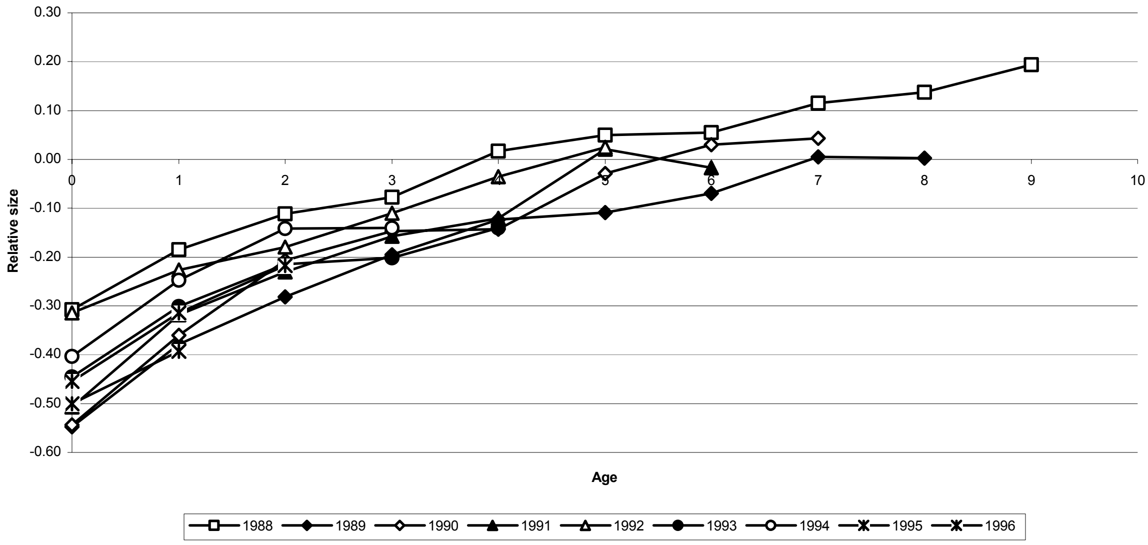

Figure 2b. Relative size of non-survivors by survival duration

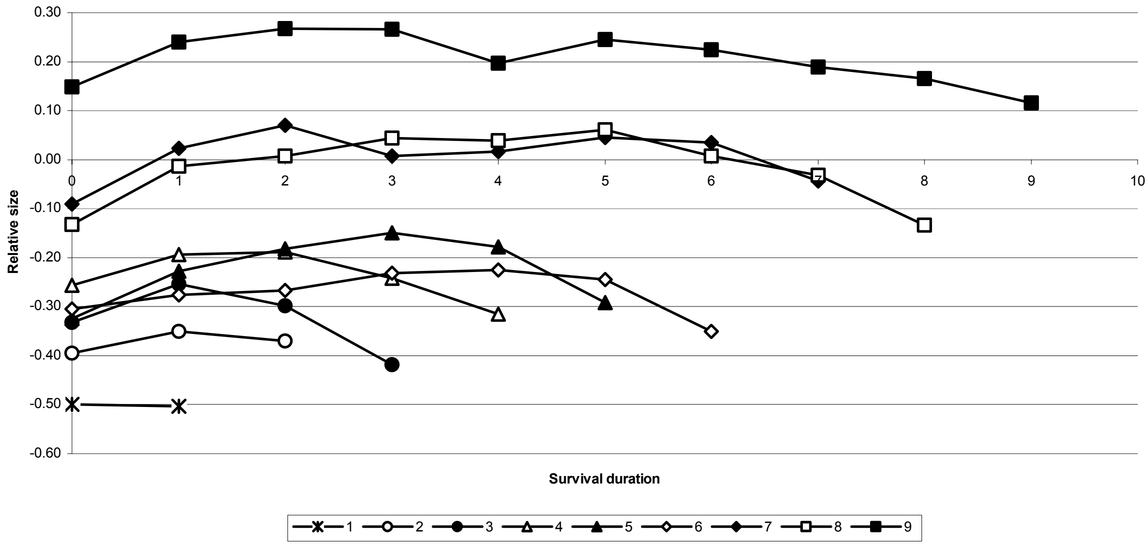

Figure 2c. Relative size or survivors by survivors' age in 1997

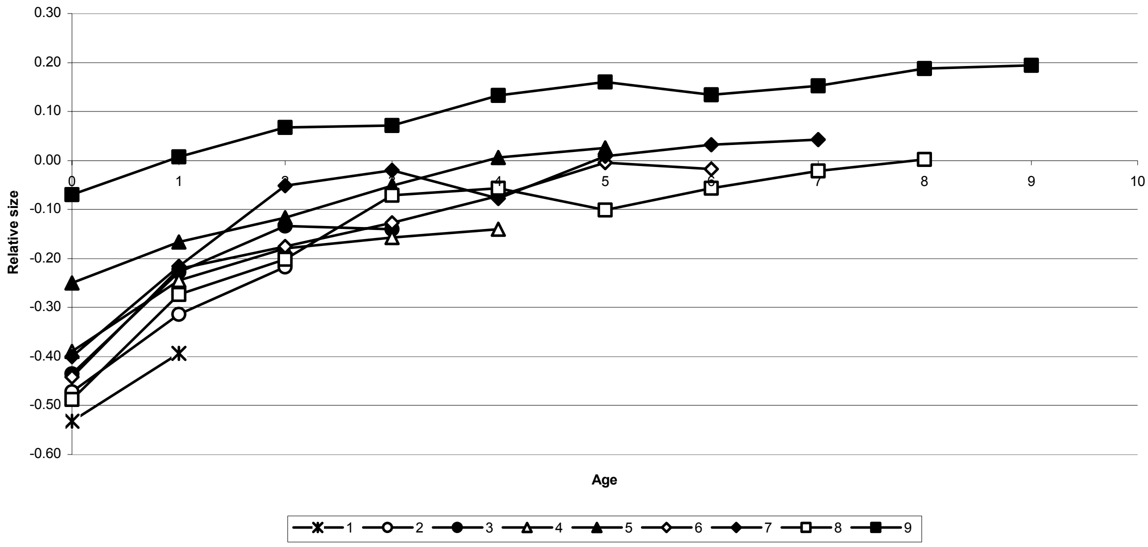

Figure 3a. Relative efficiency, cohorts of entrants

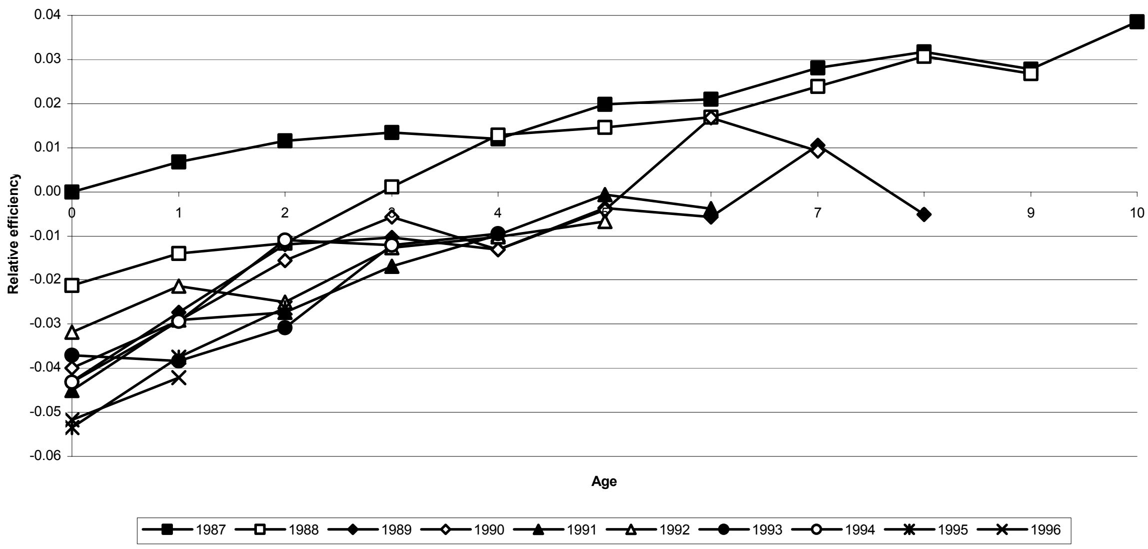

Figure 3b. Relative efficiency of non-survivors by survival duration

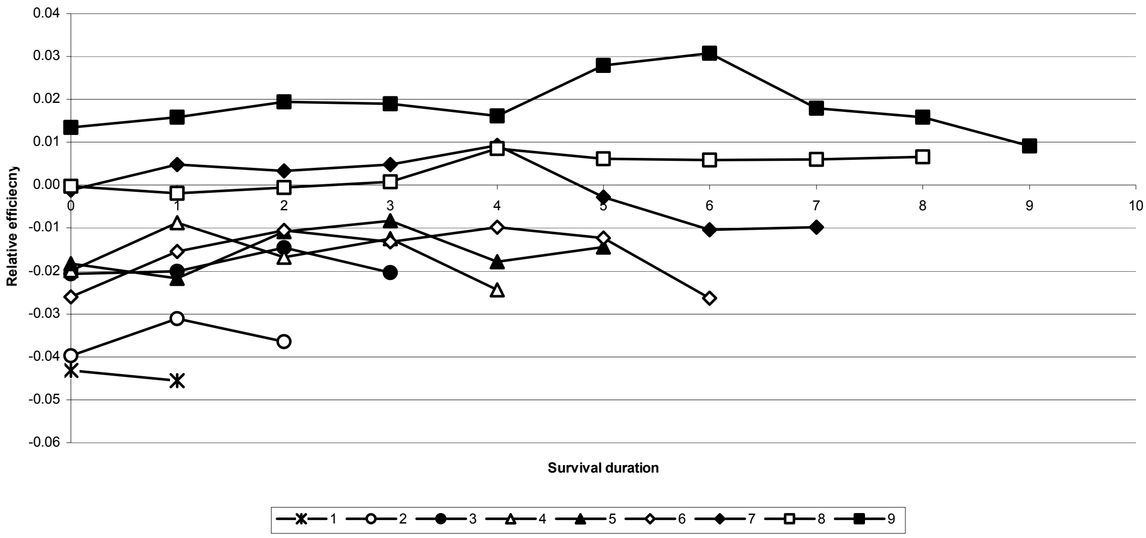

Figure 3c. Relative efficiency of survivors by survivors' age in 1997

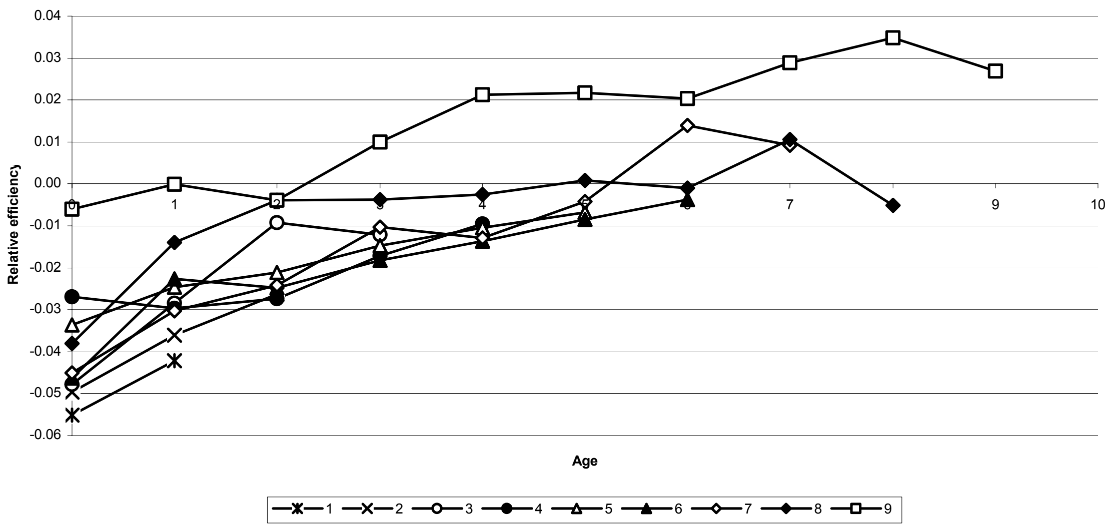

Figure 3d. Relative efficiency by entry size, cohorts of entrants

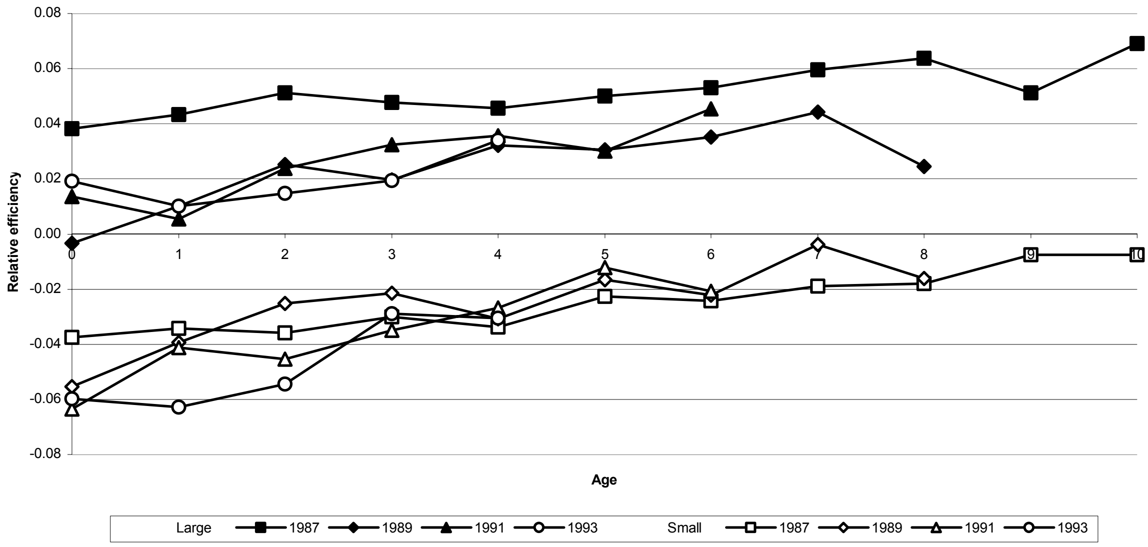

Figure 4a. Relative returns to scale, cohorts of entrants

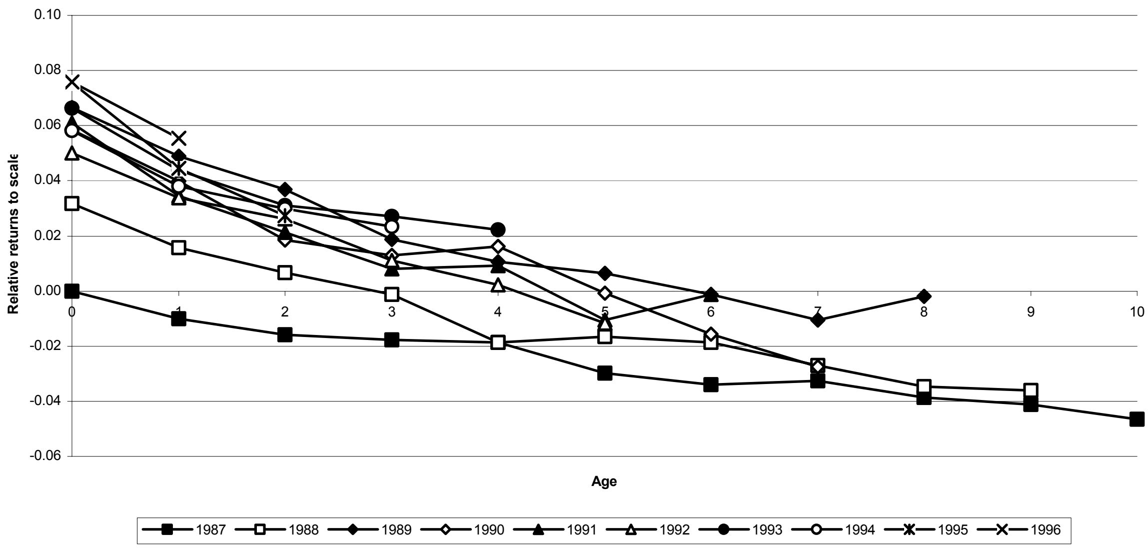

Figure 4b. Relative returns to scale by survival duration (non-survivors)

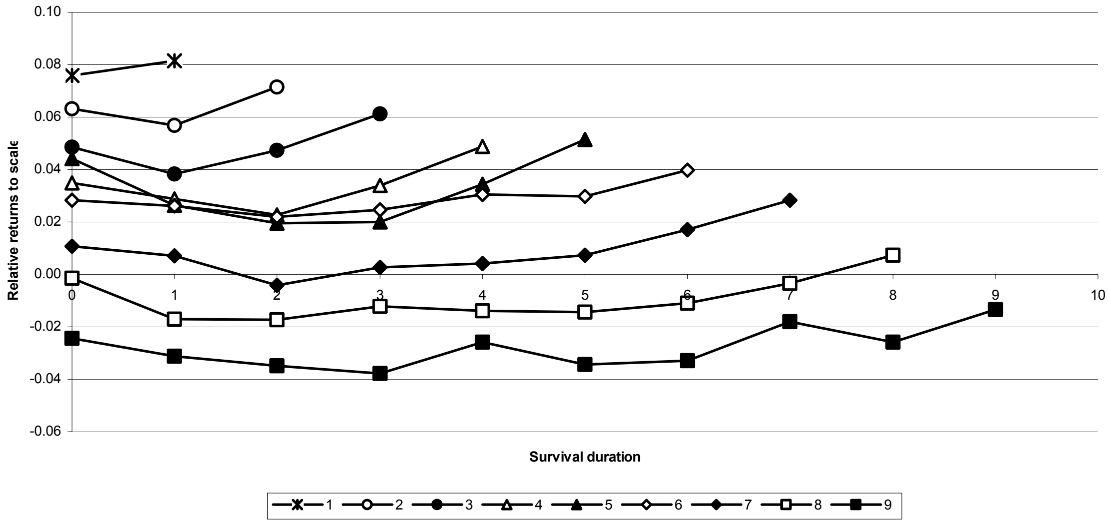

Figure 4c. Relative returns to scale, by survivors' age in 1997

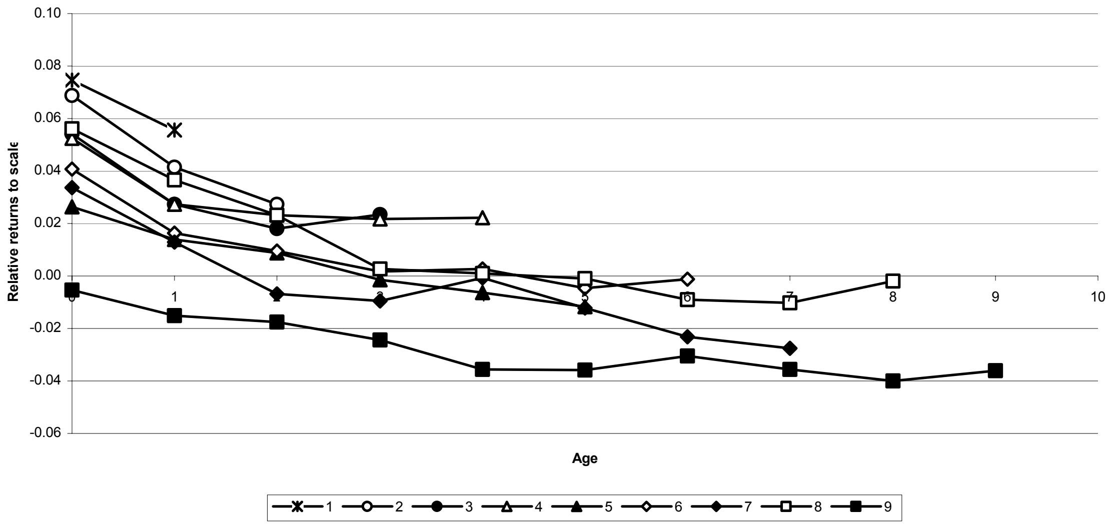

Figure 5a. Relative rate of technical change, cohorts of entrants

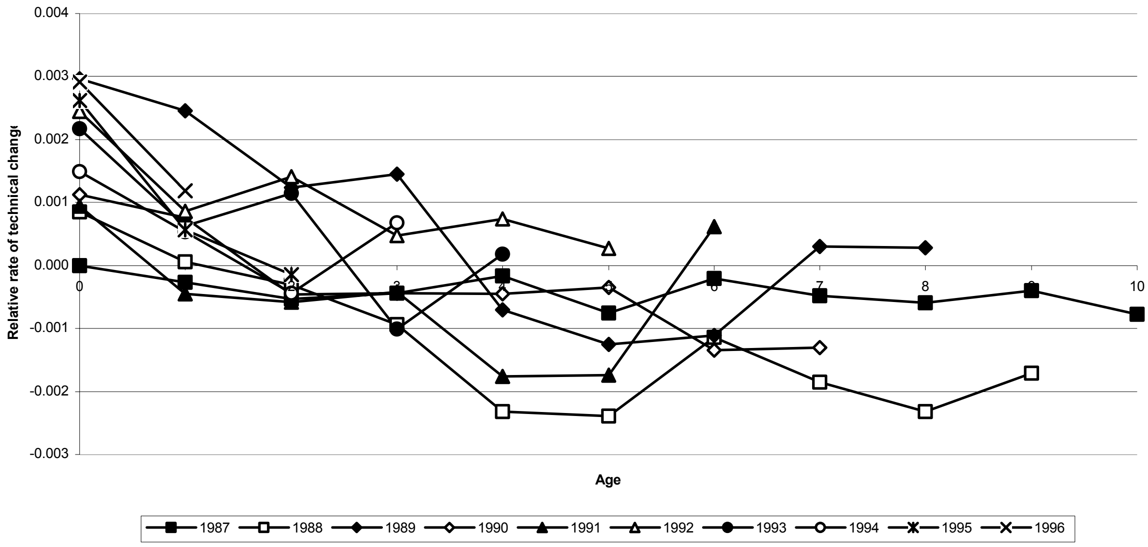

Figure 5b. Relative rate of technical change by survival duration (non-survivors)

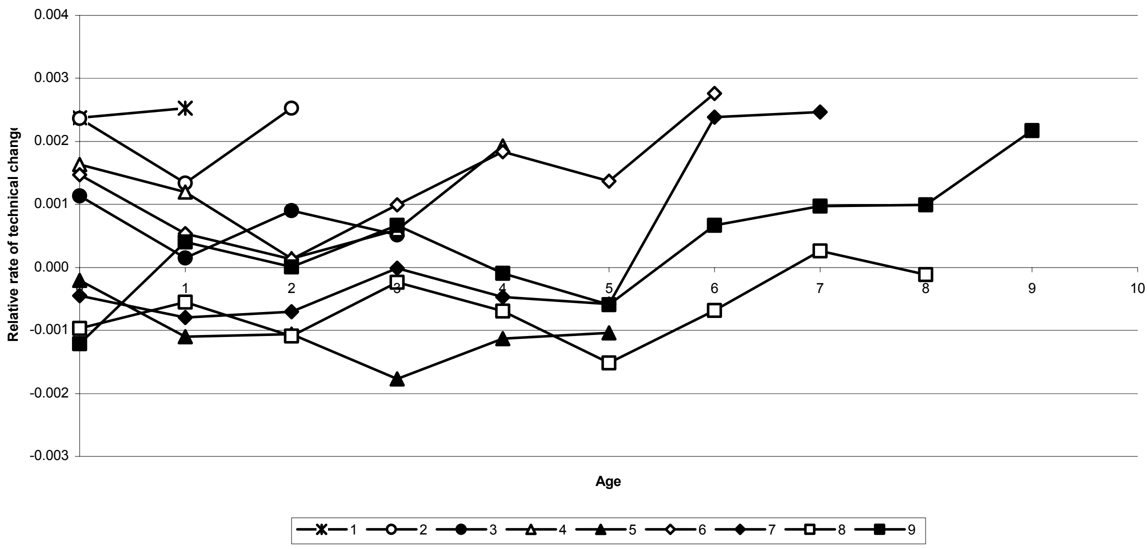

Figure 5c. Relative rate of technical change, by survivors' age in 1997