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PLANT SIZE, AGE AND GROWTH IN FINNISH MANUFACTURING[*]

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The purpose of this paper is to examine the relationships between plant size, age and employment growth in Finnish manufacturing during the period 1981–94. The findings suggest that Gibrat's law fails to hold, i.e., small plants have higher growth rates than larger ones. The findings are robust to sample selection, unobserved heterogeneity and different model specifications. It is also found that plant age is negatively related to growth at least for younger plants, which is in accordance with learning models of firm growth. Furthermore, human capital factors and macroeconomic environment have significant effects on plant growth. (JEL: J23, L11, L60)

1. Introduction

In recent years, the importance of empirical studies based on micro-level data has been widely recognised in industrial organisation. There is a large heterogeneity in firms' behaviour within industries and over the business cycle.[1] These differences are not necessarily cancelled out at the aggregate level, which restricts the applicability of the 'representative agent' hypothesis. New information on different aspects of firm and plant-level dynamics, including patterns of growth and exit, is important for the development of new policies and regulations. In particular, the assessment of the net job creation power of different-sized plants may be beneficial for developing more efficient labour market policies. Institutional settings and regulations regarding, for instance, start-up conditions, the mobility of capital and labour and business failures, have an influence on plant growth and survival through adjustment costs facing plants that are starting up, expanding, declining or shutting down.

The famous Gibrat's law of proportionate growth has been the focus of several empirical studies for many decades. According to this law, the growth rate of a firm is independent of its current size and its past growth history. Although some earlier findings lend support to Gibrat's law (e.g., Hart and Prais, 1956; Simon and Bonini, 1958), the most common finding in recent studies is that the growth rates of new and small firms are negatively related to their initial size. Thus, Gibrat's law fails to hold at

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[1] *See, for example, the International Journal of Industrial Organization 1995(4) special issue on the post-entry performance of firms.*

least for small firms (Dunne and Hughes, 1994; Mata, 1994; Hart and Oulton, 1996; Audretsch et al., 1999a; Audretsch et al., 1999b; Almus and Nerlinger, 2000; Goddard et al., 2002). In Finland, there are only a few earlier studies, which have analysed the relationship between firm size and growth (Vuori, 1981; Peisa, 1988; Berg, 1992; Hohti, 2000; Kangasharju, 2000, 2001).[2] However, the approaches used are quite different and the coverage of the data sets is mostly very limited.

This paper aims at examining factors that have contributed to the employment growth of plants in Finnish manufacturing. The study concentrates mainly on the relationship between plant size and growth, which is equivalent to testing Gibrat's law. Adding other plant and industry-level covariates, including plant age, as explanatory variables allows us to control for a considerable amount of heterogeneity among individual plants. In addition, it can be studied whether there is any evidence of a life-cycle effect based on learning, i.e., whether there is a negative relationship between plant age and growth and a positive relationship between age and the probability of survival. The analysis is also extended to take into account the effects of human capital, which have mostly been neglected in the previous literature.

Since entry and exit of plants are allowed, the data set used is an unbalanced panel covering annual growth rates of manufacturing plants over the period 1981–94. Plants with at least five employees in each year are included. The period examined covers considerable economic fluctuations, including a period of boom at the end of the 1980s followed by an exceptionally deep recession during the years 1991–94.[3] We also take into account the effect of a sample selection bias, which arises if small plants that have slow or negative growth are more likely to exit from the sample than larger plants with similar growth rates. The unobserved plant-level heterogeneity is controlled for by using panel estimation methods.

The remainder of the paper is organised as follows. In the second section different theories of firm growth are briefly reviewed. The third section describes the data used and presents some findings based on the descriptive analysis. The econometric framework and estimation results are presented in section 4. Finally, section 5 discusses the results and possibilities for further research.

2. *Theories of firm growth*

The stochastic models of firm growth are based on the Law of Proportional Effect by Robert Gibrat (1931), which in its strict form states that the expected growth rate over a specified period of time is the same for all firms regardless of their size at the beginning of the period. Thus, the assumptions of Gibrat's law are violated if the growth rate or the variance of growth is correlated with firm size. A weaker form of Gibrat's law states that the expected growth is independent of firm size only for firms in a given size class, e.g., for firms that are larger than the minimum efficient scale, MES (Simon and Bonini, 1958). According to Gibrat's law, firm's proportionate rate of growth is (e.g., Aitchison and Brown, 1957):

$$(1) \quad \frac{S_t - S_{t-1}}{S_{t-1}} = \varepsilon_t,$$

where S_t is the firm size at time t, e.g., employment, and ε_t is a random variable, which is independently distributed of S_{t-1}. As a consequence, firm size is:

$$(2) \quad S_t = (1+\varepsilon_t)S_{t-1} = S_0(1+\varepsilon_1)...(1+\varepsilon_n).$$

In short time intervals the value of ε_t is probably small, so that:

$$(3) \quad \log S_n \approx \log S_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_n.$$

Provided that log S_0 and ε_t have identical distributions with mean μ and variance σ^2, then by

[2] *In other Nordic countries, the relationship between firm size and growth has been studied, for example, in Persson (1999), Klette and Griliches (2000), Heshmati (2001), Johansson (2001), Davidsson et al. (2002) and Reichstein (2003).*

[3] *According to Statistics Finland, Finland's real gross domestic product declined by 6.4% in 1991 and the fall continued in 1992 and 1993. The unemployment reached its peak at 16.6% in 1994.*

the central limit theorem, it follows that log S_t ~ $N(\mu t, \sigma^2 t)$, when $t \rightarrow \infty$. Hence, the distribution of S_t is lognormal (or skewed) with the implication that the expected value and variance increase over time. There are many modifications of Gibrat's law, for example, the effects of entry and exit can be incorporated into the model.

During the 1980s newer profit maximisation models of firm growth and size distribution were developed. Jovanovic's (1982) life-cycle model is based on passive (Bayesian) learning. In the model entering firms differ in their relative efficiency, which is treated as a permanent characteristic of the firm. However, the firms are uncertain about their own capabilities before starting a business. After entry, new firms learn about their relative abilities only gradually through a process of natural selection. The most efficient firms grow and survive, whereas the inefficient ones exit. Jovanovic shows that young firms grow faster than the old ones when size is held constant. Jovanovic's model also implies that Gibrat's law holds for mature firms and for firms that entered the industry at the same time. In addition, the variance of growth is largest among young and small firms.

In contrast, in the model of Pakes and Ericson (1995, 1998) each firm's initial efficiency is less important because firm performance is driven by firm-specific active learning and investments in R&D and innovation activities.[4] However, this process involves significant randomness. As a result, the firm's relative efficiency changes slowly over time. The model predicts that over time the dependence between firm's current size and its initial size disappears.

In Cabral's (1995) model, capacity and technology choices involve sunk costs. Firms build only a fraction of their optimal long-run capacity in the first period after entry. This fraction is lower for small new firms because they have lower efficiency and higher probability of exit than the large ones. In the second period the firms adjust their capacity to the long-run level. As a consequence, there is a negative dependence between initial size and expected growth even after controlling for the sample selection bias. In addition, the variance of growth decreases with plant size.

Audretsch (1995) presents a theory of firm selection, which assumes that new firms typically enter at a small size relative to the minimum efficient scale. Thus, the likelihood of survival for small firms is lower because they are confronted by a cost disadvantage. However, those firms that survive will grow very rapidly in order to reach the optimal size in the industry. Thus, the model predicts that the growth rates are higher for smaller firms. Furthermore, firm growth should be higher in industries with high scale economies.

In the empirical literature there have been two main approaches in testing the validity of Gibrat's law. The first approach is to test the validity of the assumption that the firm size distribution is indeed lognormal by fitting different size distributions into the data. Even though most empirical findings confirm that the size distribution is skewed, the precise form of skewness is unknown. The second approach is based on the direct testing of the hypothesis that firm growth is independent of its size. The general view is that the plant-level heterogeneity has to be taken into account by controlling for various plant and industry-level characteristics that determine the size and growth of firms. Hence, for example, the effects of plant age, human capital and macroeconomic environment can be added to the model. In the next sections, these approaches are applied to a panel of Finnish manufacturing plants.

3. *Data and descriptive analysis*

The primary data source used in this study is the Longitudinal Data on Plants in Manufacturing (LDPM) of Statistics Finland, which is based on the annual Industrial Statistics surveys for the period 1974–2001 (Ilmakunnas et al., 2001). The Industrial Statistics covers, in principle, all Finnish manufacturing plants (or establishments) with 5 or more employees. Smaller plants are included only if their turnover corresponds to the average turnover in firms with 5–10 employees. However, over the period 1995–2001 the sample is smaller, i.e., only

[4] *Learning, in this case, could be described as evolutionary (Baldwin and Rafiquzzaman, 1995).*

plants that belong to firms with at least 20 persons are included. In addition, there are some problems with longitudinal linkages before 1980. Therefore, only the years 1981–94 are included in the analysis. In addition, only plants with at least 5 employees in each year are included in order to produce a series, which is comparable over time.[5]

The LDPM contains information on various plant-level variables, including employment, hours worked, output, value added and capital stock, which is constructed by using the perpetual inventory method.[6] The data sources also allow for the inclusion of average employee characteristics in each plant over the period 1988–94. These can be obtained from the PESA data (Plant-level Employment Statistics Data on Average Characteristics), which is formed by linking the Business Register and the Employment Statistics of Statistics Finland (Ilmakunnas et al., 2001). A plant or an establishment is defined as an economic unit that, under single ownership or control, produces as similar goods or services as possible, and usually operates at a single location.[7] The plant is chosen as the unit of analysis instead of the firm, because decisions regarding the purchase of the factors of production, including labour, are usually made at the plant level. In addition, changes in ownership and legal status do not affect the plant identification code.

A plant is considered as an entry when it appears for the first time in the LDPM during the period 1974–94. However, because of the cut-off limit, these plants may have existed before the first observation with less than five employees. Entry is thus actually defined according to the time when a plant reaches the size of five employees, which is treated as the plant's birth year. Plant age is defined as *year – birth year* + 1. However, for those plants that first appear in the LDPM in 1974 the birth year is unknown. For these plants (42.9% of the sample) information on age is obtained from the Business Register.[8] Still, information on birth year is missing in the BR for 11.7% of the plants. Subsequently, plants with no age information are excluded from the analysis. Unfortunately, the age information in the BR is not entirely reliable, and furthermore, differences in the size threshold cause the definition of age to depart from that of the LDPM. As a consequence, only age categories are used for plants born before 1975. Therefore, the basic models are estimated separately for young and old plants.

Exit is defined as concerning only those plants that are missing from the database for at least two consecutive years. If a plant is absent from the data for one year but then reappears, it is treated as a continuing plant. In this way temporary disappearances, which may be caused by a number of other reasons than permanent end of operations, for example, human errors and changes in sampling criteria, are not defined as exits. However, permanent reclassifications to or from other sectors, e.g., services, cannot be distinguished from 'true' entries or exits. In the majority of the missing observations, the plant is missing for only one year. For these plants, the missing variables are imputed as the average of the previous and subsequent year in order to calculate growth for all sub-periods. If a plant reappears after two or more years, it is excluded from the data.[9] As a consequence, the final data set consists of 10 447 plants. 63.5% of the plants (6 633 plants) in the final sample are born after 1974, which leaves 3 814 plants in the sample of older plants.[10]

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[5] *This cut-off limit may lead to a selection problem associated with excluding the smallest plants. However, further analysis is possible with data from the Business Register (BR) of Statistics Finland, which also includes the smallest firms and plants.*

[6] *The employment figures are reported as annual averages. The number of employees includes persons who are, for example, on maternity leave, on annual leave or temporarily laid-off, which may bias some of the results.*

[7] *The plant-level data used in this study includes only plants in manufacturing (mining, electricity, gas and water are excluded) which are active production plants, e.g., headquarters, service units or plants in the investment phase are not included.*

[8] *The earliest recorded start-up year in the BR is 1901.*

[9] *There were 632 plants (4.7% of the total sample) excluded for this reason.*

[10] *It should be noted that the number of exits may be biased upwards in 1993, because the plants that do not exist in 1994 may reappear in 1995, which in turn cannot be observed. By definition, these plants would be considered as continuers. However, the exit rate in 1993 is 7.2%, which*

Table 1. Growth rate, exit rate and the number of plants by size and age 1981–94.

		Age in t–1					
Size in t–1	(%)	1–7	8–15	16–29	30–59	60–	All
5–9	Growth rate	7.9	4.1	3.0	1.2	2.3	5.7
	Exit rate	14.2	15.6	16.2	11.5	12.8	14.7
	N	7643	3824	2120	885	203	14675
10–19	Growth rate	3.6	–0.9	–0.4	–1.4	–1.5	1.0
	Exit rate	7.9	7.0	7.4	3.3	5.2	7.1
	N	8789	5792	4022	1811	503	20917
20–49	Growth rate	2.6	–1.2	–1.9	–2.3	–2.0	–0.5
	Exit rate	7.9	6.2	5.7	2.3	3.6	6.0
	N	6095	5842	5847	2707	889	21380
50–99	Growth rate	2.2	–2.0	–2.9	–2.7	–1.4	–1.6
	Exit rate	6.6	4.9	4.8	2.3	2.3	4.6
	N	1856	2557	3417	1460	611	9901
100–249	Growth rate	–0.7	–2.1	–3.2	–3.3	–3.5	–2.7
	Exit rate	3.4	2.2	2.9	1.5	1.7	2.5
	N	1008	1872	3113	1321	691	8005
250–499	Growth rate	–1.7	–2.7	–4.0	–4.4	–3.9	–3.6
	Exit rate	0.4	0.7	1.3	0.2	0.3	0.8
	N	250	584	1357	446	333	2970
500–	Growth rate	–4.4	–3.8	–3.6	–2.7	–3.6	–3.5
	Exit rate	2.3	1.1	0.8	0.9	0.0	0.9
	N	129	269	744	317	202	1661
Mean growth rate		1.0	–2.2	–3.3	–3.1	–3.3	–2.4
Mean exit rate		9.4	7.4	6.1	3.1	3.2	7.1
Total number of plants in t–1 (pooled data)		25770	20740	20620	8947	3432	79509

[1] Growth rate is calculated as the logarithmic change in employment for plants in the size class between t and t–1 times 100.
[2] Exit rate is defined as the percentage of plants that exit before t.

Plant size is defined as the logarithm of employment, and subsequently, growth is the difference of plant size in two consecutive years.[11] As a consequence, the data set used is an unbalanced panel of manufacturing plants over the period 1981–94. To get some indication of the effects of plant size and age on their growth and risk of failure, Table 1 presents growth rates and exit rates for plants in each age-size category over the period 1981–94 when annual observations are pooled. Employment growth rate can only be calculated for those plants that exist in the age-size category in both years t–1 and t. Exit rate is the percentage of plants that exit before t, i.e., on average 7.1% of all manufacturing plants operating in t–1 do not survive until t. This would suggest that the possibility of a sample selection bias is rather small. The growth rate clearly declines with plant size when plant age is controlled for. The relationship between plant age and growth is also negative.[12] When the exit rates are compared for different size and age categories, the probabili-

does not seem to be too large compared to other years. During the first recession years 1990–1992 exit rates varied from 9.4% to 11.9% and before that between 3.6% and 7.9%.

[11] *Employment is chosen as a measure for plant size in order to allow for comparisons with various earlier studies, to avoid the effects of inflation and to draw policy conclusions from the employment perspective.*

[12] *It should be noted that there is a clear declining trend in the Finnish manufacturing employment over the entire period 1981–94, i.e., the mean growth rate for the whole sample is –2.4%. Furthermore, this period covers substantial business cycle fluctuations, but the growth rate is also found to be non-monotonically declining with plant size for various sub-periods.*

ty of plant failure is also non-monotonically declining with size and age.

The validity of Gibrat's law can also be evaluated by assessing the normality of the plant size distribution. The mean of the logarithm of employment in the total sample is 3.36 with a standard deviation 1.18 and a median 3.14. The fact that the median is lower than the mean suggests that there is positive skewness in the distribution. It is also found that the size distribution is fairly stable over time, except for the recession years 1991–93. During these years the skewness and the kurtosis of the size distribution clearly increases, whereas the mean slightly decreases. To conclude, the descriptive results indicate that Gibrat's law does not hold for Finnish manufacturing. However, to verify this result, an econometric approach testing the impact of plant size on its subsequent growth is needed.

4. The determinants of plant growth

4.1 Econometric framework

A standard regression model for testing Gibrat's law can be formulated as follows:

$$\text{(4)} \qquad s_{it} = \alpha + \beta s_{i,t-1} + \varepsilon_{it}$$

or equivalently:

$$\text{(5)} \qquad s_{it} - s_{i,t-1} = \alpha + (\beta - 1) s_{i,t-1} + \varepsilon_{it},$$

where plant size s_{it} is the logarithm of the employment in plant i at time t and ε_{it} is an i.i.d. white noise process.[13] The parameter $\gamma = \beta - 1$ determines the relationship between size and annual logarithmic growth.[14] If $\gamma = 0$, Gibrat's law holds, and thus plant size evolves according to a random walk. If $\gamma < 0$, plant sizes are mean-reverting, i.e., small plants grow faster than the large ones. If $\gamma > 0$, plant growth paths are explosive, so that large plants grow faster than the smaller ones. Plant age and other factors related to growth can also be included in the model. A negative coefficient on the age variable suggests that learning is important since it implies that young plants grow faster than the older ones. In addition, fixed time effects can be added to the model.

The starting point of the econometric analysis is a pooled ordinary least squares (OLS) regression including only fixed time effects.[15] However, there is little basis for assuming that individual plant effects are homogeneous, which would imply that the constant term is fixed across plants and thus all plants would tend to move towards the same long-run equilibrium. Furthermore, this unobserved heterogeneity may cause the pooled OLS estimates to be biased. Using α_i instead of α in equation (5) allows for individual plant effects. The Hausman test implies that the individual plant effects are correlated with the explanatory variables in the model. Hence, the within estimator seems to be more appropriate than the generalised least squares (GLS) approach, because the GLS estimator assumes zero correlation between the disturbances and the explanatory variables. The within estimator eliminates most forms of unobserved heterogeneity, including time constant selection process and the effects of non-random entry, because it wipes out the time-invariant plant effects. The plant-specific determinants of entry can be assumed to be constant after entry has taken place.

Based on the earlier empirical findings and theories of firm growth, it can be expected that plant growth decreases with size and age. In addition, it can be hypothesised that growth increases with relative wages, labour productivity and capital intensity, because these factors can be interpreted as indicators of plant-level efficiency. Furthermore, in order to grow the plant must offer higher wages to attract more work force. Including capital intensity also allows us to control for differences in technology use across plants. The effect of human capital factors has been largely ignored in the pre-

[13] It is usually assumed that the slopes are the same for all plants, so $\beta_i = \beta$.

[14] Growth is calculated over one-year intervals to minimise the possible sample selection bias.

[15] OLS estimates can also be compared with the results of the Heckman selection model in order to assess the magnitude of the sample selection bias.

vious literature. Highly educated and experienced workers have skills that are crucial for the growth potential of the firm. It may be argued that they are faster learners, are more able to create and implement new technologies, have better management and organisational capabilities and are more productive. The share of women employees in the plant may also be related to employment growth. Thus, relative seniority, relative education and relative share of women in the plant are included in the growth equation.[16] At the industry level, R&D intensity and scale economies are expected to have a positive relationship with growth because they may act as entry barriers, and hence, reduce the average start-up size in the industry. Subsequently, entering plants have to grow rapidly in order to reach the minimum efficient scale level of output.[17]

4.2 Empirical results for young and old plants

Estimations are performed separately for young and old plants because of the problems in defining plant age. In addition, it is interesting to see whether there are differences between younger and older plants in the hypothesised relationships. Table 2 reports the summary statistics for both young and old plants. It should be noted that the growth of young plants is rather heterogenous, which is implied by the relatively large standard deviation of the growth variable. The standard deviation of growth is somewhat smaller for older plants than for younger ones. In addition, the average growth of older firms has been more negative. Other variables indicate that younger plants have, for example, higher labour productivity, higher share of educated workers and they are more likely situated in R&D intensive industries.

The estimation results for surviving young plants are reported in Table 3. The first model includes only size, age and year dummies as explanatory variables. Growth rate is clearly declining in plant size and age. As expected, year dummies show that the employment growth is more negative during the recession years 1990–92 when compared to 1981 (not reported). It should be noted that the pooled OLS displays a relatively small R^2 (0.044), which suggests that the model fit is not very good. However, this is not uncommon in large data sets.

In the second model, the growth equation is approximated by a second-order logarithmic expansion of size and age following Evans (1987a, 1987b). This flexible functional form can capture many forms of non-linearity. In the growth equation the squared terms of size and age are positive and significant. The product of size and age has a positive coefficient, which implies that the growth rate decreases with size more slowly for older plants, and correspondingly, with age more slowly for larger plants. The total effect of plant size and age on growth can be assessed by taking the partial derivatives of growth or elasticity with respect to a percentage change in size, $E_{SIZE} = (\partial \ln G/\partial \ln S)$, and age, $E_{AGE} = (\partial \ln G/\partial \ln A)$. At the sample mean, i.e., for a plant that has 19.5 employees and is 5.1 years old, $E_{SIZE} = -0.024$ and $E_{AGE} = -0.021$. Since these partial derivatives are negative, plants below average grow faster than those above it. At the turning point, where both elasticities are zero, the plant is 11.7 years old and has 84.8 employees. Above the turning point the elasticities with respect to size and age are positive. It should be noted that the higher-order terms are highly correlated with size and age, which may bias the results.

In the third model, other plant and industry-level covariates that are strongly correlated with growth are also controlled for. Due to possible multicollinearity, the higher-order terms are

[16] *Hourly wages, labour productivity, capital intensity, price-cost margin and the human capital variables are measured in relation to the industry average, which is measured at the 4-digit industry level using the SIC (Standard Industrial Classification) adopted in 1979. Labour productivity is defined as the ratio of value added to hours worked, capital intensity is the capital–labour ratio and price-cost margin is calculated as the ratio of (value added – wages – materials) to value added. Average seniority is defined as the average number of months in the firm, whereas average education is the average number of schooling years.*

[17] *Scale economies, measured with MES, are defined as the mean size of the largest plants in each industry accounting for one half of the industry value of gross real output. R&D intensity is measured as the ratio of R&D expenditures to the number of employees in the industry based on OECD database (the Analytical Business Enterprise Research and Development (ANBERD) database, OECD).*

Table 2. Descriptive statistics for young and old plants 1981–94.

	Young plants				
Variable	N	Mean	Std	Min	Max
Growth = $size_t - size_{t-1}$	37560	–0.003	0.236	–3.824	3.041
Size = ln(employment)	37560	2.968	0.963	1.609	7.952
$Size^2$	37560	9.734	6.831	2.590	63.227
Age = ln(age)	37560	1.621	0.804	0.000	2.944
Age^2	37560	3.276	2.320	0.000	8.670
Size*age	37560	4.940	3.136	0.000	21.034
Relative wages	37550	0.886	0.261	0.000	11.262
Relative labour productivity	37549	0.989	0.797	0.000	32.071
Relative capital intensity	35831	0.690	1.371	0.000	85.468
Relative seniority	16152	0.678	0.428	0.005	4.437
Relative education	16152	1.003	0.079	0.685	1.533
Relative share of women	16152	0.861	0.732	0.000	11.301
Scale economies	37560	0.072	0.117	0.000	4.210
R&D intensity	37560	0.062	0.100	0.002	0.917
	Old plants				
Variable	N	Mean	Std	Min	Max
Growth = $size_t - size_{t-1}$	36341	–0.035	0.197	–3.499	2.435
Size = ln(employment)	36341	3.838	1.235	1.609	8.715
$Size^2$	36341	16.257	10.376	2.590	75.958
Age = ln(age)	36341	3.226	0.518	2.079	4.533
Relative wages	36338	0.948	0.213	0.000	11.223
Relative labour productivity	36336	0.970	0.806	0.000	43.297
Relative capital intensity	34776	0.930	1.566	0.000	107.553
Relative seniority	12412	1.090	0.443	0.008	9.382
Relative education	12412	0.984	0.067	0.735	1.598
Relative share of women	12412	0.952	0.552	0.000	6.904
Scale economies	36341	0.096	0.197	0.005	6.964
R&D intensity	36341	0.048	0.074	0.002	0.917

[1] It should be noted that some variables are scaled for presentation purposes: Scale economies is measured in terms of 100 million Finnish marks. R&D intensity is divided by 100 000.

now excluded. Size and age are still negatively related to growth. As expected, having higher wages, labour productivity and capital intensity than the industry average increases the growth rate. In addition, growth increases with industry scale economies and R&D intensity.[18] The coefficients of the year dummies correspond to the earlier results. R^2 is still quite low (0.055) after adding other covariates, which would suggest that they do not add much explanatory power to the model.

The focus of interest in the fourth model is on the effects of employee characteristics on growth. The inclusion of human capital variables does not have any effect on the size coefficient. Growth is higher for plants with less experienced workers relative to the industry average.[19] It should be noted, however, that seniority is likely to be positively related to plant age, which may be reflected in the results. The relationship between relative education and growth is positive, but insignificant. However, excluding seniority leads to a significant coefficient for education. Using data on Swedish manufacturing 1987–95, Persson (1999) also finds that plants employing highly educated people grow

[18] *The results should be interpreted with caution because of possible endogeneity problems with some of these variables. However, when the estimation is repeated with lagged values of wages, productivity and capital intensity, the magnitude and significance of the coefficients do not change notably (not reported).*

[19] *Heshmati (2001) has studied the effects of the availability of human capital at the regional level, which could be an interesting alternative for further analysis.*

Table 3. Growth models for young plants.

Variable	Pooled OLS Model (1)	Model (2)	Model (3)	Model (4)	Within Model (5)
Size	–0.021 (0.001)***	–0.078 (0.007)***	–0.025 (0.001)***	–0.024 (0.002)***	–0.507 (0.009)***
Size^2		0.007 (0.001)***			
Age	–0.028 (0.002)***	–0.063 (0.007)***	–0.028 (0.002)***	–0.021 (0.002)***	–0.000 (0.009)
Age^2		0.009 (0.002)***			
Size*age		0.004 (0.002)**			
Relative wages			0.024 (0.005)***	0.026 (0.008)***	0.031 (0.015)**
Relative labour productivity			0.020 (0.002)***	0.028 (0.003)***	0.034 (0.004)***
Relative capital intensity			0.009 (0.001)***	0.008 (0.001)***	0.000 (0.004)
Relative seniority				–0.028 (0.005)***	–0.041 (0.011)***
Relative education				0.021 (0.025)	–0.079 (0.046)*
Relative share of women				–0.004 (0.003)	–0.012 (0.005)***
Scale economies			0.044 (0.011)***	0.063 (0.015)***	0.005 (0.051)
R&D intensity			0.108 (0.013)***	0.106 (0.015)***	0.163 (0.046)***
Constant	0.094 (0.006)***	0.206 (0.013)***	0.057 (0.007)***	0.052 (0.026)**	1.624 (0.060)***
N of obs.	37560	37560	35830	15223	15223
N of plants					4015
R^2	0.044	0.046	0.055	0.071	0.279

[1] Standard errors in parantheses.
[2] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.
[3] Year dummies are included in all estimations.

more rapidly than plants dominated by less-educated workers.

Finally, the within estimates are compared to the OLS estimates in model (5), which includes all the covariates. The coefficient for seniority remains negative and significant, whereas the negative effect of the share of women becomes highly significant. Somewhat surprisingly, the coefficient for education is negative. This conflicting result may be explained by the empirical finding that the personnel structure is determined during the early stages of the plant life cycle and does not change much over time (Davis et al., 2000). Thus, the within estimator may wipe out some of the effects. It may be argued that having highly educated workers is relatively more important for younger and smaller plants. When interactions of education and age and education and size are added to the OLS estimation, it is found that the positive effect of education on growth declines with plant age and size (not reported). However, the interaction terms are very highly correlated with age and size. In contrast, Maliranta (2003) finds a positive relationship between the plant's average education level and net employment growth using both OLS and plant fixed effects. However, different measures for size and growth are used.[20]

[20] *The growth patterns of those plants that belong to firms with more than one plant may differ from the growth*

Table 4. Growth models for old plants.

	Pooled OLS				Within
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Size	–0.011	–0.043	–0.013	–0.012	–0.373
	(0.001)***	(0.005)***		(0.002)***	(0.011)***
$Size^2$		0.004			
		(0.001)***	(0.001)***		
Age 16–29	0.005	0.005	0.005	–0.055	–0.053
	(0.003)	(0.003)	(0.004)	(0.028)**	(0.029)*
Age 30–59	0.007	0.007	0.008	–0.054	–0.065
	(0.004)**	(0.004)**	(0.004)**	(0.028)*	(0.033)**
Age 60–	0.010	0.010	0.012	–0.051	–0.044
	(0.005)**	(0.005)**	(0.005)**	(0.028)*	(0.044)
Relative wages		0.066	0.008	0.028	0.024
		(0.010)***	(0.005)	(0.011)***	(0.020)
Relative labour productivity			0.014	0.014	0.013
			(0.001)***	(0.002)***	(0.004)***
Relative capital intensity			0.002	0.005	0.007
			(0.001)***	(0.002)***	(0.005)
Relative seniority				–0.037	–0.052
				(0.004)***	(0.009)***
Relative education				–0.033	–0.168
				(0.030)	(0.046)***
Relative share of women				–0.003	–0.009
				(0.004)	(0.007)
Scale economies			0.017	0.027	0.078
			(0.005)***	(0.009)***	(0.048)
R&D intensity			0.068	0.070	0.161
			(0.015)***	(0.020)***	(0.077)**
Constant	0.005	0.066	–0.015	0.100	1.715
	(0.005)	(0.010)***	(0.006)**	(0.041)**	(0.078)***
N of obs.	36341	36341	34774	11643	11643
N of plants					2393
R^2	0.025	0.026	0.03	0.041	0.177

[1] Standard errors in parantheses.
[2] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.
[3] Year dummies are included in all estimations.

The same specifications are also estimated for the older plants with the exception that age is included as a categorical variable (the reference group is the plants aged between 8 and 15 years). Table 4 shows that growth decreases with plant size, but the absolute effect becomes smaller. However, for older plants the relationship between age and growth seems to be positive, although the result may be partly due to the inaccuracy of the age measure. Time dummies pick up the business cycle effects rather well. The estimates for the third model for older plants correspond to the earlier findings for young plants on the relationships between other plant and industry-level variables and growth. The fourth model shows that the effect of the relative level of education of the employees is more negative for older plants both according to the OLS and the within estimates. The relative share of women is no longer significant in the within estimation.[21]

of single plants. However, when these models are estimated on plants belonging to single plant firms only, the results do not change very much. In addition, the share of multiplant observations in the sample is pretty low (17.7%).

[21] *In order to take into account the cut-off limit of 5 employees, we also estimate truncated regression models for the first three specifications with truncation from below ln5 (not reported). The negative effect of size on growth becomes weaker, but is still significant. As expected, for old plants the effect of truncation is negligible. However, there*

In the previous estimations the data is pooled across manufacturing due to the inclusion of relative and industry-level covariates. Since it is difficult to include all the relevant variables needed to control for the industry-level heterogeneity, it may also be worthwhile to test the significance of industry-level dummies. Subsequently, the previous models are estimated with only plant-level variables and controls for each industry disaggregated at the 2-digit industry level (not reported). However, the main findings remain the same. Roughly speaking, manufacturers of paper, pulp and chemicals are among the fast growers, whereas textile and wood industries have lost their employment share.

The variability of growth decreases with plant size according to many studies (e.g., Evans, 1987a), which suggests that the variance of ε_{it} is not constant across plants. However, the interpretation of the results does not change when heteroscedasticity-consistent estimates of the standard errors are calculated using the robust estimation method (White, 1982). The growth of plants may also be autocorrelated. Due to the large number of cross-sectional observations relative to the number of time periods available, it can be argued that the effect of autocorrelation should be negligible in this analysis.

4.3 Sample selection bias

Several studies find that a negative relationship exists between firm size and growth, which is consistent with the newer theoretical models on learning and selection including, e.g., Jovanovic (1982). However, Mansfield (1962) first suggested that this finding could simply be an artifact of the sample selection bias, which arises because small firms that have slow or negative growth are more likely to disappear from the sample than the larger ones. Larger firms may simply move downwards through the size distribution delaying exit, whereas smaller firms probably hit the exit threshold much sooner. This may lead to a downward biased estimate of the relationship between size and growth when only surviving firms are included. Using Cox proportional hazards model, Nurmi (2004) finds that there is a significant, negative relationship between plant size and the risk of failure in Finnish manufacturing.

Following the approach used by Evans (1987a, 1987b) and Hall (1987) to control for the effect of sample selection, a probit equation for survival is estimated jointly with the growth equation using maximum likelihood (ML), i.e., using a standard sample selection model (e.g., Heckman, 1976, 1979). It is found that the generalised tobit results closely resemble the OLS estimates (not reported). In contrast, the correlation coefficient between the disturbances of the growth and survival equations for young plants is significantly different from zero, which would indicate the presence of a sample selection bias.[22] For older plants, the effect of sample selection is not significant. In addition, the results show that the probability of survival increases with plant size and age, which gives further support to the learning hypothesis and corresponds to earlier empirical findings.

It should be emphasised that there are several problems in estimating the joint ML. Firstly, the identification of the model is problematic, because it is very difficult to find instruments that would strongly affect survival but not growth. As a consequence, the nonlinearity of the functional form is often used to improve identification, but nonlinearity may be hard to separate from the sample selection bias. Secondly, this method relies heavily on the assumption of joint normality and leads to inconsistent estimates if normality fails. Thirdly, there may be problems with heteroscedasticity, because it is often found that the variability of growth decreases with plant size. A non-constant variance for growth suggests a non-constant variance for survival as well. Due to these problems, the results for the sample selection model estimated may not be very reliable. However, due to the short growth interval used and the low number of exits, the selection bias is not

may still remain a bias due to the lower bound for growth for the smallest plants, i.e., they cannot experience high negative growth rates without disappearing from the sample (see Mata, 1994).

[22] *However, the high number of observations increases the probability that the null hypothesis will be rejected.*

likely to be very large for the data set used. Furthermore, most of the earlier studies (e.g., Evans, 1987b; Hall, 1987; Mata, 1994; Dunne and Hughes, 1994; Heshmati, 2001) conclude that the negative relationship between firm size and growth is not merely due to the sample selection bias.

4.4 Sensitivity analysis

In the last part of the analysis, the sensitivity of the results is tested using different model specifications and sub-samples of the data. Table 5 presents the within estimation results when all plants, both young and old, are included in the growth models. In addition to size, only age and growth in real gross domestic product (GDP) are included as explanatory variables. Age is used as a categorical variable because of the measurement problems described earlier. Pooled OLS is used as a starting point, and the results correspond to the earlier findings. However, the F-test rejects the hypothesis of homogeneous plant-specific effects, which would indicate that the OLS estimates are biased.

With fixed plant effects in model (2), the coefficient of size increases considerably in absolute magnitude (–0.265 compared to –0.015). Hence, the estimates are rather sensitive to the inclusion of plant-level heterogeneity. Furthermore, plants appear to be converging towards different steady-state sizes. Since the effect of plant size on growth is not necessarily linear, a categorical size variable is also tested (not reported), but the results remain very similar.[23] When size squared is added, it turns out to be positive and significant, but quite small in magnitude and highly correlated with size. Employment growth decreases with plant age, at least for younger plants.[24] Growth in real GDP has a positive effect on growth, as expected.[25] It should be noted that R^2 (0.138) is notably higher when fixed plant effects are included than for pooled OLS. When other plant and industry-level variables are added to the model, they only have a negligible impact on growth.

In model (3) lagged size (s_{t-2}) is used as a regressor instead of current size (s_{t-1}) in order to control for the possible endogeneity problem resulting from having size in both sides of the growth equation. Lagged size seems to be almost as good a predictor of growth as current size and the effect is still strongly negative. Measurement of growth over one-year periods minimises the sample selection bias and maximises the number of observations available. However, it can be argued that annual growth rates are noisy and that measurement over longer periods might decrease the randomness.[26] For comparison, in model (4) growth is calculated over two-year periods, but the results are very similar to equation (2), although the number of observations is much lower.[27]

It might be interesting to see how the effect of size differs for those plants that have experienced positive (or zero) growth and for those that have declined in size, because there may be substantial differences in, for instance, adjustment costs between these two groups. Model (5) reports the results including additive and interaction effects for decliners (*decliner* = 1 if

[23] The results are also robust to the exclusion of extreme values in the dependent variable, i.e., growth rates that are more than four standard deviations away from the mean.

[24] The reference group is plants younger than 3 years, but one-year plants drop out because growth cannot be calculated for them. Plants older than 15 years have not been divided into age categories because the age measure is most reliable for young plants, and furthermore, the effect of age on growth is likely to be the strongest at the lower end of the age distribution.

[25] When fixed time effects are used instead of growth in real GDP to control for macroeconomic influences on growth, the coefficient for the size variable does not change much (–0.269). However, the effect of age changes considerably, so that there no longer is any clear relationship between age and growth. This may be due to a high correlation between plant age and the year effects, so GDP growth is preferred to year dummies.

[26] A negative relation between plant growth and size may also imply that there is Galton's regression, i.e., regression towards the mean in plant sizes, due to transitory measurement errors. However, when growth is regressed on plant size calculated as a two-year average, ($s_{t-1} + s_{t-2}$)/2, suggested by Davis et al. (1996), the results remain very similar (not reported).

[27] An alternative way might be to include lagged annual growth in the estimation to allow for persistence in growth over time. The coefficient of lagged growth turns out to be positive and highly significant suggesting that there is some positive persistence in growth (not reported). However, the effect of size does not change much and lagged growth does not add explanatory power to the model.

Table 5. Within estimates for some model variants using all plants.

Model Variable	(1) Pooled OLS	(2) Within	(3) Lagged size	(4) Two-year growth	(5) Growers & decliners	(6) GDP & size
Size	–0.015 (0.001)***	–0.265 (0.003)***		–0.249 (0.003)***	–0.163 (0.003)***	–0.267 (0.003)***
Lagged size			–0.209 (0.003)***			
Age 3–6	–0.040 (0.003)***	–0.019 (0.003)***	–0.009 (0.004)**	–0.022 (0.004)***	–0.020 (0.003)*	–0.020 (0.003)***
Age 7–14	–0.060 (0.003)***	–0.038 (0.004)***	–0.025 (0.005)***	–0.051 (0.004)***	–0.035 (0.004)***	–0.040 (0.004)***
Age 15–	–0.063 (0.003)***	–0.074 (0.005)***	–0.051 (0.006)***	–0.097 (0.005)***	–0.071 (0.005)***	–0.076 (0.005)***
Growth in real GDP	0.700 (0.025)***	1.200 (0.027)***	0.938 (0.028)***	0.601 (0.023)***	0.276 (0.032)***	0.786 (0.082)***
GDP*size						0.118 (0.022)***
Decliner					–0.359 (0.006)***	
Decliner*size					0.021 (0.001)***	
Decliner*age 3–6					0.010 (0.006)***	
Decliner*age 7–14					0.027 (0.006)***	
Decliner*age 15–					0.055 (0.006)***	
Decliner*growth in real GDP					0.640 (0.043)***	
Constant	0.074 (0.003)***	0.908 (0.010)***	0.713 (0.011)***	0.890 (0.011)***	0.671 (0.009)***	0.917 (0.010)***
N of obs.	73901	73901	69980	32422	73901	73901
N of plants		9663	9061	8468	9665	9663
R^2	0.028	0.138	0.091	0.245	0.400	0.138

[1] Standard errors in parantheses.
[2] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

growth < 0, otherwise *decliner* = 0).[28] The effect of size is more negative for the growing plants (–0.163) than for the declining ones (–0.142), and the interaction term is highly significant. Similarly, the effect of age is somewhat stronger for plants that have experienced non-negative growth. As expected, cyclical effects are considerably higher for declining plants, i.e., higher growth in real GDP decreases negative growth more than it increases positive growth. It should be noted that the average size of growing plants (51.3 persons) is considerably lower than the average size for declining plants (99.7 persons). Growing plants are also younger on average. According to earlier results, the effect of size is more negative for young plants than for older ones, which may partly explain the results for the growing and declining plants.

Model (6) includes the interaction of plant size with growth in real GDP in the model. It turns out to be positive and highly significant implying that the business cycle effects are stronger for large plants. Hence, an improvement (deterioration) in the macroeconomic environment increases (decreases) growth more for large plants. On the other hand, holding GDP constant, an increase in size decreases

[28] *This analysis may be compared with the analysis of job creation and job destruction although the measures for plant size and growth are different. Hohti (2000) also finds that the rates of job creation and job destruction decline with plant size in Finnish manufacturing.*

growth more during recessions than during boom periods. Hence, the negative relationship between size and growth becomes stronger during recessions.[29] In contrast, when the interactions of plant age categories and GPD are included, there is no clear pattern with age (not reported). Kangasharju (2000) concludes that macroeconomic fluctuations do not alter the negative relationship between firm age and the probability of growth.

5. Conclusions

The purpose of this study was to examine the validity of Gibrat's law after controlling for other explanatory factors, unobserved plant-level heterogeneity and sample selection bias. Using data on young Finnish manufacturing plants over the period 1981–94, it is found that plant growth decreases with plant size and age. For older plants, the negative relationship between size and growth is weaker and there is no clear relationship between age and growth. Human capital factors also seem to have significant effects on growth. However, other observed plant and industry characteristics only explain a modest fraction of the variation in growth. This suggests that random elements and unobserved factors remain responsible for a large part of variation in plant growth. The results correspond to several earlier studies regarding the effects of plant size and age. The effects of employee characteristics on growth, however, would deserve more attention in the literature.

The empirical findings support the predictions of various life-cycle models on growth. The negative relationship between plant size and growth seems to hold even after controlling for the sample selection bias, which supports, for example, the sunk costs hypothesis by Cabral (1995). Furthermore, the findings of a negative relationship between plant age and growth and a positive relationship between age and survival are broadly consistent with the predictions of Jovanovic's (1982) model of firm growth, where firms uncover their true efficiencies only gradually over time. The results on a positive relationship between plant growth and industry scale economies also correspond to the theory by Audretsch (1995). The findings suggest that caution is necessary in applying Gibrat's law to the complete size distribution of firms when building theories. Furthermore, there is a need for new more comprehensive theories on firm growth that can explain the empirical finding of the inverse relationship between size and growth.

In future work, the analysis should be extended to other sectors of the economy because the patterns of growth may vary substantially between manufacturing and the service sector. The preliminary analysis using the Business Register data for the period 1989–98 with size cutoff of 3 employees shows that the relationship between size and growth is even more negative in services than manufacturing. This corresponds to our expectations because the average plant size in services is lower than in manufacturing. A more careful analysis is still needed to confirm these results.

Traditionally, similar empirical specifications testing Gibrat's law have been treated as static models. However, the dynamic context should not be forgotten. It is generally known that the within estimator generates inconsistent estimates in dynamic specifications. In addition, the bias diminishes only when the number of time periods approaches infinity despite the large number of cross-sectional observations. As a consequence, further analysis with, e.g., the Arellano-Bond (1991) generalised method of moments (GMM) might be useful.

[29] It should be noted that the correlation between GDP and its interaction with size is very high (0.93). However, when interactions of GDP with four plant size categories are used, the results remain the same.

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