THE INFLUENCE OF SIZE AND R&D ON THE GROWTH OF FIRMS IN THE U.S.

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INTRODUCTION

The literature on firm size and firm growth takes "Gibrat's Law", also called the "law of proportionate effect", as its starting point. This law postulates that firm size has no systematic effect on the rate of growth of firms, implying that although the actual rate of growth of a firm is stochastic, the expected growth rate is the same across all size classes of firms. Gibrat's Law also has been used by Herbert Simon and others to explain the size-distribution of large firms in the United States. The objective of this paper is to extend the analysis, in terms of both the growth rates and the size-distribution of firms, by addressing the question: Do innovative activities and the resulting technological competition imply a qualification to Gibrat's Law? More specifically, do the size-growth relationships and the consequential size-distribution of firms depend on whether or not the firms are operating in R&D-intensive industries?

STUDIES ON GIBRAT'S LAW AND THE SIZE-DISTRIBUTION OF FIRMS

Gibrat's Law is essentially an assumption and is not based on a theoretical foundation derived from the theory of the firm. Its appeal lies in the fact that this simple law is quite successful in approximately describing the actual growth process in large groups of firms. The size-distribution of firms that is generated from the growth process also conforms, albeit as a first approximation, to the pattern that is to be expected from this law.

A number of studies have tested Gibrat's Law by investigating the empirical relationship between growth rates and size. Evans [1987] and Hall [1987], among others, studied the relationship for U.S. firms; Singh and Whittington [1975] and Kumar [1985] for firms in the U.K. The studies by Evans and Hall both based on very large samples, report mixed results. Evans finds a negative effect of size on the growth rate, while Hall finds a weak positive effect for the smaller firms and none for larger firms. For the United Kingdom, Kumar finds a weak negative relationship between size and growth, while Singh and Whittington show a mildly positive one.
Drouopoulos (1982, 1983) examined the same issue for the largest international (industrial) firms, and finds a weak positive relationship. In another international study by Buckley, Dunning, and Pearce (1984) the evidence reveals a mildly negative relationship for the world’s largest firms, including those in the U.S.

There are many proposed reasons why Gibb’s Law may or may not hold. The argument that very large firms face constraints in terms of managerial control (Penrose, 1959) has been well received. Unfortunately, there is no easy way to test this theory empirically. Another possible factor in the size-growth relationship is the “persistence of growth,” which, in econometric models, appears as serial correlation in growth rates (Singh and Whitmington, 1975; Chaveral, 1979). Persistence of growth may arise due to special talents or circumstantial advantages available to some firms who become big and continue to enjoy a higher-than-average growth rate. The empirical formulation of this paper includes the testing for autocorrelated growth, while our main purpose is to investigate the possibility that innovative activity is an additional systematic factor influencing the size-growth relationship.

Another approach is to analyse the size-distribution of firms at any particular time. Simon (1959) and Jiri and Simon (1974) show that on average proportionate growth effects generate skewed distributions, depending on variations in the specification of the stochastic model. In particular, if it is assumed that new firms are “born” in the smallest size-class at a relatively constant rate, then in the steady state, the firm-size-distribution approximates the Pareto distribution at the upper tail. In other words, if the largest firms in an economy are ranked according to size, then the size distribution follows the Pareto law. According to the Pareto law, the size of the nth firm (Sn) and its rank (n) are related and can be stated as Sn = Kn, where A and n are constants. Empirically, the actual size distribution of the largest firms in the U.S. deviates from Pareto, yielding a concave rank-size relationship. Jiri and Simon (1974) sought to explain this departure of the actual from Pareto in terms of firm mergers and autocorrelation in growth rates. Vining (1976) later showed that it is not autocorrelation per se, but the negative effect of large size on growth rate that generates the concavity. In one part of this study, the Vining result is used to compare the size-growth relationship of the R&D-intensive group of firms with that of the other group.

FIRM GROWTH UNDER TECHNOLOGICAL COMPETITION

The question as to whether R&D influences the size-growth relationship arises in context of the well-known Schumpeterian hypothesis. This hypothesis suggests that bigger firms have an advantage in the R&D process by enjoying an economy of scale in the R&D effort and also having a superior ability to exploit the results of research (Schumpeter, 1950; Kamien and Schwartz, 1982). These potential advantages, to the extent they exist, can be expected to lead to a higher level of research output for bigger firms. Size then would have a positive impact on growth on this account in the technologically progressive industries, whereas the non-R&D-intensive industries would be largely unaffected by this size-advantage of R&D. Thus, the size-growth relationship will be different between these two groups of industries.

The higher research output of bigger firms might not always translate into a positive impact on growth rates, since a successful innovator might decide to increase price and short-run profit at the expense of growth. Even in this case, however, the long-run strategy of the firm would be growth-oriented if there were both a threat of competition fromimitating rivals and an expected lasting advantage of expanded market share. Moreover, a higher level of profit itself would facilitate expansion of a firm through reinvestment. Nevertheless, the implication of the Schumpeterian advantage of size on the growth rate depends on assumptions about the behavior of the firm. The simulation models formulated by Nelson and Winter (1977, 1982a, 1982b) incorporate certain behavioral assumptions that generate a higher expected growth rate for the larger firms that is attributable to their research advantage in technological competition.

The validity of the Schumpeterian hypothesis, however, has not been firmly established. Baldwin and Scott, in a recent extensive review of the empirical literature, conclude that “among the larger enterprises in individual industries the causal relationships running from firm size to R&D effort and innovative output are, if identifiable at all, weak” (1967, 111). Differences in the size-growth relation between the technologically progressive and the other group of firms might have provided an indirect test of the Schumpeterian hypothesis itself, but it is impossible to separate out the Schumpeterian effect on the size-growth relationship since bigger firms may have some disadvantages in the growth process in R&D industries.

There are two important reasons why the bigger firms may have lower growth rates in the process of technological competition. First, in the presence of technological opportunity in a growing market, entry of the smaller firms tends to erode the market shares of the larger firms. This is what seems to have happened in the R&D-intensive industries in the U.S. at least during the 1965-77 period (Mukhopadhyay, 1982). Second, irrespective of technological opportunity, faster growth of demand, by itself, usually reduces the market share of the larger firms because of constraints on capacity expansion. Since the R&D-intensive industries are known to grow faster on the average, the larger firms may grow slower than the smaller firms in these industries. In our data set, there is no way to control for the impact of the differential growth rates of individual industries, since many firms in our sample are diversified, and there is no information on the industry-wise distribution of a firm’s total sales.

Therefore, there is no a priori expectation that larger firms will have either a higher or a lower rate of growth because of their operating in the R&D-intensive industries. In other words, it is an empirical question.

THE DATA, THE MODELS AND THE EMPIRICAL RESULTS

Our sample consists of data for 231 firms who maintain their identity over the 1965-87 period. Those firms are chosen from the Fortune list of 1000 (until 1979).
The Firm Size Growth Model

We start with the hypothesis (hypothesis 1) that firms belonging to the R&D-intensive group have the same size-growth relationship as those in the other group. Our model for testing the above hypothesis is derived from equation (1) which is the basic relationship for testing Gibrat's Law.

\[ \ln S_i = \alpha + \beta_s \ln S_{i-1} + \epsilon_i, \quad i = 1, 2, \ldots, N \]

where \( S_i \) represents the size of the \( i \)th firm (denoted by sales in this study), \( \alpha \) and \( \beta_s \) are parameters, and \( \epsilon_i \) is the random term. Subscripts \( t-1 \) and \( t \) refer to the beginning-of-the-period and the end-of-the-period values of the variables, respectively. In this model, Gibrat's Law holds if \( \beta_s = 1 \) (i.e., firm growth is independent of size). If \( \beta_s < 1 \), we expect smaller firms to grow faster, and if \( \beta_s > 1 \) then the opposite would be true. Serial correlation in the random term \( \epsilon_i \) would result in inconsistent estimates of \( \beta_s \). This is likely and would open this test to serious question (Chesher, 1979).

Now define the growth rate of the \( i \)th firm as:

\[ G_i = (S_i - S_{i-1})/S_{i-1} \]

Then it holds approximately that

\[ G_i = \alpha + (\beta_s - 1) \ln S_{i-1} + \epsilon_i \]

and, on the basis of the assumption that the \( \epsilon_i \)s are generated by the first-order autoregressive scheme,

\[ G_i = \alpha(1-\rho) + \beta \epsilon_{i-1} + (1-1)(1-\rho) \ln S_{i-1} + \epsilon_i \]

where \( \rho \) is the coefficient of autocorrelation and \( \epsilon_i \)s are serially uncorrelated with constant variance. In other words, it is assumed that autocorrelation results not from purely serial correlation in \( \epsilon_i \)s, but from misspecified dynamics arising from the exclusion of the lagged growth rate variable.

Let

\[ \beta_s = \alpha(1-\rho), \quad \beta_s = \beta \rho \quad \text{and} \quad \beta_s = (\beta - 1)/(1-\rho). \]
TABLE 1
Regression Results

<table>
<thead>
<tr>
<th>Period</th>
<th>( \hat{\beta}_1 )</th>
<th>( \hat{\beta}_2 )</th>
<th>( \hat{\beta}_3 )</th>
<th>( \hat{\beta}_4 )</th>
<th>( \hat{\beta}_5 )</th>
<th>( \hat{\beta}_6 )</th>
<th>( \hat{F}_1 )</th>
<th>( \hat{F}_2 )</th>
<th>( \hat{F}_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1972-79</td>
<td>.0108* (0.003)</td>
<td>(.0100) (0.004)</td>
<td>(.0063) (0.003)</td>
<td>(.0066) (0.003)</td>
<td>(.0071) (0.003)</td>
<td>(.0071) (0.003)</td>
<td>5.87* (0.043)</td>
<td>6.07* (0.043)</td>
<td>2.98* (0.043)</td>
</tr>
<tr>
<td>1979-83</td>
<td>.0265* (0.006)</td>
<td>(.0125) (0.002)</td>
<td>(.0160) (0.003)</td>
<td>(.0160) (0.003)</td>
<td>(.0180) (0.003)</td>
<td>(.0180) (0.003)</td>
<td>2.34* (0.034)</td>
<td>4.13* (0.034)</td>
<td>1.89* (0.034)</td>
</tr>
<tr>
<td>1983-87</td>
<td>.0293* (0.009)</td>
<td>(.0195) (0.003)</td>
<td>(.0215) (0.003)</td>
<td>(.0230) (0.003)</td>
<td>(.0280) (0.003)</td>
<td>(.0280) (0.003)</td>
<td>3.47* (0.023)</td>
<td>7.36* (0.023)</td>
<td>2.21* (0.023)</td>
</tr>
</tbody>
</table>

The numbers in parentheses are standard errors.
F1: F ratio for testing the overall significance of the model.
F2: F ratio for testing the joint significance of \( \beta_1 \) and \( \beta_2 \).
F3: F ratio for testing the joint significance of \( \beta_3, \beta_4, \beta_5, \) and \( \beta_6 \).
* indicates significance at the 10 percent level.

Table 2 reports a summary measure of firm size inequality, as indicated by the coefficient of variation.1 Despite increases in inequality in the 1983-87 period for the RD firms and the total group, and in the 1972-79 period for the NRD firms, the inequality coefficients follow a decreasing trend from 1965-87. This trend suggests a faster growth rate for the relatively smaller firms in both groups. However, the relatively larger and continuing size-inequality among RD firms could be interpreted as a reflection of the fact that the relative growth disadvantage of the larger firms in this category did not persist in the subsequent periods. Concentration within the total group (all firms) also has been affected as a result, as seen from the increasing coefficient of inequality during the 1983-87 period.

The Firm Size-Distribution Model

The use of the same set of firms over the period is necessary to study the growth pattern. However, this might create a selection bias, since the entering, exiting, and merging firms who lose their identity are eliminated. Results in Hall [1987] show that this potential bias is unlikely to be serious if the period under study is short, which is not the case here. Therefore, we supplement the empirical results of the previous section by using the alternative method of inferring about growth rates from the size-distributions of the largest 1000 firms for each of the years 1972 and 1979. The only remaining selection bias in this approach is due to the elimination of firms ranking below 1000. The Simon-Ijiri-Vining method of relating growth rate to size-distribution adjusts for this bias by deriving the distribution at the upper tail of the distribution of all firms in the economy.

For the 1972-79 period, the regression results for equation (4) above showed clearly that the disadvantage of size on growth is greater for the RD - intensive group of firms. In this section we set up this result as the hypothesis (hypothesis 2) and wish to test whether it is corroborated by the alternative method. The merit of the size-distribution approach of testing lies in the fact that it endogenizes the effects of entry and attrition of firms, and indeed, of any other factor such as merger, which might be systematically influenced because of the effect of R&D on the size-growth relationship.

The testing procedure here follows Vining [1976], whose work established that a negative effect of large size on the growth rate generates concavity in the size-distribution of firms. Null hypothesis (2), that the larger firms in the R&D group had a lower mean growth rate during 1972-79, then means that the size-distribution for this group would acquire a greater degree of concavity over this period as compared with the other group. Note that by this interpretation of the hypothesis in terms of changing size-distribution, we are adopting the view that the size-distribution in 1972 was not an equilibrium distribution in the sense of being the asymptotic result of the growth and entry process. Rather, we assume that the process at work continued to change the size-distribution, so that it is possible to test the null hypothesis (2) by comparing how the distributions for the two groups of firms changed over the period 1972-79.

To determine the degree of concavity of size-distribution, we estimate the following quadratic model suggested by Ijiri and Simon [1974]:

\[
\ln S_t = \delta_0 + \delta_1 \ln R_t + \delta_2 (\ln R_t)^2 + \epsilon_t
\]

where \( R_t \) represents the rank of the \( t \)th firm, \( \delta_0 \)'s are parameters, and \( \epsilon_t \)'s are the stochastic disturbances. Since our sample consists of firms at the upper tail of the size distribution of all the firms in the economy, the rank-size distribution should be
TABLE 3
Regression Results

<table>
<thead>
<tr>
<th></th>
<th>1972</th>
<th></th>
<th>1979</th>
<th></th>
<th>N</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β₁</td>
<td>β₂</td>
<td>β₃</td>
<td>β₄</td>
<td>β₅</td>
<td>β₆</td>
</tr>
<tr>
<td>RD</td>
<td>17.8</td>
<td>-0.021</td>
<td>-0.027</td>
<td>238</td>
<td>18.4</td>
<td>-0.689</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.056)</td>
<td></td>
<td></td>
<td>(0.040)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>NRD</td>
<td>17.4</td>
<td>-0.287</td>
<td>-0.085</td>
<td>628</td>
<td>18.3</td>
<td>-0.484</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.003)</td>
<td></td>
<td></td>
<td>(0.015)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>All Firms</td>
<td>17.7</td>
<td>-0.401</td>
<td>-0.071</td>
<td>856</td>
<td>18.4</td>
<td>-0.560</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td>(0.017)</td>
<td>(0.004)</td>
</tr>
</tbody>
</table>

The regression equations for the different groups are significantly different from each other according to the Chow F test. All coefficients are significantly different from zero at the 1 percent level.

Pareto, that is, plot as a straight line on a double log scale when Gibrat's Law holds. In terms of equation (9), the Pareto case follows when the coefficient β₁ is zero. Thus, the test for the significance of this coefficient is a test for the departure of the actual distribution from the Pareto law. It may be noted that equation (5) is a stochastic version of the deterministic Pareto relation.³

The coefficient β₅ is the rate of change of slope of the rank-size distribution, and thus indicates the degree of concavity. Regression results, presented in Table 3, show that in 1972 the R&D-intensive group had a less concave distribution indicating a greater firm size inequality, which conforms to the result, presented in Table 1, for the sample of identity-maintaining firms examined in the previous section. But concavity for this group increased during the 1972-79 period while the opposite happened for the non-R&D intensive group. This result verifies the null hypothesis for this part of our test. In addition, it conforms to the trend of the inequality coefficients in Table 2 for the 1972-79 period.⁴ Therefore, it appears that the potential selection bias in the sample of identity-maintaining firms does not affect the basic direction of the result that the size-disadvantage of growth was greater for the RD group of firms between 1972 and 1979.

SUMMARY AND CONCLUDING REMARKS

The results suggest that Gibrat's Law does not hold for the firms examined in this study. Thus, not only is there a weak negative relationship between a firm's size and its growth rate, but in addition, growth rates appear to be strongly autocorrelated throughout the period under study. This paper examined whether the size-growth relationship in the firms involved in the R&D-intensive industries is distinct from that in the other group. The results clearly show that the relationship is significantly different between the two groups in two of the three periods. During 1972-79, the disadvantage of the larger firms in growth seems to be greater in the R&D-intensive industries, a conclusion which is also supported when using the alternative procedure for inferring the growth rates from the size-distribution of firms. This result is reversed for the sub-period 1983-87, when the larger firms had a greater growth advantage in the RD group as compared with the other group. Why such a reversal might have occurred is a question that cannot be analysed within the framework of our model. One could speculate that merger activity in this period affected the growth of the larger firms more favorably in the R&D-intensive industries. Whether or not such an event remains a research question which is interesting also because of its implication regarding the relation between merger and aggregate concentration in the United States. Muller [1987, 48] notes that aggregate concentration in the U.S. started rising as merger activity intensified since 1978. A similar result shows up in our Table 2 in terms of the size-inequality of the larger firms themselves: the inequality coefficient increased during the 1983-87 period. Yet, when the NRD firms are considered separately, the inequality coefficient actually went down for this group. This suggests the possibility that the trend in the overall concentration in the U.S., the research intensive sector had a distinctly different trend compared with the other sector during the current era of increased merger activity.

NOTES

1. This is a constant elasticity model that can be linearized as \( \ln S = \alpha + \beta \ln R \). A denotes the size of the largest firm and the elasticity coefficient \( \beta \) is called Pareto's constant. Indeed, the Pareto-distribution has been extensively used to explain data on economic variables which have distributions with very long right tails. For more on the Pareto law and distribution, see Johnson and Katz [1970, 283-49].

2. Industries which are distributed to using R&D intensive are: chemicals and pharmaceuticals (38.42), measuring, scientific and photographic equipment (38.38), electric and electronic equipment (38.00), office equipment (44), motor vehicles (46), and shipbuilding and transportation equipment (35). The numbers in parentheses are Fama codes.

3. In the four sub-periods considered, the economy passed through four distinct stages. In the first sub-period, the economy enjoyed steady growth along with stable priors. The 1972-79 period represented years of slower economic growth but higher inflation rates. The third sub-period covered a recession, and the 1983-87 period consisted of recovery years with stable priors.

4. According to the above definition, \( \alpha + \beta > 1 \) for \( S_{i,t} \). Now using the Taylor expansion it follows that \( \ln(S_{i,t} + 1) \) approximates equally \( S_{i,t} \) and accordingly \( G_{i,t} + \beta G_{i,t-1} \). In all cases, the model estimated in this paper performed after other models on the basis of minimum means-square error of prediction \( E[N] \) with \( K_{i} \) and \( R \) being the number of parameters and residual sum of squares for the \( i \)th model, respectively.

5. In addition to the above model, we also estimated some alternative models suggested in the literature and also in the literature of the previous sub-period. In all cases, the model estimated in this paper performed after other models on the basis of minimum means-square error of prediction \( E[N+K_{i}, R] \) where \( N \) gives the number of observations and \( K_{i} \) and \( R_{i} \) are the number of parameters and residual sum of squares for the \( i \)th model, respectively.
6. We also calculated the average annual growth rate and an index of its stability over the mentioned sub-periods for each category. Although up and down in firm growth rate appear to differ those of the economy, it is interesting that only over the 1972-79 period, the NRD firms outperformed the other category. On the other hand, the growth rates of RD firms appear to be more static than those of the NRD group. This stability might be explained by the relatively larger size of firms in the former group.

7. The coefficient of variation (C) has the following expression \( C = S / \bar{S} \) where \( S \) and \( \bar{S} \) denote the standard deviation and the average size respectively. \( C \) implies a regular measure of concentration, the Herfindahl index \( H \), by the relation \( H = C^2 \).

8. The null hypothesis itself implies only a difference in the degree of concavity of the distributions for the two groups and does not imply that either group will have either a concave or a convex distribution. If the distributions are convex, then the null hypothesis requires the RD group to acquire a greater tendency towards concavity over the period.

9. One way of rationalizing such a stochastic curvilinear relationship is that the Pareto relation \( S_i = \alpha R_i^z \) can be written as \( S_i = \alpha R_i^{z+1} \) where \( S_i = S + \epsilon \), \( \epsilon \) is a random variable. With this adjustment, the Pareto relation reduces to equation (5) above.

10. The relative disadvantage of the larger firms in the RD group in this size-distribution study leads to a reversal of relative concavity, making the distribution for the RD group the more concave one in 1979. In terms of the coefficient of variation (C), the value of C decreased for the RD group but increased for the NRD group, over the 1972-79 period; making the NRD group more concentrated than before.

REFERENCES


