Determinants of Firm Growth: An Integrated Empirical Assessment [1]

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Abstract

The aim of the paper is to improve our understanding of the empirical determinants of firm growth by extending the literature to include new groups of variables, namely sunk costs, financial structure and multinationality as well as by using more appropriate econometric techniques. Quantile regression analysis, performed on a sample of 2600 Greek manufacturing firms, offers an integrated picture of the underlying relationships and provides reassuring support to our choice of variables. Next to the well known negative effects on growth of initial size becoming less important and age becoming more important for the upper quantiles of surviving firms, sunk costs exert a strong positive effect doubling in size at the upper end of the conditional size distribution. Foreign ownership together with liquidity exert a positive effect stronger in the middle of the distribution, while leverage becomes important in a negative way only for slow growing firms.

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I. Introduction

The aim of this research is to *empirically* investigate the determinants of firm growth drawing on a sample of around 2,600 Greek firms over the 1992-1997 period. Literature on this subject has a long history of contributions that have essentially revolved around issues regarding the determinants and trends of industry concentration and to a lesser extent the determinants of firm growth *per se.*

While reviewing the literature on firm growth, the researcher will meet rigid statements such as:

"It is now generally accepted that corporate growth rates vary (more or less) randomly across firms and over time. In fact, the data seem to be fairly well described by a Gibrat process which allows for reversion to the mean. Although these conclusions have been replicated in numerous studies, many scholars remain uneasy about accepting them. One source of concern is that of reconciling these empirical results with conventional theories of the firm" (Geroski et al. [1997] p. 171).

Whereupon corporate growth is described as an essentially random process which needs to be reconciled with traditional theories of firm growth. On the other hand, milder statements include:

"We are all so thoroughly imbued with the belief that chance favors the well-prepared that is difficult to accept a model making corporate success the result of mere chance. Still is not essential to interpret the stochastic growth models quite so literally" (Scherer and Ross [1990] p.144).

In conjunction, these statements point out that if firm growth is a random process, then some effort is needed to account for 'mean reversion' and, if firm growth is not quite literally random, then the same effort is needed to identify at least some deterministic factors affecting its evolution.

On more theoretical grounds, Cabral [1995] developed a model that attempts to provide an explanation to the inverse firm size and growth relationship that has been a commonplace finding in the more recent wave of empirical literature. His model, underlining the role of sunk costs in building capacity, leads to a number of propositions regarding the effect of sunk costs on firm growth. Namely, the propositions of interest are: a) "*If capacity costs are sunk, then small firms grow faster than large firms*". [ibid. p.165], b) "*Everything else constant, new firms' expected growth rates and the degree of sunkness of investment costs are positively correlated across industries*" [ibid. p.168], and c) "*Everything else constant, new firms' expected growth rates and the degree of sunkness of investment costs are negatively correlated across industries when firms are cash constrained and positively correlated when they cease to be cash constrained*" [ibid. p. 169] Empirically testing for the effect of sunk costs on firm growth, when the effect of other firm attributes has already been accounted for, has been a strong motivation for the present research along with the overall paucity of evidence on firm growth regarding Greek firms.

Equally important for the present research is to seek additional candidate variables that would possibly account for firm growth in the financial economics literature as well as the literature examining the effects of foreign ownership, whilst not taking so literally the suggestion that the whole process may be entirely stochastic. To this end, previous research has distinguished between multi-establishment and single-establishment firms [Dunne, Roberts and Samuelson, 1989; Variyam and Kraybill , 1992], examined growth patterns of cooperative firms [Kamshad, 1994] and the effect of multinationality on growth of parent companies [Cantwell and Sanna-Randaccio, 1993], but not on subsidiaries.

Key findings of the present research suggest that firm size, age and financial leverage are inversely related to firm growth. On the other hand, liquidity and foreign participation, defined at the firm and industry levels, have a positive effect on firm growth. In support of Cabral's [1995] theoretical propositions, sunk costs defined at the industry level exert a strong positive effect.

On the novelty side, this research also explores the effects of regressors in different quantiles of the conditional distribution of the dependent variable on the independent variables used. The results point to significant and interesting differences of these effects along the conditional distribution.

In the following section, the most important (to our view) studies within the large literature on firm growth are reviewed and the key empirical results are highlighted, paving the way for the empirical investigation to be undertaken. Next, in the third section descriptive statistics and ordinary-least-squares results are provided, whilst in the fourth section, a brief introduction to quantile regression is provided along with results on several quantiles. The final section concludes the paper.

II. Theoretical considerations and evidence on firm growth.

There is a vast literature on firm growth that has been concentrated on a nexus that runs from the shape of the size distribution of firms and the statistical generating mechanism that is capable of producing it, to the implications of the latter on firm growth and ultimately on industry concentration. The firm size distribution is skew: there are more small firms than there are large firms. This is portrayed in a graph of a probability density function where the probability mass is concentrated closer to the origin of the axes, i.e. corresponding to small firms, and has a long right tail that relates to larger firm sizes. Gibrat [1931] assumed that the lognormal distribution was a good description of the observed firm size distribution and Hart and Prais [1956] suggested the variance of the logarithms of firm sizes as an index of business concentration.

Aitchison and Brown [1957, p. 22] explain in detail how a lognormal distribution of firm sizes emerges. Following their exposition, we suppose that the variate firm size is initially S_0. It becomes S_t after the t^{th} step in a process and it reaches its final value S_n after n steps. The change in the variate at the t^{th} step is a random proportion of some function of its previous value S_{t-1}, that is $S_t - S_{t-1} = \varepsilon_t \varphi(S_{t-1})$. The *law of proportionate effect* (LPE) emerges in the special case where $\varphi(S_{t-1}) = S_{t-1}$. A formal definition for the LPE is “ *A variate subject to a process of change is said to obey the law of proportionate effect if the change in the variate at any step of the process is a random proportion of the previous value of the variate”* [ibid.]. This implies that $S_t - S_{t-1} = \varepsilon_t S_{t-1}$, or alternatively $\frac{S_t - S_{t-1}}{S_{t-1}} = \varepsilon_t$. Summing up both sides of the last expression for n steps in the process we get $\sum_{t=1}^{n} \frac{S_t - S_{t-1}}{S_{t-1}} = \sum_{t=1}^{n} \varepsilon_t$. Aitchison and Brown [ibid.] show that for small time intervals and values of the percentage increment ε_t the above relationship becomes approximately

$$\sum_{t=1}^{n} \frac{S_t - S_{t-1}}{S_{t-1}} \approx \int_{S_0}^{S_n} \frac{1}{S} dS = \log S_n - \log S_0$$

Subsequently, $\log S_n = \log S_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_n$. Steindl [1965 p.30] shows that the logarithm of firm size comes about from an additive effect of many small random variables and the logarithm of the initial size. If these random variables have identical distributions with mean μ and variance σ^2, then by the Central Limit Theorem the sum of these random variables is normally distributed with mean μt and variance $\sigma^2 t$. When $t \to \infty$, the contribution of the original size in the sum would be minuscule involving that $\log S_t \sim N[\mu t, \sigma^2 t]$. Hence S_t is log-normally distributed and in effect LPE describes a generating process for a firm size distribution that is skew, provided of course that one accepts that the actual firm size distribution is indeed lognormal[2].

The LPE, or Gibrat's law, in its strict version implies that over a period of time all firms have equal chances for the same amount of proportionate growth independently of their size at the beginning of the period. The assumptions of Gibrat's law are violated if growth rates or their variance is correlated with firm size. A weaker form of Gibrat's assumption used in Ijiri and Simon [1977] states that expected growth is independent of attained size, but only for firms in given size class.

In the context of a linear model and in a cross section setting LPE may be expressed as

$$(1)\ s_i(t) = \beta s_i(t-1) + \varepsilon_i(t)$$

where $s_i(t)$ and $s_i(t-1)$ denote differences from the cross-section mean of the logarithms of firm sizes in time t and t-1, and i indexes the i^{th} firm in a cross section of firms. Gibrat's law implies that $\beta = 1$. If $\beta < 1$ firms below average grow faster than those above it, whereas when $\beta > 1$ the opposite is the case. A number of authors have suggested [Friedman, 1992; Quah, 1993] that it is fallacious to believe that when $\beta < 1$ it necessarily suggests convergence. Or that over time there is a decrease in the variance of the variable of interest i.e. a trend for concentration of its values around its mean. Indeed,

[2] Ijiri and Simon [1977] point out that a lognormal firm size distribution can be derived from a random-walk Gibrat fashion only when it is assumed that firms start the random walk at the same time. Allowing for new entrants once the process has already started destroys lognormality (ibid. p. 138). An alternative process that allows for new entry at the smallest size class leads to Yule distribution (also skew), but at the cost that it cannot hold declines in firm sizes.

Hart and Prais [1956], Prais [1958], and Hart [1995] explain why in the context of (1) $\beta < 1$ is necessary but not a sufficient condition for decrement in the variance of firm size over time. In particular since the variance of $s_i(t)$ is

$$(2)\ \ V[s(t)] = \beta^2 V[s(t-1)] + \sigma^2$$

and it holds that $\rho^2 = \dfrac{\beta^2 V[s(t-1)]}{V[s(t)]}$,where ρ is the correlation between s(t) and s(t-1), it follows that:

$$(3)\ \ V[s(t)]/V[s(t-1)] = \beta^2 / \rho^2$$

Since $\rho \leq 1$ and given (3), an increasing variance when $\beta < 1$ can emerge only when $\rho < \beta < 1$. When $\beta > 1$ the variance always increases.

A variant of (1) in testing the relationship between firm size and growth has been proposed by Evans [1987a, 1987b].

$$S(t) = [g(A(t-1), S(t-1)]^p S(t-1)e(t),$$

where g is some growth function, A is firm age, p is the length of period over which growth of firms is being considered and e is a lognormally distributed error term. Thus,

$$[\ln S(t) - \ln S(t-1)]/p = \ln g(A(t-1), S(t-1)) + u(t),$$

where u(t) is normally distributed with zero mean and independent of A(t-1) and S(t-1). This formulation allows for more flexible specifications of the growth function. Evans, taking a second order expansion, accounts for squared terms and interaction terms between the right hand side (RHS) variables, whereas his dependent variable is essentially an annualised change in firm sizes. The effect of firm size on growth can be assessed by taking the partial derivative $g_S = (\partial \ln g / \partial \ln S)$. A $\beta < 1$ from (1) is consistent with a negative partial derivative with respect to initial size (see for example Kumar [1985]) in Evans' framework. A more direct comparison with (1) can be made if the elasticity of the end-of-period size with respect to initial size is calculated as $E_S = \dfrac{\partial \ln(S_t)}{\partial \ln(S_{1-1})} = 1 + pg_s$. In case S_{t-1} is not raised to any power and there are no interaction terms involving initial size in RHS, then it is easy to see that $1 + pg_s = \beta$.

In applied research there have been two kinds of tests regarding the validity of Gibrat's Law. The first regards direct testing of the hypothesis that firm growth is independent of firm size, i.e.β=1. The second pertains to the validity of the assumption that the firm size distribution, although admittedly skew, is indeed lognormal. The evidence on the second sort of trial of Gibrat's Law is rather limited, since the first has always been of much more interest. Interestingly, the vast majority of empirical studies testing β=1 *a priori* accept that the firm size distribution is lognormal[3].

Thus, it appears that the only discerning voices regarding the appropriateness of lognormal and similar distributions have been those of Quandt [1966] and Silberman [1967] who, using elaborated tests and econometric techniques, have concluded that these are rather a poor fit. On the other hand, Hart and Oulton [1996; 1997] notice that the usual tests tend to reject the hypothesis of normality of the log-transformed firm sizes in large samples. Arguing that no theoretical distribution could fit real data exactly, they propose that *"if a particular distribution is approximately true and if it simplifies the task before us"* (ibid. 1997 p. 206) it should be used.

Early studies (Hart and Prais [1956]; Hart [1962]) using UK data that span from the 1850s to 1950s provide evidence in support to the operation of Gibrat's Law. Hart in particular (ibid. p. 39) makes the point that his*" results reinforce the view that there is a large stochastic component in the forces determining the growth of firms, which makes it difficult to adopt a deterministic explanation"*. Samuels [1965], on the other hand, using data on quoted companies finds that in the 1951-1960 period large firms were growing at a faster proportional rate than small firms resulting in concentration levels that were higher than if Gibrat's law was in operation. In the US, Simon and Bonini [1958] studied growth rates of the 500 largest firms for 1954-56 and found evidence that there is no difference in the growth rates of firms above some critical value. Hymer and Pashigian [1962], using data on the 1000 largest US firms between 1946 and 1955, found an insignificant, although positive, effect of firm size on firm growth suggesting that there had not been significant differences in growth rates of large and small firms. However, the variance of growth rates was inversely related to firm size. On these grounds Gibrat's law was rejected. The inverse size and variance of growth relationship was attributed to the increased probability of decline and exit of small firms due to their cost disadvantages

[3] This is aptly put by Ijiri and Simon [1977] who point out that "… in applying the assumptions to the logarithm of the variate, we have in effect, assumed the law of proportionate effect" (ibid. p.141)

which, however, are at the same time a great motivation for small firms to try and grow faster. The argument is summarised as *"grow or go out of business"* (Hay and Morris [1991], p.543). Singh and Whittington [1975] explained the smaller variance of growth rates found in larger UK firm size-classes, arguing that large firms could be more diversified which in turn allows them to offset adverse growth prospects in one market by a good performance in another. The basic implication of Gibrat's law was also rejected in this study as it was found that in almost all industries independently considered, but also when taken together, large firms were growing faster than smaller ones (β>1) over the period 1948-1960. To further explore the substance of this result the authors examined the "persistence of growth" hypothesis, that is to regress firm growth rates over 1954-1960 on firm growth rates over 1948-1954. The coefficient obtained was positive and significant although the overall variance accounted for was small. This result suggested *"a definite tendency for the relative growth rates of individual firms to persist"* [ibid. p.21]. In a step forward this research incorporating past growth in the RHS of the basic growth equation, yielded that, to a great extent, the positive relationship between size and growth was due to positive serial correlation of growth rates.[4] Chesher [1979] pursued this point further and demonstrated that serial correlation in the error term may lead to inconsistent estimates of the parameter β. The extent of inconsistency is proved to be an inverse function of the length of study period, that is the longer the unit of time, the smaller the serial correlation in growth and the less unreliable the estimates obtained. Wagner [1992] following Chesher's framework of analysis finds evidence of 'persistence of chance' in the sense that German firms that happened to grow faster had also been growing faster in the past. In the same estimation framework and country context Armus and Nerlinger [2000] do not find significant persistence of chance and their results reject LPE by pointing out that small firms grow faster than large ones.

Mansfield [1962] finds that smaller firm exhibit more variable, but higher, growth rates than larger US firms. In testing a variant of LPE for firms of larger than minimum efficient size, Mansfield's results rejected the LPE, obtaining β<1 in all cases considered but one: that for the petroleum industry for the 1945-1954 period (β=1.01). Mansfield made the point that restricting the testing of the relationship between firm size and growth for only surviving firms may introduce a downward bias in the estimation of β, due to exclusion of laggard small firms. Dunne and Hughes [1994] further explain that

[4] Ijiri and Simon [1977] using simulations have shown that skew firm-size distributions may be brought about even in the presence of serial correlation in firms' growth rates.

the rationale behind this is that whereas slow growing large firms could slowly slip downwards through the firm size distribution which essentially could delay or even avoid their exit, shrinking small firms sooner than later pass the exit threshold in an industry. Including only surviving firms in a sample creates, *ceteris paribus*, a selectivity bias as surviving small firms are most probably faster growing ones. Despite the intellectual appeal of Mansfield's argument, it has been demonstrated in several studies which properly accounted for such source of bias, that obtaining $\beta<1$ was not in fact an artefact of sample selection (Hall [1987], Evans, [1987a,b], Dunne, Roberts and Samuelson [1989], Dunne and Hughes [1994]). However, in Hall [1987] Gibrat's Law was accepted for the larger firms, whereas Evans [1987b] notices that departures from Gibrat's law decrease for larger firm sizes. Hart and Oulton [1996] in a recent study of the relationship between firm size and growth in UK firms over 1989-1993, using an extensive and comprehensive data set, analyse in detail possible departures from Gibrat's law along the firm size distribution. In particular, using (1) and various definitions of firm size, Hart and Oulton consistently obtain $\beta<1$ for periods that span from one to four years. If, however, variables are measured with error, ordinary least squares estimates of β would be biased downwards (see Hart [1995]). This would, in turn, suggest that when $\beta<1$ in short spanned studies, this may be due to firms with transitorily small size, because of measurement error, growing faster than firms with transitorily larger size, for the same reason,. Hart and Oulton account for this potential source of bias by calculating a geometric mean β and the reciprocal of a coefficient derived from the reverse of (1).[5] This geometric mean was very close to unity raising concerns for the possibility of earlier unjust rejection of Gibrat's law. However, using sequential regressions in ascending size direction, β increased from about 0.43 to 0.80, whereas in sequential regression in descending size direction, β declined from about 1.10 to 0.86. What these findings point out is that whereas an overall regression towards the mean shows a negative relation between firm size and growth, there are significant differences of the effect of size on growth along the firm size distribution. Differences as such tend to accept Gibrat's law for large but not small firms. Farinas and Moreno [2000] using non-parametric techniques find a negative effect of size on firm growth using Spanish data, that is robust to error-in-variables bias.[6]

[5] See Prais [1958] for uses of reverse regression and Maddala [1992] for alternative remedies to this potential source of bias.
[6] To account for possible bias the authors used as regressor the average of the period instead of initial size. This has been suggested Davis et al. [1996]

Kumar [1985] investigates the relationship between firm size and growth in the UK over 1960-1976 distinguishing also growth by acquisition. His results contrast with those of Singh and Whittington [1975] in that small firms were found to be faster growing than larger ones and persistence of growth was weaker. A negative relationship between size and growth was also evident when growth by acquisition was considered. Kamshad [1994] finds a negative size growth relationship for French co-operative firms that is robust to sample selectivity. In a quite different setting Cantwell and Sanna-Randacio [1993] explore the effect of multinationality on growth of the world's largest (parent) firms and find firm size to be inversely related to growth. Audretsch et al [1999] provide evidence that rejects Gibrat's law for newborn Italian manufacturing firms. Mata [1994] finds a negative relationship between size and growth of new Portuguese firms that belong to the same cohort. In contrast, Wagner's [1994] results on new German manufacturing firm growth seem to point out that new firms small and large face the same distribution of growth probabilities. In Dunne et al [1989] research on the survival and growth of US manufacturing plants, size has been inversely related to growth of surviving plants. However, when distinction is made between plants owned by single-plant and multi-plant firms the effect of plant size turns to positive when growth of plants owned by multi-plant firms is considered. On the contrary, Variyam and Kraybill [1992] find that when the effect of other firm characteristics is held constant, the rate of growth is significantly smaller for single establishment vs. multi-establishment firms.

Jovanovic [1982] developed a theoretical model that could account for these deviations from LPE uncovered by empirical research. His model of "noisy" selection predicts a negative relationship between firm size and growth, and firm age and growth. The model assumes that firms are heterogeneous with respect to their true efficiencies and, consequently, cost levels. Firms learn about their true efficiencies as they operate in an industry. In a Bayesian learning process firms update, through experience, their expectations regarding the value of their efficiency. Those that make positive discoveries about their true efficiencies survive and grow, whereas the others decline and exit. Failure, but also growth rates decrease with firm size and age. An old, large operating firm is most probably one that has already made a series of positive discoveries about its true efficiency that leave less scope for further efficiency gains from learning. A negative age growth relation has been uncovered in a number of empirical studies and different country contexts (Evans [1987b], Dunne et al [1989] and Variyam and Kraybill [1992] for US; Dunne and Hughes [1994] for UK; Kamshad [1994] for France; Farinas and

Moreno [2000] for Spain). An exception is provided by Das [1995] who studies firm growth in the computer hardware industry in India. Firm age was found to have a positive effect on firm growth, but only when unobserved firm heterogeneity was accounted for by using firm-specific fixed effects in a panel data estimation setting.

III. Research setting, data and regressions towards the mean

From the discussion in the previous section we conclude that in most of the empirical studies that set to test the validity of Gibrat's law, the evidence has been largely unfavourable at least in what relates to its strict form. It may also be evident that there has been a time evolution in the predominant sign of the effect of initial size on firm growth. Thus, in contrast to earlier studies, it has been fairly established that small firms have tended, on average, to grow faster than larger ones. The phenomenon has often been termed as 'reversion to the mean' or regression to the mean in the Galtonian sense. In a recent paper, Hart [2000] reassesses the evidence and examines its compatibility with theoretical views regarding firm growth and the shape of cost curves. Interesting conclusions underline that persistence of growth is low. In the last decades small and young firms may be growing faster due to favourable technological progress offsetting much of the comparative advantage of large firms and to favourable government policies. Foremost, *"The systematic tendency for small and younger firms to grow more quickly is the main reason why firm growth is not entirely stochastic"* (ibid. p. 229).

It is true that the unease to accept that firm growth is governed by a Gibrat process has been expressed early in the literature. If such a process was meant to be for all and not just for surviving firms, then the incidence of firm decline (negative growth) and eventually firm death would have been independent of firm size. It was soon recognised that this could not be the case (Mansfield [1962], Singh and Whittington [1975]). Such a version of the law would have been largely incorrect, as far as a number of studies have pointed out that size and age are positively related to firm survival. Moreover, Fotopoulos and Louri [2000] demonstrated that financial structure does matter in affecting the hazard confronting new firms in Greek manufacturing industries and that firm survival may be sensitive to the economic cycle.[7] It is equally true, that proponents of 'stochastic' approaches to firm growth have always been careful to avoid suggesting that systematic forces have no effect on firms' growth (see Hart and Oulton [1996], Scherer and Ross [1990], Hay and Morris [1991], Audretsch et al [1999] and references therein).

Steindl [1965] points out that: "*To many econometricians it may seem superfluous to ask for a stochastic approach. Is it not a basic tenet of econometrics that economics deals with random processes? Of course it is, but in fact most of existing models are deterministic in character. Random elements can be introduced into the formal apparatus in two ways ... functional equations are set up for the distribution functions of the random variables… to explain how certain patterns of distributions arise…*[or in] *a deterministic approach, where the random elements play the subordinate role of a disturbance term introduced after everything essential has been already settled"* [ibid. p. 19]. Regarding the first approach it seems that there are many stochastic models of firm growth which can account for positively skew distributions (Hart and Oulton [1996]). Thus, in constructing theoretical models: *"Most authors now claim only that the distribution will be "skew", but do not specify the extent of skewness, or the particular form which the size distribution might take"* Sutton ([1997] p. 42).

In another strand of economic literature, attempts have been made to account for differences in corporate growth across firms drawing on possible effects of firms' financial structure, and giving random elements the subordinate role of a disturbance term as discussed above. A central issue is whether financial leverage affects a firm's investment decision and ultimately its growth, given its investment opportunities.[8] It seems that there is dichotomy on the effect of leverage on firm investment policies. On the one hand a firm with good investment projects is assumed to be able to raise funds whatever its debt exposure is, and on the other it is argued that a large debt may prevent the firm from financing positive net present value projects with external funds. Lang et al [1996] examine the relation between leverage and firm growth over a 20-year period using a large sample of large industrial firms and find a significant negative relation. This result places some additional weight on the effect of leverage on firm growth, as this would be expected to be weaker for the large firms used in the analysis that have access to stock markets. Lang et al. [1996] further clarify their result in that this strong negative effect holds for firms known to have low growth opportunities (low Tobin's q), but not significantly so for firms with known good growth prospects (high q). Low leverage might be signalling management's private information about a firm's future growth prospects, i.e. managers of such firms are aware that they might not be able to seize opportunities with a large debt overhang and the need to raise outside funds. At the other

[7] See discussion and references therein on the determinants on firm survival.

[8] Much discussion on these issues can be found in Lang et al. [1996] and a thorough review of theories of capital structure in Harris and Raviv [1991]

end of the spectrum in a firm with low investment opportunities, a large debt may prevent management from undertaking poor projects. Here too a negative relation between leverage and firm growth might be discerned. Opler and Titman [1994] also find that firms in the higher three deciles of leverage in their data are those with lower rates of sales growth.

Although such efforts to account for the effect of firm characteristics, other than size and age, should be welcome, it is also evident that such exercises accounted only for modest fractions of the variation in firm growth. In Lang et al [1996], their formulations account for between 6%-15% of the variation in firm growth. This seems to suggest that even if random elements are reduced, chance and unaccounted for factors remain responsible for the largest part of variation in firm growth.

The present study makes use of a sample of 2623 Greek manufacturing firms operating in both 1992 and 1997, i.e. surviving firms.[9] Individual firm information has been derived from the ICAP directory that provides financial data based on the accounts of all Plc. and Ltd. firms in Greece. About 38% of the firms in the sample are less than 10 years old, the oldest firm is 132 years old, whereas the average age is about 17 years with a standard deviation of 16.26 years.

An analytical framework as the one in (1) constitutes the basis for the empirical research undertaken here.[10] Firm size, the variable of interest, was measured in terms of total assets. Provided that the firm size distribution has often been claimed as lognormal (see for example the opening statement in Chesher [1979]) and consequently its logarithmic transformation as normal, it is worth exploring its properties in our sample. The mean of the log firm size in 1997 was about 13.67 with a standard deviation of 1.40 and a median value of 13.47. The relation of mean and median offers an indication of positive skewness. Indeed, the coefficient of skewness is about 0.65 (0 for normal distribution), whereas its coefficient of kurtosis is 3.50 (3 for normal distribution) indicating a rather leptokurtic distribution. Although, these deviations from normality do not appear to be severe, a Shapiro-Wilkinson test performed on the data confidently rejected the normality hypothesis. This may not be surprising given the discussion in Hart and Oulton [1996, 1997] presented earlier.

[9] The initial sample of about 4,000 firms that was truncated due to missing observations essential for the construction of some of the independent variables used in the econometric analyses.
[10] With a minor modification that includes a constant instead of taking deviations from the means of the variables involved as implied by (1).

To help explore the firm size distribution in our data and its deviations from normality a non-parametric kernel density estimation (Silverman [1986]) was performed. To further facilitate exploration, the data on the logarithm of firm size in 1997 ($\log S_{it}$) were taken in deviation from their mean so that the resulting variable has a zero mean.[11]

A kernel density estimator at value x is found as $\hat{f}(x) = \frac{1}{nh}\sum_{i}^{n} K\left[\frac{x - X_i}{h}\right]$ with kernel K that has the property $\int_{-\infty}^{\infty} K(x)dx = 1$, where h is bandwidth (smoothing parameter) (ibid. p. 14-15) and X_is are the values of X that fall in the same interval (bin) with width h around x.

Here $h = \frac{0.9}{n^{1/5}} m$, where $m = \min(\sqrt{\mathrm{var}[X]}, \text{interquartile range } X/1.349)$ (ibid. p. 47-48) and K is the Epanechnikov kernel (see Silverman [1986] p. 43). The result of this estimation appears in Figure 1, where a normal distribution that has the same mean and standard deviation, has been superimposed for comparison purposes.

_________________Figure1 here ________________

The log-transformation of the firm size distribution (thicker line) exhibits a right skew, and it peaks more than the corresponding normal.

Putting concerns about possible importance of these deviations from normality aside for a while, the analysis proceeds to some econometric investigations on the determinants of firm growth. For this purpose, a number of potential explanatory variables have been deployed. These are, apart from the logarithm of firm size in 1992 and the logarithm of firm age in 1992 that need not a further justification here, an industry sunk costs proxy, a financial leverage, a measure of liquidity, and the extent of foreign participation at the firm level and at the industry level.

At the industry level the present research adds to the list of already suggested variables, by employing a sunk cost proxy (SUNK). This has been defined as 1 minus the ratio of second hand machinery and equipment over total investment in machinery and equipment. This proxy provides an approximation for the extent of second hand markets

[11] The other moments of the variable in deviation form remain the same as in $\log S_{it}$

for capital components.[12] This definition follows suggestions made by Cabral [1995] and it has been applied in research dealing with the question of firm survival (Fotopoulos and Louri [2000]). Its introduction follows Gabral's theorisation and seeks to examine whether a higher level of sunk cost at the industry level induces faster growth of firms in these industries. Also at the industry level, an index of the extent of foreign firm presence was calculated as the share of an industry's fixed assets accounted for by firms with foreign participation (FSHARE). The rationale behind the introduction of this variable derives from Barrell and Pain [1993], Globerman, Ries and Vertinsky [1994], Blomstrom and Kokko [1998], Blomstrom and Sjoholm [1998], Chhibber and Majumdar [1999] and Aitken and Harrison [1999] suggesting a positive effect of multinational ownership on firm productivity growth or performance. The public good nature of the knowledge-based assets transferred to the host country by multinational firms is a main source of spillovers. Appropriation of their qualities may take place through reverse engineering, (skilled) employment turnover or direct contact with local agents. Local suppliers and sub-contractors may benefit from new technology information disseminated by multinationals in order to satisfy their advanced technical standards. Such technology diffusion improves the technical efficiency of domestic firms and enhances growth. The ensuing increase in competition has a similar effect.

At the firm level, this research adds in similar fashion with Lang et al [1996] a variable that accounts for the effect of the degree of debt burden overhang at the base year 1992. LEVERAGE has been defined by the ratio of book values of total liabilities to total assets.[13] Its introduction follows the justification made in Lang et al [1996] presented earlier. Unfortunately, since the vast majority of our firms are not introduced to the Athens Stock Exchange market, it has not been feasible to calculate Tobin's q as an index of a firm's known growth opportunities. An index of 'liquidity' in a firm's capital structure was also employed. LIQUIDITY has been defined as current assets minus inventories over total assets. It is thought that it provides some information on the extent of a firm's assets more readily available for exploiting investment opportunities, and hence its effect on firm growth is hypothesised to be positive. An index of the extent of foreign ownership at the firm level was also taken into account. FOWN is essentially a percentage of foreign participation. Firms with more than 5% percentage of foreign

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[12] Data for constructing this variable have been provided by the 1992 Annual Industrial Survey conducted by the National Statistical Service of Greece.
[13] See Lang et al [1996] for some justification for using book values.

participation represent about 6% firms in our data.[14] The introduction of this variable follows the literature mentioned in the former paragraph about the efficiency benefits of multinational vs. domestic firms. Foreign subsidiaries are expected to be more productive than their domestic counterparts due to higher technology inputs and more efficient organization in production and distribution. They tend to operate on a lower (production and distribution) cost curve than domestic firms, hence their ability to compete successfully although their knowledge of local markets and consumer preferences may be inferior. Their higher efficiency may induce higher growth in order to satisfy increasing proportions of the market. All our variables have been subjected to logarithmic transformation.[15]

The results of estimating variants of (1) are presented in Table 1 below. The results presented have been arranged as to avoid problems brought about by correlation between the RHS variables of the estimated equations.[16]

______________Table 1 here_______________

Column 1 of the table presents results of the standard, in the literature, equation.[17] The coefficient of initial size (β) is less than 1, implying that small firms are growing faster than larger ones, and the coefficient of age is negative, suggesting that younger firms are growing faster than older ones.[18] These results agree with those of earlier studies reviewed in the previous section. It has been argued that in large cross-section data sets, the null hypothesis seems to be more frequently rejected than in small samples[19] (Leamer, [1978] pp. 100-120; Chow [1983] pp. 300-302). As explained aptly by Deaton ([1997] p.130) "*larger samples are like greater resolving power on a telescope; features that are not visible from a distance become more and more sharply delineated as the*

[14] The mean of FOWN is 4% and its standard deviation 17.29%

[15] It was preferred to use FOWN in a 'continuous' variable fashion instead of choosing a cut-off point in foreign participation and construct a dummy variable that distinguishes between 'foreign' and 'domestic' firms. Doing the latter does not alter the interpretation of our results. To overcome the problem of taking logs of zero values of foreign participation 1 was added to all observations.

[16] None of the partial correlation coefficients in the RHS exceeds 25%.

[17] Accounting for industry heterogeneity by introducing industry dummies gets an estimated β of 0.907 and a coefficient on age of –0.107. In what follows industry dummies have not been included as far as inclusion of variables defined at the industry level was preferred and putting everything together would have resulted in perfect collinearity.

[18] Had the dependent variable been defined as $(\ln S_{it} - \ln S_{i,t-1})/d$ the coefficient of initial size that would been obtained is –0.0162 and can be recovered from present estimation as $(\beta - 1)/d$ where d equals 5 in the present case. Other coefficients could be recovered by simply dividing those appearing in Table 1 by d.

[19] See Evans [1987a] and Hart and Oulton [1996] for a discussion of this issue in the present research context.

magnification is turned up". Leamer [1978] suggests appropriate adjustments, regarding χ^2 and F tests, that account for the effect of sample size. These adjustments were adopted here to test a number of hypotheses by using appropriate Wald-χ^2 tests. First, the hypothesis that β=1 and second the hypothesis that all coefficients, other than that of SIZE and the constant, are jointly zero were rejected in all alternative specifications as shown in Table 1.

The effect of SUNK defined at the industry level on firm growth has been found to be positive. That is, firms in industries with higher levels of sunk costs grow faster. Foremost, this result remains positive and significant, in both conventional and sample adjusted hypothesis-testing procedures, across all alternative specifications. This suggests, that having accounted for the effect of inter-industry differences in sunk costs and other firm specific attributes, small and younger firms grow faster. The rationale for this outcome may be that growth is an insurance against exit and consequently against incurring sunk costs and this is especially true for smaller and younger firms. This agrees with propositions made by Cabral [1995] that small firms grow faster than large firms do, if capacity building costs are sunk, as it is optimal for small firms to invest more gradually than large ones.

In terms of capital structure higher 'liquidity' appears to positively affect growth, whereas a larger debt overhang negatively affects growth which accords with findings by Lang et al [1996]. However, the effect of the latter variable is statistically significant only by conventional, but not by sample-adjusted, testing procedures.

Foreign ownership at firm level has a direct and statistically sound effect on firm growth. At the same time firms in sectors with higher foreign participation appear to be faster growing than the rest. Direct access of firms to technology, experience and practices of foreign market participants has been beneficial to them. Indirect effects, at the industry level, also appear to play a positive role on firm growth, indicating the possibility of spillovers but also of competition effects.

V. Quantile regression estimations

Earlier studies have suggested that the growth-size relationship varies over the size distribution of firms (Evans [1987b]), and that the growth process followed by the smallest firms differ from that of the larger firms (Hart and Oulton [1996]). This has been inferred by running sequential regressions up and down on the *unconditional* firm size distribution. In this section, the research being motivated from these earlier findings explores the relation between firm growth and, but not only, firm size using quantile regressions suggested by Koenker and Basset [1978], (see also Koenker and Bassett [1982]). Quantile regressions are able to characterise the entire *conditional* distribution of a dependent variable given a set of repressors. Whereas, the least-squares estimation measures the effect of covariates on the conditional mean of the dependent variable, quantile regression can trace this effect at various quantiles of the conditional distribution of the dependent variable providing a more complete picture of the relationship between the dependent and independent variables.

The θth quantile $(0 < \theta < 1)$ of a random variable Y or of its corresponding distribution, denoted by ξ_θ, is defined as the smallest number ξ satisfying $F_Y(\xi) \geq \theta$. For continuous variable Y, its θth quantile is given as the smallest number ξ satisfying $F_Y(\xi_\theta) = \theta$ (Mood et al [1974] p.73). As suggested by Koenker and Bassett [1978] θth can be derived as a solution to the minimisation problem, or what is called a 'location' model[20]:

$$\min_{\beta} \frac{1}{n}\left[\sum_{i:y_t \geq \beta\}} \theta|y_i - \beta| + \sum_{i:y_t < \beta\}} (1-\theta)|y_i - \beta|\right]$$

The solution to this problem, $\hat{\beta}$, is the θth sample quantile of y.[21] The regression θth quantile is derived as an extension of the location problem and is the solution to the minimisation problem:

$$\min_{\beta} \frac{1}{n}\left[\sum_{i:y_t \geq \mathbf{x}_i'\beta\}} \theta\left|y_i - \mathbf{x}_i'\beta\right| + \sum_{i:y_i < \mathbf{x}_i'\beta\}} (1-\theta)\left|y_i - \mathbf{x}_i'\beta\right|\right]$$

The solution vector $\hat{\beta}_\theta$ has interesting properties, including that: a) it makes the θth quantile of the residuals equal to zero, b) the estimation error vector has as many zeros as the number of RHS variables, c) it holds that $\bar{y}_t = \bar{\mathbf{x}}_t'\hat{\beta}_\theta + \bar{\varepsilon}_\theta$ where $\bar{\varepsilon}_\theta$ denotes the mean of the residuals obtained from θth quantile regression, and d) the appropriate $\hat{\beta}_\theta$ solution vector is estimated using all n observations.

Buchinsky [1998] summarises the attractions of quantile regressions. Some are of particular importance for the present research. These are: a) the quantile objective function being a weighted sum of absolute deviations makes the estimated coefficient

[20] Basic exposition here follows Buchinsky [1998].
[21] For an algorithm see Koenker and D'Orey [1987].

vector robust to outlier observations, b) different solutions at various quantiles could be interpreted as differences in the response of the dependent variable to changes in the regressors taking place at various points of its conditional distribution, and d) in case of non-normal errors, quantile regressions may be more efficient than least square estimators (ibid. p. 89). This last feature seems to be particularly relevant as the unconditional distribution of firm size seems to remain skew and leptokurtic after its logarithmic transformations and Jarque-Bera tests, performed on the residuals of the regressions presented in Table 1, reject normality by all means.

Quantile regressions were performed at various quantiles and the results of the estimation are presented in Table 2. Estimation is based on the fifth column of Table1. Maintaining, the basic logarithmic formulation (variant of (1) as explained earlier) does not seem to be a problem as far as quantile regressions are equivariant to monotonic transformations, and it has been suggested that the firm size distribution is approximately, but also somehow doubtfully, lognormal.[22]

The estimated standard errors reported in Table 2 have been derived by bootstrapping since this has been suggested as both suitable and well performing method (Buchinsky [1998]) for quantile regressions. The asymptotic variance-covariance matrix was estimated by:

$$\text{Est.Var}[\beta_\theta] = \frac{1}{R-1}\sum_{r=1}^{R}(\hat{\beta}^B_{\theta r} - \overline{\beta}^B_\theta)\,(\hat{\beta}^B_{\theta r} - \overline{\beta}^B_\theta)'$$

where $\overline{\beta}^B_\theta = 1\Big/ R\sum_{r}^{R}\hat{\beta}^B_{\theta r}$, R stands for the number of replications and $\hat{\beta}^B_{\theta r}$ is the bootstrap estimator of β_θ in the rth replication. In this case, 600 replications, that is 600 drawings with replacement from the data and quantile regression runs, in order to derive the results presented in Table.2. The Pseudo-R^2 provided as a local measure of fit is suggested by Koenker and Machado [1999] and is given as $\text{Pseudo\_}R^2_\theta = 1 - \hat{V}_\theta / \tilde{V}_\theta$ where $\hat{V}_\theta$ and $\tilde{V}_\theta$ are the values of the objective function for the unrestricted and restricted[23] models respectively.

_____________Table 2 here______________

[22] This issue has been raised and clearly discussed in Mata and Machado [1996].

The quantile-regressions results could be interpreted in the same fashion as those in Table 1, i.e. a coefficient of SIZE that is less than one implies a negative effect on firm growth (the formula suggested in fn. 18 still applies), however, this time with respect to relative regression quantile. Some interesting observations emerge from inspecting the quantile regression results. The coefficient of SIZE declines as we move from lower to upper quantiles (except for θ[0.25]). This suggests that the effect of initial size has been even less decisive for the fastest growing firms. In Hart and Oulton [1996] the sequential regression results suggested the implied negative effect of size on growth was particularly true for small but not so much for large firms. In a quantile-regression conditional distribution reasoning the negative effect[24] of initial size is certainly more pronounced in faster growing firms. The negative effect of AGE increases steadily from lower to upper quantiles; again it is confirmed that younger firms were faster growing. A similar gradation has been observed for the effect of SUNK which increases sharply from lower to higher quantiles of the conditional size distribution. In contrast the effect of LEVERAGE has been of larger negative magnitude for firms in the lowest quantile. The positive effect of liquidity seems to be of particular relevance for the middle quantiles, less important for the highest and irrelevant for the lowest. Finally, the positive effect of foreign ownership at the firm level follows a similar pattern. FOWN did not benefit the laggards or the fastest growing firms but concentrated its positive effect in the middle of the distribution. A test devised by Gould [1997], testing for interquantile differences of the coefficients, was performed and accompanies the basic results in the last column of Table 2. With the notable exception of foreign ownership coefficients, and less so of LEVERAGE this tests provides that there are significant differences across quantiles for most coefficients of interest.

VI. Conclusions

The main aim of this research was to provide an empirical assessment of the determinants of firm growth using a large sample of Greek firms for the first time examined. The research has benefited from rich earlier literature on the subject. An effort, however, has been made to improve the existing understanding by examining some additional possibilities. Thus, this research extends previous results by accounting for the effect of

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[23] 'Location model' or quantile regression on a constant only.

[24] To facilitate interpretation of the coefficient of size in quantile regressions, if the dependent variable was defined as $(\ln S_{it} - \ln S_{it-1}) / d$ then the coefficients of SIZE would have been : for θ[0.10] –0.0076, for θ[0.25] –0.0050, for θ[0.50] –0.0105, for θ[0.75] –0.0172, and for θ[0.90]

sunk costs, foreign ownership, leverage and liquidity. Most of these variables vindicated their selection. Foremost, the effects of these new additions together with that of initial size and age were traced along the *conditional size distribution* producing some interesting 'snap-shots'.

Overall, the results of quantile regressions offer some reassuring support to those obtained earlier by least squares, although admittedly provide a more integrated picture of the underlying relations. Firm size and age both have a definitely negative effect on growth, age becoming much more important for the faster growing firms, while size affects more slow growing firms. Sunk costs make growth a necessity for smaller surviving firms. Foreign ownership has a positive effect on growth, which is less significant at the tails of the conditional distribution. The same applies for the effect of liquidity. The effect of leverage has been negative but is significant only for the slow growing firms at the lower tail of the distribution.

The main implication of our findings is that firm growth is not quite random. Theory provides us with new determinants, some of which have been estimated here to exert a strong influence on firm growth. Further developments in the literature may include additional explanatory variables, such as R&D and advertising or marketing intensity. Also, distinction among different degrees of foreign ownership could provide some deeper understanding of the way multinationality enhances the growth process. Policy suggestions may ensue.

–0.0230, these can easily be derived from those reported in Table2.

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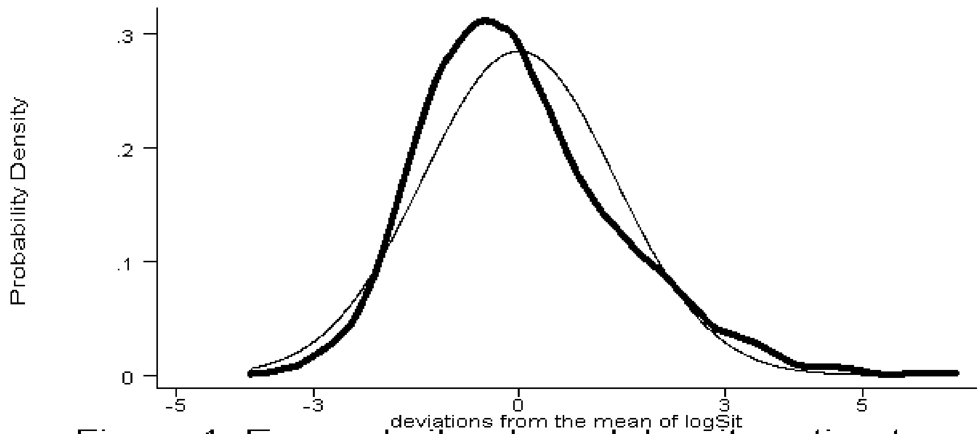

Figure 1. Epanechnikov kernel density estimate

∗**Summary statistics:** $\log S_{it}$ (total assets in 1997)**:**
Mean: 13.67589 *Median:* 13.47709 *Standard Deviation*: 1.402563 *Skewness*: 0.6562567
Kurtosis: 3.508211

Table 1 Ordinary Least Squares results (heteroskedasticity consistent standard errors)

Variables	Estimated coefficients (standard errors in parentheses)				
	(1)	(2)	(3)	(4)	(5)
SIZE (β)	0.918***	0.918***	0.903***	0.904***	0.909***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)
AGE	-0.101***	-0.104***	-0.102***	-0.103***	-0.108***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
SUNK	-	2.188***	-	2.010***	2.037***
		(0.396)		(0.396)	(0.403)
FOWN	-	-	0.069***	0.069***	0.066***
			(0.020)	(0.019)	(0.019)
FSHARE	-	-	0.163**	-	-
			(0.076)		
LEVERAGE	-	-	-	-	-0.076*
					(0.044)
LIQUIDITY	-	-	-	-	0.059***
					(0.022)
CONSTANT	2.033***	2.090***	2.187***	2.251***	2.211***
	(0.155)	(0.156)	(0.184)	(0.182)	(0.154)
$\overline{R}^2$	0.813	0.815	0.816	0.817	0.818
Wald χ^2 H_0 β=1	52.62†	54.04†	51.89†	51.43†	58.72†
	(1df)	(1df)	(1df)	(1df)	(1df)
‡Joint Wald χ^2		74.32†	62.28†	74.13†	72.87†
		(2 df)	(3 df)	(3df)	(4df)
N	2623	2623	2623	2623	2623

Leamer's adjusted for N χ^2 critical values: 7.86 (1df), 15.74 (2df), 23.61 (3df), 31.48(4df). † rejects H_0

‡ tests of the null hypothesis that all coefficients, other than those of size and constant, are jointly zero

*** significant at 1%, ** significant at 5%, * significant at 10%

Table 2. Quantile Regression Estimates
(standard errors in parentheses)

	(1) θ[0.10]	(2) θ [0.25]	(3) θ[0.50]	(4) θ[0.75]	(5) θ[0.90]	Joint Test (1) θ[0.10]- θ[0.25]=0 (2) θ[0.25]- θ[0.50]=0 (3) θ[0.50]- θ[0.75]=0 (4) q[0.75]- θ[0.90]=0 $F_{(4,2616)}$
SIZE(β)	0.962*** (0.015)	0.975*** (0.011)	0.947*** (0.012)	0.914*** (0.014)	0.885*** (0.016)	7.31***
AGE	-0.028* (0.017)	-0.034*** (0.013)	-0.082*** (0.018)	-0.138*** (0.019)	-0.207*** (0.024)	9.39***
FOWN	0.026 (0.020)	0.031*** (0.012)	0.033*** (0.012)	0.030** (0.014)	0.047* (0.027)	0.24
LEVERAGE	-0.069*** (0.025)	-0.025 (0.025)	0.002 (0.019)	-0.020 (0.037)	-0.018 (0.046)	2.52**
LIQUIDITY	0.006 (0.023)	0.044*** (0.018)	0.088*** (0.020)	0.089*** (0.029)	0.057* (0.034)	3.24***
SUNK	0.498 (0.385)	1.555*** (0.374)	2.101*** (0.415)	2.476*** (0.421)	3.136*** (0.812)	4.27***
CONSTANT	0.632*** (0.191)	0.813*** (0.136)	1.681*** (0.162)	2.623*** (0.169)	3.521*** (0.195)	
Pseudo R^2	0.591	0.604	0.608	0.607	0.584	

*** significant at 1%, ** significant at 5%, *significant at 10% level *