Satu Nurmi

ESSAYS ON PLANT SIZE, EMPLOYMENT DYNAMICS AND SURVIVAL

HELSINKI SCHOOL OF ECONOMICS

ACTA UNIVERSITATIS OECONOMICAE HELSINGIENSIS

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To my parents

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Helsinki, February 2004

Satu Nurmi

Abstract

This thesis consists of a theoretical introduction and four empirical essays which examine the effect of plant size on its employment dynamics and the likelihood of survival. Furthermore, the thesis investigates various industry-level and regional characteristics that have an impact on the choice of plant start-up scale. In addition to plant size, the focus of interest is on the effect of plant age and human capital on employment patterns. The data sets used also make it possible to analyse the plant-level consequences of the exceptionally deep recession experienced in Finland at the beginning of the 1990s. The primary data source used is a plant-level panel data set which is based on the Industrial Statistics of Statistics Finland over the period 1980–94 covering in principle all Finnish manufacturing plants with at least five employees. In some parts the analysis is also extended to cover service-sector plants with the data from the Business Register of Statistics Finland. In addition, it is possible to use linked employer-employee data sets, which include information on worker flows and background characteristics of employees in each plant based on the Employment Statistics of Statistics Finland.

According to the results, the choice of plant start-up size is affected by various industry attributes, which may differ depending on whether a plant belongs to a multi-unit or a single-unit firm. There are no significant differences between the findings for manufacturing and services except for the different role of regional employee characteristics in the choice of start-up size. The findings indicate that small plants create and destroy relatively more jobs than their employment share would imply. In addition, there is a negative relationship between plant size and relative employment growth, in other words small plants grow relatively faster than the larger ones. The results also suggest that young plants have faster relative growth than the older ones. However, the methods of study have a considerable effect on the results. Furthermore, assessing the total welfare effect is difficult, because differences in the qualitative factors between the jobs created in different-sized plants should be taken into account. It is also found that current size predicts the likelihood of plant survival better than initial size, so that smaller plants have clearly lower chances of survival. According to the findings, small and young plants seem to have been most severely hit by the negative consequences of the recession. However, the macroeconomic effects do not alter the central findings on the relationships between plant size, growth and survival.

The findings lend support to the predictions of newer theoretical firm growth models, which describe the post-entry process of learning and adaptation that eliminates the less efficient units from the markets. The start-up scale of new plants is affected, for example, by the sunk costs and optimal size in the industry. Small new plants have a high risk of failure. However, those that are able to survive grow fast. The variance of growth decreases and the likelihood of survival increases with plant size and age through a process of learning. In addition, the findings show that the effects of human capital on firm growth and survival would deserve more attention both in the theoretical and empirical literature.

Keywords: plant size, employment, growth, survival, human capital, manufacturing

Tiivistelmä

Tämä tutkimus koostuu teoreettisesta johdannosta ja neljästä empiirisestä esseestä, joissa tarkastellaan toimipaikan koon vaikutusta sen työllisyysdynamiikkaan ja henkiinjäämisen todennäköisyyteen. Lisäksi tarkastellaan toimipaikan aloituskokoon vaikuttavia toimiala- ja aluetason tekijöitä. Toimipaikan koon lisäksi erityisenä kiinnostuksen kohteena ovat toimipaikan iän ja inhimillisen pääoman vaikutukset työllisyyskehitykseen. Aineisto mahdollistaa myös 1990-luvun alun lamavuosien toimipaikkatason seurausten analysoinnin. Ensisijaisena tutkimusaineistona on Tilastokeskuksen Teollisuustilastoon perustuva toimipaikkatason paneeliaineisto vuosilta 1980–94, joka kattaa periaatteessa kaikki suomalaiset vähintään viiden henkilön teolliset toimipaikat. Joiltakin osin analyysiä laajennetaan myös palvelusektorin toimipaikkoihin Tilastokeskuksen Yritysrekisterin avulla. Tutkimuksessa käytetään myös yhdistettyjä työnantaja–työntekijä-aineistoja, jotka sisältävät tietoa kunkin toimipaikan työntekijävirroista ja henkilöstön taustaominaisuuksista Tilastokeskuksen Työssäkäyntitilastosta.

Tulokset osoittavat, että toimipaikan aloituskoon valintaan vaikuttavat useat toimialakohtaiset tekijät, joiden vaikutus riippuu myös siitä kuuluuko toimipaikka moni- vai yksitoimipaikkaiseen yritykseen. Teollisuuden ja palvelualojen tulosten välillä ei ole merkittävää eroa lukuun ottamatta alueellisten työvoimaominaisuuksien erilaista merkitystä aloituskoon valinnassa. Tulosten mukaan pienet toimipaikat luovat ja hävittävät työpaikkoja työvoimaosuuteensa nähden suhteellisesti enemmän kuin suuret toimipaikat. Lisäksi toimipaikan koon ja työllisyyden suhteellisen kasvun välillä on negatiivinen suhde, toisin sanoen pienet toimipaikat kasvavat suuria suhteellisesti nopeammin. Tulokset osoittavat myös, että nuorilla toimipaikoilla on vanhoja nopeampi suhteellinen kasvu. Tutkimusmenetelmillä on kuitenkin huomattava vaikutus tuloksiin. Kokonaisvaltaisten hyvinvointivaikutusten arviointi on vaikeaa, koska erot erikokoisten toimipaikkojen luomien työpaikkojen laadullisissa tekijöissä tulisi myös ottaa huomioon. Tulokset osoittavat myös, että nykyinen koko ennustaa toimipaikkojen henkiinjäämistä aloituskokoa paremmin siten, että pienillä toimipaikoilla on selvästi alhaisempi henkiinjäämisen todennäköisyys. Tulosten mukaan lamavuosien negatiiviset vaikutukset kohdistuivat erityisesti pieniin ja nuoriin toimipaikkoihin, mutta makrotaloudellisten vaikutusten huomioiminen ei muuta keskeisiä tuloksia koon, kasvun ja henkiinjäämisen välisistä suhteista.

Tulokset tukevat uudempien teoreettisten yritysten kasvumallien ennustuksia, joiden mukaan yritysten elinkaareen liittyy oppimis- ja valikoitumisprosessi, joka karsii markkinoilta tehottomat yritykset. Uusien toimipaikkojen aloituskokoon vaikuttavat muun muassa uponneet kustannukset ja toimialan optimikoko. Pienillä ja nuorilla toimipaikoilla on korkea konkurssiriski, mutta ne, jotka selviävät, kasvavat nopeasti. Kasvun varianssi alenee ja henkiinjäämisen todennäköisyys kasvaa oppimisen myötä koon ja iän kasvaessa. Lisäksi tulokset osoittavat, että inhimillisen pääoman vaikutukset yritysten kasvuun ja henkiinjäämiseen ansaitsisivat lisähuomiota sekä teoreettisessa että empiirisessä alan kirjallisuudessa.

Avainsanat: koko, työllisyys, kasvu, henkiinjääminen, inhimillinen pääoma, teollisuus

CONTENTS

Acknowledgements
Abstract
Abstract in Finnish (Tiivistelmä)

I INTRODUCTION

II SECTORAL DIFFERENCES IN PLANT START-UP SIZE IN THE FINNISH ECONOMY, unpublished.

III JOB FLOWS AND JOB QUALITY BY ESTABLISHMENT SIZE IN THE FINNISH MANUFACTURING SECTOR 1980–94, *Small Business Economics* **15**: 265–281, 2000.

IV PLANT SIZE, AGE AND GROWTH IN FINNISH MANUFACTURING, unpublished.

V THE DETERMINANTS OF PLANT SURVIVAL IN TURBULENT MACROECONOMIC CONDITIONS, unpublished.

I

I

INTRODUCTION

Contents

1 Background **2**

2 Theoretical literature **5**

2.1 Gibrat's law 5

2.2 Life-cycle models on firm growth 8

2.3 Basic model on firm size and growth 9

2.4 Sunk costs in human capital 11

2.5 Worker heterogeneity and growth 13

3 Structure and aims of the study **17**

4 Main results **20**

5 Concluding comments **24**

A Data appendix **27**

1 Background

In recent years, there has been an upsurge in empirical studies related to plant-level demographics in industrial organisation literature. Clearly, this is to a large extent due to the increased availability of micro-level data on plants and firms. These panel data sets permit us to follow various plant characteristics from the moment of a plant start-up until its exit from the markets, thus allowing the analysis of the employment dynamics over the plant life cycle. As a consequence, these studies are closely related to the analysis of labour demand in labour economics literature. In addition, recent developments in theoretical models on firm turbulence and growth, accompanied by new econometric methods and advanced software, have enabled new approaches to the data.

Applied studies using comparable data sets from different countries are important for the purposes of testing the implications of theoretical models. In addition, country comparisons may reveal profound differences in institutional settings between countries. If institutions and regulations create adjustment costs impeding firm turnover, growth and the restructuring process, the country's economic performance may deteriorate (see e.g. Audretsch et al., 2002). However, there are some difficulties in comparing the results because of a large variation in methods and data sets used. First of all, the unit of observation, a plant or a firm, varies and may be defined differently depending on the data source. Secondly, the key variable, plant size, can be measured in several ways using, for example, employment, sales or assets. In addition, there are various methods of calculating growth. Thirdly, the time periods and sectors covered differ depending on the availability of the data. Most of the empirical studies are based on manufacturing, although more research on services would be needed. In addition, studies covering cyclical fluctuations over longer time periods are important. Coverage of the data may also affect the definition of entry and exit depending on, for example, possible size thresholds and the treatment of ownership changes. Finally, the econometric methods and model specifications used differ enormously.

Despite all these problems, some stylised facts on the patterns of industry turbulence and the post-entry performance of new firms have been summarised in recent surveys (e.g. Geroski, 1991; Baldwin, 1995; Sutton, 1997; Caves, 1998). It has been found that regardless of the industry or time period, there is a considerable amount of entry in the economy. Typically, entering firms are small and a large fraction of them exit within a short period after entry. Many empirical studies also conclude that start-up size is an important determinant of the likelihood of survival facing a new firm after entry. However, the evidence on the sign of this relationship is somewhat mixed. (Mata & Portugal, 1994; Audretsch, 1995; Mata et al., 1995; Disney et al., 2003). There are only a few earlier studies examining directly the determinants of the scale at which a firm or a plant enters (Mata and Machado, 1996; Görg et al., 2000).

Most of the recent studies on the post-entry performance of firms find that firm growth is negatively related to firm size and age, whereas firm survival is positively related to current size and age (e.g. Evans, 1987b; Dunne et al., 1989; Dunne & Hughes, 1994). However, there is some evidence that these relationships differ between the samples of small and large firms. Some of the earlier studies, using a sample of large firms only, find support for Gibrat's law, which states that there is no relationship between firm size and its expected rate of growth (e.g. Simon & Bonini, 1958; Hart & Prais, 1956).[1]

However, in Finland the determinants of plant start-up size, employment growth and the likelihood of survival have not been studied earlier using comprehensive micro-level data sets. In addition, there are only a few previous studies related to plant size and employment dynamics. Vainiomäki and Laaksonen (1999), Kangasharju (2001), Ilmakunnas and Maliranta (2002) and Maliranta (2003) include some analysis on job flows, net employment growth and plant size, but the main emphasis is not on size. Laaksonen and Teikari (1999) have studied the effect of ownership changes on the relationship between size and job flows by constructing so-called synthetic enterprise units. Section III in this thesis is based on Hohti[2] (2000), which analyses plant size, job flows and job quality more extensively. Empirical studies by Vuori (1981), Peisa (1988) and Berg (1992) are related to testing Gibrat's law, but the data sets used cover only a very limited number of firms and the approaches are rather different.[3] Kangasharju (2000a) has studied the determinants of small firm growth taking into account firm age, entrepreneurial human capital and macroeconomic fluctuations. To my knowledge, the determinants of entry and exit have been studied only by Ilmakunnas and Topi (1999) and Koski and Sierimo (2003), but these studies use an industry-level approach. Kangasharju (2000b) and Kangasharju and Moisio (1998) have studied firm formation and the interdependence of entry and exit at the regional level. In addition, there are various Finnish studies related to entrepreneurship.

An important question is whether the results for such a small country as Finland could contribute to the current knowledge on the relationships between plant size, employment dynamics and survival. During the period examined the Finnish economy has been in turmoil, including rapidly changing institutional settings, turbulent economic conditions and extensive sectoral restructuring. The deregulation of the financial markets in the 1980s and a rapid growth in credit supply led to an overheating of the economy in the late 1980s. The high level of indebtness of both firms and households and declining net exports due to slow international trade and the collapse in foreign trade with the former Soviet Union led to a severe economic crisis at the beginning of the 1990s. The recession was characterised by a major restructuring of the banking sector, record-high unem-

[1] Geroski et al. (2003) find that growth rates of firms that survive for at least 30 years are random.

[2] Hohti is the maiden name of the author.

[3] 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).

ployment and a serious fall in the real gross domestic product.[4] It may be argued that this was one of the most serious cyclical downswings in the industrialised countries since the Great Depression of the 1930s.[5]

At the same time, the industrial structure of Finland has changed dramatically. There has been a strong declining trend in the overall manufacturing employment, while the service sector has increased in importance during the last two decades.[6] Furthermore, the structure of manufacturing has shifted in emphasis from the heavy metals, steel and paper industries to the information and communications technology (ICT) sector, which witnessed remarkable growth during the 1990s. These developments make Finland an interesting and exceptional case to study, in particular, when it comes to the business cycle effects. The effects of macroeconomic fluctuations on firm growth and survival have not received sufficient attention in the literature, which is at least partly due to the lack of suitable data. New information about the plant-level consequences of the recession at the beginning of the 1990s is very valuable. In addition, it is interesting to see how the sectoral shifts in employment are reflected in the growth rates of different-sized plants.

New knowledge on plant-level growth and exit dynamics is important for policy makers in order to justify and evaluate the effects of industrial and labour market policy decisions in the long run. In particular, it is crucial to assess what determines the employment decisions of different-sized plants in different business environments and time periods. Every plant-level decision on start-up, expansion, decline and exit has an obvious effect on the aggregate employment patterns. New knowledge on the factors behind the choice of plant entry scale is important for understanding the entry process and the recruitment and investment decisions of new plants in different sectors of the economy. In addition, it is important to examine the determinants of business growth because new jobs and economic welfare are created by the expanding units. Finally, knowledge on the factors determining the survival chances of plants helps in directing subsidies for those plants that create sustained long-term employment.

Plant size is one of the key factors considered when public funds are allocated for economic activity. Traditionally, the small business sector is seen as an engine of growth in the economy. Small and medium-sized businesses play an important role in job creation, innovative activity and technological progress. As agents of change they stimulate industry evolution and the efficiency of the markets. These arguments have frequently been presented as the justification for tax incentives, regulatory policies and other government programs favouring small business. However, in the literature the role of the small business sector in

[4] According to Statistics Finland, Finland's real gross domestic product declined by 11.1% from 1990 to 1993 and the unemployment reached its peak at 16.6% in 1994.

[5] For example, Kiander and Vartia (1996) and Honkapohja and Koskela (1999) have studied the causes and consequences of the recession.

[6] According to the Industrial Statistics of Statistics Finland, the number of manufacturing employees fell 38% from 1980 to 1994.

creating employment is a controversial topic. The results depend on the definition of small business and the data sets and growth measures used. Furthermore, the total effect depends on both the likelihood of survival and growth because a large number of small businesses are new firms, which have a high probability of exit. However, rapid growth of the surviving units may compensate for the employment losses. In addition to extending the previous empirical literature by using rich Finnish panel data sets, this thesis gives new information about the job creation power of small and large businesses in Finland, which should be of interest to policy makers and researchers.

Investments in education, and thus human capital, play a very central role in the economy. However, there are only a few theoretical and empirical studies about the effects of human capital on plant employment dynamics and the chances of survival. There is considerable heterogeneity between plants in different sectors of the economy in the demand for high-skilled labour. For instance, plants in the high-tech service sectors usually require a large share of the high-skilled work force. The dependence on human capital investments may create an entry barrier in the form of sunk costs to these sectors. In addition, high-skilled labour may be a necessary requirement for the creation and implementation of successful innovations. Having higher-quality human capital may also increase the chances of plant growth and survival. New information on these relationships may help us in understanding the role of human capital in the entry process and post-entry performance of plants.

The introduction of this thesis is structured as follows. In the second section, the theoretical literature is briefly described. In addition, a simple theoretical growth model, which also includes the human capital effects, is formulated based on the model by Cabral (1995). The third section introduces the structure and aims of the thesis. The main results based on the four empirical essays are summarised in the fourth section. Finally, the fifth section discusses the policy implications of the findings and concludes.

2 Theoretical literature

2.1 Gibrat's law

Theoretical literature analysing the relationship between the size and growth of firms dates back to the Law of Proportional Effect formulated by Robert Gibrat (1931). A strict form of this law states that the expected relative growth of a firm over a specified period of time does not depend on the firm 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 (Simon & Bonini, 1958).

SECTION I: INTRODUCTION

According to Gibrat's law, a firm's proportionate rate of growth is (e.g. Aitchison & Brown, 1957):

$$\frac{X_t - X_{t-1}}{X_{t-1}} = \varepsilon_t, \tag{1}$$

where X_t is the firm size at time t, e.g. employment, and ε_t is a random variable which is independently distributed of X_{t-1}. Assuming that the initial value is X_0 and there are n steps before the final value X_n is reached, and summing up gives:

$$\sum_{t=1}^{n} \frac{X_t - X_{t-1}}{X_{t-1}} = \sum_{t=1}^{n} \varepsilon_t. \tag{2}$$

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

$$\sum_{t=1}^{n} \frac{X_t - X_{t-1}}{X_{t-1}} \cong \int_{X_0}^{X_n} \frac{dX}{X} = \log X_n - \log X_0, \tag{3}$$

which gives:

$$\log X_n = \log X_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_n. \tag{4}$$

Equivalently:

$$X_t = (1 + \varepsilon_t)X_{t-1} = X_0(1 + \varepsilon_1)...(1 + \varepsilon_n). \tag{5}$$

Provided that $\log X_0$ and ε_t have identical distributions with mean μ and variance σ^2, then by the central limit theorem, it follows that $\log X_t \sim N(\mu t, \sigma^2 t)$, when $t \to \infty$. Hence, when a large number of small, independent random forces act on firm size multiplicatively, the generated distribution of X_t is lognormal. This implied skewed distribution of firms closely resembles the size distribution of firms often observed in practice, with only a few large firms and many small firms. Another implication of the law is that the expected value and variance of the size distribution increase over time, i.e. the relative dispersion of firm sizes and thus industry concentration tend to increase over time. To avoid this unrealistic assumption, the model is extended by Simon and Bonini (1958) who argue that the simple lognormal distribution is a special case of the Yule distribution, which is generated when an entry process is incorporated into the model. Various other possible modifications of the law are also presented, for example, the inclusion of the persistence of growth or firm age in the model.

Another approach would be to use an error correction framework from the labour demand literature as a starting point. According to a simple dynamic employment equation with adjustment costs, firms optimise their behaviour with respect to a quadratic loss function (e.g. Nickell, 1985):

$$L = \frac{\alpha}{2}(X_t - X_{t-1})^2 + \frac{\beta}{2}(X_t - X_t^*)^2 - \gamma(X_t - X_{t-1})(X_t^* - X_{t-1}^*), \tag{6}$$

where the first term describes standard quadratic adjustment cost, the second term penalises deviations from the optimal value of employment X_t^*, and the third term implies that the loss is attenuated if the firm moves in the right direction. Minimising L with respect to X_t and rearranging gives:

$$X_t = \frac{\alpha}{\alpha+\beta}X_{t-1} + \frac{\beta}{\alpha+\beta}X_t^* + \frac{\gamma}{\alpha+\beta}(X_t^* - X_{t-1}^*), \quad (7)$$

where $\frac{\alpha}{\alpha+\beta} \to 1$ if $\beta \to 0$. Thus, Gibrat's law is just a special case if X is measured in logarithms and disequilibrium costs are zero. It may be assumed that $X_t^* - X_{t-1}^*$ describes stochastic shocks related to, for example, demand or production costs, which have an effect on output and wages and thus on the optimum firm size.[7]

In the empirical literature there are 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. However, it is difficult to differentiate between distributions in statistical tests. 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, either by grouping firms into size classes and testing for significant differences in the mean and variance of growth, or by regressing the growth rate on initial firm size.[8] Gibrat's law implicitly assumes a homogenous environment for all firms in operation. In particular, it assumes that the growth rates for all firms are drawn from a common distribution. However, 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.

Despite the differences in the interpretation of the law and in the research methods and samples used, the key finding of the present empirical research seems to be that the growth rates of new and small firms are negatively related to their initial size. Thus, Gibrat's law fails to hold at least for small firms (Hart & Oulton, 1996; Audretsch, Santarelli & Vivarelli, 1999; Mata, 1994; Dunne & Hughes, 1994). However, some earlier studies based on samples of only large firms have found support for the law (Simon & Bonini, 1958; Hart & Prais, 1956). Studies that have also taken into account firm age and survival suggest that firm size and age are inversely related to firm growth even after controlling for the sample selection bias due to higher failure rates of slowly-growing small firms (Evans, 1987a, 1987b; Hall, 1987; Dunne et al., 1989). Furthermore, the probability of firm survival increases with firm size and age. Subsequently, there is a need for more comprehensive theories of firm growth which could explain the departures from Gibrat's law.

[7] Longer lags and optimisation over time may be easily added to the model. For example, Geroski et al. (1997) have used a more sophisticated formulation based on profit maximisation over time.

[8] An equivalent approach would be to regress current firm size on initial size. Testing Gibrat's law is also closely related to the tests of unit roots.

2.2 Life-cycle models on firm growth

In order to find a theoretical explanation for the empirically observed negative relationship between firm size and growth, newer models of firm growth have been developed during the last two decades. Instead of assuming a purely stochastic process of firm growth, many of the newer growth models are based on profit maximisation. The models of industry dynamics by Jovanovic (1982), Pakes & Ericson (1998, 1995), Hopenhayn (1992) and Lambson (1991) describe the patterns of growth and failure characterising individual businesses. These models are useful in explaining differences in plant heterogeneity and market structure, including plant growth and turbulence, across different time periods and industries.

Jovanovic's (1982) life-cycle model is based on passive (Bayesian) learning. A central feature of the model is that entering firms have different cost structures, which are not directly observable. It is assumed that any two simultaneous entrants will hold the same prior beliefs and therefore enter at the same scale of operation. The unit costs are revealed only gradually through the profits achieved after production has started. Hence, the emerging size distribution of firms reflects differences in the firms' ability to learn about their relative efficiency, not only the fixity of capital. Through a process of natural selection, the most efficient firms grow and survive, while the inefficient ones exit the industry. Jovanovic shows that young and small firms grow on average faster than the old and larger ones, and this result holds even when the sample selection bias due to the higher probability of failure of small firms is eliminated. However, the model implies that Gibrat's law holds for mature firms and for firms that entered the industry at the same time. An additional implication is that the variance of growth is largest among young and small firms.

The model of Pakes and Ericson (1998, 1995) offers an analysis of firm and industry dynamics as a steady state phenomenon within a game-theoretic setting. This model is based on an active learning process, where profit maximising firms can affect their productivity by investing in research and development activities. However, due to firm-specific uncertainty, firms cannot predict what is the effect of investments on their productivity. As a consequence, the relative efficiency of each firm changes gradually over time. Contrary to the model of Jovanovic, the Pakes-Ericson model predicts that over time the dependence between firm's current size and initial size disappears.

Hopenhayn (1992) develops an industry equilibrium model of turbulence and firm dynamics. In this model the only sources of uncertainty are the firm-specific productivity shocks, which follow a Markov process. Entry involves a sunk investment. The model implies that, by creating a barrier to entry, sunk entry costs increase the chances of survival of incumbents in the industry. Hence, another implication is that high sunk costs of entry result in lower plant turnover. The model also predicts the evolution of the firm size distribution by age cohorts. In particular, the size distribution of firms increases with age. In addition, the probability of survival will be higher for older and larger firms. Under certain assumptions, the model is also consistent with the negative relationship observed between firm size and growth, at least for small firms.

Lambson (1991) presents a model of industry evolution with sunk costs and uncertainty. In this model firms face exogenous shocks to demand or input prices, which occur at infrequent intervals. An entrant incurs a sunk cost associated with establishing a plant using a given technology. In this context, the level of sunk costs incurred by firms will influence entry and exit rates, conditional on the volatility of industry demand. The model also predicts that industries with high rates of turnover should be characterized by low sunk costs and a high elasticity of substitution between inputs.

2.3 Basic model on firm size and growth

Cabral's (1995) model on firm size, growth and sunk capacity costs provides an easy starting point for the illustration of firm growth models. The basic model without sunk costs can be described as follows, when, in contrast to Cabral, firm size is measured with the number of employees instead of the quantity produced. Assume that there is an infinite-period competitive industry characterised by some demand function, where each firm is a price taker and price is constant in all periods. At the steady state, the growth rate is zero but entry and exit of firms are allowed. Only one cohort of firms is followed. Entering firms face a production technology $s_t f(l_t)$, where l_t is the number of employees and s_t is the firm's efficiency or productivity type at age t. Firms of higher type s_t are more efficient. $f(l_t)$ is a standard concave production function, where capital is ignored for simplicity. Fixed costs, F, are assumed to be the same for all firms.

Each firm maximises profit according to the following equation:

$$\max_{l} \pi(l, s_t) = p s_t f(l) - wl - F, \tag{8}$$

which yields the first-order condition with respect to l:

$$s_t f'(l) = \frac{w}{p}. \tag{9}$$

Thus, firms with a higher efficiency parameter s_t are larger, both in terms of the level of employment and output. In addition, profits are increasing in s_t, because costs do not depend on efficiency. The concavity of the production function determines how strongly the returns diminish with scale, thus measuring how much one can benefit from high efficiency. In the extreme case of constant returns to scale, the most efficient firm captures the whole market. In the case of decreasing returns to scale, the ability to expand is more limited.

A passive learning process similar to the models of Jovanovic (1982) and Hopenhayn (1992) is assumed. More precisely, productivity in period 1 provides a signal of the future productivity and from period 2 onwards the exact value of s_t is known. The timing of a firm's decisions is as follows. After paying the sunk cost of entry, a firm observes its first period efficiency type s_1 and chooses whether to stay or exit. If it decides to stay, then the first period labour l_1 and quantity q_1 are chosen and payoff received. Then the firm observes the second period efficiency type s_2 and chooses the labour l_2 and output q_2. After that it chooses whether to stay or exit and if it decides to stay, second period payoff is received. However, the second period labour and output are conditional on staying in the industry, so for exiting firms the realized growth rates ($\frac{Il_2 - l_1}{l_1}$, where I equals 1 if the firm continues and 0 if the firm exits) differ from the potential growth rates ($\frac{l_2 - l_1}{l_1}$). This formulation ensures that the expected growth rates include all firms. In the third and subsequent periods the pattern for the second period is repeated.

The distribution of s_t is assumed to be:

$$s_t \in \{H, M, L\}, \tag{10}$$

where $H > M > L$, and a transition matrix A from s_1 to s_2 is:

$$A = \left\{ \begin{array}{ccc} 1 & 0 & 0 \\ \alpha & \beta & 1 - \alpha - \beta \\ 0 & 0 & 1 \end{array} \right\}, \tag{11}$$

where $\alpha + \beta < 1$. Under the assumption that $L < F < H$, this structure implies that the probability of survival increases with initial size because l_1 and q_1 are increasing in s_1. In other words, all firms with $s_1 = L$ exit the market, firms with $s_1 = M$ survive with the probability $0 < \alpha + \beta < 1$ and firms with $s_1 = H$ have a 100% probability of survival. The transition matrix also implies that the variance of growth decreases with firm size.

The exit of slowly growing small firms from the sample may cause the relationship between size and growth to be biased downwards. Cabral shows that Gibrat's law holds when this sample selection bias is corrected for if it is assumed that $E(s_2 \mid s_1) = s_1$. In contrast, the expected growth of surviving firms decreases with size. This is implied by the model because in the second period firms with $s_2 = L$ exit. Expected growth for surviving firms with $s_1 = M$ is in turn given by:

$$E\left(\frac{l_2 - l_1}{l_1} \mid s_1 = M\right) = \frac{\alpha \times \left(\frac{l_2(H) - l_1(M)}{l_1(M)}\right) + \beta \times 0}{\alpha + \beta} > 0, \tag{12}$$

because l_t is an increasing function of s_t. Finally, the expected growth for surviving firms starting with $s_1 = H$ is zero, since all high-efficiency firms survive. Hence, the expected growth of surviving firms decreases with size.

Maintaining these assumptions, Cabral then includes sunk costs in the model to show that even correcting for the sample selection bias, a negative relationship between size and growth emerges when there are sunk capacity or technology costs. Suppose instead that investments in human capital are considered, i.e. acquiring high-skilled employees, which requires sunk costs of recruiting and training. This creates an asset, firm-specific human capital, which does not have a resale value, so it is lost upon exit. The next section shows that the results remain the same: larger firms can afford to invest more heavily in the first period and thus grow more slowly.

2.4 Sunk costs in human capital

There are only a few previous models of firm size distribution considering the role of human capital. Lucas (1978) proposes a theory of the size distribution of firms where a central element is the division of persons into managers and employees on the basis of varying business or managerial ability. In equilibrium, only the most talented persons become managers and choose the optimal levels of employment and capital in the firm. Under certain assumptions, the model implies that firm size increases with capital intensity, because an increase in per capita capital raises wages relative to managerial rents, and thus increases the ratio of employees to managers.

Similarly to Lucas model, in Rosen's (1982) model of organisational hierarchy, managerial skill enters the production function multiplicatively, and unskilled labor enters with standard diminishing returns. Higher skill people become managers and supervise more employees. The model implies a positive relationship between the level of available human capital and firm size. In addition, the distribution of firm size is skewed relative to the underlying distribution of talent.

In the models by Lucas and Rosen the emphasis is on the human capital of managers, whereas in the model of Kremer (1993) human capital is defined as the probability of a worker successfully completing a task. In equilibrium, workers of the same skill level are matched together. The model implies that firms using technologies where several tasks are needed will employ highly-skilled workers because mistakes are more costly for these firms. Since the number of tasks and the number of workers are likely to be positively correlated, it can be concluded that there is a positive relationship between the average level of human capital and firm size. Another implication is that firm size should be positively correlated with the wage per worker because higher wages imply that higher quality workers, and hence a higher number of tasks and workers, can be used.

Cabral's (1995) model can be modified to take into account investments in human capital that involve some degree of sunkness.[9] Firms incur a sunk capacity cost of h per unit of human capital. In each period firms must choose the human capital stock H_t and pay $h(H_t - H_{t-1})$ before choosing the number of employees l_t. For simplicity, it is assumed that the human capital stock is approximated by the number of employees and adjustment costs are linear.[10] Now assume that there is a continuous, time-invariant efficiency parameter θ instead of s_t. In addition, it is

[9] In many respects, the formulation follows the model by Cabral and Mata (1996) with sunk costs in physical capital. The model is not included in the published version of the paper (Cabral & Mata, 2003).

[10] Strictly speaking, $h\,|H_t - H_{t-1}|$ should be used, but the assumption here is that growth is positive.

assumed that a firm continues with a probability $\rho(\theta)$ and exits with a probability $1-\rho(\theta)$, where $\rho'(\theta)>0$, so the probability of survival increases with long-run efficiency. For a two-period model, where the second period describes the whole future, the second period maximisation problem for the firm that has survived is:

$$\max_{l_2} \pi_2 = \frac{1}{1-\delta}\left(p\theta f(l_2) - wl_2 - F\right) - h(l_2 - l_1) = \gamma(\theta) - h(l_2 - l_1), \qquad (13)$$

where l_1 and l_2 are the first and second period number of employees and δ is the discount rate ($0<\delta<1$). The first-order condition is given by:

$$\theta f'(l_2) = \frac{w + (1-\delta)h}{p}. \qquad (14)$$

The maximisation problem for the first period is then:

$$\max_{l_1} \pi_1 = p\theta f(l_1) - wl_1 - F - hl_1 + \delta\rho(\theta)(\gamma^*(\theta) - h(l_2^*(\theta) - l_1)). \qquad (15)$$

This implies the break-even condition for the first period:

$$\theta f'(l_1) = \frac{w + (1-\delta\rho(\theta))h}{p}. \qquad (16)$$

Thus, the optimal number of employees and output in the first period will be lower than the second period (or long-run) employment if the probability of survival $\rho(\theta)$ is less than one. The lower the probability of survival the smaller the first period size and thus the higher the growth.[11] Hence, if it is assumed that small firms have a lower likelihood of survival, the inclusion of sunk costs implies that small firms grow faster than large firms. The intuition is that in the first period small firms, facing a higher probability of exit, invest less than the long-run capacity level (in terms of human capital) would require, whereas large firms invest directly to their optimal capacity. Hence, in the second period, small firms experience higher growth while adjusting their capacity to the long-run level. Thus, the model implies a negative relationship between initial size and expected growth.[12]

In order to derive an additional implication, production function is assumed to take the form $f(l) = l^\alpha$, where $0<\alpha<1$. As a consequence, the optimal number of employees in the first and the second period are:

$$l_1 = \left(\frac{w + (1-\delta\rho(\theta))h}{p\theta\alpha}\right)^{\frac{1}{\alpha-1}} \quad \text{and} \qquad (17a)$$

$$l_2 = \left(\frac{w + (1-\delta)h}{p\theta\alpha}\right)^{\frac{1}{\alpha-1}}. \qquad (17b)$$

[11] It should be noted that the effects of δ and ρ are symmetric. So a lower discount rate would mitigate the effects of a higher probability of survival on growth.

[12] In this analysis, it is assumed that capacity costs are entirely sunk. However, according to Cabral (1995), it can also be shown that expected growth rates are increasing in the degree of sunkness of capacity costs.

Hence, the growth rate of surviving firms is:

$$\frac{l_2 - l_1}{l_1} = \left(\frac{w + (1-\delta)h}{w + (1 - \delta\rho(\theta))h} \right)^{\frac{1}{\alpha - 1}} - 1 \tag{18}$$

It can be shown that the effect of higher adjustment costs related to human capital investments, h, on the relative growth of surviving firms is positive:

$$\frac{\partial(\frac{l_2 - l_1}{l_1})}{\partial h} = \frac{\delta w\,(\rho(\theta) - 1)}{(w + (1 - \delta\rho(\theta))h)^2\,(\alpha - 1)} \left(\frac{w + (1 - \delta\rho(\theta))h}{w + (1-\delta)h} \right)^{\frac{\alpha}{1-\alpha}} > 0, \tag{19}$$

because both terms are positive if $\rho(\theta) < 1$. Hence, higher adjustment costs increase the relative growth of firms. Since recruiting higher-skilled labour may be more costly, this result implies that firms with higher labour quality have higher growth rates, which is in accordance with the implications of the model developed in the next section.

Life-cycle models do not have many implications when it comes to the determination of firm start-up size. Usually it is assumed that any two simultaneous entrants will hold the same prior beliefs and therefore enter at the same scale of operation. In contrast, Cabral's model assumes that the entrants have differing beliefs concerning their own future profitability and growth paths. A smaller start-up size is selected if the risk of failure is higher, especially if there are high sunk costs upon entry. The model implies that sunk capacity costs have an influence on decisions regarding optimal start-up scale. The model predicts that, ceteris paribus, new firms' expected growth rates and the degree of sunkness of investment costs are positively correlated across industries. The empirical finding that high industry turbulence, or low sunk costs, increase plant start-up size is consistent with this prediction. In future theoretical work, more attention should be given to the determination of start-up scale in different sectors of the economy.

2.5 Worker heterogeneity and growth

Ignoring sunk costs in human capital, the effects of human capital on growth can be added more directly into the previously described model using a simple framework with two types of firms and two types of workers.[13] Previous studies on firm post-entry performance have been able to describe the process of entry with a number of stylised facts. Entering firms are generally quite small in comparison to incumbents in the markets, and a large proportion of firms exit within a short period after entry. However, those that survive seem to grow very fast in order to approach the minimum efficient scale. As firms age and become larger, their relative growth and the variability of growth decrease, whereas the probability of survival increases.

[13] I would like to thank Juuso Välimäki for suggesting this kind of theoretical formulation.

According to these findings, it seems that the first phases of firm life cycle are characterised by a process of learning and experimentation. Entering firms are uncertain about their future profitability and the success of their investments. This is why they only invest a fraction of their long-run capacity in the first period before gaining experience and learning about their competitive position. At this stage it is important for the firms to learn more about their true efficiency. Revealing their competencies through experimentation usually requires human capital effort. It can be hypothesised that highly-educated workers have a comparative advantage in creating, adopting and implementing new technologies. High-skilled work force may be needed in learning about the potential success of the firm, e.g. which location or product mix is an optimal one. Alternatively, new product or process innovations can be developed through research and development activities. If the investments and innovations are successful, the firms decide to continue and expand. When approaching the optimal size their chances of survival increase with accumulated experience, and thus, less high-skilled effort is needed.[14] However, in addition to high-growth, R&D intensive firms, naturally there are also entering firms which produce a standard product or service, and thus only need unskilled work force. These firms may also have a quite stable size.

Hence, it may be argued that there are two kinds of entering firms in the markets. Type A firms have a "certain" future and they start directly on their optimal size path. Because they do not need to experiment, they hire only less-skilled low-wage workers. In contrast, type B firms are uncertain about their future, so they start with a sub-optimal size. They are willing to take a risk and invest in human capital and R&D in the first period in order to create an invention which will be very profitable in the future. Hence, they hire high-skilled work force in order to learn about their efficiency and to guide the firm onto a growth path. This also means that these firms may not gain a profit in the first period. Later these firms may also hire low-skilled personnel, when no more experimentation is needed.[15] Figure 1 illustrates the growth paths of these two types of firms. Thus, firm B has two alternative growth paths and a certain exit threshold, whereas the size of firm A stays constant over time.

The model can be formulated as a simple two-period model with perfect competition in the product markets. Labour force is divided to low-skilled ($\underline{l}$) and high-skilled ($\bar{l}$) workers earning wages ($\underline{w}, \bar{w}$), respectively. In the first period, type A firm has a production technology $f(\underline{l}+\bar{l})$, where $\underline{l}$ and $\bar{l}$ are perfect substitutes and $\bar{l} = 0$ in optimum, whereas type B firm has a production technology $s_1 f(\underline{l}+\bar{l})$, where the efficiency parameter $s_1 < 1$. In addition, it is assumed that high-skilled workers have a comparative advantage in doing R&D rather than in working in production. The production function $f(\cdot)$ is assumed to exhibit

[14] Bartel and Lichtenberg (1987) find that the relative demand for educated workers declines with plant age, especially in R&D intensive industries.

[15] However, if the wage agreements are binding and firms cannot fire workers, it may be assumed that the high-skilled workers will continue to remain in the firm.

constant returns to scale and capital is ignored for simplicity.

In the second period, the distribution of s_2 for type B firms is as follows:

$$s_2 = \begin{cases} s_H & \text{with prob. } \rho \text{ if } \bar{l}_1 = 1 \\ s_1 & \text{if } \bar{l}_1 = 0 \\ s_L & \text{with prob. } \rho - 1 \text{ if } \bar{l}_1 = 1 \end{cases}, \tag{20}$$

where $s_L < s_1 < 1 < s_H$. As a consequence, it is profitable to continue only if $s_2 = s_H$. The firms with $s_2 = \{s_1, s_L\}$ will exit, because they are making losses in the second period if it is assumed that type A firms have zero profits in optimum. In contrast, type A firms will continue with probability 1.

Type B firms, which need to hire only less-skilled employees in the second period, maximise their second-period profits according to:

$$\max_{\underline{l}} \pi_2^B = p s_H f(\underline{l}) - \underline{w}\underline{l}. \tag{21}$$

First-order condition gives:

$$s_H f'(\underline{l}) = \frac{\underline{w}}{p}. \tag{22}$$

Since $s_H > 1$, type B firms will hire more employees in the second period than type A firms whose first-order condition is $f'(\underline{l}) = \frac{\underline{w}}{p}$. Thus, the model implies that $\underline{l}^B > \underline{l}^A$.

The first-period profits for type B firms are maximised according to:

$$\max_{l} \pi_1^B = p s_1 f(\underline{l}+\bar{l}) - \underline{w}\underline{l} - \bar{w}\bar{l} + \rho \pi_2^B. \tag{23}$$

In the first period, type B firms have to hire at least one high-skilled employee in order be able to innovate and thus achieve an opportunity to increase their efficiency and profits in the second period. In addition, since it is more profitable in the long run to use the high-skilled workers in R&D than in production, the firm does not produce anything in the first period because hiring low-skilled workers would only result in additional losses.[16] Hence, first-period losses are minimised and long-run profits maximised when $\underline{l} = 0$ and $\bar{l} = 1$. As a consequence, the profits for firm B are determined according to:

$$\pi_1^B = -\bar{w} + \rho \pi_2^B. \tag{24}$$

Hence, type B firms have high growth rates determined by $l_2 - 1$. Type A firms face a similar maximisation problem in both periods. Hence, these firms hire as many employees in period 2 as in period 1 and do not grow.

According to the model, high-skilled high-wage workers end up in fast-growing firms, so this implication corresponds to the empirically observed wage differential between different-sized firms (Brown et al., 1990). Zábojník and Bernhardt (2001)

[16] It is assumed that wage $\bar{w}$ for high-skilled workers is the same regardless of whether they are used in production or R&D.

show that large firms have higher wages and higher level of human capital than the smaller ones. Haltiwanger et al. (2000) describe a model on learning and the choice of work force composition, which also implies that firms with higher efficiency will have more skilled workers and higher wages. In addition, they find that there are persistent differences in the work force composition across firms within narrowly defined industries, so the work force mix changes fairly little over time. In addition, the model predicts that a low level of work force skills predicts exit.

The model presented above implies that firms with high-skilled work force will grow faster than firms with low-skilled personnel. The model also implies that having high-skilled labour is relatively more important for younger and smaller firms. In addition, it may be argued that firms with a higher level of human capital are more likely to exit, if these firms are like the type B firms which take more risks and may fail if their R&D efforts turn out to be unsuccessful. These findings can be empirically tested by including explanatory variables describing human capital in each plant or firm in the growth and survival models.[17] Human capital can be measured, for instance, with the education, age or work experience of employees in each plant. Interactions of plant size, age and human capital factors can be added to the model in order to test whether smaller and younger plants have larger human capital effects on growth.

The empirical results of this study on the effects of human capital on growth show that young plants have a higher share of educated workers and they are more likely to be situated in R&D intensive industries than the older plants. The effect of the relative education level of employees on growth is positive according to the ordinary least squares (OLS) estimates, but negative according to the within plants specification.[18] This is in accordance with the empirical finding that personnel structure is determined during the initial stages of the firm life cycle and does not change much over time. Hence, the fixed effects estimation may wipe out some of the effects. In contrast, Maliranta (2003) finds a positive relationship between average education and net employment growth using both OLS and fixed effects, but the measures for growth and size are different. Closely related are also the studies on human capital and productivity growth. According to Maliranta (2003), many studies fail to find a positive relationship between the change in human capital and productivity growth. It is also found that technical and scientific university-level education has a negative effect on productivity growth, whereas non-technical skills have a significantly positive relationship with productivity (Ilmakunnas & Maliranta, 2003). One explanation may be that the technically-skilled personnel is more involved in R&D, whose effects on production are revealed with a considerable lag.

[17] It may be argued that the implications of this model could also be tested using plant-level R&D-intensity (and its interaction with plant age) as an explanatory variable.

[18] Relative education was defined as the average number of schooling years in the plant relative to the industry average.

When interactions of education and size and education and age are included in the model, it is found that the positive effect of education on growth declines with plant age and size. Or correspondingly, the negative effect of size on growth becomes stronger when the quality of human capital increases. However, the interaction terms are very highly correlated with age and size. According to other results, growth is higher for plants with less experienced workers relative to the industry average, when experience is measured with seniority.[19] However, it should be noted that seniority is positively related to plant age, which may be reflected in the results. Increase in the share of women in the plant in relation to the industry average is observed to decrease growth. The empirical results on the effects of human capital on plant survival also correspond to theoretical implications. It is noted that plants with older, more experienced and more educated work force than the industry average have a higher probability of exit. Human capital factors seem to be more important for the survival of new manufacturing plants than for the service sector entrants.

3 Structure and aims of the study

This thesis consists of a theoretical introduction and four empirical essays on the determinants of plant start-up size, employment dynamics, including job flows and net employment growth, and the likelihood of survival. In particular, the focus of interest is on the relationship between plant size and the prospects of plant growth and survival, where plant size and growth are measured with employment.[20] In addition, the industry-level determinants of start-up size in different sectors of the economy are examined.

Hence, the primary focus of this thesis is to evaluate the role of plant size in employment changes during the whole plant life cycle, which may have some important consequences and policy implications at the aggregate level. In addition, it is interesting to study the effects of human capital, i.e. the characteristics of employees in each plant, on growth and the likelihood of survival. Another aim of this study is to shed light on the plant-level consequences of the recession at the beginning of the 1990s. The period examined allows the analysis of the impact of macroeconomic fluctuations on plant employment dynamics and survival. In addition, it can be studied whether small and young plants are more sensitive to the cyclical effects.

The empirical framework in each of the four essays builds on the existing literature on firm growth. The special emphasis is on testing Gibrat's law and the implications of theoretical firm life-cycle models. In addition, it is possible to test the implications of the growth model including the human capital effects intro-

[19] Measuring work experience with the age of employees instead of seniority, i.e. the number of months in the firm, produced very similar results.

[20] Employment is chosen as a key variable to avoid problems with inflation, to compare the results with the earlier studies and to draw policy conclusions on job creation.

duced in section I.2.5. The results obtained are compared with previous empirical findings. The basic unit of analysis is the plant or the establishment, which is preferred to the firm level because decisions regarding the purchase of the factors of production, including labour, are usually made at the plant level. More importantly, changes in ownership and legal status do not affect the plant identification code.[21] The primary data source used in all essays is the Longitudinal Data on Plants in Manufacturing (LDPM) based on the Industrial Statistics data of Statistics Finland. The data set used covers basically all Finnish manufacturing plants with at least five employees over the period 1980–1994. In addition, some parts of the analysis are extended to include the whole business sector using the Business Register (BR) data over the years 1988–2001, which also includes the service sector. In addition, information on plant-level employee characteristics and worker flows can be linked to the data from the Employment Statistics (ES) of Statistics Finland (Ilmakunnas et al., 2001). Data sources are described in more detail in the data appendix A.

The main research question is: "What is the role of plant size in employment dynamics over the life cycle of Finnish manufacturing plants, including start-up, employment dynamics and exit?" This research problem can be divided into the following set of more detailed research questions, which are studied in the different sections of the thesis:

1. What determines plant start-up size in different sectors of the economy?
2. What is the role of the small business sector in net job creation in manufacturing?
3. Does Gibrat's law hold for Finnish manufacturing over the period examined, i.e. does any relationship exist between plant size and its relative growth or variance of growth?
4. Is there any evidence in favour of Jovanovic's life-cycle model , i.e. does a negative relationship exist between plant age and growth and a positive relationship between age (or size) and survival?
5. What is the effect of a strongly evolving macroeconomic environment on plant employment dynamics and survival for different-sized and aged plants?
6. What are the effects of human capital on plant start-up size, employment growth and the risk of failure?

The different essays try to answer these questions by focusing on different phases of the plant life cycle. The aim of the first essay *Sectoral Differences in*

[21] The findings can be applied to the firm level with certain reservations because less than 10% of the firms in the data have more than one plant. In addition, the employment distribution of firms has developed in a rather similar manner as the employment distribution of plants.

Plant Start-up Size in the Finnish Economy in section II is to examine the effect of various industry-level and regional attributes on plant start-up size in the Finnish business sector over the period 1981–2000. Sectoral factors may affect small and large entrants differently. In addition, this essay tries to fill the gap in the literature by including the service sector in the analysis, because there may be considerable differences in the determinants of entry scale between manufacturing and services. For example, the availability of a high-skilled work force in the region may have a different role in the choice of start-up size in services and manufacturing. In addition, it has to be taken into account that plants belonging to multi-unit firms may face a different entry environment than single plant entrants. The sensitivity of the results to the data sets and different model specifications used is also assessed.

The second essay on *Job Flows and Job Quality by Establishment Size in the Finnish Manufacturing Sector 1980–94* in section III examines the relative contribution of small and medium-sized plants to employment decline and job turnover in Finnish manufacturing. This is studied by calculating different measures of job flows, including the rates of job creation, job destruction and net employment growth, by plant size category. The results also give some indication on the validity of Gibrat's law. In assessing the role of the small business sector in net job creation, it is also important to evaluate the quality of the jobs created in different-sized plants. This is why various aspects of job quality by plant size are examined, including wages, labour productivity, working hours, labour turnover (measured by worker flows) and the persistence of jobs created and destroyed. Special emphasis is on the alternative measures of plant size and net employment growth in order to see whether the results on the relationship between plant size and growth are sensitive to the methods of measurement.

The primary purpose of the third essay *Plant Size, Age and Growth in Finnish Manufacturing* in section IV is to examine more formally whether Gibrat's law holds for Finnish manufacturing over the period 1981–94, i.e. whether the relative employment growth is independent of plant size. The effect of a sample selection bias, due to the higher exit probability of small plants having slow or negative growth, is also controlled for. Furthermore, unobserved heterogeneity and the dynamic nature of the model are taken into account. In addition to testing Gibrat's law, this essay tries to evaluate whether there is any evidence of a life-cycle effect based on learning. According to Jovanovic's (1982) theory, firms need time to uncover their true efficiencies, so that a negative relationship emerges between plant age and growth and a positive relationship between age and survival. Furthermore, the effects of plant employee characteristics and macroeconomic fluctuations on employment growth are considered.

The fourth essay on *The Determinants of Plant Survival in Turbulent Macroeconomic Conditions* in section V focuses on the determinants of the risk of failure facing a plant during a highly fluctuating macroeconomic environment. It is studied whether the hypothesised relationships between various plant and industry-specific factors, including different measures of plant size, and the likelihood of survival hold during strong macroeconomic fluctuations, and furthermore, which kind of plants are most sensitive to changes in the macroeconomic environment. In addition, the essay includes some analysis on the cyclical sensitivity of employment growth in new plants. The discrete nature of the data and unobserved heterogeneity are also taken into account. In the last part, the analysis is extended to include a comparison of the determinants of survival between manufacturing and services. In addition, the effects of employee characteristics on plant survival are studied.

The main purpose of this thesis is to contribute to the scarce empirical literature in these fields in Finland, by taking advantage of the recent access to the extensive micro-level data sets and the most advanced econometric methods. The thesis also contributes to the internationally growing literature on the effect of plant size on job flows, employment growth and plant survival by using the rich and comprehensive panel data sets covering almost the total population of Finnish manufacturing plants in employment terms. It also extends the scarce literature on the determinants of plant start-up size. The panel data sets used include a rich set of explanatory variables and allow a comparison of the results with earlier empirical studies and theoretical models. In addition, a richer model specification can often be used to control for as much heterogeneity as possible. Availability of linked plant-level employer-employee data sets allows the inclusion of worker flows and employee characteristics. As a consequence, the analysis gives new results, for example, on the effects of macroeconomic fluctuations and human capital on growth and survival. Special methods are used to control for unobserved heterogeneity. Furthermore, in many cases the availability of comparable data sets allows the evaluation of the sensitivity of the findings to the data used.

Some parts of the analysis are also extended to include the service sector, which has been mainly neglected in previous studies on entry and post-entry performance of new firms. Inclusion of these sectors in the analysis is particularly essential because, over the last decades, the service sector has increased in importance as an employer, while the employment share of manufacturing has declined steadily. Furthermore, it should be noted that, according to some previous results (e.g. Audretsch, Klomp & Thurik, 1999), services may not, in fact, simply mirror the patterns of entry, growth and survival in manufacturing. However, the analysis in this thesis is mainly focused on manufacturing, because the LDPM data has a larger information content and there are less problems in longitudinal linkages than in the BR data covering the whole business sector.

4 Main results

The main purpose of this thesis is to evaluate the role of plant size in employment creation in different phases of the plant life cycle. To answer the main research question, it can be concluded that plant size has a significant role in determining the patterns of plant employment change and exit. First of all, different-sized entrants are not affected by similar factors when they are choosing the scale of operations. Secondly, it is found that there is a clear negative relationship between job flows and plant size. In addition, the relationship between net employment growth and size turns out to be negative according to the econometric analysis. Thirdly, current size seems to predict the likelihood of survival better than initial size, implying that the chances for survival increase as the plant grows. The job creation power of different-sized plants is harder to evaluate because different aspects of job quality have to be taken into account in considering the overall welfare effect. Furthermore, various methods of measuring growth have a considerable effect on the results.

The contents and main findings of the four essays are summarised in Table 1. The first essay on plant start-up size finds that there is a large variation in entry scale between different industries. The size-related plant-level heterogeneity is taken into account by using a quantile regression approach. It is found that the determinants of start-up size in services and manufacturing do not differ much when data for the entire business sector over the period 1989–2000 is used. However, the regional availability of human capital has a different role in the choice of start-up size in services than in manufacturing, which may simply reflect the different nature of these sectors. The findings suggest that scale economies and industry turbulence are more important for the start-up decision of the largest entrants than the smaller ones. The differences in the factors influencing the start-up decision of large and small entrants may be explained by the fact that the new branch of an existing firm faces an entry environment which is quite different from that of genuinely new plants, which are usually smaller. When plants belonging to multi- and single-plant firms are analysed separately, it is found that they are, in fact, affected by different industry attributes.

The main finding of the second essay on job flows and job quality is that there is a considerable amount of turbulence among the small plants. Small plants create and destroy jobs relatively more than the larger ones. In addition, in the smallest size categories both the share of gross job creation and the share of gross job destruction is larger than the size category's share of employment, so small plants seem to 'over'contribute to job flows. Entry and exit account for a remarkable share of job turnover. Since job destruction varies cyclically more than job creation, job reallocation is found to be countercyclical except for the largest size category. An important finding is that the results regarding the relationship between plant size and employment growth are very sensitive to the methods of measurement used. The results also change notably when only recession years are included in the analysis. As a consequence, the effect of plant size on net employment change remains unclear. Furthermore, the total welfare effect is difficult to evaluate without taking into account the quality of jobs created in different-sized plants, and the evidence is mixed. However, adjusting job flows for the observed wage differential between small and large plants does not change the results notably.

The third essay on plant growth concludes that Gibrat's law does not hold for manufacturing despite the exceptional macroeconomic development and declining trend in manufacturing employment. 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). However, there may be some problems with the identification and the distributional assumptions of the selection model estimated. Panel data methods and generalised method of moments (GMM) estimation are also used to take into account the unobserved plant-level heterogeneity. In addition, there is strong evidence both on a negative relationship between plant age and growth and a positive relationship between age and the likelihood of survival. This supports the presence of a life-cycle effect implied by the model of Jovanovic (1982). In addition, the negative relationship between plant size and growth is robust for different model specifications and sub-samples, including a comparison between declining and growing plants. Business cycle effects seem to be stronger for larger plants, thus making the relationship between size and growth even more negative during recessions. The effects of human capital on employment growth seem to be important, but the results are somewhat controversial. The findings on human capital are described in more detail in connection to the theoretical model in section I.2.5.

The findings of the fourth essay on plant survival show that a large proportion, 35%, of new manufacturing plants die within the first four years after entry. The risk of failure was high especially during the recession at the beginning of the 1990s. In addition, the employment growth of the surviving new plants is found to be sensitive to the business cycle effects. Cox's (1972) semi-parametric proportional hazards model is employed to study the role of plant size and various other time-varying covariates in explaining the risk of failure. According to the results, current size is a better predictor of survival than initial size. The recession had a notable effect on the risk of failure faced by, in particular, small and young plants. Despite the strong cyclical fluctuations in the observation period, the findings for other covariates resemble the results obtained in many other studies, a fact which speaks in favour of strong idiosyncratic effects. The results are also robust to interval censoring, caused by the annual nature of the data, and unobserved heterogeneity. When results are compared between plants born in manufacturing and services, the main findings are rather similar. However, it is found that a higher level of human capital, in particular the relative experience and education of employees, seems to increase the risk of failure more in manufacturing than in services. In contrast, foreign ownership turns out to be important in increasing the survival chances of service sector plants.

Finally, the empirical findings can be compared to the implications of the theoretical models. Gibrat's law does not seem to hold for the Finnish manufacturing plants, i.e. there is a negative relationship between plant size and its employment growth. However, the observed plant and industry-level determinants explain only a small proportion of the variation in growth, which implies that there is still a large stochastic component in the forces determining the growth of plants. According to some interpretations, Gibrat's law is also rejected when the variance of growth depends on plant size. Therefore, the law can also be rejected on the basis of the observed negative relationship between plant size and job flows, which, to some extent, describe the variance of growth.

However, the descriptive analysis gives a rather different picture on the relationship between plant size and net employment growth. It should be noted that aggregation of plants into size categories conceals the dynamic growth patterns of individual plants and may exaggerate the contribution of large plants, since there are relocations between size classes due to high growth of some small plants and decline of the larger ones. The inclusion of growth rates for entering and exiting plants may also distort the results. The relative growth rates naturally favour growth in small firms, whereas absolute growth biases the results in favour of large firms, which makes the interpretation of the results difficult. In addition, the methods of measuring plant size and relative growth seem to have a considerable effect on the results. Using the compound interest method, the relationship between size and growth is negative, whereas with an arithmetic average it is positive. Hart & Oulton (1998) discuss the differences in measuring proportionate growth using arithmetic or geometric means. They argue that annual geometric average growth reflects the typical firm and is most relevant to the study of firm growth, whereas it is necessary to use the (weighted) arithmetic average growth in studying the generation of jobs.

The findings on a negative relationship between plant size and its relative growth are consistent with various life-cycle models described in section I.2, including the models by Jovanovic (1982) and Cabral (1995). The fact that plants need time to discover their own efficiency levels, can be seen in the rise of hazard rates in the first years after start-up. This also results in a negative relationship between age and growth as the plants adjust their behaviour to the long-run level. Similarly, decreasing variance of growth as the plant matures corresponds to the predictions of these models. Furthermore, there are significant human capital effects on plant growth and survival. However, the results on the effect of the relative education level of employees on plant growth and survival are somewhat contradictory. Subsequently, a more detailed further investigation is needed before any definite conclusions can be drawn on human capital and plant performance. However, the results suggest that there is a need for more comprehensive theories on firm growth based on economic theory. Gibrat's law, which is a purely statistical explanation for the observed size distribution of firms, is clearly not adequate in explaining the empirically observed regularities.

5 Concluding comments

It is important to understand the micro-level factors behind the aggregate developments when considering the allocation of business subsidies to different kinds of firms and plants. Young and small plants have a very central role as innovators and job contributors in the economy. In addition, the shifting size distribution of employment seems to emphasise their role as employers. The findings in this thesis show that new and small plants are major job creators. However, a large number of jobs created in new plants are destroyed within a short time period due to their high probability of exit. Nevertheless, it seems that small plants have managed quite well as net job contributors relative to large plants. According to the results, the relative growth of small plants is also higher than that of the larger ones. Naturally, in absolute magnitude, large plants are important employers especially in the long run.

However, various factors related to recent developments in Finnish manufacturing should be taken into account when considering the shifting size distribution of employment. First, the sectoral shifts in employment due to structural change may have affected the size composition of employment. In recent years there has been a large amount of entries by new small firms introducing new products and advanced technologies in the markets, whereas the employment share of large manufacturing plants has declined. Furthermore, during the recession many large plants had to downsize a large fraction of their work force. Second, during the 1980s there was a large amount of subcontracting and outsourcing, so at least some of the growth in small businesses is the result of a direct transfer of activity from large plants. Finally, due to technological development, increased productivity in large plants may have freed up resources for small plants, thus creating more employment in small plants. All of these factors may explain the observed negative relationship between plant size and growth, but do not necessarily justify the subsidies directed to small firms and plants.

When considering the public policy focused on small firms, it is also essential to assess the role of different-sized firms and plants in the total welfare creation. There is some evidence that a shift in industry structure towards small firms may increase economic growth (Audretsch et al., 2002). Small businesses have a particularly important role in introducing new ideas and technologies in the markets. The shift of employment to the small business sector may also result in a higher level of flexibility in terms of lower adjustment costs and higher worker turnover. It may be argued that small firms are able to customise their products and occupy available market niches more easily. In addition, higher job satisfaction may lead to higher commitment and motivation. On the other hand, higher turbulence, uncertainty and lower quality of jobs measured by wages and productivity may cause welfare losses to the economy.

The thesis also brings up the important question about whether it is reasonable to study the effects of plant size on plant performance. The endogeneity of size remains a problematic issue. It can be argued that plant size is being strongly affected by other plant and market characteristics describing plant's technological, financial and organisational capabilities. Moreover, it should be kept in mind that there is considerable heterogeneity among small plants as well among the larger ones. Still, it can be claimed that there are many factors that are more relevant in explaining the employment patterns of small plants than the larger ones. It may also be argued that a more important factor in explaining employment growth would be plant age and not size. Since most of the small plants are young entrants, the role of small businesses in employment growth may simply reflect the central role of plant start-ups in job creation.

From the policy perspective, it is important to ensure that there are enough plant start-ups in order to keep the continuous process of innovation and experimentation as vivid as possible. Successful entrants will achieve a high growth rate and create employment opportunities in the future. Thus, new firm formation and employment growth can be facilitated by destroying barriers to new firm entry and encouraging the mobility of resources. However, positive employment effects may appear rather slowly due to two phenomena closely related to the entry of new firms (e.g. Audretsch, 1995). First, there is a displacement effect of entry, i.e. entry of new, more efficient firms may displace a large share of less efficient incumbent firms and drive them from the market. Second, there may be a 'revolving door' phenomenon, according to which the bulk of new entrants subsequently exit from the industry within a relatively short period.

It may also be argued that identification and financial assistance of the potential new growth firms during the initial stages of their life cycle may be more important than the support to the declining ones. Finding significant effects on plant growth confirms that plant growth is not solely a stochastic process, but there are deterministic elements in growth, which can be influenced by economic policy. Measures to improve the physical and human capital structure of new plants may also enhance their employment growth. For example, the successful innovative activity of new firms may be supported by improving the structure of the educational system. If high-skilled labour is needed in the creation and implementation of new technologies, the increased availability of highly-educated employees removes entry barriers, speeds up R&D efforts and increases the chances of success and growth. It may be argued that small firms, in particular, may face more problems in recruiting qualified labour because of lower wages and more restricted career opportunities.[22]

According to Jovanovic (1982), after entry firms are faced with a natural process of learning and selection which ensures that the successful entrants survive, whereas the less efficient ones exit. Schumpeter (1942) argues that the processes of exit and decline are necessary and inevitable components of economic development. This phenomenon of 'creative destruction' frees up resources

[22] Kangasharju and Venetoklis (2002) have studied the effect of business subsidies on employment. Naturally, differences in the level of subsidies for different-sized firms may also have an effect on the survival and growth estimates.

for more efficient use and improves performance and competition in the markets. The finding of a negative relationship between productivity and the risk of failure supports this 'cleansing effect'. Small and medium-sized businesses are at the heart of the process of creative destruction and restructuring in the economy due to their higher turnover and flexibility. From the viewpoint of natural selection, supporting declining industries and plants may not be necessary, or even desirable. Economic downturns may also be viewed as a necessary tool for structural change and development of the markets despite their undesirable short-run consequences. However, there is some evidence that small and young firms are hit harder by recessions, which may also damage the innovative processes in the economy.

In addition to the need for further analysis of the topics studied in this thesis, including a more detailed examination of the effects of human capital and differences between services and manufacturing, there are various other directions for further study. For example, the models of financial theory could be linked to the firm growth literature. Decisions regarding plant start-up are closely connected to the availability of financing. Furthermore, financing constraints may have a considerable effect on plant growth and the likelihood of survival. In addition, differences in the employment patterns of foreign multinationals and those of domestic plants deserve more attention. It would also be interesting to study how globalisation and the changing structure of foreign trade have affected the survival prospects of Finnish plants. These issues remain challenging topics for future research.

A Data appendix

The data sources used in this study are from Statistics Finland. The basic unit of analysis is a plant or an establishment, which 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, i.e. a local kind-of-activity unit.

The primary data source used in this study is the Longitudinal Data on Plants in Manufacturing (LDPM), which is based on the annual Industrial Statistics surveys for the period 1974–1994 and on the annual Statistics on the Structure of Industry and Construction for the period 1995–2001 (Ilmakunnas et al., 2001). The Industrial Statistics covers, in principle, all Finnish manufacturing plants with 5 or more employees. Smaller plants are included only if their turnover corresponds to the average turnover of firms with 5–10 employees. However, during the period 1995–2001 the sample is smaller, i.e. only plants that belong to firms with at least 20 persons are included. The LDPM contains information on various plant level variables, including employment, hours worked, output, value added and capital stock. The employment figures are reported as annual averages.

The second data source used is the Business Register (BR), which also includes the other sectors of the economy in addition to manufacturing. The BR covers registered employers and enterprises subject to value added tax in Finland annually over the period 1988–2001. In addition, plant-level data is available. To illustrate, in 1998 the BR covered, in terms of personnel, 99 per cent of the non-agricultural enterprise sector in Finland, i.e. over 200 000 business sector plants. The missing one per cent was comprised of the public utilities of municipalities. The BR contains basic information on plant location, industry, ownership, sales and employment. The number of employees, in terms of full-time workers, comprises paid employees and entrepreneurs. However, there are some problems with longitudinal linkages in the BR, due to changes in taxation and statistical practices. These statistical reforms have had an effect especially on the coverage of the smallest plants in certain years.

Individual-level information can be linked to these data sources from the Employment Statistics (ES), which is based on various administrative registers. The ES covers effectively the entire population of Finland, i.e. over 2 million employees. The ES compiles information on individuals and their background characteristics, including the identity of their employer. The BR and the ES have been linked to form the Plant-level Employment Statistics Data on Flows (PESF) database, which contains information on job and worker flows in each plant over the years 1988–1997 (Ilmakunnas et al., 2001). In addition, information on, for example, the average age, education and seniority of employees at the plant level is gathered in the Plant-level Employment Statistics Data on Average Characteristics (PESA) data over the years 1988–2000.

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Table 1. Contents of the essays and the main findings

Essay	*Section II: Start-up size*	*Section III: Job flows*	*Section IV: Growth*	*Section V: Survival*
Main research question	What are the determinants of start-up size in services and manufacturing?	What are the relationships between plant size, job flows and job quality in Finnish manufacturing?	What is the relationship between plant size, age and growth conditional on survival, i.e. does the Gibrat's law hold? What is the effect of human capital on growth?	What determines the risk of failure in strongly fluctuating macroeconomic environment?
Methods used	OLS, quantile regression, truncated regression	Calculation of job and worker flows	OLS, joint ML (Heckman), within groups, between groups, GLS, 2SLS, GMM, truncated regression	Cox proportional hazards model, complementary log-log model (with unobserved heterogeneity)
Measure for plant size	Employment at start-up	2-year average employment, LR average employment, initial employment	Current employment, lagged employment, 2-year average employment	Employment at start-up, current employment, relative employment
Data sets used	BR, LDPM, ES	LDPM, ES	LDPM, ES, BR	LDPM, ES, BR
Time period	1989–2000, 1981–94	1980–94	1981–94	1981–93, 1989–2000
Main findings	The findings on industry turbulence and scale economies correspond to the earlier studies, i.e. they have stronger effects on entrants with higher start-up scale. Foreign ownership and multi/single plant dimensions are important. There are no notable differences between the results for services and manufacturing. However, regional human capital seems to play a different role in the choice of start-up size in these two sectors.	There is a negative relationship between job flows and size, but no clear relationship between net employment change and size. The methods of measurement have a considerable effect on the results. The relationship between size and growth is also affected by the recession. Job quality has to be taken into account when considering the total welfare effect. However, wage adjustment does not change the findings on job flows and size.	There is a negative relationship between plant size and growth even after controlling for sample selection bias and unobserved heterogeneity, i.e. Gibrat's law fails to hold. Age is negatively related to growth and positively to survival at least for young plants, thus supporting the life-cycle effect by Jovanovic. Human capital factors are important in explaining growth.	A large fraction of new plants die within the first few years, but the surviving plants grow fast. Current size is a better predictor of survival than initial size. Plant survival and growth are very sensitive to macroeconomic fluctuations. Small and young plants seem to be more affected by the business cycle. The main results are rather similar for services. However, human capital factors seem to be more important in manufacturing.

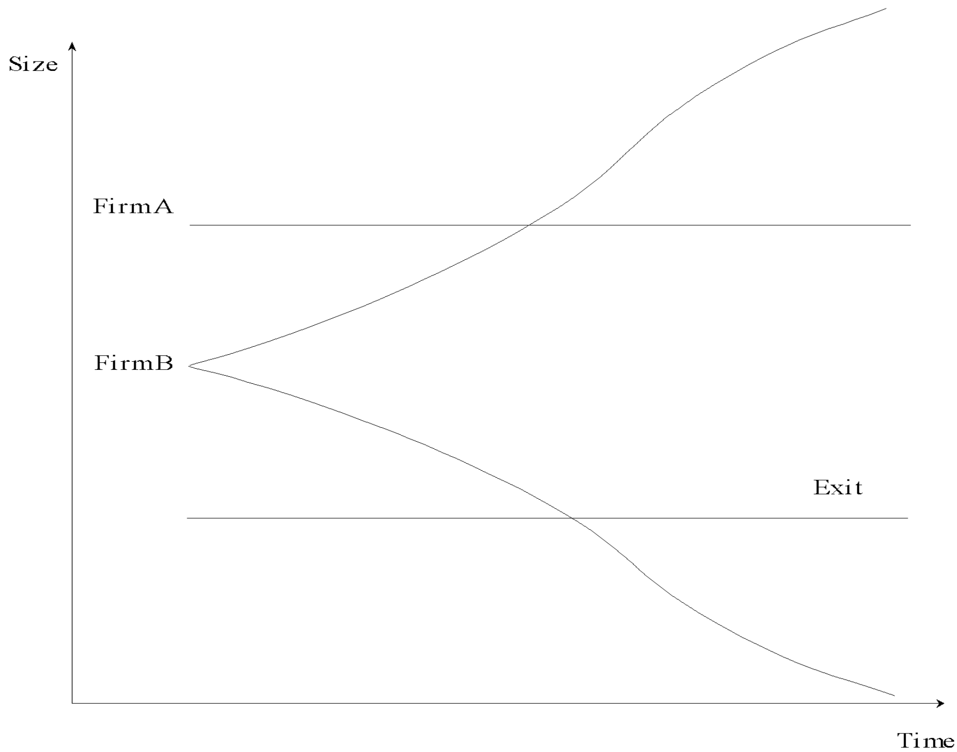

Figure 1. Two types of firms and their growth paths

II

II

SECTORAL DIFFERENCES IN PLANT START-UP SIZE IN THE FINNISH ECONOMY

Contents

1 Introduction **2**

2 The size of entering plants **4**
2.1 The data 4
2.2 Start-up size by industry 6

3 The determinants of plant start-up size **8**
3.1 Industry attributes and start-up size 8
3.2 Quantile regression approach 10

4 Results **11**
4.1 Comparison of manufacturing and services 11
4.2 The extended model for manufacturing 14

5 Conclusions **16**

1 Introduction

New firms play a fundamental role in the economy by creating a large number of new jobs and introducing new product innovations and technology enhancements in the markets. Since entry is a response to perceived profit opportunities, new firms drive prices towards the competitive level and improve efficiency in the industry. Through displacement effects and competitive pressures entrants speed up creative destruction which is often seen as an inevitable prerequisite for the evolution of the markets.

There is a vast literature on the extent and determinants of entry and on the post-entry performance of firms and plants (Geroski, 1991; Caves, 1998). It is found that regardless of the industry or time period, there is a considerable amount of entry in the economy. Typically, entering firms are small and a large fraction of them exit within a short period after entry. Many empirical studies also conclude that start-up size, measured with employment, is an important determinant of the likelihood of survival facing a new firm after entry. More precisely, there is a positive relationship between start-up size and the chances of survival (e.g. Mata & Portugal, 1994; Audretsch, 1995).[1] Furthermore, entrant's size has an effect on its subsequent growth. Among others Evans (1987) and Dunne et al. (1989) show that small firms have higher growth, which may be due to the cost disadvantage induced by operating at a sub-optimal size.

Acs and Audretsch (1989) and Mata (1991) take into account the fact that small and large-scale entry may be affected by different factors by using as the dependent variable the small firm entry share or the numbers of small and large entrants. However, to my knowledge, there are only a few earlier studies directly examining the determinants of the scale at which a firm or a plant enters, namely, the studies by Mata and Machado (1996) and Görg et al. (2000). Furthermore, these studies are based solely on manufacturing data with fairly short time periods and limited coverage of explanatory variables. New information on the determination of plant start-up size in different sectors of the economy may be very useful for decision making in industrial and labour market policy. Examining the choice of entry scale may also create new knowledge about the factors behind employment creation and recruitment decisions of new plants.

The purpose of this paper is, firstly, to study the industry-level and regional determinants of plant start-up size in the Finnish business sector during the years 1989–2000, i.e. including also the service sector in addition to manufacturing. Examining non-manufacturing sectors is important since these sectors cover a large share of all small businesses and the effect of industry characteristics on the entry scale may be quite different in this environment. Very small entrants may not respond to market conditions to the same extent as large entrants. In addition, human capital factors may play a different role in manufacturing and

[1] However, there are also opposite findings of a negative relationship between start-up size and the probability of survival (e.g. Mata et al., 1995; Disney et al., 1999).

services. Secondly, a richer data set on manufacturing, containing information on various aspects of industry performance and competitive environment, is used in order to extend the previous empirical literature. Thirdly, the data allows the sensitivity analysis of the results to the different data sets and size thresholds used. In addition, possible business cycle effects on plant start-ups can be controlled for when panel data is used. The plant is chosen as a unit of analysis instead of the firm, because decisions regarding the purchase of factors of production, including labour, are usually made at the plant level. More importantly, changes in ownership and legal status do not affect the plant identification code.

Previous studies have found that industry-level variables describing, for example, industry scale economies, growth and turbulence, are important determinants of start-up size. However, according to Mata and Machado (1996), industry attributes may have different effects on small and large-scale entrants. In addition, there are vast differences in firm start-up size even within narrowly defined markets. These findings emphasise the importance of taking into account the size-related plant-level heterogeneity in addition to the industry-level factors. However, the sources of this heterogeneity generally remain unobserved due to a lack of micro-level data that would be sufficiently comprehensive. As a consequence, previous studies have used quantile regression techniques where the effect of the covariates is allowed to vary across plants over the size distribution. In economics the number of empirical applications using more flexible quantile regression methods has been rapidly increasing in recent years (Koenker & Hallock, 2001).

Theoretical literature on the choice of firm start-up size is scarce. However, there are four alternative approaches explaining the determinants of optimal firm size in general (You, 1995). In the traditional technological approach, firm size is determined by technical and allocational efficiency. However, this approach cannot explain the vast heterogeneity in firm size, because it relies on the concept of the representative agent. As a result, more advanced approaches have been developed. In the transaction cost approach (or institutional approach) firm size is determined by transaction cost efficiency, whereas in the industrial organisation approach, size distribution is explained by market power. Lastly, the growth literature focuses on the dynamics of the size distribution of firms. This approach includes stochastic models, life-cycle models and evolutionary models of firm growth. It may be argued that the growth literature is more appropriate in explaining differences in start-up size than the theories explaining the size differences of existing firms in equilibrium.

Jovanovic's (1982) life-cycle model, for instance, assumes that firms enter at a similar scale. Since firms have no prior knowledge about their true ability, a typical entry is at a small scale. The model implies that young and small firms show on average higher and more volatile growth rates but also have lower survival rates. Survival is unaffected by start-up size but is heavily conditioned on growth. According to Cabral (1995), firms enter at a small scale especially if entry involves sunk costs which cannot be recovered in the case of failure. It should be noted that the determinants of entry size may to some extent be related to the determinants of entry, which are described in the theoretical models on firm entry. It is found, for example, that different-sized entrants respond to entry barriers in different ways (Mata, 1991).

The paper is organised as follows. Section 2 presents the data used and gives some evidence on the inter-industry differences in plant start-up size and average plant size. The empirical framework and explanatory variables related to start-up size are introduced in section 3. Section 4 presents the empirical results including a comparison of the results for manufacturing and services, and an extended model for manufacturing. Finally, section 5 concludes and discusses the possibilities for further research.

2 The size of entering plants

2.1 The data

The first data source used is the Business Register (BR) of Statistics Finland, which allows the inclusion of other sectors of the economy in addition to manufacturing in the analysis. The BR covers registered employers and enterprises subject to value added tax in Finland annually over the period 1988–2001.[2] In addition, plant-level data is available. A plant or an establishment is defined as a production unit of an enterprise that produces as similar goods or services as possible, and usually operates at a single location. Only active production plants are included in the analysis, e.g. headquarters and service units are excluded. The BR contains basic information on plant location, industry, ownership, sales and employment. The number of employees comprises paid employees and entrepreneurs. The number is given in terms of full-time workers. Information on average employee characteristics in each plant over the period 1988–2000 can be linked to the BR from the PESA data (Plant-level Employment Statistics Data on Average Characteristics) formed by linking the Business Register and the Employment Statistics of Statistics Finland (Ilmakunnas et al., 2001).

However, there are some problems with longitudinal linkages in the BR, due to changes in taxation and statistical practices. These statistical reforms have had an effect especially on the coverage of the smallest plants in certain years. Therefore, in order to produce as reliable a series as possible, only plants with at least three employees are included.[3] An entry or a start-up is defined according to the year when a plant appears for the first time in the Business Register during the

[2] To illustrate, in 1998 the BR covered, in terms of personnel, 99 per cent of the non-agricultural enterprise sector in Finland, i.e. over 200 000 business sector plants.

[3] Furthermore, plants with less than three employees are likely to be small family businesses where the choice of start-up size may be strongly influenced by factors which are very different from the industry or regional attributes used in this analysis.

period 1988–2000. As a consequence, entries in 1988 cannot be identified. Hence, the interest is on genuinely new plants but they may also be new subsidiaries of existing firms. The actual birth date for a firm cannot be identified due to possible changes in ownership structure, whereas the plant identification code does not change after entry. Diversified entry, i.e. changing industry, is not considered as a start-up when the data comes from the BR. In addition, it should be noted that due to the cut-off limit, these plants may have existed before the first observation with less than three employees. Entry is thus actually defined according to the time when a plant reaches the size of three employees, and this is treated as the plant's birth year. As a consequence, the period analysed covers the start-ups during the period 1989–2000, and the final data set used in the comparison of manufacturing and services consists of 69 322 observations on plant start-ups.[4]

The second data source used in this study is the LDPM (Longitudinal Data on Plants in Manufacturing) of Statistics Finland, which is based on the annual Industrial Statistics surveys over the period 1974–01 (Ilmakunnas et al., 2001). The Industrial Statistics covers, in principle, all Finnish manufacturing plants 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 plants that belong to firms with at least 20 persons are included. Therefore, these years cannot be included in this analysis. The information content of the LDPM is more extensive, i.e. it contains information on various plant-level variables, including employment, output, value added and capital stock.[5] The employment figures are reported as annual averages. The number of hours worked are also reported.[6]

A plant is considered as a start-up when it appears for the first time in the LDPM during the period 1974–94. Hence, also transitions from outside the manufacturing sector are now considered as entries. However, these broad industry changes are probably not very common. In addition, the fact that only those plants that do not appear in the files during the entire period 1974–80 are defined as entrants increases confidence that entrants are genuinely new plants in the data. The size cut-off of 5 employees has also been used by Mata and Machado (1996) and Görg et al. (2000). Subsequently, the period analysed covers the start-ups during the period 1981–94, and the final data set used in the extended model for manufacturing consists of 4 739 observations on plant start-ups.

Table 1 describes the size distribution of new plants in both data sets separately for manufacturing and services. Plant size is measured with the number of employees. According to the BR data, the number of entries is exceptionally high in 1989 and 1990 in both sectors, whereas it decreases during the recession years

[4] Agriculture and public sector are excluded from this analysis.

[5] Capital stock is estimated as the real value of machinery, equipment, transportation equipment, buildings and structures using the perpetual inventory method.

[6] 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.

at the beginning of the 1990s.[7] As expected the mean size of an entering plant is higher in manufacturing than in services. In addition, the standard deviation of size is clearly higher in manufacturing.[8] However, the quantile regression method used is not very sensitive to outliers. Both the high coefficient of skewness and the median which is lower than the mean imply that the size distribution is highly skewed to the right.

It can be seen that the number of entries in the LDPM data is higher than usual in 1982 and 1991. The latter can be explained by the increased number of small plants in the Industrial Statistics sample in 1991.[9] The average start-up size is considerable higher than in the BR data, 24.86 employees with a standard deviation of 53.48. Naturally, this is mainly due to the higher cut-off limit of size.[10] The size distribution is still clearly dominated by the small plants. Median is higher than in the BR data but notably lower than the mean. Differences in the largest start-up sizes in the two data sets are probably due to different definitions of entry.

2.2 Start-up size by industry

There are large inter-industry differences in plant size due to the different roles played by scale economies, capital intensity and technology in different sectors of the economy. These differences in optimal size have an effect on the typical start-up size in the industry. Table 2 lists 2-digit industries in the order of average start-up size during the period 1989–2000 using the BR data.[11] The average start-up size can be compared with the average size of plants in each industry. The table also reports the relative size of entrants with respect to all plants and the number of start-ups and plants in the industry. Average start-up size varies from 37.1 employees in the manufacture of pulp and paper to 3 employees in tobacco products. The average plant size varies from 241.6 employees in tobacco products to 6.8 employees in collection, purification and distribution of water. At the 3-digit industry level used in the regression analysis the variation is likely to be even higher.

The relative size of entrants with respect to all plants is on average 0.43 in the total business sector. This reflects the fact that the entrants' share of the number of plants in the sample is 10.8%, whereas the employment share of new

[7] Higher number of start-ups in 1989 and 1990 may be partly explained by the business cycle effects, partly by the changes in the statistical system. However, when these years are excluded from the estimations, the results are consistent across the two alternative samples.

[8] The largest plant start-up size in the BR is 1300 employees, which is very high and may have been recorded incorrectly.

[9] However, the main results do not change when these years are dropped from the estimations.

[10] There seem to be some large start-ups in 1989, which temporarily increase the mean and standard deviation of the size distribution.

[11] It should be noted that the average start-up size according to the mean may be influenced by only a few large outliers. However, the quantile regression method used in the further analysis relies on the median, which is less suspicious to outliers than the mean.

entrants is only 4.6%. On the other hand, the small plants' share of all entering plants is 99% when the plant is considered to be small if it has less than 100 employees. The small entrants' share of all new employment is 83%. The last column in Table 2 gives the entry penetration rate in each industry measured as the share of employment in start-ups relative to total industry employment. It can been seen that in most industries the entrants' share of employment is very low. There are only a few industries with entry penetration rate higher than 10%. This corresponds to earlier findings on entry penetration (see e.g. Geroski, 1991, pp.16-23).

Figure 1 presents the evolution of average plant start-up size in relation to the average size of all plants over the period 1989–2000, separately for the whole business sector, as well as manufacturing and services.[12] The figure shows that the relative size of entrants in manufacturing is considerable lower than that in the service sector. This reflects the fact that most of the service sector plants are rather small. In addition, the variation of relative start-up size is slightly higher in services. There are some peaks in the relative start-up size, i.e. in 1992 and 1995. In addition, at the end of 1990s there is a clear upward trend in all sectors. These changes may be due to changes in the statistical system or the effect of a temporary increase in the number of larger start-ups.[13]

The relative size of entrants in manufacturing over the period 1981–94 based on the LDPM data is presented in Figure 2. The earlier years show that there is an increasing trend in the relative start-up size during the 1980s, which is mostly due to the two large upswings in 1985 and 1989. However, this figure gives a completely different picture of the relative start-up size in manufacturing over the years 1989–94. Contrary to the rather stable pattern of the relative entry size around 25% in Figure 1, Figure 2 shows a relative entry size that is highly fluctuating between 30 and 60 per cent. It should be noted that there are many differences in these two data sets with regard to the coverage of plants in terms of size threshold, definition of entry and differential treatment of small multiplants in the LDPM.[14] This leads to a larger number of observations in the BR for most years. However, the higher cut-off for the LDPM sample alone does not explain the peaks in 1989 and 1990, which may also be partly due to an exceptionally large number of very large start-ups in these years. Even though these differences cannot be fully explained, this finding puts special emphasis on the importance of taking into account the effect of data set used on the results.

[12] The business sector is defined as the total economy minus agriculture, hunting, forestry and fishing, and community social and personal services. Manufacturing does not include mining and quarrying or electricity, gas and water supply. Services include wholesale and retail trade, restaurants and hotels, transport, storage and communication, finance, insurance, real estate and business services.

[13] The exclusion of the largest outliers (start-ups with more than 500 employees) decreases the relative start-up size in 1995.

[14] Small firms (having less than 20 employees) with multiple plants are treated as a single plant in the Industrial Statistics survey. In addition, industrial plants located in the same area or plants engaged in secondary activities in another industry may be combined.

3 The determinants of plant start-up size

3.1 Industry attributes and start-up size

The data content in the BR allows the use of similar covariates as earlier studies. As an extension, the results for manufacturing and services can be compared. Furthermore, the model can be extended by using additional covariates. The BR data allows the inclusion of human capital variables, whereas the richer LDPM data set allows the construction of variables describing industry-level profitability, capital intensity and investments. In addition, industry-level data on R&D activity and foreign trade is available for manufacturing.

Variables describing the structural barriers to entry and the possibility of strategic action of incumbents against the entrants are the most important deterrents of entry, whereas higher industry profits and demand attract more entry. These factors are likely to affect entry differently depending on the scale of entry. Earlier studies by Mata and Machado (1996) and Görg et al. (2000) characterise some important relationships between industry attributes and start-up size. Scale economies are clearly an important determinant for plant start-up size. Higher Minimum Efficient Scale (MES) increases the cost disadvantage faced by sub-optimal entrants and worsens their competitive position. Hence, higher MES is expected to increase the start-up size. Mata and Machado find that large firms are created only in those sectors which are characterised by considerable economies of scale but at the same time smaller firms are not deterred from entering the market.

However, in markets where a large number of plants operate below MES, small entrants may have better chances of being successful. They may overcome the scale-related disadvantages by, for example, occupying a niche with a differentiated product or taking advantage of the more flexible organisational structure that small units often have. Sub-optimal scale, which is measured as the proportion of industry employment in plants smaller than MES, describes this within industry heterogeneity. A large number of plants operating below MES may simply reflect the fact that large and small plants do not compete with each other, so small entrants do not necessarily suffer from any cost disadvantage resulting from inefficient size. Thus, a negative relationship is expected between sub-optimal scale and start-up size.[15]

Choosing to enter on a small scale, entrants intend to reduce the likelihood of aggressive response from incumbents because the payoff of retaliatory behaviour against small entrants is likely to be small. In large markets the competitive and retaliatory action against entrants is likely to be less severe. Furthermore, the potential for increasing market share in the future will be higher. Subsequently, for a given MES, the larger the market size measured with the natural logarithm

[15] In addition, an alternative measure can be used to characterise the small plant cost disadvantage, i.e. small plant (plants with less than industry average number of employees) productivity in relation to the average productivity in the industry.

of industry employment, the larger the expected entry scale. If markets are growing fast, the likelihood of survival is greater and the reactions from incumbents weaker, so a higher start-up size is possible. Industry growth is measured as the logarithmic difference in the industry employment between consecutive years. Similarly to earlier studies, industry turbulence is used as an indirect measure for the sunk costs faced by entrants. Mata and Machado suggest measuring industry turbulence as the product (instead of the sum) of employment-weighted entry and exit rates. The advantage of this new measure is that it attains high values only if both entry and exit are high, suggesting that the sunk costs in the industry are low. Since low sunk costs reduce the losses in case of failure and increase the benefits of exploiting the existing scale economies, industry turbulence is expected to be positively related to the scale of entrants.

The regional availability of experienced and educated work force may be important for the choice of start-up scale. An increased supply of high-skilled workers may improve an entrant's opportunity to raise productivity through learning by doing and R&D, which increases the chances of survival and thus start-up size. Hence, the previous studies could be extended by controlling for the regional composition of the work force, which could be measured with the average education and experience of the employees and the share of women in each region.

In the second section the focus is on manufacturing only. This allows the introduction of various new variables describing the ownership structure of entering plants as well as industry structure and performance. The choice of start-up scale reflects differences in the perceived ability and expectations about efficiency and profitability. Plants belonging to firms with more than one plant may gain from prior experience, accumulated managerial knowledge, and financial or distribution channels of their parents. This probably makes them more confident about their future performance, which may result in a larger start-up size. Hence, the employment share of entering multiplants in the industry is also controlled for. Correspondingly, the higher employment share of entering foreign-owned plants may increase the start-up size. It can be argued that foreign-owned firms have better initial conditions and more funding available, which allows a larger scale of operations at start-up. On the other hand, the presence of new foreign-owned firms in the markets may have an impact on the entry size of domestic firms through the introduction of higher levels of competition, lower prices and increased demand in the markets.[16]

Industry profitability is described with the price-cost margin, which is measured as the difference between the industry value added and costs of labour and raw materials in relation to the industry value added. Thus, it captures differences in technology, demand conditions and the intensity of competition between industries, and is expected to be positively related to entry in general. However, small-scale entry may be less affected by industry profitability because small en-

[16] Görg and Strobl (2002) study the impacts of foreign multinationals on the start-up size of domestic entrants in Irish manufacturing.

trants often rely on new product innovations or market niches. The standard deviation of price-cost margins in the industry is included as a measure of market heterogeneity, which may increase the entry scale as there are higher profit opportunities.

High capital requirements impede especially small-scale entry, so higher capital intensity in the industry is expected to increase start-up size. Investment rate measures capacity expansion in the industry and can be seen as a sign of strategic action against new entrants, which also decreases the expected start-up size. R&D intensity, measured as R&D expenditures per employee, may be thought of as measuring product differentiation effort which is directed towards deterring entry. This may result in entrants preferring smaller start-up size. However, since small plants have an evident scale disadvantage in innovative activity, high R&D intensity may also increase the entry scale. In markets with high export intensity, growth potential is greater and economies of scale can be exploited more easily. As a result, a higher start-up size can be expected. On the other hand, import penetration measures the extent of foreign competition in the industry, and this may decrease the chances for survival of inefficiently-scaled entrants.

3.2 Quantile regression approach

Ordinary least squares estimation is restricted to measuring the effect of covariates on the conditional mean of the dependent variable. It does not take into account the plant-level heterogeneity which is likely to have an effect on the estimated coefficients. It is very likely that the effect of the industry-level covariates on start-up size will vary across different-sized plants in the industry. The regression quantiles estimator developed by Koenker and Bassett (1978) allows for this neglected heterogeneity and enables the evaluation of the determinants of plant start-up size at various quantiles of the plant size distribution. Thus, it provides a more complete picture of the relationship between industry characteristics and plant start-up size. In addition, quantile regression is robust to outliers and deviations from normality, and equivariant to monotonic linear and non-linear transformations of the dependent variable.

The most common form of quantile regression models is median regression, where the objective is to estimate the median of the dependent variable, conditional on the values of the independent variables. Median regression minimises the sum of the absolute residuals rather than the sum of squared residuals. Generalised quantile regression allows the estimation of the other quantiles of the distribution.

The quantile regression model can be viewed as a location model. The θth sample quantile, $0 < \theta < 1$, may be defined as any solution to the minimisation problem:

$$\min_{b \in R} \left\{ \sum_{i:y_i \geq b} \theta \left| y_i - b \right| + \sum_{i:y_i < b} (1-\theta) \left| y_i - b \right| \right\},$$

where $\{y_i : i = 1, ..., n\}$ is a random sample on a random variable Y having distribution function F. The analogue of the linear model for the θth quantile is defined in a similar manner. Let $\{x_i : i = 1, ..., n\}$ denote a sequence of (row) K-vectors and suppose $\{y_i : i = 1, ..., n\}$ is a random sample on the regression process $u_i = y_i - x_i'\beta$ having distribution function F. Then the θth regression quantile, $0 < \theta < 1$, is defined as any solution to the minimisation problem:

$$\min_{b \in R^K} \left\{ \sum_{i: y_i \geq x_i' b} \theta \left| y_i - x_i' b \right| + \sum_{i: y_i < x_i' b} (1 - \theta) \left| y_i - x_i' b \right| \right\}.$$

4 Results

4.1 Comparison of manufacturing and services

There may be vast differences between the patterns of start-up size in manufacturing and the service sector. One of the main differences between the two sectors is the absence of scale economies in services. As a consequence, in services a lower start-up size is possible. This is consistent with the observation of mean plant size of 13.0 employees for services and 38.2 employees for manufacturing. Instead of scale economies, the entry process in services may depend more on other industry-level and regional characteristics.

In order to compare the results for manufacturing and services with the previous results by Mata and Machado (1996) and Görg et al. (2000), a regression model which is comparable to the earlier studies is estimated first. Hence, the model includes as explanatory variables MES, sub-optimal scale, industry size, industry growth and turbulence. It has been suggested that the size distribution is approximately lognormal, although empirical results do not always support this assumption. In addition, there are some extreme observations in the data, and the differences in start-up size between manufacturing and services may be large. Hence, in the regressions the logarithm of employment during the year of entry is preferred as a measure for plant start-up size.

The definitions of the variables used in the paper are described more thoroughly in Table 3. In the regression analysis industry attributes are calculated at the 3-digit industry level using the SIC (Standard Industrial Classification) adopted in 1995, which amounts to having information on 181 industries (101 manufacturing industries). All explanatory variables are measured at the year of start-up. The descriptive statistics for manufacturing and services are reported in Table 4. As expected, the average start-up size in services is lower than in manufacturing, both according to the mean and the median. Furthermore, the optimal scale according to MES is considerably higher in manufacturing than services, whereas the proportion of sub-optimal scaled plants is higher in services. Industry turbulence is somewhat higher in services.

Table 5 shows the OLS and quantile regression estimates for manufacturing using the BR data with a size cut-off of 3 employees. All estimations include time dummies in order to control for the cyclical effects.[17] Moulton (1990) showed that standard errors can be seriously biased downwards when the effects of aggregate explanatory variables on micro-level variables are estimated, because the disturbance terms are correlated within groups. Therefore, heteroscedasticity-consistent estimates of the standard errors with clustering on industry have been calculated for the OLS regressions (White, 1982).[18] Similarly, for the quantile regression results the estimated standard errors have been derived by bootstrapping (using 300 replications) and using clustering on industry, which allows observations to be independent across industries, but not necessarily within industries.[19] According to Buchinsky (1998), bootstrapping is an appropriate and well-behaving method for quantile regressions. Especially in cases of heteroscedastic errors the estimated standard errors can be understated if bootstrapping is not used. Following Mata and Machado the lowest quantile estimated is 0.15 due to the low variability of start-up size at the left tail of the size distribution.

The results for manufacturing show that scale economies have a highly significant, positive effect on start-up size and the effect increases towards the higher quantiles. However, according to the OLS estimates the coefficient of sub-optimal scale is positive, but not significant. Surprisingly, it also turns out to be positive and increasing in the quantile estimations, except for the highest quantile. This contradicts the earlier results by Mata and Machado and Görg et al. who find that the effect of sub-optimal scale on start-up size is negative for all quantiles. However, the result may be affected by the high correlation between MES and sub-optimal scale (-0.53 in the total sample).[20] As a consequence, another variable describing small plant (with less than the industry average number of employees) cost disadvantage, measured as the ratio of small plant productivity to the industry average productivity, was used alternatively, but this covariate was insignificant in all quantiles.

Industry size is positive and increasing in all estimations, but significant only in OLS. Previous studies have also found that industry size does not have strong explanatory power. Similarly, industry growth turns out to have no significant effect on start-up size in manufacturing. Industry turbulence has a clear positive

[17]The model assumes that the impact of the different covariates remains constant over the period, which may not be a valid assumption. However, the main findings do not change when the model is reestimated using data on separate years.

[18]Using clustering has a clear effect on the standard errors and some coefficients lose their significance compared to the earlier analysis without clustering (Nurmi, 2003).

[19]In the models with regional human capital effects, clustering is based on a grouping variable which combines industry and region.

[20]When plants in the information and communications technology (ICT) sectors are excluded from the analysis, the relationship between sub-optimal scale and start-up size becomes more negative in services. This finding may suggest that ICT-plants are affected differently by the industry's size distribution. The average start-up size for ICT-plants in the sample is 9.6 employees, whereas for non ICT-plants it is 7.5 employees.

effect on start-up size and it becomes increasingly important as we move upwards in the conditional size distribution. Overall, these results suggest that large plants mostly enter those industries where scale economies are important or sunk costs are low (turbulence is high). This is in accordance with previous findings.[21]

In the service sector the effects of scale economies and turbulence correspond to the results for manufacturing. Only scale economies and turbulence have statistically significant effects on plant start-up size. Sub-optimal scale is again positive for most quantiles. On the contrary, the alternative measure, small plant cost disadvantage, turns out to be negative but insignificant in all regressions (not reported).[22] It can be concluded that, contrary to expectations, the results for services and manufacturing seem to be surprisingly similar.[23] This may be due to the limited number of explanatory variables which may lead to the omission of some relevant factors. For example, the availability of skilled labour may be more important for start-ups in services than in manufacturing. For example, high-tech service sectors may be even more dependent on the availability of educated and experienced employees in creating and implementing new innovations than the manufacturing industries using high technology.

Table 6 shows the results for manufacturing and services when regional average education, work experience and share of women employees are controlled for. The regional division is based on the regional classification of Statistics Finland, where Finland is divided into 20 regions or provinces corresponding to the so-called NUTS level 3 of the European Union. To decrease the possibility of simultaneity bias, human capital variables are measured in the year prior to start-up. According to the descriptive statistics (Table 3) plant start-ups in services are located in regions where employees are on average better educated but slightly less experienced than in manufacturing. As expected, the share of women is higher in services.

The inclusion of the human capital variables in the model increases the significance of other coefficients. The availability of educated personnel in the region seems to have a positive and increasing effect on plant start-up size. This in accordance with the hypothesis that the availability of qualified work force increases the plant's prospects of survival and thus start-up size. Another explanation may

[21] It may be argued that there are endogeneity problems in some of the covariates, eg. MES and sub-optimal scale, which describe the size distribution of plants in the industry. In addition, some variables may affect the entry decisions with a lag. However, when the basic model is reestimated using one-year lags of all the variables, the most notable change is that the coefficient for turbulence loses its significance in services.

[22] It can be tested whether the effects of the covariates are the same between different quantiles. F-tests show that there are significant differences between different quantiles for most of those coefficients, which are significant in the estimations (not reported).

[23] In order to take into account the cut-off limit of 3 employees, we also estimate a truncated regression model with robust standard errors for start-up size with truncation from below ln3 (not reported). The coefficient signs are as expected and the absolute effects increase considerably. However, while for services most relationships are statistically significant, for manufacturing they are not.

be that the shift in demand towards better educated workers due to recent changes in firms' production technology, i.e. skill-biased technological change, is reflected in the results.[24] It can be argued that this process has increased the average level of education of workers, and at the same time, average plant (start-up) size has increased due to higher productivity and increased competition. However, education turns out to be more important for start-ups in services, whereas in manufacturing the effect is significant only for the largest plants. This may simply describe the different nature of these sectors, i.e. services having a large share of small high-tech and business services plants with highly educated employees. In addition, it may be argued that physical and human capital are more complementary in services where larger plant size increases the demand for skilled work force more than in manufacturing.

Regions characterised by experienced work force may include older firms in the mature phase of their life cycle, which could be expected to increase plant start-up size. However, these regions may also offer market niches for new small plants. The effect of regional work experience, measured with worker seniority, on the start-up size of service sector plants turns out to be positive and somewhat significant in the 0.5 and 0.75 quantiles. In manufacturing the coefficient of experience is insignificant. Using average age of employees instead of seniority to approximate work experience does not change the results much. The average share of female employees in the region also seems to be more closely connected to start-up size in services.[25] The share of women is positively related to the start-up size in services, whereas in manufacturing the relationship is mostly negative and insignificant. Overall, the results seem to indicate that it is important to consider the different role of human capital in manufacturing and services. However, it should be emphasised that these results have to be interpreted with caution because of possible simultaneity problems. In addition, the distinction between demand and supply effects of regional skilled work force are difficult to separate.

4.2 The extended model for manufacturing

In the second part of the analysis the model for manufacturing is extended by using additional covariates described earlier. For the LDPM data, industry attributes are calculated at the 4-digit industry level using the SIC adopted in 1979, which closely corresponds to the level used in the previous analysis with the BR data.[26] Table 7 presents the descriptive statistics for the analysis using LDPM data. Comparison of the corresponding variables shows that the mean values for manufacturing are higher for the LDPM data than the BR data, except for in-

[24] Chennells and Van Reenen (1999) provide a survey of the effects of technical change.

[25] It should be noted that variables for seniority and the share of women are highly correlated (-0.65).

[26] This amounts to having 79 industries in manufacturing. R&D expenditures and imports are available at the 4-digit industry level only for some industries, others are aggregated to the 2- or 3-digit levels.

dustry growth and turbulence. This is most likely due to the higher cut-off limit of 5 employees in the LDPM data. In order to assess the sensitivity of the results to the data set used, the basic model comparable to Table 5 is estimated (not reported). However, it should be noted that different size thresholds, time periods and definitions of entry may have some influence on the results. Nevertheless, the results seem to correspond closely to the earlier findings.[27]

Table 8 reports the estimation results for the extended model for manufacturing. The effects of scale economies and industry turbulence on start-up size remain positive and increasing along the size distribution. The coefficients of industry size and growth are mostly insignificant. Sub-optimal scale is replaced with small plant cost disadvantage, which turns out to be negative and significant for most quantiles. However, the absolute effect is non-monotonically decreasing, which contradicts the earlier results. This finding may be explained by some differences in the industrial structure or business environment in Finland in comparison to Portugal and Ireland, but further analysis is needed. Among the new variables the share of multiplants of all entrants is highly significant and more important for the larger quantiles. The employment share of foreign-owned entrants is also positive and non-monotonically increasing. This gives some evidence that larger start-ups often belong to firms with multiple plants and which have a high share of foreign ownership.

Most other variables turn out to be insignificant. Industry price-cost margin does not have a considerable effect on the start-up size. The variability of price-cost margins or industry heterogeneity turns out to be positively related to the start-up size. However, the coefficient for variability in profits is insignificant in all quantile regressions. Capital intensity has a weak positive effect on start-up scale. As expected, investment rate has a negative sign in most parts of the size distribution. R&D intensity is also negative and significant only for the 0.25 quantile. This would suggest that R&D intensity decreases the start-up size, especially for small entrants. However, this variable is not measured very accurately. In accordance with the expectations, both higher export intensity and higher import penetration seem to be positively related to the start-up size, but they turn out to be insignificant.[28]

Since it may take some time for some industry attributes to affect the entry decisions of new plants, the model is reestimated using one-year lags of industry profitability, growth and turbulence. These variables turn out to be mostly insignificant and sometimes negative (not reported). Past profits are not found to

[27]The results with truncation from below ln5 are very similar to the OLS estimates when the LDPM data set is used.

[28]It should be noted that due to high correlations between some of the variables there may be some degree of multicollinearity in this specification. Due to a high correlation between export intensity and import penetration (0.45), these variables were included in separate models (not reported). In addition, R&D intensity was excluded because of its high correlation with imports (0.48). However, the effects of foreign trade remain insignificant and other findings do not change.

have much predictive power in explaining expected post-entry profitability in earlier studies either. The problem of simultaneity, i.e. an individual entry affecting industry performance and growth, is not likely to very severe because the entry penetration rates measured with employment are very low in most industries (see Table 2).

It seems that the variable describing multiplant status is rather significant in explaining plant start-up size. It can be hypothesised that a new plant belonging to a firm with other plants has better financial and other connections, more experience and more realistic expectations about its future possibilities than a new single plant firm. In this environment a higher entry size can be expected. In fact, the average start-up size for multiplants in the sample is 64 employees, whereas the average start-up size for single plants is only 17.4 employees. In addition, the industry-level factors determining start-up size may differ substantially between these two groups. Tables 9 and 10 include the estimates separately for multi- and single plant entries, i.e. new plants belonging to firms with more than one plant or only a single plant. Unfortunately, it is very difficult to trace reliably the number of plants of the parent firm in the year preceding entry due to possible changes in the firm ownership structure, and hence, firm identification code. For the same reason, firms that have entered by establishing several plants at the same time cannot be reliably identified.

The results show that very different industry characteristics determine the start-up size of multi- and single plants. Scale economies seem to be more important for multiplants. However, the effect of MES is still non-monotonically increasing for both groups. Small plant cost disadvantage does not have a clear effect on the start-up size of multiplants, while for single plants its coefficient is always negative and mostly significant. Industry size and growth turn out to be mostly insignificant, but for the highest single plant quantiles the positive coefficient for growth is highly significant. Industry turbulence and the share of foreign-owned plants have positive, non-monotonically increasing effects on start-up size, but both covariates seem to be more important for single plants. According to the quantile regression results multiplants do not seem to be significantly affected by the rest of the industry attributes, with a few exceptions. On the contrary, for single plants capital intensity turns out to be positive and significant for the highest quantiles, whereas investments reduce the start-up size especially in the 0.5 and 0.75 quantiles. The effect of R&D activity is negative and significant in the 0.5 quantile. Export intensity turns out to be insignificant and the coefficient for import penetration is only significant in the highest quantile. Overall, the entry scale of single plants seems to be more affected by the entry environment.

5 Conclusions

The first aim of this paper was to examine whether the earlier findings based on data from the manufacturing sector also hold for the service sector. It is found that the results are remarkably similar for these two sectors of the economy when only a restricted set of explanatory variables is used. Further analysis is needed to shed some light on this surprising result. For example, regional work force composition seems to have a different role in the choice of start-up size in manufacturing and services. The results show that the availability of educated personnel is positively related to start-up size both in manufacturing and services, but the effect is more important in the service sector. Work experience and share of women seem to be more closely connected to the start-up size in services. However, when considering the effects of human capital on the choice of start-up scale, simultaneity of these decisions may cause problems.

The second purpose was to test the effects of some additional covariates on plant start-up size using data on manufacturing only. The findings suggest that the effects of some industry characteristics on plant start-up size differ considerably depending on the scale of entry, so the OLS estimates can be highly misleading. It is found that large plants are less likely than small plants to enter industries with low scale economies or high sunk costs. In addition, belonging to a multi-unit firm or having a large share of foreign ownership increases the start-up size. There is also some evidence on the negative effect of R&D intensity on the entry scale of small plants. In addition, it is found that the start-up scale of single plant entrants is more affected by the industry attributes than that of multiplant entrants, who face a rather different entry environment.

In each industry there are barriers to entry which may increase the optimal start-up size. The results suggest that large-scale entry is preferable when the need for sunk investments or the possibility of strategic action against entrants is low. Being small allows entrants to minimise capital requirements and to avoid aggressive responses from the incumbents. In particular, the start-up scale of single plant entrants seems to be more affected by strategic behaviour in the industry than that of entrants belonging to multiplant firms. Through a learning process small entrants become more certain about their performance and their prospects of growth and survival improve.

In further analysis, the effect of financial constraints on entry scale would be worth studying. In public policy debate, financial factors are often seen as a very central and interesting determinant of firm start-ups and job creation. In addition, the effects of regulation and business environment on the entry patterns in different industries could be studied more extensively. For example, pharmacies and the banking sector are affected by very different rules and legislation regarding start-ups. In addition, entry patterns may vary considerably over the phase of the industry life cycle. The data would also allow the analysis of cyclical effects on start-up size. It could be studied whether the business cycle has had similar effects on the rate and scale of entry in different industries.

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Table 1. Descriptive statistics for plant start-up size 1989–2000 (BR) and 1981–1994 (LDPM)

Manufacturing (the BR data)								
Year	N	Mean	Std	Median	Min	Max	Skewness	Kurtosis
1989	1262	10.96	41.25	4.10	3.00	998.00	16.32	334.23
1990	1156	8.90	23.88	4.00	3.00	400.00	10.08	131.44
1991	690	10.09	24.14	4.10	3.00	276.00	7.60	71.77
1992	585	10.97	30.02	4.30	3.00	415.00	9.16	103.12
1993	978	8.66	23.24	4.10	3.00	367.00	9.57	113.04
1994	820	8.47	19.70	4.10	3.00	306.00	8.71	99.45
1995	856	10.72	36.62	4.00	3.00	555.70	10.01	120.74
1996	817	11.02	43.91	4.00	3.00	857.10	12.37	197.53
1997	821	8.23	18.67	4.00	3.00	274.50	9.31	108.48
1998	637	10.07	30.08	3.90	3.00	568.00	12.08	198.6
1999	541	13.11	45.67	3.90	3.00	592.10	9.44	105.36
2000	651	13.03	44.95	4.80	3.00	779.80	11.77	169.15
All	9814	10.17	32.90	4.00	3.00	998.00	13.54	260.32
Services (the BR data)								
Year	N	Mean	Std	Median	Min	Max	Skewness	Kurtosis
1989	5312	8.41	28.95	3.80	3.00	1300.00	22.78	825.78
1990	5874	7.75	19.55	3.80	3.00	568.50	14.21	285.3
1991	3445	7.50	21.58	3.90	3.00	770.00	21.64	640.6
1992	2974	8.36	16.20	4.00	3.00	241.00	7.48	76.72
1993	3602	6.17	10.43	3.90	3.00	231.00	10.68	168.5
1994	3959	6.33	11.12	4.00	3.00	264.00	11.03	175.73
1995	3908	8.12	37.78	3.80	3.00	1222.00	21.97	589.59
1996	3836	6.01	10.02	3.70	3.00	220.00	9.20	121.77
1997	4007	6.74	20.97	3.80	3.00	658.60	19.73	506.51
1998	3774	6.46	13.12	3.70	3.00	355.10	13.99	276.91
1999	3675	7.88	20.62	3.90	3.00	685.50	15.71	385.8
2000	3977	8.03	17.31	4.00	3.00	355.00	10.52	153.64
All	48343	7.35	20.90	3.80	3.00	1300.00	24.39	1006.97
Manufacturing (the LDPM data)								
Year	N	Mean	Std	Median	Min	Max	Skewness	Kurtosis
1981	299	21.78	33.55	12.00	5.00	321.00	5.40	38.25
1982	775	18.93	47.06	10.00	5.00	746.00	10.83	141.63
1983	280	19.76	29.79	11.00	5.00	336.00	6.37	54.51
1984	360	22.08	36.15	11.00	5.00	313.00	5.05	29.87
1985	201	31.86	59.28	14.00	5.00	489.00	4.87	28.55
1986	222	31.49	53.78	16.00	5.00	508.00	5.12	33.38
1987	354	31.46	78.01	13.00	5.00	744.00	6.66	50.27
1988	243	29.65	70.81	12.00	5.00	824.00	8.07	78.69
1989	256	42.82	105.00	14.00	5.00	995.00	5.58	37.39
1990	271	35.58	57.52	16.00	5.00	548.00	4.72	30.55
1991	825	19.07	32.97	11.00	5.00	586.00	9.01	120.69
1992	270	24.94	57.10	12.00	5.00	813.00	10.45	137.11
1993	207	19.86	31.12	11.00	5.00	287.00	5.53	37.25
1994	176	23.89	32.05	13.00	5.00	237.00	3.88	19.07
All	4739	24.86	53.48	12.00	5.00	995.00	8.51	97.86

[1] Mean start-up size without the largest outliers (start-ups with more than 500 employees) is 9.56 employees in manufacturing and 7.12 employees in services using the BR data. The corresponding value for the LDPM data is 22.89 employees.

Table 2. Average start-up size, average size, relative start-up size, the number of start-ups and plants, and entry penetration by industry (averages 1989–2000)

SIC	Industry description (manufacturing 15–37)	Average start-up size	Average plant size	Relative start-up size	Number of start-ups	Number of plants	Entry pene-tration
21	Pulp and paper	37.05	181.55	0.20	128	2338	0.01
32	Radio, television and communication equipment	35.21	108.68	0.32	206	1977	0.03
61	Water transport	29.71	86.06	0.34	131	1218	0.03
27	Basic metals	28.61	138.40	0.21	87	1368	0.01
40	Electricity, gas etc.	26.85	29.59	0.90	240	5140	0.04
23	Coke, refined petroleum products and nuclear fuel	23.50	198.63	0.12	4	131	0.01
31	Electrical machinery	22.36	52.62	0.41	276	3459	0.04
30	Office machinery and computers	19.89	78.87	0.22	31	293	0.02
64	Post and telecommunication	18.93	22.47	0.85	2708	21683	0.10
35	Other transport equipment	16.65	86.20	0.19	249	2192	0.02
24	Chemicals	16.49	75.07	0.22	156	2762	0.01
66	Insurance and pension funding	16.25	22.34	0.73	305	5721	0.04
13	Mining of metal ores	12.06	113.33	0.11	6	79	0.03
29	Machinery and equipment n.e.c.	11.75	40.57	0.29	1417	15248	0.03
73	Research and development	10.45	38.87	0.28	114	583	0.06
72	Computer and related activities	10.32	19.74	0.52	1829	9476	0.10
25	Rubber and plastics	10.09	35.15	0.28	331	4636	0.02
63	Supporting transport activities, travel agencies	9.82	20.78	0.46	1192	11094	0.05
26	Other non-metallic mineral products	9.51	29.54	0.32	431	5897	0.02
19	Leather	9.40	28.48	0.33	84	1453	0.02
15	Food and beverages	9.23	40.77	0.23	707	11727	0.01
67	Activities auxiliary to financial intermediation	9.01	15.23	0.59	275	944	0.24
65	Financial intermediation	8.78	18.59	0.47	741	23944	0.02
22	Publishing and printing	8.29	23.79	0.35	1135	14729	0.03
62	Air transport	7.91	92.81	0.08	57	666	0.01
33	Medical instruments etc.	7.77	28.58	0.27	296	3275	0.02
74	Other business activities	7.45	14.60	0.51	8888	54576	0.08
60	Land transport	7.39	13.27	0.55	3918	34466	0.07
34	Transport equipment	7.30	43.71	0.17	128	1912	0.01
28	Fabricated metal products	6.80	18.74	0.36	1884	19037	0.04
18	Wearing apparel	6.65	29.13	0.23	287	3693	0.02
20	Wood	6.55	30.28	0.22	1005	10659	0.02
45	Construction	6.33	14.00	0.46	10587	73907	0.07
51	Wholesale trade	6.33	14.07	0.45	6904	57463	0.05
70	Real estate activities	6.24	10.62	0.59	2577	16095	0.09
17	Textiles	6.17	27.65	0.22	245	3377	0.02
36	Furniture	6.05	20.38	0.30	698	8341	0.02
37	Recycling	5.99	7.86	0.76	28	221	0.10
14	Other mining and quarrying	5.80	15.00	0.38	157	1781	0.03
55	Hotels and restaurants	5.75	9.60	0.60	5649	49819	0.07
52	Retail trade	5.61	9.04	0.62	9244	107953	0.05
41	Collection, purification and distribution of water	5.40	6.81	0.80	22	466	0.05
50	Sale and repair of motor vehicles	4.95	8.17	0.61	3327	40089	0.05
71	Renting of machinery and equipment	4.48	7.05	0.64	484	2787	0.11
10	Mining of coal and lignite	4.22	8.04	0.53	153	925	0.09
16	Tobacco products	3.00	241.64	0.02	1	40	0.00
10–74	Total business sector	7.63	17.91	0.43	69322	639640	0.05

Table 3. Variable definitions

Variable	*Description*
Start-up size	Logarithm of the number of employees at start-up
Scale economies	Mean size of the largest plants in each industry accounting for one half of the industry's employment (Comanor & Wilson, 1967)
Sub-optimal scale	Proportion of industry's employment in plants smaller than MES
Small plant cost disadvantage	(Small plant (with less than industry average number of employees) sales or shipments / Employment) / (Industry sales or shipments / Employment)
Industry size	Logarithm of the number of employees in the industry
Industry growth	Logarithmic change in industry employment in two consecutive periods
Turbulence	(Employment of entrants / Total number of employees in the industry) * (Employment of exits / Total number of employees in the industry)
Average experience	Average seniority (=number of months in the firm) of the employees in the region in the previous year
Average education	Average number of schooling years in the region in the previous year
Share of women	Average share of women employment in the region in the previous year
Share of multiplant entrants	Share of employment in entering plants that belong to firms with more than one plant
Share of foreign-owned entrants	Share of employment in entering plants in which more than 50% of the equity is held by non-Finnish residents
Profitability	Price-cost margin = (Value added – Wages – Materials) / Value added in the industry
Variability of profits	Standard deviation of price-cost margins in the industry
Capital intensity	Industry capital-labour ratio
Investment rate	Gross investments / Gross output in the industry
R&D intensity	R&D expenditures / Number of employees in the industry
Export intensity	Exports / Gross output in the industry
Import penetration	Imports / (Gross output + imports – exports) in the industry
Year dummies	Dummy variables for different entry years (reference groups are the first years in the analyses, i.e. 1981 and 1989)

Table 4. Descriptive statistics for manufacturing and services using the BR data

			Manufacturing			
Variable	N	Mean	Std	Median	Min	Max
Start-up size	9814	1.690	0.779	1.386	1.099	6.906
Scale economies	9814	0.064	0.072	0.048	0.004	1.202
Sub-optimal scale	9814	0.397	0.078	0.387	0.000	0.757
Industry size	9814	8.757	1.069	9.131	1.435	10.366
Industry growth	9797	0.003	0.152	-0.002	-1.211	1.215
Turbulence	9814	0.004	0.017	0.001	0.000	0.458
Average experience	9814	0.124	0.015	0.121	0.091	0.172
Average education	9814	11.740	0.345	11.717	11.036	12.641
Share of women	9814	0.407	0.035	0.409	0.307	0.494
			Services			
Variable	N	Mean	Std	Median	Min	Max
Start-up size	48343	1.570	0.654	1.335	1.099	7.170
Scale economies	48343	0.022	0.019	0.018	0.003	0.726
Sub-optimal scale	48343	0.519	0.083	0.510	0.000	0.821
Industry size	48343	9.424	1.039	9.686	1.194	10.857
Industry growth	48196	0.023	0.122	0.027	-1.010	1.067
Turbulence	48343	0.013	0.029	0.005	0.000	0.927
Average experience	48343	0.121	0.016	0.118	0.091	0.172
Average education	48343	11.848	0.392	11.798	11.036	12.641
Share of women	48343	0.413	0.036	0.419	0.307	0.494

[1] Scale economies and average experience are divided by 1 000 to generate easily readable coefficients.

Table 5. Quantile regression results for manufacturing and services using the BR data

	Manufacturing (SIC 15–37, 9 797 observations)					
Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	2.410	0.185	0.532	1.666	5.431	7.249
economies	(0.338)***	(0.082)**	(0.142)***	(0.405)***	(0.678)***	(1.562)***
Sub-optimal	0.049	0.036	0.072	0.210	0.769	0.217
scale	(0.176)	(0.024)	(0.053)	(0.136)	(0.279)***	(0.712)
Industry	0.025	0.001	0.004	0.010	0.027	0.053
size	(0.013)*	(0.001)	(0.003)	(0.007)	(0.019)	(0.039)
Industry	0.007	0.000	0.008	0.019	-0.047	-0.212
growth	(0.088)	(0.011)	(0.022)	(0.069)	(0.159)	(0.252)
Turbulence	6.372	1.693	3.812	7.067	5.724	20.492
	(0.701)***	(1.126)	(1.263)***	(1.472)***	(4.370)	(9.595)**
Constant	1.318	1.086	1.084	1.120	1.063	1.700
	(0.165)***	(0.023)***	(0.042)***	(0.113)***	(0.235)***	(0.573)***
R^2	0.075					
F (H_0: β_i=0)	22.16***	306.39***	214.55***	102.22***	148.18***	82.73***
	Services (SIC 50–74, 48 196 observations)					
Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	7.223	0.442	2.340	6.996	17.028	22.344
economies	(1.770)***	(0.358)	(1.015)**	(2.100)***	(4.445)***	(5.531)***
Sub-optimal	-0.419	0.021	0.016	0.104	0.170	-0.841
scale	(0.282)	(0.021)	(0.130)	(0.260)	(0.554)	(0.861)
Industry	0.018	0.000	0.000	0.005	0.015	0.031
size	(0.016)	(0.000)	(0.004)	(0.011)	(0.023)	(0.040)
Industry	0.043	0.001	0.034	0.048	-0.032	0.143
growth	(0.085)	(0.005)	(0.023)	(0.052)	(0.119)	(0.213)
Turbulence	2.625	0.199	0.762	1.638	3.670	3.779
	(0.674)***	(0.152)	(0.303)**	(0.669)**	(1.270)***	(1.352)***
Constant	1.435	1.077	1.061	1.056	1.086	2.009
	(0.208)***	(0.019)***	(0.101)***	(0.200)***	(0.390)***	(0.648)***
R^2	0.073					
F (H_0: β_i=0)	15.04***	4.88	145.98***	99.66***	127.34***	185.44***

[1] All estimations include time dummies.
[2] Robust standard errors in parantheses.
[3] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

Table 6. Quantile regression results on the effects of human capital in manufacturing and services

	Manufacturing (SIC 15–37, 9 797 observations)					
Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	2.404	0.185	0.550	1.656	5.367	7.810
economies	(0.273)***	(0.085)**	(0.094)***	(0.352)***	(0.643)***	(1.016)***
Sub-optimal	0.058	0.039	0.075	0.206	0.829	0.379
scale	(0.141)	(0.025)	(0.046)*	(0.118)*	(0.242)***	(0.493)
Industry size	0.025	0.001	0.004	0.010	0.034	0.059
	(0.008)***	(0.001)	(0.003)	(0.006)*	(0.013)**	(0.028)**
Industry	0.006	0.003	0.007	0.017	-0.033	-0.198
growth	(0.059)	(0.009)	(0.019)	(0.037)	(0.101)	(0.148)
Turbulence	6.358	1.679	3.797	7.048	5.725	19.887
	(0.894)***	(0.838)**	(0.986)***	(1.153)***	(2.160)***	(6.857)***
Average	0.001	-0.000	0.000	0.000	0.001	0.003
experience	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)
Average	0.139	0.002	0.013	0.026	0.155	0.388
education	(0.050)***	(0.004)	(0.017)	(0.033)	(0.076)**	(0.142)***
Share of	-0.516	-0.017	0.069	0.035	-0.383	-1.152
women	(0.549)	(0.027)	(0.124)	(0.258)	(0.697)	(1.449)
Constant	-0.148	1.075	0.904	0.812	-0.685	-2.734
	(0.639)	(0.050)***	(0.220)***	(0.405)**	(0.995)	(2.059)
R^2	0.076					
F (H_0: β_i=0)	12.47***	248.70***	224.83***	120.15***	192.99***	176.15***
	Services (SIC 50–74, 48 196 observations)					
Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	7.323	0.424	2.469	7.318	17.179	23.674
economies	(0.852)***	(0.244)*	(0.537)***	(0.815)***	(2.141)***	(2.455)***
Sub-optimal	-0.352	0.021	0.051	0.234	0.262	-0.525
scale	(0.149)**	(0.012)*	(0.057)	(0.102)**	(0.237)	(0.370)
Industry size	0.023	0.000	0.003	0.008	0.021	0.039
	(0.008)***	(0.000)	(0.001)*	(0.004)*	(0.009)**	(0.017)**
Industry	0.032	0.001	0.037	0.042	-0.021	0.062
growth	(0.050)	(0.002)	(0.014)***	(0.032)	(0.065)	(0.147)
Turbulence	2.654	0.199	0.782	1.622	3.623	4.202
	(0.384)***	(0.112)*	(0.171)***	(0.361)***	(0.692)***	(0.783)***
Average	0.001	0.000	-0.000	0.001	0.002	0.003
experience	(0.001)	(0.000)	(0.000)	(0.000)*	(0.001)*	(0.002)
Average	0.165	0.001	0.033	0.107	0.223	0.434
education	(0.041)***	(0.001)	(0.008)***	(0.022)***	(0.058)***	(0.118)***
Share of	0.973	0.002	0.100	0.525	1.279	2.544
women	(0.334)***	(0.004)	(0.050)**	(0.183)***	(0.397)***	(0.862)***
Constant	-1.083	1.068	0.599	-0.584	-2.302	-4.705
	(0.617)*	(0.022)***	(0.129)***	(0.327)*	(0.829)***	(1.631)***
R^2	0.081					
F (H_0: β_i=0)	20.84***	7.51	653.92***	315.106***	406.27***	679.22***

[1] All estimations include time dummies.
[2] Robust standard errors in parantheses.
[3] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

Table 7. Descriptive statistics for manufacturing using the LPDM data

Variable	N	Mean	Std	Median	Min	Max
Start-up size	4739	2.658	0.854	2.485	1.609	6.903
Scale economies	4739	0.119	0.087	0.096	0.007	1.068
Sub-optimal scale	4739	0.418	0.075	0.410	0.090	0.779
Small plant cost disadvantage	4739	0.893	0.169	0.871	0.311	2.384
Industry size	4739	9.259	1.068	9.446	2.565	10.663
Industry growth	4737	-0.026	0.085	-0.020	-0.543	0.660
Turbulence	4739	0.003	0.013	0.000	0.001	0.538
Share of multiplants	4739	0.255	0.272	0.171	0.000	1.000
Share of foreign-owned plants	4739	0.029	0.119	0.000	0.000	1.000
Profitability	4739	0.157	0.057	0.157	-0.132	0.531
Variability of profits	4739	0.002	0.019	0.000	0.000	0.915
Capital intensity	4739	0.121	0.094	0.101	0.003	0.985
Investment rate	4739	0.052	0.025	0.049	0.001	0.439
R&D intensity	4739	0.068	0.118	0.032	0.002	1.049
Export intensity	4739	0.292	0.189	0.256	0.000	1.064
Import penetration	4739	0.294	0.227	0.286	-1.432	1.308

[1] R&D intensity is divided by 100 000 and scale economies, variability of profits and capital intensity by 1 000 to generate easily readable coefficients.

Table 8. Quantile regression results for manufacturing using the LDPM data (4737 observations)

	OLS	0.15	0.25	0.50	0.75	0.90
Scale economies	1.719	0.598	0.938	1.565	2.474	2.724
	(0.310)***	(0.264)**	(0.329)***	(0.507)***	(0.554)***	(0.487)***
Small plant cost	-0.247	-0.307	-0.346	-0.266	-0.257	-0.060
disadvantage	(0.102)**	(0.093)***	(0.097)***	(0.117)**	(0.152)*	(0.171)
Industry size	-0.021	-0.010	-0.018	-0.033	-0.023	0.033
	(0.018)	(0.014)	(0.018)	(0.027)	(0.034)	(0.034)
Industry growth	0.333	0.196	0.284	0.232	0.375	0.761
	(0.156)**	(0.207)	(0.191)	(0.201)	(0.256)	(0.331)**
Turbulence	8.398	4.637	7.832	6.163	12.390	26.554
	(2.408)***	(3.603)	(3.514)**	(4.902)	(7.523)*	(14.308)*
Share of	0.616	0.157	0.233	0.432	0.878	1.239
multiplant entrants	(0.056)***	(0.053)***	(0.060)***	(0.097)***	(0.106)***	(0.146)***
Share of foreign-	0.351	0.095	0.256	0.191	0.431	0.665
owned entrants	(0.124)***	(0.171)	(0.147)*	(0.199)	(0.282)	(0.330)**
Profitability	0.064	0.286	0.364	0.125	0.001	0.151
	(0.401)	(0.298)	(0.398)	(0.545)	(0.456)	(0.673)
Variability of	1.560	2.527	2.080	1.643	0.675	0.147
profits	(0.348)***	(5.077)	(5.434)	(3.670)	(3.109)	(4.769)
Capital intensity	0.279	0.101	0.127	0.409	0.553	-0.066
	(0.224)	(0.256)	(0.261)	(0.362)	(0.436)	(0.549)
Investment rate	-0.121	0.232	-0.262	-1.404	-0.256	0.690
	(0.878)	(0.667)	(0.746)	(1.029)	(1.195)	(1.278)
R&D intensity	-0.181	-0.269	-0.395	-0.237	-0.185	0.096
	(0.166)	(0.166)	(0.234)*	(0.339)	(0.411)	(0.531)
Export intensity	0.060	0.106	0.095	0.180	0.124	-0.102
	(0.149)	(0.144)	(0.164)	(0.246)	(0.289)	(0.305)
Import	0.107	0.007	0.031	0.006	0.175	0.297
penetration	(0.075)	(0.088)	(0.095)	(0.129)	(0.182)	(0.201)
Constant	2.561	1.962	2.149	2.676	2.888	2.577
	(0.205)***	(0.190)***	(0.237)***	(0.288)***	(0.371)***	(0.447)***
R^2	0.146					
F (H_0: β_i=0)	49.05***	151.16***	265.96***	354.13***	458.22***	614.44***

[1] All estimations include time dummies.
[2] Robust standard errors in parantheses.
[3] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

Table 9. Quantile regression results for start-ups belonging to firms with more than one plant (758 observations)

Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	3.408	2.437	3.140	4.011	4.418	3.284
economies	(0.535)***	(1.232)**	(0.979)***	(0.915)***	(0.734)***	(0.994)***
Small plant cost	0.075	-0.432	-0.043	0.289	0.423	0.773
disadvantage	(0.243)	(0.490)	(0.454)	(0.484)	(0.389)	(0.506)
Industry size	0.045	-0.036	-0.019	-0.046	0.094	0.135
	(0.044)	(0.087)	(0.080)	(0.077)	(0.069)	(0.085)
Industry growth	-0.373	-0.016	-0.355	-0.271	0.047	-1.028
	(0.514)	(0.659)	(0.599)	(0.698)	(0.870)	(1.236)
Turbulence	13.258	11.747	12.875	22.533	11.635	18.631
	(5.799)**	(16.394)	(16.494)	(15.971)	(19.846)	(30.339)
Share of foreign-	0.465	0.229	0.207	0.062	0.788	0.519
owned entrants	(0.231)**	(0.392)	(0.366)	(0.360)	(0.472)*	(0.555)
Profitability	-1.068	-1.490	-1.077	-0.626	-0.888	-1.216
	(0.553)*	(1.279)	(1.218)	(1.169)	(1.001)	(1.233)
Variability of	2.699	3.229	3.038	2.536	1.658	1.776
profits	(0.469)***	(12.662)	(11.302)	(9.202)	(11.322)	(12.609)
Capital intensity	-0.400	-0.128	-0.524	-0.837	-0.125	-0.278
	(0.284)	(0.771)	(0.686)	(0.696)	(0.636)	(0.800)
Investment rate	0.408	-1.320	-0.888	0.287	-2.066	1.856
	(1.465)	(2.703)	(2.469)	(2.396)	(2.507)	(3.861)
R&D intensity	0.333	-0.181	0.056	-0.122	0.619	1.203
	(0.478)	(0.957)	(0.980)	(1.080)	(0.822)	(0.917)
Export intensity	0.054	0.095	0.857	0.566	-0.463	-0.512
	(0.333)	(0.742)	(0.624)	(0.511)	(0.489)	(0.644)
Import	0.225	0.119	-0.005	0.416	0.412	0.455
penetration	(0.226)	(0.506)	(0.482)	(0.423)	(0.451)	(0.562)
Constant	2.143	2.505	2.108	2.522	2.184	2.323
	(0.495)***	(0.949)***	(0.952)**	(1.008)**	(0.926)**	(0.986)**
R^2	0.215					
F (H_0: β_i=0)	30.87***	42.47**	81.54***	186.48***	156.22***	66.88***

[1] All estimations include time dummies.
[2] Robust standard errors in parantheses.
[3] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

Table 10. Quantile regression results for start-ups belonging to firms with one plant (3 979 observations)

Quantiles	OLS	0.15	0.25	0.50	0.75	0.90
Scale	0.737	0.395	0.593	0.924	0.819	1.052
economies	(0.286)**	(0.232)*	(0.241)**	(0.409)**	(0.548)	(0.603)*
Small plant cost	-0.208	-0.221	-0.372	-0.196	-0.282	-0.056
disadvantage	(0.136)	(0.095)**	(0.098)***	(0.101)*	(0.140)**	(0.224)
Industry size	0.005	0.001	-0.015	-0.013	0.002	0.042
	(0.016)	(0.013)	(0.016)	(0.024)	(0.032)	(0.038)
Industry growth	0.416	-0.094	0.161	0.120	0.544	1.253
	(0.177)**	(0.213)	(0.211)	(0.202)	(0.257)**	(0.338)***
Turbulence	7.852	3.627	5.918	6.731	19.022	30.382
	(2.335)***	(4.149)	(4.612)	(3.672)*	(9.910)*	(15.134)**
Share of foreign-	0.441	0.119	0.276	0.209	0.511	0.931
owned entrants	(0.142)***	(0.164)	(0.161)*	(0.207)	(0.333)	(0.440)**
Profitability	0.340	0.308	0.779	0.474	-0.064	0.384
	(0.441)	(0.266)	(0.346)**	(0.598)	(0.565)	(0.672)
Variability of	-0.707	-0.474	1.530	-0.184	-4.002	-7.465
profits	(2.240)	(5.204)	(6.150)	(6.244)	(5.974)	(8.093)
Capital intensity	0.369	-0.127	-0.065	0.175	0.867	1.091
	(0.227)	(0.217)	(0.262)	(0.435)	(0.433)**	(0.533)**
Investment rate	-1.124	0.714	-0.059	-1.793	-2.425	-1.435
	(0.769)	(0.608)	(0.612)	(0.977)*	(1.118)**	(1.673)
R&D intensity	-0.185	-0.052	-0.370	-0.344	-0.094	0.075
	(0.177)	(0.167)	(0.196)*	(0.351)	(0.439)	(0.590)
Export intensity	0.186	0.076	0.183	0.209	0.370	0.297
	(0.140)	(0.121)	(0.136)	(0.211)	(0.287)	(0.293)
Import	0.132	-0.026	0.006	0.052	0.118	0.375
penetration	(0.090)	(0.094)	(0.096)	(0.145)	(0.178)	(0.194)*
Constant	2.442	1.825	2.179	2.538	2.970	2.678
	(0.199)***	(0.179)***	(0.223)***	(0.276)***	(0.330)***	(0.491)***
R^2	0.060					
F (H_0: β_i=0)	12.32***	91.69***	199.84***	286.40***	166.61***	193.55***

[1] All estimations include time dummies.
[2] Robust standard errors in parantheses.
[3] ***, ** and * indicate significant at 1, 5 and 10 per cent level, respectively.

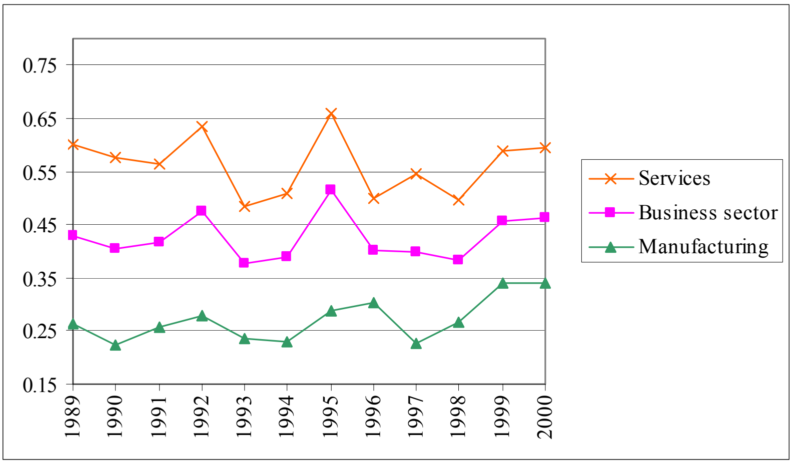

Figure 1. The relative size of entrants in broad sectors 1989–2000 (the BR data)

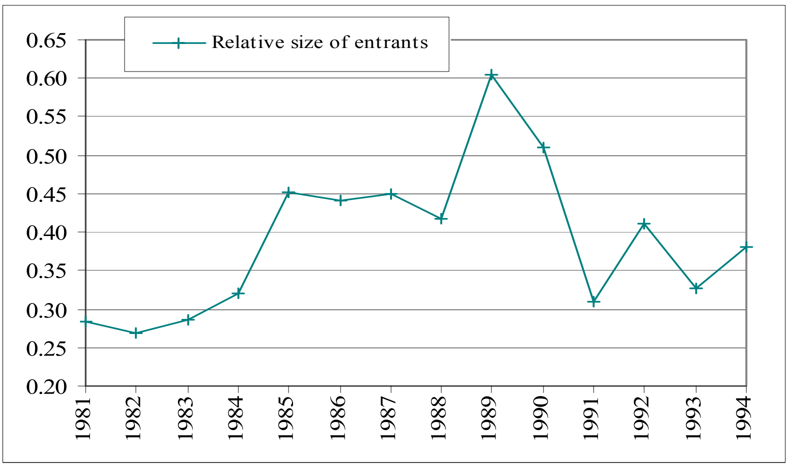

Figure 2. The relative size of entrants in manufacturing 1981–1994 (the LDPM data)

III

III

JOB FLOWS AND JOB QUALITY BY ESTABLISHMENT SIZE IN THE FINNISH MANUFACTURING SECTOR 1980–94*

Contents

1 Introduction **2**

2 Theories of firm growth **3**
2.1 Gibrat's law 3
2.2 The new literature 4
2.3 Empirical findings 4

3 Job creation and job destruction by establishment size **5**
3.1 Definitions 5
3.2 Empirical findings 7
3.3 Job flows by establishment size in Finland 7

4 Job quality by establishment size **11**
4.1 Wages 11
4.2 Wage adjusted job flows 12
4.3 Labour productivity 13
4.4 Working hours 13
4.5 Labour turnover 14
4.6 Persistence of job creation and job destruction 15

5 Conclusions **16**

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A few minor differences exist between this section and the published paper.

1 Introduction

Small and medium-sized firms are often seen as engines of growth in the economy. In economic policy this is a general argument for supporting small business. The role of small business in creating jobs was earlier mainly studied with small firms' labour shares. Recently increased availability of microdata on establishments and firms has made it possible to study job dynamics behind the net employment flows. There has been a growing interest in gross job creation and gross job destruction rates by firm or establishment size, but the findings have been quite conflicting. Some of the latest studies have questioned the superior role of small business in net job creation and emphasised the role of measurement errors (e.g. Davis et al., 1996).

The purpose of this paper is to study the role of small and medium-sized establishments in job dynamics in the Finnish manufacturing sector over the period 1980–1994. From the international perspective, Finland is an interesting example of a small open economy which is characterised by strong cyclical fluctuations and extensive trade union movement in the labour market. The Finnish economy experienced an exceptionally deep recession at the beginning of the 1990s. Finland's gross domestic product decreased by 6.3% in 1991 and the fall continued over the period 1992–93. At the same time unemployment rose dramatically and reached a peak of 16.6% in 1994 (according to the Unemployment Statistics of Statistics Finland).

In this paper gross job creation, gross job destruction and net employment change are studied by size category. In addition to the traditional study of job dynamics, it is also essential to know what kind of jobs are created in different-sized establishments. That's why the paper also examines various aspects of job quality by establishment size, including wages, labour productivity, working hours, labour turnover and the persistence of newly created and newly destroyed jobs.

Data sources are the Industrial Statistics from the period 1980–94 and the register-based Employment Statistics from the period 1988–95. The Industrial Statistics allows the examination of job flows, wages, labour productivity and the persistence of jobs in establishments of different sizes. The data is collected with annual surveys. The Industrial Statistics covers, in principle, all the Finnish manufacturing establishments or plants with 5 employees or more. Also smaller establishments are included if their turnover corresponds to average turnover in firms with 5–10 employees but there are only a few cases where this condition holds. The number of employees includes also persons who are, for example, on maternity leave, on annual leave or temporarily laid-off, which may bias some of the results. The number of cases where an establishment temporarily disappears from the panel is negligible. If an establishment falls temporarily below the 5 employees border it is not immediately dropped from the panel.

Attrition, mergers, take-overs and other reconstruction of enterprises are not a problem because the analysis is at the establishment level and ownership changes do not affect the identification number of the establishment. Laaksonen and

Teikari (1999) have constructed so-called synthetic enterprises of Finnish manufacturing establishments. Synthetic enterprises describe the changes in establishments only, not the changes which result from the reconstruction of businesses. As a consequence, a synthetic enterprise can be a combination of establishments that do not belong to it in reality. According to Ilmakunnas et al. (1999) job flows are fairly similar in their profile over the size categories whether using establishments or synthetic enterprises. Therefore, using establishment level instead of the firm level is preferable because the establishment level results probably describe the reality better than the findings based on actual firms.

Worker flows, which describe labour turnover, are calculated from the Employment Statistics, which compiles information on individuals and their background characteristics, including the identity of their employer. The data is collected from various administrative registers. Job flows are also calculated from the Employment Statistics in order to facilitate comparisons with worker flows.

In the theoretical background there are various models of firm growth. The most famous hypothesis of the earliest stochastic models of firm size distribution is Gibrat's law, which states that the firm's expected growth in each period is proportional to the current size of the firm. Many studies have found that small firms grow faster than the large ones (e.g. Dunne & Hughes, 1994) and growth declines when the firm ages (e.g. Evans 1987). Among others Jovanovic (1982), Pakes and Ericson (1998) and Cabral (1995) have created newer models of firm growth that are based on profit maximisation.

Section 2 briefly introduces theoretical background. Section 3 defines the measures for job flows, reviews some empirical results, and finally presents the findings in Finnish manufacturing. In section 4 job flows are adjusted for size-wage differential and some other aspects of job quality are also considered. Section 5 gives the summary and conclusions.

2 Theories of firm growth

2.1 Gibrat's law

In 1931 Robert Gibrat presented the Law of Proportional Effect which states that the growth rate of a firm is independent of its current size and its past growth history. According to Gibrat's law, firm's proportionate rate of growth is:

$$\frac{X_t - X_{t-1}}{X_{t-1}} = \varepsilon_t,$$

where X_t is firm size at time t, e.g. employment or turnover, and ε_t is a random variable which describes the growth rate of the firm from $t-1$ to t and is independently distributed of X_{t-1}. As a consequence firm size is:

$$X_t = (1+\varepsilon_t)X_{t-1} = X_0(1+\varepsilon_1)(1+\varepsilon_2)...(1+\varepsilon_t).$$

In a short time period ε_t is probably small, so that:

$$\log X_t \approx \log X_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_t.$$

Let us assume that $E\varepsilon_t = m$ and $Var(\varepsilon_t) = \sigma^2$. When $t \to \infty$, $\log X_t \sim N(mt, \sigma^2 t)$. Thus expected value and variance increase over time and the distribution of X_t is lognormal or the size distribution is skewed. There are many modifications of Gibrat's law, for example the effects of entry and exit can be incorporated into the model (Sutton, 1997, pp. 40–43).

2.2 The new literature

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 learning. Entering firms differ by their unit costs, which are not directly observable. A firm learns about its efficiency only gradually after production has started. The most efficient firms grow and survive and some of the inefficient ones exit. Jovanovic shows that young firms grow faster than the old ones. Because young firms are usually small, there is a negative correlation between firm size and growth, too. In addition, the variance of growth is largest among young and small firms. Empirical findings support the predictions of Jovanovic's model (e.g. Evans, 1987; Dunne et al., 1989).

The model of Pakes and Ericson (1998) is based on active learning, which can be speeded up by investing in R&D activities. However, the firms do not know for certain what effect the investments have on their productivity. The firms maximise the net present value of their expected cash flow. The model predicts that over time the dependence between firm's current size and its initial size disappears. Pakes and Ericson test both their model and Jovanovic's model with a panel of Wisconsin firms 1978–86 and conclude that their model is consistent with the manufacturing data, whereas Jovanovic's model is consistent with the data on retail trade.

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 upon 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, small firms grow faster than the large ones or there is a negative dependence between initial size and expected growth. In addition, the variance of growth decreases as the firm gets larger.

2.3 Empirical findings

Gibrat's law has been empirically tested in numerous studies but the findings have been conflicting. Different findings might be caused by various interpretations of the law or by the different methods, time periods and size measures used in testing for the validity of the law (Audretsch et al., 1999, p. 976). Some earlier findings lend support to Gibrat's law, for example Hart and Prais (1956) found that firm growth is roughly independent of firm size. After comparing the frequency distributions of growth between different size categories, Mansfield (1962) concluded instead that there is no strong evidence in favour of Gibrat's law. According to Mansfield the observed negative dependence between firm size and growth is at least partially caused by sample selection bias. Slowly growing small firms have higher probability of exit, and therefore estimates of growth of survived firms are biased so that small firms grow relatively faster than the large ones.

Later studies have not found much evidence in favour of Gibrat's law even though sample selection is usually controlled for. These studies are often based on the maximisation models and use larger data sets than earlier studies. The most common finding seems to be that the growth rates of new and small firms are negatively related to their initial size. Thus, Gibrat's law fails to hold at least for small firms. (Hart & Oulton, 1996; Audretsch et al., 1999; Mata, 1994; Dunne & Hughes, 1994) Many studies have also taken into account firm age and survival. Evans (1987) used a sample of the US manufacturing firms 1976–82. According to the findings, firm growth declines with firm age and firm size. Evans also controlled the effect of sample selection. When the firm's probability of survival was taken into account, the main finding was that the firm's relative growth subject to that the firm has survived declines with firm size and age. The probability of firm survival increases with firm size and age. (Evans, 1987; Hall, 1987; Dunne et al., 1989)

Gibrat's law and its modifications can also be tested by fitting different size distributions into the data. The findings suggest that there is no particular distribution which would describe all industries well (Schmalensee, 1989, p. 994). Nowadays researchers usually state that the size distribution is skewed, but they do not define the more precise form of the distribution. To summarise, the overall impression from the various empirical studies is that Gibrat's law is not valid.

Firm size and growth can be measured with employment, which leads to the examination of job dynamics by employer size. Gibrat's law implies that the relative net employment growth should be the same in every size category. The findings of the higher variance of growth in small firms may be reflected in higher rates of gross job creation and gross job destruction in small size categories.

3 Job creation and job destruction by establishment size

3.1 Definitions

In this paper the measures for job flows are defined according to Davis et al. (1996, pp. 10–13). First, the net employment change from period $t-1$ to period

t is calculated at the establishment level:

$$\Delta E_i = E_{it} - E_{i,t-1}.$$

(Gross) job creation, JC, is the sum of the positive net changes at the establishment level. Similarly, (gross) job destruction, JD, is the sum of the absolute values of the negative net changes.

$$JC = \sum_i \Delta E_i^+$$

$$JD = \sum_i \left| \Delta E_i^- \right|$$

The net employment change in the manufacturing, NET, is the difference between job creation and job destruction:

$$NET = JC - JD.$$

The sum of job creation and job destruction is called (gross) job reallocation, JR, or absolute job flow or job turnover:

$$JR = JC + JD.$$

Job reallocation describes the reshuffling of employment opportunities across establishments. However, job reallocation is larger than what is needed to accommodate the net employment change. The difference is called excess job reallocation, ER, or volatility (Roberts, 1996):

$$ER = JR - |NET| = JC + JD - |JC - JD|.$$

Excess job reallocation describes simultaneous job creation and job destruction, which is partly due to job flows between different sectors or the structural change in the economy. High value of excess job reallocation can also be a sign of considerable heterogeneity among establishments.

The figures are transformed into rates by dividing them by establishment size. Davis et al. (1996, pp. 58–59) use four different concepts of establishment size, two of which are used in this study. Current size is the simple average of the establishment's current employment and its employment one year earlier, $EA = (1/2(E_{it} - E_{i,t-1})$. Thus, the net employment change divided by current size is always between (–2, 2). By using current size we can avoid the regression-towards-the-mean problem (also called Galton's regression), which is due to transitory fluctuations in size, and mitigate the effects of establishments crossing size borders. Therefore, the tendency to exaggerate job destruction in large establishments and job creation in small establishments is at least partly avoided. An alternative measure for establishment size is average establishment size, which is the weighted mean number of employees, computed over all observations on the establishment during the 1979–94 period. Some calculations are made with average establishment size in order to compare the results.

3.2 Empirical findings

David Birch (1981, pp. 7–8) was one of the first to claim that small firms create proportionally more jobs than the larger ones. His argument was based on the observation that 82% of employment growth took place in firms with 100 or fewer employees in the United States 1969–76. The real contribution of small business to employment growth has been the focus of interest in many recent studies. However, the findings are quite conflicting which is partly due to differences in measurement and data sets.

Among others Davis et al. (1996) have questioned the superior role of small firms in employment growth. According to them, the arguments have been based on unsuitable data sets. In addition, the interpretation of the data may have been fallacious and the transitions between different size categories are not taken into account. Regression-towards-the-mean bias may also cause problems. After some corrections Davis et al. (1996) find that although small firms and plants have much higher job creation and job destruction rates, there is no systematic relationship between firm size and net employment growth. After studying job flows with data on manufacturing firms in Lower Saxony, Germany, 1978–93, Wagner (1995) also concludes that Galton's regression leads to the exaggeration of the role of small business in employment growth.

However, there are also opposite views about the impact of measurement problems on the results. Baldwin and Picot (1995) have studied job creation and job destruction in the Canadian manufacturing sector over the period 1970–90. According to their findings, net job creation for small establishments is greater than that of large establishments, even though corrections have been made to avoid regression-to-the-mean problem. Broersma and Gautier (1997) come to the same conclusion with data on manufacturing firms in the Netherlands 1978–91. Despite the differing opinions about the relationship between net employment growth and firm size, most of the studies share the view that small establishments or firms 'over'contribute to job creation and job destruction in relation to their employment share, whereas larger establishments or firms 'under'contribute.

3.3 Job flows by establishment size in Finland

There has been a strong declining trend in the Finnish manufacturing employment during the whole period 1980–94. The number of manufacturing employees has fallen 38% from 1980 to 1994 and the average size of establishment has decreased from 74.2 persons to 60.7 persons. However, these averages are biased because the Industrial Statistics covers only a fraction of establishments with less than 5 employees. Figure 1 shows that also manufacturing's share of total employment has fallen steadily, except for the last recession years when total employment decreased considerably.

Figure 2 shows how the employment decline has affected different-sized establishments. The employment share of establishments with less than 100 employees has increased 5 percentage points, while the employment share of establishments with 500 employees or more has decreased 6 percentage points over the period. During the deep recession in the early 1990s employment was cut down especially in the largest establishments. Technological change and rationalisation have been most intense in large establishments, which can also be seen in the development of employment shares. In addition, outsourcing of computer services and other business services has become more common in large establishments. In Finland the employment share of micro establishments (less than 10 employees) is very small. Small and medium-sized establishments (10–499 employees) account for 70% of the total manufacturing employment.

Job flows give valuable information of the job dynamics behind the employment shares. Table 1 presents average annual job flow rates over the period 1980–94 in different size categories: gross job creation rate (JCR), gross job destruction rate (JDR), net employment change rate ($NETR$), gross job reallocation rate (JRR) and excess job reallocation rate (ERR).[1] Job creation and job destruction rates are calculated separately for new manufacturing establishments ($ENTRY$) and for establishments that exit from manufacturing ($EXIT$). New establishments are those who exist in the data at time t but are not yet present at time $t-1$, whereas exiting establishments exist in the data at time $t-1$ but are no longer present at time t.

The figures in parentheses show each size category's share of the total flow. These shares can be compared with the last column ($SHARE$) that shows the average annual employment share of each size category over the period. Establishment size is measured with current size. Employment shares at the beginning ($SH80$) and at the end ($SH94$) of the time period are also reported. Employment share has increased in size categories with less than 500 employees and decreased in the largest size categories over the period.

Average annual job flow rates, except for net employment change, decline with establishment size. The gross rates of the smallest establishments are even 10 times higher than the rates of the largest establishments. Net employment change is negative in each category and differences between size categories are rather small. In large establishments (100 or more employees) the absolute value of net change is on average 1.5 percentage points smaller than in establishments with less than 100 employees. Broersma and Gautier (1997, p. 216) find similar job creation and job destruction rates for the Dutch manufacturing firms, but according to their results, net employment has increased in small firms and decreased in large firms. Also Klette and Mathiassen (1996) conclude that net employment change has been more negative for larger plants in the Norwegian manufacturing sector 1976–86.

New establishments have particularly high job creation rates in the smallest size category. Similarly, exiting establishments have high job destruction rates

[1] The relationship $ERR = JRR - |NETR|$ holds in each year, but not necessarily over time because the average of $NETR$ figures does not equal the average of $|NETR|$ figures.

in the smallest establishments. Entry's share of all job creation in the smallest size category is on average 87.2%, whereas the corresponding average share in the total manufacturing is only 34.6%. Similarly, the share of exiting smallest establishments of the job destruction in the smallest size category is 82.8% and the corresponding share of all establishments is 34.8%.

Since the employment share of smaller establishments is lower, high gross rates actually lead to rather small job flows in absolute terms. That is why it is more reasonable to compare each size category's share of the total flow to its employment share. Table 1 shows that the contribution of the smallest size categories (less than 100 employees) to job flows is greater than their employment shares would imply. On the contrary, largest size categories' (100 employees or more) shares of total job flows are smaller than their employment shares. Because the same applies to the negative net change, small establishments seem to have 'over'contributed to the employment decline.

Job flows can also be calculated using average establishment size that takes into account the long-run changes in employment. The mean number of employees over the period 1979–94 is weighted by each year's employment in the establishment. Average rates for each size category over the period are calculated as unweighted averages of the annual gross rates where employment change is divided by current size. Table 2 reports the findings with average establishment size. Job flow rates are considerably lower especially in the smallest size category. However, there is still a negative dependence between gross rates and establishment size, but no clear relationship between net employment change and size.[2] When the shares of total flows and employment are compared in each size category the findings do not notably change from Table 1.

Mean annual growth for the examined period could also be calculated from the first and the last year's figures using compound interest method. Table 3 shows the findings with this method and three different size measures for the whole period 1980–94 and for two sub-periods 1980–90 and 1991–94. In addition to earlier size measures also the observation year's size is used as a measure for establishment size. The choice of size measure has an obvious effect on the findings because especially during the deep recession transitions between size categories increased through employment cuts.

Average establishment size smoothes the differences between size categories in the long run, whereas with other size measures the employment change has been markedly more negative in large size categories than in the smaller ones over the period 1980–94. This corresponds to Figure 2 where the employment share of small establishments grows relative to large establishments and establishment size is observation year's size. Average establishment size gives almost the same results as in Table 2.

[2] Despite some differences in weighting, the results correspond quite well to the earlier results by Vainiomäki and Laaksonen (1999), who have studied technology and job flows in Finnish manufacturing over the period 1987–93.

Table 3 contradicts the results in Table 1 where small establishments have more negative net employment change. This can be explained, first, by the different method of calculation: arithmetic average in Table 1 may give rather different results from compound interest method, especially when there is a lot of variation within the period. The cohort of establishments varies from year to year when annual job flows are calculated by size category, while the mean annual growth of the whole period is calculated using only the establishments that exist in the initial year of the whole period (but not necessarily in the last year) and those that exist in the last year (but not necessarily in the first year). These establishment cohorts are probably quite different. Second, the scaling of the figures or dividing them by the average of current and previous year's employment may have a major effect on the results.

The findings might also be biased by the last years' exceptional development during the recession. However, when mean annual growth is calculated without the recession years, i.e. over the period 1980–90, the conclusions do not change considerably. On the contrary, during the recession period 1991–94 mean annual growth and establishment size have a clear negative dependence when average establishment size is used. One possible explanation may be that the influence of exiting establishments may be emphasised with average establishment size measure. In other words, there are many establishments that are on average small and during the recession exit rate is high in this group. Therefore, the net employment change is more negative for smaller establishments. When establishment size is instead measured with observation year's size or current size, there are fewer exiting establishments.

Table 4 presents the unweighted annual averages of job flows in a period of boom, 1987–90, and in a recession, 1991–93. Average job creation rate was smaller in the recession than in the boom except for the smallest size category where it increased 2.4 percentage points. The main reason for this deviation is temporarily enlarged sample of the smallest establishments in the Industrial Statistics in 1991. In addition, many establishments probably dropped to a smaller size category during the recession, which raised the creation rate of small establishments temporarily. Job destruction rate rose from boom to recession particularly in the two smallest size categories. Job creation seems to be procyclical and job destruction countercyclical.

Since job destruction varies cyclically more than job creation, job reallocation rate appears to be countercyclical except for the largest size category. This contradicts the results of Broersma and Gautier (1997, p. 216) who found that job reallocation is countercyclical only for large firms. Their explanation is that large firms adjust more slowly to shifts in economic circumstances than small firms and it is more advantageous for them to reallocate jobs during recessions. In Finland the increased number of layoffs in large establishments during the recession lowered the number of hours worked, but did not change the number of employees correspondingly because of the incomplete treatment of layoffs in the Industrial

Statistics. As a consequence, job destruction rate and job reallocation rate are probably biased downwards in the largest size category. In addition, the number of voluntary quits probably decreases during recessions, which may also cause job destruction rate to decrease.

4 Job quality by establishment size

4.1 Wages

In addition to examining whether the small business is the main contributor to employment growth, it is also worth asking whether it is desirable for the whole economy that the share of employment in small and medium-sized establishments increases. This requires the study of job quality by establishment size. One of the most important aspects of job quality is wage. There is a lot of empirical evidence of the wage differential between small and large firms or establishments. According to Brown et al. (1990, p. 30) employees in companies with 500 or more employees earned 35% more than those in smaller companies and the same differential was 37% for locations with 100 or more employees in the United States in 1983.

Some possible explanations for the size-wage premium are worker quality, working conditions, labour turnover, monitoring, labour unionisation, imperfect competition in the labour market and monopoly power. According to Brown et al. (1990, p. 42) the size-wage differential is considerable (10–15%) even though differences in education, work experience, working conditions and industry characteristics are taken into account. A search model of Burdett and Mortensen (1998, p. 269) implies that more productive employers offer higher wages and, as a consequence, they have larger work forces, are more profitable and have lower quit rates than less productive firms, which explains the wage and profit differentials between different-sized firms.

Figure 3 presents each size category's average yearly wage in relation to the manufacturing average in Finland 1980–94 according to the Industrial Statistics. Although the employment share of small establishments has increased, they pay considerably lower wages than the large ones on average. In small establishments (less than 100 employees) average wage falls below the average wage of manufacturing during the whole period. The average wage in the large establishments (500 or more employees) exceeds the manufacturing average by at least 10% in most of the years.

Wage differentials have been quite stable over the period 1980–94 except for two size categories (0–9 and 250–499) where the relative wage clearly rises. The drop in the largest size category after 1991 is probably caused by the increased number of layoffs during the recession. In the Industrial Statistics layoffs do not change the number of employees, but they drop wages and, as a consequence, the average wage decreases.

4.2 Wage adjusted job flows

Baldwin (1998) studies job flows in the Canadian manufacturing sector over the period 1973–92 and creates a measure of employment that is adjusted for the fact that small firms pay lower wages. Changes in the metric might affect the view of the role that small firms play in the growth process because the jobs created in small and large firms are not qualitatively comparable, at least not with respect to wages. The new measure weights employment in each establishment by the ratio of the establishment's average wage to the average wage paid by all manufacturing establishments. The new measure, the equivalent employment unit (EEP), is thus equivalent to total wages in an establishment divided by the average wage rate in all establishments. EEP is less than the normal employment measure if the average wage in that establishment is lower than the average wage in manufacturing.

Using the notation:

$$\begin{aligned} e_i &= \text{employment in establishment } i, i = 1, ..., N, \\ w_i &= \text{average wage in establishment } i, \\ E &= \text{total employment in manufacturing} = \sum_{i=1}^{N} e_i \text{ and} \\ W &= \text{average wage in manufacturing} = \frac{\sum\limits_{i=1}^{N} w_i e_i}{\sum\limits_{i=1}^{N} e_i} =, \end{aligned}$$

annual EEP is defined as $EEP_i = e_i \times \left\{\frac{w_i}{W}\right\}$ and $\sum\limits_{i=1}^{N} EEP_i = \sum\limits_{i=1}^{N} e_i$.

EEP is used as a measure of employment to calculate the wage adjusted job flows in the Finnish manufacturing sector. Job flows are transformed into rates by dividing them by average of EEP in periods t and $t-1$. In order to facilitate comparisons with previous results, establishments are divided into size categories on the basis of actual employment using current size measure.

The results after wage adjustment are summarised in Table 5. The gross rates increase in every size category but the net employment change is still negative. When each size category's shares of total flows are compared with its employment share, the results change only slightly. Small establishments' shares increase but they still 'over'contribute to job flows. Similarly, large establishments' shares decline, but their contribution to job flows is still lower than their employment share. The relationship between net employment change and establishment size corresponds to previous results in Table 1. In other words, wage adjustment does not change the results significantly unlike in Baldwin's study, where small plants no longer outperformed large producers in net employment growth after wage adjustment. One reason for the differing results may be better downward flexibility of wages in Canada. In Finland the generally binding collective labour agreements cover also the non-unionised small firms, so wages are inflexible downwards.

4.3 Labour productivity

In addition to wages, there are various other important aspects of job quality, including labour productivity, working hours, labour turnover and persistence of newly created and newly destroyed jobs. Figure 4 presents each size category's average labour productivity in relation to the manufacturing average in Finland 1980–94 according to the Industrial Statistics. In the legend of the figure, size categories are put in order according to the geometric average of each category over the period. Labour productivity is measured by industrial value added divided by the number of employees. The results are very similar if hours worked are used instead of the number of employees.

There is a clear, although not monotonous, positive relationship between labour productivity and establishment size. In establishments with 10–49 employees average labour productivity has been 16–35% lower than the manufacturing average. Establishments with 50–249 employees also fall below the average in most of the years. The results in the smallest size category may be biased because of the boundary of 5 employees in the Industrial Statistics. The relative labour productivity of large establishments (250 employees or more) exceeds the manufacturing average in practically all years. In addition, the productivity gap between small and large establishments has widened through the whole period. The result may be partly explained by the search model of Burdett & Mortensen (1998), which implies that highly productive workers may select themselves in firms where wages and productivity are high.

4.4 Working hours

The number of hours worked is also an important indicator of job quality. Longer working hours may have a negative effect on job satisfaction but a positive effect on productivity. According to Paoli's (1997) European survey of working conditions, average working hours per week decline by firm size, but working shifts, at night and weekends is more common in large firms. Drolet and Morissette (1998) find that there is no evidence that workweek is longer in large Canadian firms, except for women employed part-time. However, the timing of work varies considerably with firm size in the goods-producing sector. Shift work is heavily concentrated in large firms, while irregular work schedules are more common in small firms.

Figure 5 presents average yearly working hours per person by size category relative to the manufacturing average, which are calculated from the Industrial Statistics over the period 1980–94. Hours worked per person decline as the establishment size increases but the differences are quite small. The share of part-time workers is probably higher in large establishments, which may have an effect on the results. In addition, there is a pattern of convergence during the years 1990–94. In other words, during the recession average working time has decreased in small establishments and increased in the large ones. In 1993 the average working hours of the largest size category (1000 employees or more) are clearly below the manufacturing average. The explanation is again the inclusion of the temporarily laid-off employees in the Industrial Statistics. As a consequence, hours worked per person have decreased considerably in the largest size category during the recession.

4.5 Labour turnover

Labour turnover can be measured by worker flows which describe transitions to and from the establishment. The net change of employment in establishment i is the difference between hires H_i and separations S_i:

$$\Delta E_i = H_i - S_i.$$

Worker flow or worker turnover in establishment i, WF_i, is the sum of hires and separations:

$$WF_i = H_i + S_i.$$

$WF = \sum WF_i$ is the worker flow in the manufacturing. Worker flow is larger than gross job reallocation because worker flow includes also the employee changes in permanent vacancies. Their difference is called churning flow, CF (Burgess et al., 1994, p. 6):

$$CF = WF - JR.$$

At the establishment level churning can arise from simultaneous hiring and firing by establishment or workers quitting and being replaced:

$$CF_i = H_i + S_i - |\Delta E_i| .$$

Excessive labour turnover can been seen as a negative phenomenon because it creates costs of recruiting and job search. On the other hand, churning can have positive consequences in terms of more efficient resource allocation. According to Burgess et al. (2000, pp. 15–19) churning flows account for 71% of all worker flows in the non-manufacturing (46% in the manufacturing) and churning flow rate declines with firm age and size in the state of Maryland.

Worker flows are transformed to rates by dividing them by the average of current and previous year's employment (current size). Table 6 summarises worker and job flow rates by establishment size in Finnish manufacturing: hiring rate (HR), separation rate (SR), worker flow rate (WFR), gross job reallocation rate (JRR) and churning flow rate (CFR). The figures are annual averages over the period 1988–95 according to the Employment Statistics. Establishment size is measured with current size. Job flow rates that are calculated from the Employment Statistics are larger than the ones previously calculated from the Industrial

Statistics, except for the smallest size category. One reason for the differences may be that the data in Employment Statistics describes the situation in the last week of each year, whereas the figures in the Industrial Statistics are yearly averages, which probably decreases job reallocation rate. In addition, the Employment Statistics covers also the establishments with less than 5 employees.

Worker flows are very large relative to job flows in every size category. The average job reallocation in total manufacturing covers only 58% of the worker flow and the churning rate is 20%. There is a clear negative relationship between worker flows and establishment size. Churning flow also declines with size if the smallest size category is ignored. In other words, labour turnover is more intense in small establishments. On the one hand, this can be interpreted as a sign of more flexible labour market in small establishments but, on the other hand, larger labour turnover may cause more uncertainty and costs for small employers and their employees.

4.6 Persistence of job creation and job destruction

In order to draw conclusions on the development of jobs in the longer run, it is important to know how persistent the newly created and destroyed jobs are. Davis et al. (1996, p. 191) define measures for the persistence of job creation and job destruction. N-period persistence rate for job creation shows what fraction of jobs created in period t continue to exist through period $t+ N$. N-period persistence rate for job destruction is defined similarly as a fraction of jobs destroyed in period t that do not exist through period $t + N$.

Let $\delta_{ist}(N)$ be the number of jobs newly created in establishment i in size category s in period t that are present in period $t + N$, and define:

$$P^c_{ist}(N) = \min\left\{\delta_{ist}(1), \delta_{ist}(2), ..., \delta_{ist}(N)\right\}.$$

In other words, $P^c_{ist}(N)$ equals the number of jobs newly created in establishment i in size category s in period t that remain present in all periods from $t+1$ through $t + N$. Thus, the N-period persistence rate for jobs created at t in size category s is:

$$P^c_{st}(N) = \sum_{i\in S^+_t} \frac{P^c_{ist}(N)}{JC_{st}}.$$

Analogously, the N-period persistence rate for jobs destroyed at t in size category s is:

$$P^d_{st}(N) = \sum_{i\in S^-_t} \frac{P^d_{ist}(N)}{JD_{st}}.$$

By definition, one-year persistence rate is always at least as large as two-year persistence. Since job reallocation equals the sum of job creation and job destruction, the definitions above imply a persistence measure for job reallocation, too.

Table 7 presents one-year (1) and two-year (2) persistence rates for job creation (PCR) and job destruction (PDR) rates, which are calculated as annual averages over the period 1980–92 from the Industrial Statistics. Current size is used as a measure of establishment size. At the level of total manufacturing on average 76% of newly created jobs still exist after one year but after two years only 61% of them are present. The probability that newly destroyed jobs do not reappear is after one year 91% and after two years 86%. In other words, job destruction is more persistent than job creation. Recession years at the end of the period may change the results because during recession job destruction was probably more persistent than on average and the persistence rate for job creation was lower than the average.

There is a weak negative dependence between establishment size and the persistence of newly created jobs, whereas the persistence of newly destroyed jobs seems to be unrelated to establishment size. On the contrary, Davis et al. (1996, pp. 78–81) find that there is a weak positive dependence between establishment size and the two-year persistence rate for job creation with current size measure. According to Broersma and Gautier (1997, p. 220), jobs created in small firms are more persistent than jobs created in large firms and the opposite is true for newly destroyed jobs.

According to Davis et al. the measure of establishment size changes the results considerably. Average establishment size is used as a measure of size in Table 8. The persistence for job creation and establishment size are now positively related, but there is still no clear pattern between the persistence of job destruction and size. When Davis et al. use average establishment size measure, the positive relationship between size and the persistence of job creation strengthens. In addition, the persistence rates for job destruction are slightly higher in smaller size categories according to almost all size measures they use.

The one-year survival rate for all establishments can be calculated as $1-$ job destruction rate. According to the previous results, the average one-year survival rate for manufacturing is 90.8% in the period 1980–94. Thus, all jobs are clearly more persistent than the new ones. In addition, there is a strong positive dependence between establishment size and the survival rate for all establishments.

The findings on the relationship between establishment size and persistence rates for new and destroyed jobs have been rather conflicting. Many studies have found that the newly created and destroyed jobs are more persistent in large establishments, but the dependencies are weak and the size measure can have a considerable effect on the results.

5 Conclusions

There has been a distinct negative trend in the Finnish manufacturing employment over the period 1980–94. Changes in the employment shares of different-sized establishments would imply that the employment decline has concentrated on large establishments, which may be due to more intense restructuring and technological change. However, the examination of job flows by size category gives different results.

According to the findings, job creation and job destruction rates are much higher in small establishments (less than 100 employees) than in the larger ones. Furthermore, entry and exit account for a remarkable share of job creation and job destruction. The negative net employment changes are only slightly higher in small size categories than in the large ones. When each size category's shares of total flows are compared with their employment shares, it is obvious that small establishments have 'over'contributed to job flows, whereas large establishments create and destroy jobs less than their employment share would imply.

The choice of a measure for establishment size has a considerable effect on the results on net employment change. When long-run average employment size is used instead of current size, there is no longer a relationship between establishment size and net change. Also the method of calculating growth, arithmetic average or compound interest, changes the results. With compound interest, the net change is in most cases more negative in larger establishments, but the differences are still quite small. It should also be noted that the results change notably over the period of exceptionally deep recession 1990–94. The sensitivity of the results to the data and to the methods of measurement emphasises the need for caution in interpreting earlier results on the superior role of small business.

The findings on job creation and job destruction correspond to the predictions of recent theoretical models of firm growth. Many of these models predict that firm size and the variance of firm growth are negatively correlated. The finding that there is no clear relationship between establishment size and net employment growth lends support to Gibrat's law.

In this paper, some aspects of job quality are also examined. First of all, there is a clear positive relationship between relative average wage and establishment size. Therefore, job flows are wage adjusted with a new measure of employment, EEP. However, the results are essentially the same as before the wage adjustment. Labour productivity also increases with employment size and the differences between small and large establishments have grown over the period. On the other hand, labour turnover has been more intense in small establishments, but it can be seen both as a positive and a negative phenomenon. When it comes to the persistence rates of newly created and newly destroyed jobs, there is no clear pattern between establishment size and durability. Some studies have nevertheless found that new and destroyed jobs are more persistent in large establishments.

There are also many other aspect of job quality that are worth studying, including working conditions and the share of total output by size category. Each employee values job characteristics differently and the total welfare effect of jobs created in different-sized establishments is almost impossible to evaluate. However, it is worth noticing that small employers have considerably higher job and labour turnover than larger employers, which can increase flexibility of the labour market and even facilitate structural change.

The findings can be applied to the firm level with certain reservations because only 7% of the firms in the data are multi-unit establishments. In addition, the employment distribution of firms has developed largely in the same way as the employment shares of establishments. However, firms are concentrated on larger size categories than establishments.

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Table 1. Job flow rates (average 1980–94, %) by establishment size from the Industrial Statistics, current size

Establishment size	JCR	(%)	ENTRY	(%)	JDR	(%)	EXIT	(%)	NETR	(%)	JRR	(%)	ERR	(%)	SH80	SH94	SHARE
0– 9	30.0	(11)	26.1	(28)	33.1	(9)	27.4	(20)	–3.0	(2)	63.1	(10)	48.6	(10)	2.1	2.9	2.3
10–19	14.0	(12)	8.1	(20)	17.7	(11)	11.2	(19)	–3.7	(8)	31.7	(11)	26.4	(12)	4.4	6.3	5.4
20–49	9.4	(18)	3.7	(21)	13.4	(18)	6.8	(26)	–4.0	(18)	22.8	(18)	17.7	(19)	11.4	12.8	12.3
50–99	7.2	(14)	2.2	(12)	10.8	(15)	4.1	(16)	–3.6	(17)	18.1	(15)	13.6	(15)	12.2	13.6	12.6
100–249	5.6	(20)	1.2	(13)	8.0	(19)	1.4	(11)	–2.4	(19)	13.5	(19)	10.1	(20)	21.4	22.2	22.3
250–499	4.3	(12)	0.8	(6)	6.8	(13)	0.9	(5)	–2.5	(17)	11.0	(13)	7.7	(12)	17.4	17.6	17.8
500–999	3.3	(7)	0.1	(1)	5.3	(8)	0.1	(1)	–1.9	(10)	8.6	(8)	5.6	(7)	16.4	12.6	14.1
1000–	3.0	(6)	0.0	(0)	5.1	(7)	0.4	(2)	–2.1	(10)	8.1	(7)	4.7	(5)	14.6	12.1	13.2
Total manufacturing	6.4	(100)	2.2	(100)	9.2	(100)	3.2	(100)	–2.8	(100)	15.6	(100)	12.0	(100)	100.0	100.0	100.0

Table 2. Job flow rates (average 1980–94, %) by establishment size from the Industrial Statistics, average establishment size

Establishment size	JCR	(%)	ENTRY	(%)	JDR	(%)	EXIT	(%)	NETR	(%)	JRR	(%)	ERR	(%)	SH80	SH94	SHARE
0–9	16.3	(4)	12.1	(8)	19.3	(3)	12.9	(6)	–3.0	(2)	30.0	(3)	22.4	(3)	1.5	1.5	1.4
10–19	13.1	(10)	7.8	(18)	13.7	(8)	7.6	(12)	–0.6	(1)	25.7	(9)	21.1	(8)	4.1	5.6	5.1
20–49	10.2	(19)	4.5	(25)	12.5	(17)	6.3	(24)	–2.3	(10)	21.5	(18)	18.0	(17)	11.4	12.1	12.1
50–99	8.1	(16)	2.9	(16)	11.3	(15)	5.2	(20)	–3.2	(14)	17.4	(15)	13.3	(15)	12.6	11.9	12.4
100–249	6.0	(22)	1.7	(18)	9.2	(23)	2.8	(20)	–3.2	(26)	13.9	(22)	9.9	(23)	23.3	22.1	22.9
250–499	4.7	(13)	1.0	(9)	7.9	(16)	1.5	(9)	–3.2	(22)	11.1	(15)	7.3	(16)	19.4	18.3	18.5
500–999	4.1	(9)	1.0	(6)	6.5	(10)	1.3	(6)	–2.4	(13)	10.3	(10)	7.2	(10)	14.5	15.7	14.7
1000–	3.1	(6)	0.1	(1)	6.2	(9)	0.8	(4)	–3.0	(14)	21.1	(8)	16.8	(9)	13.3	12.7	12.9
Total manufacturing	6.4	(100)	2.2	(100)	9.2	(100)	3.2	(100)	–2.8	(100)	15.6	(100)	12.0	(100)	100.0	100.0	100.0

The figure in parentheses is each size category’s share of the total flow in each column.
The last column (SHARE) is the size category’s employment share, when establishment size is measured with current size.

Table 3. Mean annual growth (%) by establishment size

Size category	1980–94			1980–90			1991–94		
	Obs. Year's size	Current size	Average establish-ment size	Obs. year's size	Current size	Average establish-ment size	Obs. year's size	Current size	Average establish-ment size
0–9	–1.0	–0.9	–3.0	–2.2	–2.3	–2.9	–6.5	–5.5	–9.0
10–19	–1.0	–0.7	–1.1	–0.6	0.1	0.2	–5.7	–4.4	–6.8
20–49	–2.3	–2.4	–2.9	–0.9	–0.7	–1.3	–6.0	–7.0	–7.0
50–99	–3.0	–2.5	–3.9	–1.6	–1.3	–2.8	–7.3	–6.2	–6.2
100–249	–2.8	–2.9	–3.9	–1.7	–1.6	–2.7	–4.5	–6.3	–6.0
250–499	–3.4	–3.1	–3.8	–2.0	–1.3	–2.7	–4.8	–6.8	–5.4
500–999	–5.3	–5.0	–2.8	–3.4	–2.9	–2.0	–9.8	–11.3	–3.6
1000–	–4.5	–4.5	–3.2	–5.5	–4.7	–3.6	2.1	–1.3	–0.8
Total manufacturing	–3.3	–3.2	–3.3	–2.4	–1.9	–2.3	–5.2	–6.5	–5.4

Table 4. Job flow rates (%) by establishment size, current size (averages 1987–90 and 1991–93)

Size category		1987–90	1991–93	Change
0–19	**JCR**	17.7	20.2	2.4
	JDR	22.1	32.3	10.2
	NETR	–4.3	–12.1	–7.8
	JRR	39.8	52.5	12.7
20–99	**JCR**	8.9	6.7	–2.3
	JDR	12.1	17.9	5.9
	NETR	–3.1	–11.2	–8.1
	JRR	21.0	24.6	3.6
100–499	**JCR**	5.9	3.6	–2.4
	JDR	7.6	11.0	3.4
	NETR	–1.7	–7.4	–5.7
	JRR	13.6	14.6	1.0
500–	**JCR**	3.1	2.6	–0.5
	JDR	6.6	6.0	–0.6
	NETR	–3.5	–3.5	0.1
	JRR	9.7	8.6	–1.1
Total manufacturing	**JCR**	6.8	5.7	–1.2
	JDR	9.5	13.7	4.1
	NETR	–2.7	–8.0	–5.3
	JRR	16.4	19.3	3.0

Table 5. Job flow rates (%) by establishment size from the Industrial Statistics, *EEP* (average 1980–94)

Establishment size	**JCR**	**(%)**	**JDR**	**(%)**	**NETR**	**(%)**	**JRR**	**(%)**	**ERR**	**(%)**	**SHARE**
0–9	32.6	(9)	34.8	(7)	–2.3	(1)	67.4	(8)	52.8	(8)	1.8
10–19	15.5	(10)	19.3	(9)	–3.8	(7)	34.8	(10)	29.2	(11)	4.5
20–49	10.6	(17)	14.4	(17)	–3.8	(15)	25.0	(17)	20.1	(18)	10.9
50–99	8.2	(14)	11.6	(14)	–3.5	(15)	19.8	(14)	15.4	(15)	11.8
100–249	6.4	(21)	8.9	(20)	–2.5	(19)	15.4	(21)	11.6	(21)	21.9
250–499	4.8	(13)	7.5	(15)	–2.7	(19)	12.3	(14)	8.8	(13)	18.5
500–999	3.8	(9)	5.6	(9)	–1.8	(11)	9.4	(9)	6.3	(8)	15.7
1000–	3.3	(7)	5.8	(9)	–2.5	(13)	9.1	(8)	5.6	(7)	14.8
Total manufacturing	6.8	(100)	9.6	(100)	–2.8	(100)	16.4	(100)	13.6	(100)	100.0

Size category assignment for each establishment is made on the basis of current size and actual employment
The figure in parentheses is each size category's share of the total flow in each column.
The last column (SHARE) is the size category's employment share, when establishment size is measured with current size based on *EEP*.

Table 6. Worker and job flow rates (%) from the Employment Statistics (average 1988–95)

Establishment size	HR	SR	WFR	JRR	CFR
0–9	38.8	38.4	77.2	57.6	19.6
10–19	29.4	31.9	61.3	39.5	21.9
20–49	25.4	28.2	53.6	31.7	21.8
50–99	23.8	25.8	49.6	29.5	20.1
100–249	22.6	23.9	46.5	26.5	20.0
250–499	20.2	21.4	41.5	20.8	20.7
500–999	15.3	18.1	33.4	15.1	18.4
1000–	12.1	15.0	27.2	11.6	15.6
Total manufacturing	23.0	24.8	47.9	27.9	20.0

Table 7. Persistence rates (%) for job creation and job destruction by size category, current size (average 1980–92)

Establishment size	PCR(1)	PCR(2)	PDR(1)	PDR(2)
0–9	81.7	67.7	90.7	87.6
10–19	78.8	64.0	89.8	85.7
20–49	76.2	62.0	89.6	85.1
50–99	76.2	61.9	89.1	84.2
100–249	73.2	60.6	90.6	85.3
250–499	70.4	54.5	90.9	85.1
500–999	73.9	59.9	91.5	87.2
1000–	70.6	54.0	93.3	87.4
Total manufacturing	75.7	61.2	90.6	85.9

Table 8. Persistence rates (%) for job creation and job destruction by size category, average establishment size (average 1980–92)

Establishment size	PCR(1)	PCR(2)	PDR(1)	PDR(2)
0–9	71.8	54.6	91.4	88.7
10–19	76.3	60.1	88.9	84.5
20–49	75.8	60.4	89.1	84.6
50–99	75.1	61.6	89.4	85.1
100–249	75.9	62.0	89.9	84.7
250–499	72.8	59.9	92.0	87.5
500–999	78.5	64.5	90.3	84.9
1000–	77.5	62.4	94.2	88.4
Total manufacturing	75.7	61.2	90.6	85.9

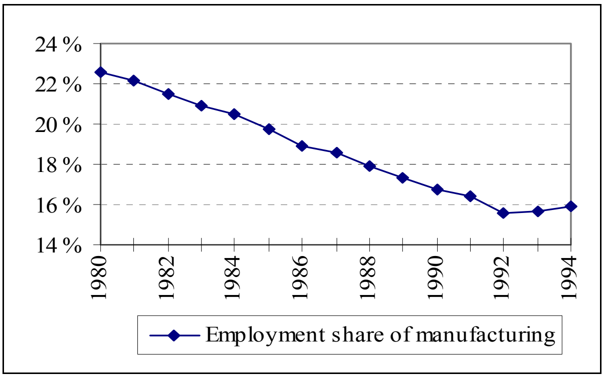

Figure 1. Employment share of manufacturing 1980–94

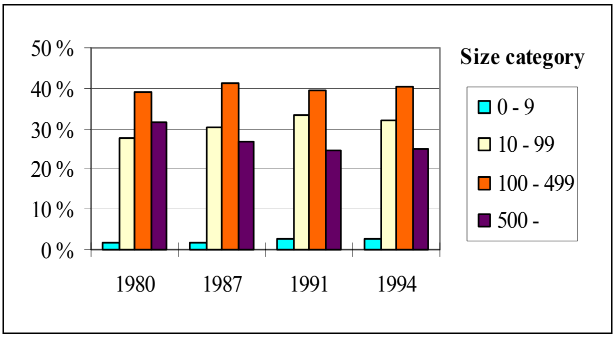

Figure 2. Employment shares by establishment size 1980–94

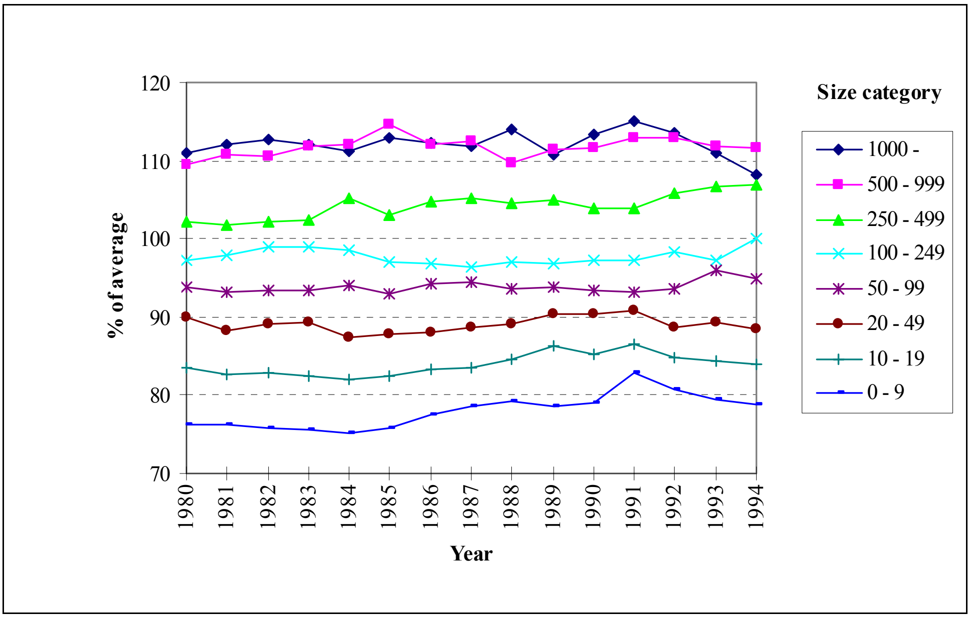

Figure 3. Relative wage by size category 1980–94

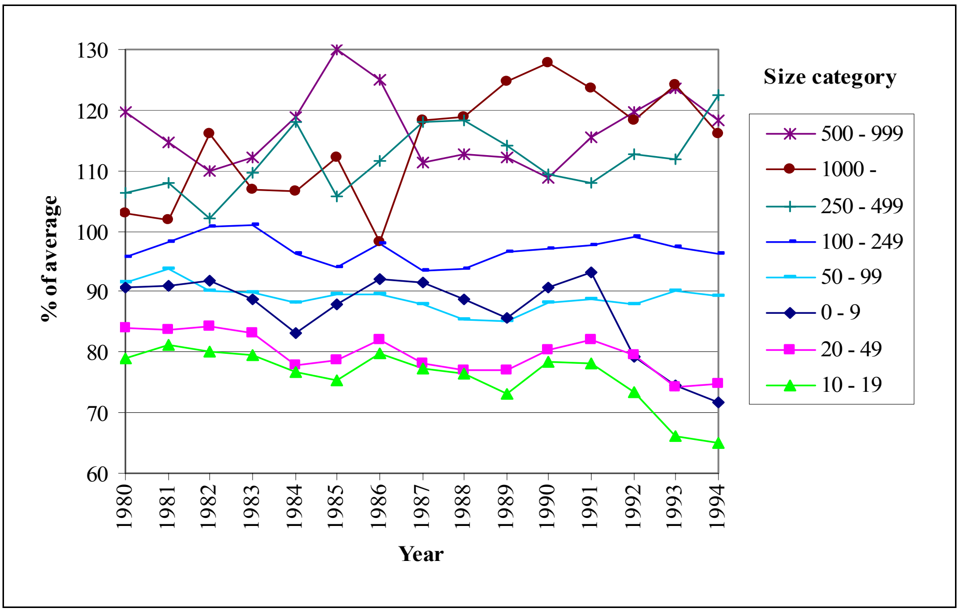

Figure 4. Relative labour productivity by size category 1980–94

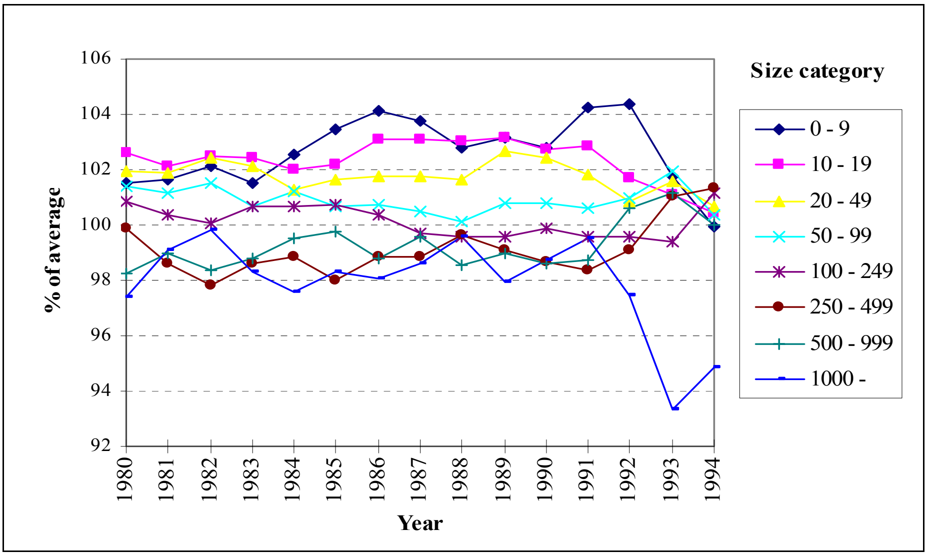

Figure 5. Relative working hours per person by size category 1980–94

IV

IV

PLANT SIZE, AGE AND GROWTH IN FINNISH MANUFACTURING*

Contents

1 Introduction **2**

2 Theories of firm growth **4**

3 Data and descriptive analysis **5**

4 Growth conditional on survival **8**
4.1 Econometric framework 8
4.2 Empirical results 11
4.3 Statistical issues 13

5 Growth and heterogeneous plant effects **15**
5.1 Basic results and sensitivity analysis 15
5.2 Human capital effects 17
5.3 Dynamic setting 19

6 Conclusions **22**

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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 & 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 least for small firms (Dunne & Hughes, 1994; Mata, 1994; Hart & Oulton, 1996; Audretsch, Klomp & Thurik, 1999; Audretsch, Santarelli & Vivarelli, 1999; Almus & Nerlinger, 2000; Goddard et al., 2002).

Studies that have also taken into account firm age and survival suggest that firm size and age are inversely related to firm growth even after controlling for the sample selection bias, due to the higher probability of exit of slowly-growing small plants. Furthermore, the probability of firm survival increases with firm size and age. (Evans, 1987a, 1987b; Hall, 1987; Dunne et al., 1989) However, in Finland the relationship between firm size and growth has not been analysed earlier using comprehensive micro-level data sets and advanced econometric methods.

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 on 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 survival. The analysis is also extended to take into account the effects of human capital, which have been mostly neglected in the previous

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

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, which may have an effect on the relative employment performance of different-sized plants.[2]

The starting point of the analysis is a pooled ordinary least squares (OLS) regression including only fixed time effects. A standard selection model proposed by Heckman (1976, 1979) is estimated in order to assess the magnitude of the sample selection bias. Since growth can only be measured for firms which have survived over the examined period and small firms having slow or negative growth are more likely to exit, small fast-growing firms may be overrepresented in the surviving sample. Hence, without an adjustment for the sample selection problem, the growth rate of small plants could be overestimated relative to that of large plants, resulting in the negative relationship often found between size and growth. After assessing the impact of the selection bias on the results, the panel nature of the data is taken into account more thoroughly by using panel methods and generalised method of moments (GMM) estimation to control for unobserved heterogeneity.

The findings show that Gibrat's law does not hold for Finnish manufacturing despite the exceptional macroeconomic development. In addition, growth is decreasing with plant age, whereas the probability of survival is increasing with age, thus giving support to the learning models of firm growth. Employee characteristics are found to have significant effects on plant growth. The sample selection bias does not seem to have a considerable effect on the results. However, there are several problems with model identification and distributional assumptions. The results are also robust to the inclusion of unobserved heterogeneity and different model specifications.

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. Estimation results with pooled OLS and Heckman selection model are presented in section 4. Section 5 discusses the empirical findings after taking into account the unobserved plant-level heterogeneity and the dynamic nature of the model. In addition, the effects of human capital on plant growth are studied. Finally, section 6 discusses the results and possibilities for further research.

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[2] 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.

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 & Bonini, 1958). According to Gibrat's law, firm's proportionate rate of growth is (e.g. Aitchison & Brown, 1957):

$$\frac{S_t - S_{t-1}}{S_{t-1}} = \varepsilon_t, \tag{1}$$

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}. Assuming that the initial value is S_0 and there are n steps before the final value S_n is reached, and summing up gives:

$$\sum_{t=1}^{n} \frac{S_t - S_{t-1}}{S_{t-1}} = \sum_{t=1}^{n} \varepsilon_t. \tag{2}$$

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

$$\sum_{t=1}^{n} \frac{S_t - S_{t-1}}{S_{t-1}} \cong \int_{S_0}^{S_n} \frac{dS}{S} = \log S_n - \log S_0, \tag{3}$$

which gives:

$$\log S_n = \log S_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_n. \tag{4}$$

Equivalently:

$$S_t = (1 + \varepsilon_t) S_{t-1} = S_0 (1 + \varepsilon_1)...(1 + \varepsilon_n). \tag{5}$$

Provided that $\log S_0$ and ε_t have identical distributions with mean μ and variance σ^2, then by the central limit theorem, it follows that $\log S_t \sim N(\mu t, \sigma^2 t)$, when $t \to \infty$. 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.[3] However, this process involves significant randomness. As a consequence, 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 upon 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 should be 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.[4] In addition, the effects of age, human capital and other variables related to growth 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 over the period 1974–01 (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

[3] Learning, in this case, could be described as evolutionary (Baldwin & Rafiquzzaman, 1995).

[4] Testing Gibrat's law is also closely related to the tests of unit roots.

their turnover corresponds to the average turnover in firms with 5–10 employees. However, over the period 1995–01 the sample is smaller, i.e. only plants that belong to firms with at least 20 persons are included. Therefore, these years cannot be included in this analysis, because the break between the years 1994 and 1995 may result in artificially high exit rates. In addition, there are some problems with longitudinal linkages before 1980, so the period used in this analysis covers only the years 1981–94.

The LDPM contains information on various plant-level variables, including employment, output, value added and capital stock which is constructed by using the perpetual inventory method. The employment figures are reported as annual averages. The number of hours worked are also reported. 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. In this study only the plants with at least 5 employees in each year are included in order to produce a series which is comparable over time. 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. 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.[5] 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.[6] 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 established before 1975.

Exit is defined as concerning only those plants that are missing from the data base for at least two consecutive years. If a plant is absent from the data for

[5]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.

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

one year but then reappears, it is treated as a continuing plant. In this way temporary disappearances which may be caused by 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.[7] As a consequence, the final data set consists of 10 447 plants over the years 1981–94. 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.[8]

Plant size is defined as the logarithm of employment, and subsequently, growth is the difference of plant size in two consecutive years.[9] 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. When the exit rates are compared for different size and age categories, it can be seen that the probability of plant failure is also non-monotonically declining with size and age. It should be noted that there is a clear declining trend in the Finnish manufacturing employment over the whole 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 (not reported).

In previous research, it has been found that the size distribution of firms conforms fairly well to the lognormal, with possibly some skewness to the right. Table 2 presents the moments of the plant size distribution when size is measured

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

[8] 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 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%.

[9] 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. However, according to Heshmati (2001), the results may be sensitive to the definition of size.

with the logarithm of employment. 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 increase, whereas the mean slightly decreases. 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.

The large size of the sample makes the formal testing of the normality hypothesis difficult because the hypothesis would easily be rejected. As a consequence, a non-parametric kernel density estimator is used to graphically assess the magnitude of the deviations of the plant size distribution from normality. Let $f(x)$ be the unknown density to be estimated. Then the general formulation of a kernel density estimator is (see e.g. Silverman, 1986):

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - X_i}{h}) \tag{6}$$

when h denotes the bandwidth (or the smoothing parameter) and n is the sample size. The kernel density function K is defined in such a way that:

$$\int_{-\infty}^{\infty} K(x)dx = 1 \tag{7}$$

As an illustration, Figure 1 presents the kernel density estimates of the logarithm of employment in 1993 compared with the normal distribution, when the Epanechnikov kernel is used as the kernel density function. It can be seen that the size distribution in 1993 is highly skewed to the right and it peaks more than the corresponding normal. To conclude, the descriptive results would seem to 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 Growth conditional on survival

4.1 Econometric framework

Several studies have found 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 (2002) finds that a significant, negative relationship exists between plant size and the risk of failure in Finnish manufacturing (see also section V of this thesis).

In this analysis the approach by Evans (1987a, 1987b) and Hall (1987) is followed in order to control for the effect of sample selection. According to Evans (1987b), the plant growth relationship for plant i in period t is given by:

$$S_{it} = G(S_{i,t-1}, A_{i,t-1})S_{i,t-1}e_{it}, \tag{8}$$

where e_{it} is a lognormally distributed error term with possibly a nonconstant variance and G is a growth equation which is a function of plant size $S_{i,t-1}$, measured with employment, and plant age $A_{i,t-1}$. Subsequently, the regression model can be formulated as:

$$\ln S_{it} - \ln S_{i,t-1} = \ln G(S_{i,t-1}, A_{i,t-1}) + u_{it}, \tag{9}$$

where u_{it} is a normally distributed error term with mean zero and possibly a nonconstant variance, and is independent of S and A.[10] If Gibrat's law holds, the coefficient for plant size should equal zero. A negative coefficient in turn would indicate that plant sizes are mean-reverting, i.e. small plants grow faster than the larger ones. According to a positive coefficient, plant growth paths would be explosive, so that large plants would grow faster than the smaller ones. A negative coefficient on the age variable suggests that learning is important since it implies that young plants grow faster than the older ones.

However, the dependent variable is not always observed because some plants exit from the sample before period t. To account for this sample selection bias, a probit equation for survival is estimated jointly with the growth equation using maximum likelihood (ML). In the selection equation, $SURV = 1$ if a plant survives and 0 if it fails. The conditional expectation of $SURV$ given initial size and age is:

$$\begin{aligned} E[SURV \mid S_{i,t-1}, A_{i,t-1}] &= \Pr[v_{it} > -V(S_{i,t-1}, A_{i,t-1})] \\ &= F[V(S_{i,t-1}, A_{i,t-1})], \end{aligned} \tag{10}$$

where V can be thought of as the value (in excess of opportunity cost) of remaining in business, v_{it} is a normally distributed error term with mean zero and unit variance, and F is the cumulative normal distribution function with unit variance. Equations (9) and (10) form a standard sample selection model (e.g. Heckman, 1976, 1979) where $\rho = corr(u_{it}, v_{it}) \neq 0$ if there is a selection bias. In other words, the model is a standard generalized tobit model. It is possible to obtain consistent estimates of the parameters of the regression functions G and V using maximum likelihood.

Dunne et al. (1989) propose another approach where surviving and all plants are first grouped into cells based on size and age. Then sample means and variances of growth are calculated as dependent variables for all groups. However,

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

regardless of the approach used, several studies find that the negative relationship between firm size and growth is not due to sample selection bias.

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. The first estimations concentrate on young plants only since the sample selection problem is potentially more serious for them. In the first specification, only size and age are included in the growth and survival equations in order to test the basic model. In the second model, the growth equation is approximated by a second-order logarithmic expansion of $\ln G(S, A)$ in size and age. This flexible functional form can capture many forms of non-linearity. In the third model, other plant and industry-level covariates that are strongly correlated with growth are also controlled for. Table 3 reports summary statistics for young plants. It should be noted that the growth of young plants seems to be rather heterogenous, which is implied by the relatively large standard deviation of the growth variable.

Based on the earlier empirical findings and theories of firm growth, it can be expected that plant growth decreases with size and age, but increases with relative wages, labour productivity and capital intensity because these factors can be interpreted as indicators of plant-level efficiency. [11] 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. At the industry level, R&D intensity and scale economies are expected to have a positive relationship to 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 MES level of output.[12]

The hypothesised relationships between plant characteristics and survival are based on the literature and on the earlier analysis by Nurmi (2002) with similar data (in section V of this thesis). The probability of survival is expected to increase with plant size, age, productivity and profitability because these factors are closely related to the plant's competitive ability. Multiplants, i.e. plants that belong to firms with more than one plant, can be expected to have a higher risk of failure, which may be due to the fact that multiplant firms can close unprofitable branches rather easily when capacity reductions are needed, whereas the owners of independent plants are willing to accept lower rates of return for a longer period without closing the plant. However, belonging to a multi-unit firm may

[11] Hourly wages, labour productivity, capital intensity and price-cost margin 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.

[12] 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 using OECD definitions (the Analytical Business Enterprise Research and Development (ANBERD) database, OECD).

also facilitate access to financial resources. Lower debt constraints in turn may lead to a lower risk of closing down. Lastly, the effect of foreign ownership on exit is unclear and has not been studied much.[13] Both equations also include time dummies for each year (not reported).

4.2 Empirical results

The estimation results with models (1) and (2) for young plants are reported in Table 4. The first model includes only size, age and year dummies as explanatory variables. The results for the growth equation in the tobit model can be interpreted exactly as though growth data for all plants in the sample was observed, whereas the pooled OLS includes only the surviving plants. If the correlation coefficient for the disturbances of the two equations $\rho \neq 0$, ordinary least squares yields biased results. A positive ρ implies that the estimated growth rates will be biased upwards. In other words, exits tend to have unusually low growth rates, as could be expected. It can be seen that ρ is 0.17 and statistically significant. However, the maximum likelihood estimates of the growth equation are very close to the OLS estimates, and furthermore, the high number of observations increases the probability that the null hypothesis will be rejected.

Growth rate clearly declines with plant size and age, whereas the probability of survival increases with size and age.[14] As expected, year dummies show that the employment growth is more negative during the recession years 1990–92 when compared to 1981 (not reported). Furthermore, the probability of survival is lower during those years. 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.

The second model also includes the second-order terms of size and age. 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

[13] These variables seem to have most explanatory power. Including all the variables from the growth equation in the survival equation does not change the results (not reported). In contrast, price-cost margin and indicators of ownership have no significant coefficients in the growth equation, whereas they are highly significant in the survival equation. This may improve the identification of the model.

[14] It should be noted that in this analysis plants that exist in the data for only one year are included, although these observations may not be entirely reliable. When one-year plants are excluded, the most notable difference is that the coefficient of age in the survival equation turns out to be negative. However, the results for the tobit growth equation remain rather similar.

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 survival equation only the size squared is added because of the high correlation between age squared and age. It turns out to be negative suggesting that the relationship between size and the probability of survival is inversely U-shaped.[15] The correlation coefficient for growth and survival equations is now slightly smaller (0.15) but still statistically significant. The ML results still correspond closely to the OLS estimates.

The third model for young plants in Table 5 also includes other covariates. Due to possible multicollinearity, the higher-order terms are now excluded. Size and age are still negatively related to growth and positively to survival. 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. The coefficients of the year dummies correspond to the earlier results (not reported). The probability of plant survival increases with productivity and profitability, but is lower for multiplants and foreign-owned plants.[16] This roughly corresponds to the earlier findings of the duration analysis with similar data. It is noteworthy that there is a tendency for ρ to become smaller when new explanatory variables are added. In some cases it is even negative. In any case, the volatility of ρ seems to be large which suggests that the results should be interpreted with caution. However, the coefficient for size does not change much when the model specification is changed. As can be seen in Table 5, the 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.[17]

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 con-

[15] It should be noted that probit does not predict the probability of survival well, i.e. estimated probabilities for survival are very high also for exiting plants. This may be due to the low number of exits in the data (Greene, 2000, p. 833). The failure of probit may have an effect on the functioning of the selection model.

[16] 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, capital intensity, price-cost margin, multiplant and foreign ownership, the magnitude and significance of the coefficients do not change much (not reported).

[17] The growth patterns of those plants that belong to firms with more than one plant may differ from the growth of single plants. However, when these models are estimated on plants belonging to single plant firms only, the results do not change notably. In addition, the share of multiplant observations in the sample is pretty low (17.7%).

trols 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. Plants in fast growing industries also have a higher probability of survival.

Models (1) and (2) are also estimated for the older plants with the exception that age is now included as a categorical variable. The descriptive statistics show that the standard deviation of growth is smaller for the older plants than for the young ones (not reported). In addition, older plants have lower labour productivity, higher capital intensity and higher wages. In addition, they are less likely situated in R&D intensive industries and in industries with low scale economies.

The estimation results are summarized in Table 6. Growth decreases with plant size, but the absolute effect becomes smaller. As before, survival increases with size. The probability of survival increases with age also for the older plants when the reference group is the plants aged between 8 to 15 years. 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 (Table 7) correspond to the earlier findings for young plants on the relationships between other plant and industry-level variables and growth. Since ρ is insignificant in both models, sample selection bias does not seem to play any significant role for mature plants. This is in accordance with our expectations, because older plants have less exits. Furthermore, maximum likelihood estimates for growth closely resemble the corresponding OLS estimates.[18]

4.3 Statistical issues

It should be emphasised that the sample selection model may suffer from several statistical problems related to identification, nonlinearity, heteroscedasticity and distributional assumptions. Furthermore, these problems may to a large extent be interrelated (Evans, 1987b). When the Heckman two-step method is used, a problem arises because the sample selection can be seen as an omitted variable in the growth equation, and this omitted variable, the inverse of the Mills' ratio, is a nonlinear function of plant size and age in the survival equation. An equivalent method would be to include higher-order terms in the growth equation, so it is difficult to separate the cause if the higher-order terms turn out to be significant. One solution to distinguish the sample selection from nonlinearity would be to

[18] In order to take into account the cut-off limit of 5 employees, we also estimate truncated regression models for all growth specifications with truncation from below ln5 (not reported). The coefficient for the size variable in the first model for young plants is -0.016, in the second -0.061, and in the third -0.021, so the negative effect of size on growth becomes weaker. As expected, for old plants the effect of truncation is negligible. However, there 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).

identify some explanatory variables that strongly affect survival but not growth. However, these variables are very hard to find because the determinants of growth and survival are to a large extent the same, which is why the identification is usually achieved through nonlinearity of the functional form. The fact that the estimate of ρ is quite similar regardless of the order of the polynomial expansion of size and age would suggest that the effect of selection bias is not affected by nonlinearity.

The variability of growth decreases with plant size according to many studies (e.g. Evans, 1987a), which suggests that the variance of u_{it} is not constant across plants. A critical assumption is that the disturbance term of the probit equation is also homoscedastic. Otherwise coefficient estimates and standard errors of both equations are inconsistent. Since growth and survival are generated by similar processes, a nonconstant variance for plant growth suggests a nonconstant variance for survival as well. Subsequently, heteroscedasticity-consistent estimates of the standard errors are calculated for both equations using the robust estimation method (White, 1982). However, the interpretation of the results does not change except for ρ becoming highly significant in all models.[19] Evans (1987b) also uses other methods in testing the effect of nonlinearity and heteroscedasticity on the results.[20]

Finally, the joint maximum likelihood method relies heavily on the distributional assumptions, including joint normality. If normality fails, it may lead to inconsistent estimates (e.g. Vella, 1998). When the tobit estimates are compared with the results from the two-step estimation (not reported), it is found that the results for models (1) and (2) differ considerably, which may be caused by the problems with identification and normality.[21] One alternative would be to use a non-parametric or semi-parametric estimator which does not rely so much on the distributional assumptions. For example, Klein and Spady (1993) propose a semi-parametric estimator for binary response models that makes no parametric assumption on the form of the distribution generating the disturbances and also permits heteroscedasticity. However, this method would still require an exclusion restriction for the identification of the model.

To conclude, the reliability of the results taking into account plant survival may suffer from the problems related to using the sample selection model. This seems to be the case especially if the Heckman 2-step method is used in the panel

[19] In order to take into account the possible bias due to the industry-level explanatory variables (see Moulton, 1990), robust standard errors are also calculated using clustering on industry (not reported). However, the explanatory variables in the growth equation remain highly significant.

[20] The growth of plants may also be autocorrelated. However, due to the large number of cross-sectional observations relative to the number of time periods available, the effect of autocorrelation should be negligible.

[21] The most notable difference is that plant size is insignificant and positive in the growth equation when two-step method is used. In addition, ρ is 1.0. When the assumption of joint normality is tested by including the inverse of the Mills' ratio (IMR), its square and its cube in the model, the joint significance of the powers of the IMR cannot be rejected, i.e. normality fails. When other explanatory variables are included in model (3), the estimates are more similar.

context. However, due to the short growth interval used and the low number of exits, it is believed that the sample selection bias is not 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 & Hughes, 1994; Heshmati, 2001) conclude that the negative relationship between firm size and growth is not merely due to the sample selection bias. Hence, it may be more beneficial to concentrate solely on the panel aspect of the data in the further analysis and leave the selection issue aside.

5 Growth and heterogeneous plant effects

5.1 Basic results and sensitivity analysis

There is little basis for assuming that individual plant effects are homogeneous, which would imply that the constant term is fixed across plants. Furthermore, this unobserved heterogeneity may cause the pooled OLS estimates to be biased. Since it is difficult to include all relevant factors in the model, an alternative is to use panel data methods to control for the unobserved plant-level heterogeneity. 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.

Table 8 presents the pooled OLS, between, within and generalised least squares (GLS) estimation results when all plants, both young and old, are included in the growth estimations. In addition to size, only age and growth in real 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 earlier findings. However, the F-test rejects the hypothesis of homogeneous plant-specific effects, which would indicate that the OLS estimates are biased. In addition, the Hausman test implies that the individual plant effects are correlated with the explanatory variables in the model. Since the GLS estimator assumes zero correlation between the disturbances and the explanatory variables, the within estimator seems to be more appropriate than the GLS approach. For comparison, between effects and GLS estimates are still reported.

With the fixed plant effects, the coefficient of the size variable increases considerably in absolute magnitude (-0.265 compared to -0.015). Since the effect of plant size on growth is not necessarily linear, a categorical size variable is also tested (not reported). However, the results are very similar. 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.[22] Growth in real GDP has a positive effect on growth,

[22] The reference group is plants younger than 3 years, but one-year plants drop out because

as expected. When fixed time effects are used instead of growth in real GDP to control for macroeconomic influences on growth, the coefficient for size 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 have been due to a high correlation between plant age and the year effects, so GDP growth is preferred to year dummies.

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 seem to have a negligible impact on the model fit. Furthermore, with fixed plant effects the coefficients for relative wages and scale economies are no longer significant. In addition, the coefficient for R&D intensity changes its sign (not reported). Industry dummies also turn out to be insignificant which is as expected because the within transformation wipes out the time-invariant plant effects and there are only a few industry switches in the data. Based on the earlier discussion on the possibility of heteroscedasticity in this kind of an analysis, heteroscedasticity-consistent estimates of the standard errors are also calculated using the robust estimation method. Despite a clear increase in the standard error for size, it is still highly significant (not reported).[23]

Table 9 reports some of the findings when the sensitivity of the within estimates is tested using different model specifications and sub-samples of the data. In model (5) lagged size ($\ln S_{t-2}$) is used as a regressor instead of current size ($\ln S_{t-1}$) 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.[24] For comparison, in model (6) growth is calculated over two-year periods. However, the results are very similar to equation (3), although the number of observations is much lower. An alternative way might be to include lagged annual growth in the estimation to allow for persistence in growth over time. Model (7) shows that the coefficient of lagged growth is positive and highly significant suggesting that there is some positive persistence in growth.[25] However, the effect of size does not change much and

growth cannot be calculated for them. Plants older than 15 years are not 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.

[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] If it is assumed that changes in employment are temporary, a negative relation between plant size and growth 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, $(\ln S_{t-1} + \ln S_{t-2})/2$, suggested by Davis et al. (1996), the results remain very similar (not reported).

[25] Ilmakunnas & Maliranta (2001) instead find a negative coefficient for the lagged employment

lagged growth does not add explanatory power to the model. Dynamic setting is examined in more detail in the next section.

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 (8) reports the results including additive and interaction effects for decliners ($decliner = 1$ if $growth < 0$, otherwise $decliner = 0$).[26] 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 (9) 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 growth more during recessions than during boom periods. Hence, the negative relationship between size and growth becomes stronger during recessions.[27] In contrast, when the interactions of plant age categories and GPD are included, there is no clear pattern with age (not reported). Using a sample of small Finnish firms, Kangasharju (2000) finds that macroeconomic fluctuations do not alter the negative relationship between firm age and the probability of growth.

5.2 Human capital effects

The effect of human capital factors is largely ignored in the previous 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

growth in the Finnish business sector over the period 1991–97. However, the empirical framework and the data set used are quite different.

[26] 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 (section III of this thesis).

[27] 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.

organisational capabilities and are more productive. In addition, the share of women employees in the plant may be related to employment growth. 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) formed by linking the Business Register and the Employment Statistics of Statistics Finland (Ilmakunnas et al., 2001).

Estimations in Table 10 include human capital factors in each plant in relation to the industry average, i.e. relative age of the employees, relative seniority measured as the number of months in the firm, relative education measured as the number of schooling years and the relative share of women, in addition to other variables used in selection model (3). The estimations are performed separately for young and old plants since young plants may have a higher demand for highly-educated workers.[28]

The results for young plants show that the inclusion of human capital variables does not have any effect on the size coefficient in the OLS estimation. It can be seen that growth is higher for plants with less experienced workers relative to the industry average.[29] However, it should be noted 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 have grown more rapidly than plants dominated by less-educated workers.[30]

The table also shows the corresponding within estimates including plant fixed effects and time dummies. The coefficient for seniority remains negative and significant, whereas the negative effect of the share of women on growth 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 (Haltiwanger et al., 2000). Thus, the within estimator may wipe out some of the effects. In contrast, Maliranta (2003) finds a positive relationship between the plant's average education level and net employment growth using both OLS and fixed effects. However, different measures for growth and size are used. 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

[28] The mean of the relative education variable is 0.98 for older plants, whereas for young plants it is 1.0.

[29] Including relative age of employees in the model instead of relative seniority produces very similar results.

[30] 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.

size. However, the interaction terms are very highly correlated with age and size.

The same specifications are also estimated for the older plants with the exception that age is included as a categorical variable. 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 effects of seniority remain negative and highly significant, but the coefficients for the relative share of women are not significant for old plants.

5.3 Dynamic setting

Traditionally, similar empirical specifications testing Gibrat's law are treated as static models. However, the dynamic context should not be forgotten.[31] 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) is needed.

In order to use the GMM estimation methods, other explanatory variables are excluded and equation (9) is reformulated as follows:

$$\ln S_{it} = c_t + \alpha \ln S_{i,t-1} + v_i + u_{it}, \tag{11}$$

where c_t is a year specific intercept, v_i is an unobserved plant-specific time-invariant effect which allows for heterogeneity across plants, and u_{it} is a disturbance term. A key assumption is that the error components v_i and u_{it} are independent across plants $i = 1, 2, ..., N$. Gibrat's law holds if $\alpha = 1$. If $\alpha < 1$, it can be concluded that small plants grow faster than large plants.

The pooled OLS estimator of α is inconsistent, since the explanatory variable, i.e. the lagged dependent variable, is positively correlated with the error term $(v_i + u_{it})$ due to the presence of plant-specific effects. Wiping out the fixed effects does not solve the endogeneity problem because the lagged dependent variable is still correlated with the error term. Since the OLS estimator is biased upwards, whereas the within estimator is biased downwards, the consistent estimator should lie in between the OLS and within estimates.[32]

Alternatively, first-differencing can be used to eliminate the plant-specific effects v_i from the model. Consistent estimates of α can then be obtained by using two-stage least squares (2SLS) with the lagged level of $\ln S_{i,t-1}$ as an instrument (Anderson & Hsiao,1981). Arellano and Bond (1991) propose the GMM procedure which is more efficient than the Anderson and Hsiao estimator. According to this approach, additional instruments can be obtained in a dynamic panel data

[31] To my knowledge, this is one of the first studies that consider testing Gibrat's law in a GMM context. Oliveira and Fortunato (2003) also present some evidence using this method.

[32] According to standard results this holds at least in large samples without other explanatory variables.

model if one utilizes the orthogonality conditions that exist between the possibly endogenous explanatory variables and the disturbances u_{it}. As a consequence, suitably lagged levels of the explanatory variables can be used as instruments for the equations in first differences. This yields a consistent estimator of α as $N \to \infty$ and T is fixed. The key assumptions are that the disturbances u_{it} are serially uncorrelated, and the initial conditions y_{i1} are predetermined.

Table 11 reports alternative estimates of α, with heteroscedasticity-consistent estimates of the asymptotic standard errors and test statistics, using a sample of all plants with $T \geq 3$ (in Table 11 $\ln S_{it} = size_t$). As expected, the pooled OLS estimate (0.983) is considerably higher than the within estimate (0.715). Significant positive serial correlation is expected in the levels residuals due to the presence of the individual effects v_i, but the bias in OLS may change the pattern. The reported test statistics for the within estimator are also biased, but there seems to be no significant second-order serial correlation in the first-differenced residuals which implies that there is no serial correlation in the u_{it} disturbances. In addition, negative first-order serial correlation is expected in the first-differenced residuals if errors are serially uncorrelated. The third column reports the simple, just-identified 2SLS estimator (which coincides with first-differenced GMM), using only $size_{t-2}$ as the instrumental variable. The resulting estimate of α is less than unity and lies below the OLS estimate but well above the within estimate. The pattern of serial correlation in the first-differenced residuals is consistent with the key identifying assumption that the u_{it} disturbances are serially uncorrelated.

The fourth column reports the results for the one-step first-differenced GMM estimator using only a restricted set of the potentially available instruments[33], i.e. instruments dated $t-2$ and $t-3$. The precision of the parameter estimates improves only slightly when the complete set of linear moment restrictions is used in the fifth column. However, the estimate of α clearly decreases. When $T > 3$ and the model is overidentified, the Sargan test of overidentifying restrictions can be used to test the validity of the instruments. The Sargan test statistics are based on the minimised value of the associated two-step estimator, which is asymptotically χ^2 distributed. Whereas the serial correlation tests do not show any evidence of model misspecification, the Sargan test rejects the null hypothesis of the validity of the complete set of moment conditions used. This may simply be due to the different power of the tests when the number of time periods is small in relation to the number of observations. The possibility of time-invariant serial correlation or higher-order serial correlation is also considered but there is no indication of these phenomena in the serial correlation matrices. As a consequence, only instruments dated $t-3$ and earlier, which are not rejected by the Sargan test, are used in columns (6) and (7). The results seem to suggest that the consistent estimate of α is clearly less than unity (0.871), so small plants grow faster than the larger ones, i.e. Gibrat's law fails to hold.

[33] Inference based on the one-step estimator is found to be more reliable than on the (asymptotically) more efficient two-step estimator (Arellano & Bond, 1991).

Adding other explanatory variables, including plant-level wages, labour productivity and capital intensity in relation to the industry average, into the model does not change the estimate of α considerably. Furthermore, under valid moment restrictions the coefficients of these variables turn out to be statistically insignificant and sometimes negative. Using industry dummies in addition to plant-level wages, labour productivity and capital intensity results in an increase in the estimate of α (0.920, not reported). However, the power of the Sargan test to detect invalid overidentifying restrictions can decline considerably when the number of moment conditions increases, which causes some problems in interpreting the results.

The first-differenced GMM estimator can be expected to perform poorly in situations where the series are close to being random walks (α approaches unity) and the number of time series observations is small. In these cases the lagged levels of the series are only weakly correlated with subsequent first differences, so that the instruments available for the first-differenced equations are weak. Under these conditions, the extended GMM (or system GMM) has been shown to have a much smaller finite sample bias (Arellano & Bover, 1995; Blundell and Bond, 1998). This estimator uses additional moment conditions based on reasonable stationarity restrictions on the initial conditions. More precisely, it is assumed that the initial conditions satisfy mean stationarity, so that the series of plant size has a constant mean $\frac{v_i}{1-\alpha}$ for each plant i. As a result, the first-differenced GMM estimator can be extended by using suitably lagged first-differences as instruments in the levels equations, which are estimated simultaneously with the equations in first differences.

Column (8) reports the results for the system GMM estimator, which uses the lagged first-differences of $size$ dated $t-2$ as additional instruments for the levels equations. However, the Sargan test clearly rejects the validity of these additional moment conditions and the estimate of α seems to be strongly biased upwards. This implies that the mean stationarity assumption may not be realistic when employment growth is studied. Adding other covariates does not change the results notably. In addition, it should be noted that the differenced GMM estimates in columns (6) and (7) do not seem to approach the within estimates, which would be a clear indication of the weak instruments problem. Furthermore, Blundell and Bond (2000) also find that for a highly persistent employment series first-differenced GMM does not appear to be seriously biased. They argue that one explanation could be that the variance of the plant-specific effects in relation to the variance of transitory shocks ($var(v_i)/var(u_{it})$) is lower for the employment series. In addition, the number of time periods in this analysis may be sufficiently large for the first-differenced GMM estimator to be well-behaved.

6 Conclusions

The purpose of this study was to examine the validity of Gibrat's law after controlling for other explanatory factors, sample selection bias and unobserved plant-level heterogeneity. Using data on young Finnish manufacturing plants over the period 1981–94, it is found that plant growth decreases with plant size and age, whereas the probability of survival increases with size and age.[34] For older plants, the negative relationship between size and growth is weaker and the relationship between age and growth is not clear.[35] When the effect of other observed plant and industry characteristics on plant growth is examined, these factors seem to explain only a modest fraction of the variation in growth. This seems to suggest that random elements and unobserved factors remain responsible for a large part of variation in plant growth. Although the disturbances of the growth and survival equations are to some extent correlated, the bias introduced is not large enough to alter the results qualitatively. The sample selection bias is even smaller for older plants. However, it should be emphasised that there may be some problems with the identification and assumptions of the selection models used.

In order to control for the unobserved plant-level heterogeneity which may bias the OLS estimates, the basic model for all plants is estimated using panel estimation methods. The within estimates seem to be most appropriate and the results are robust to various alternative model specifications. The model is extended to allow for human capital factors, which turn out to have significant effects on plant growth. Taking into account the dynamic context, first-differenced GMM estimates confirm the earlier findings that small plants experience faster employment growth. Overall, the results correspond to several earlier studies with respect to the effects of plant size and age. However, the effects of employee characteristics on growth 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 of a positive relationship between plant growth and industry scale economies also correspond to the theory by Audretsch (1995). The

[34]In contrast, Hohti (2000) finds that there is no clear relationship between plant size and net employment change (section III of this thesis). However, the definition of plant size and the methods of calculating growth are shown to have a considerable effect on the results. In addition, Maliranta (2003) finds a positive relationship exists between net employment growth and plant size. However, different measures for size and growth are used.

[35]In addition to testing the validity of Gibrat's law for incumbent firms, only a cohort of new entrants could be included in the analysis. However, it is even more likely that the law is rejected for small entrants.

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 of 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 cut-off 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. However, more careful analysis is still needed to confirm these results.

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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*.

Table 2. Moments of the size distribution

Year	N	Mean	Median	Std	Skewness	Kurtosis
1981	6514	3.44	3.26	1.21	0.74	0.14
1982	6941	3.34	3.14	1.21	0.79	0.19
1983	6869	3.35	3.14	1.20	0.79	0.20
1984	6868	3.35	3.14	1.19	0.79	0.21
1985	6633	3.37	3.18	1.19	0.79	0.22
1986	6324	3.40	3.18	1.18	0.78	0.20
1987	6295	3.39	3.18	1.17	0.80	0.23
1988	6120	3.40	3.18	1.17	0.79	0.22
1989	6001	3.41	3.22	1.17	0.77	0.18
1990	5868	3.41	3.22	1.17	0.75	0.14
1991	6136	3.28	3.04	1.16	0.83	0.26
1992	5677	3.24	3.00	1.17	0.85	0.29
1993	5308	3.23	3.00	1.17	0.86	0.31
All	81554	3.36	3.14	1.18	0.79	0.21

Table 3. Descriptive statistics for young plants 1981–94

Variable	N	Mean	Std	Min	Max
Growth equation					
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
Scale economies	37560	0.072	0.117	0.000	4.210
R&D intensity	37560	0.062	0.100	0.002	0.917
Survival equation					
Survival status	41251	0.911	0.285	0.000	1.000
Size = ln(employment	41251	2.932	0.958	1.609	7.952
$Size^2$	41251	9.512	6.721	2.590	63.227
Age = ln(age)	41251	1.610	0.809	0.000	2.944
Multiplant	41251	0.177	0.382	0.000	1.000
Foreign ownership (>50%)	41251	0.025	0.155	0.000	1.000
Relative labour productivity	41237	0.974	0.793	0.000	32.071
Relative price-cost margin	41150	0.000	0.047	-5.178	1.999

[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, whereas relative price-cost margin is divided by 1 000.

Table 4. Selection models (1) and (2) for young plants

Variable	TOBIT (1)		OLS (1)	TOBIT (2)		OLS (2)
Dependent	Growth	Survival	Growth	Growth	Survival	Growth
Size	-0.018	0.262	-0.021	-0.072	0.651	-0.078
	(0.001)***	(0.011)***	(0.001)***	(0.007)***	(0.050)***	(0.007)***
Size²				0.007	-0.061	0.007
				(0.001)***	(0.007)***	(0.001)***
Age	-0.027	0.082	-0.028	-0.062	0.080	-0.063
	(0.002)***	(0.011)***	(0.002)***	(0.007)***	(0.011)***	(0.007)***
Age²				0.009		0.009
				(0.002)***		(0.002)***
Size*age				0.004		0.004
				(0.002)**		(0.002)**
Constant	0.082	0.695	0.094	0.188	0.137	0.206
	(0.007)***	(0.050)***	(0.006)***	(0.014)***	(0.087)	(0.013)***
ρ	0.169			0.145		
	(0.038)			(0.043)		
LR-test (ρ=0):	7.85***			4.51**		
N of obs.	37560	41251	37560	37560	41251	37560
Log likelihood	-10073.2			-9993.5		
Wald test	1670.2***		122.0***	1764.4***		106.9***
R^2			0.044			0.046

[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.

Table 5. Selection model (3) for young plants

Variable	TOBIT (3)		OLS (3)
Dependent	Growth	Survival	Growth
Size	-0.024	0.297	-0.025
	(0.002)***	(0.012)***	(0.001)***
Age	-0.028	0.079	-0.028
	(0.002)***	(0.011)***	(0.002)***
Relative wages	0.023		0.024
	(0.005)***		(0.005)***
Relative labour productivity	0.021	0.193	0.020
	(0.002)***	(0.015)***	(0.002)***
Relative capital intensity	0.008		0.009
	(0.001)***		(0.001)***
Relative price-cost margin		0.295	
		(0.133)**	
Scale economies	0.046		0.044
	(0.011)***		(0.011)***
R&D intensity	0.107		0.108
	(0.013)***		(0.013)***
Multiplant		-0.174	
		(0.026)***	
Foreign ownership		-0.136	
		(0.063)**	
Constant	0.049	0.451	0.057
	(0.009)***	(0.053)***	(0.007)***
ρ	0.105		
	(0.056)		
LR-test (ρ=0)	1.52		
N of obs.	35759	39421	35830
Log likelihood	-9343.6		
Wald test	2106.2***		110.6***
R^2			0.055

[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.

Table 6. Selection models (1) and (2) for old plants

Variable	TOBIT (1)		OLS (1)	TOBIT (2)		OLS (2)
Dependent	Growth	Survival	Growth	Growth	Survival	Growth
Size	-0.010	0.288	-0.011	-0.042	0.607	-0.043
	(0.001)***	(0.011)***	(0.001)***	(0.005)***	(0.052)***	(0.005)***
Size^2				0.004	-0.043	0.004
				(0.001)***	(0.007)***	(0.001)***
Age 16–29	0.006	0.294	0.005	0.005	0.297	0.005
	(0.004)	(0.040)***	(0.003)	(0.004)	(0.040)***	(0.003)
Age 30–59	0.008	0.656	0.007	0.008	0.658	0.007
	(0.004)**	(0.047)***	(0.004)**	(0.004)**	(0.047)***	(0.004)**
Age 60–	0.010	0.540	0.010	0.010	0.541	0.010
	(0.005)**	(0.058)***	(0.005)**	(0.005)**	(0.058)***	(0.005)**
Constant	0.003	0.711	0.005	0.063	0.188	0.066
	(0.005)	(0.054)***	(0.005)	(0.010)***	(0.099)*	(0.010)***
ρ	0.041			0.025		
	(0.033)			(0.038)		
LR-test (ρ=0)	1.23			0.36		
N of obs.	36341	38258	36341	36341	38258	36341
Log likelihood	1022.7			1066.6		
Wald test	920.1***		57.6***	969.9***		57.3***
R^2			0.025			0.026

[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.

Table 7. Selection model (3) for old plants

Variable	TOBIT (3)		OLS (3)
Dependent	Growth	Survival	Growth
Size	-0.013	0.339	-0.013
	(0.001)***	(0.012)***	(0.001)***
Age 16–29	0.005	0.293	0.005
	(0.004)	(0.041)***	(0.004)
Age 30–59	0.007	0.647	0.008
	(0.004)*	(0.048)***	(0.004)**
Age 60–	0.012	0.538	0.012
	(0.005)***	(0.060)***	(0.005)**
Relative wages	0.008		0.008
	(0.005)		(0.005)
Relative labour productivity	0.014	0.218	0.014
	(0.001)***	(0.019)***	(0.001)***
Relative capital intensity	0.002		0.002
	(0.001)***		(0.001)***
Relative price-cost margin		0.619	
		(0.181)***	
Scale economies	0.017		0.017
	(0.005)***		(0.005)***
R&D intensity	0.068		0.068
	(0.015)***		(0.015)***
Multiplant		-0.269	
		(0.026)***	
Foreign ownership		-0.224	
		(0.070)***	
Constant	-0.015	0.447	-0.015
	(0.006)**	(0.057)***	(0.006)**
ρ	0.001		
	(0.041)		
LR-test (ρ=0)	0.00		
N of obs.	34740	36644	34774
Log likelihood	1238.9		
Wald test	1078.9***		51.2***
R^2			0.03

[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.

Table 8. Pooled OLS, between, within and GLS estimates for all plants

Model Variable	(1) Pooled OLS	(2) Between	(3) Within	(4) GLS
Size	-0.015	-0.006	-0.265	-0.040
	(0.001)***	(0.001)***	(0.003)***	(0.001)***
Age 3–6	-0.040	-0.050	-0.019	-0.038
	(0.003)***	(0.007)***	(0.003)***	(0.003)***
Age 7–14	-0.060	-0.059	-0.038	-0.057
	(0.003)***	(0.005)***	(0.004)***	(0.003)***
Age 15–	-0.063	-0.055	-0.074	-0.052
	(0.003)***	(0.005)***	(0.005)***	(0.003)***
Growth in real GDP	0.700		1.200	0.855
	(0.025)***		(0.027)***	(0.025)***
Constant	0.074	0.043	0.908	0.140
	(0.003)***	(0.005)***	(0.010)***	(0.004)***
N of obs.	73901	73901	73901	73901
N of plants		9663	9663	9663
R^2	0.028	0.027	0.138	

[1] Standard errors in parantheses.

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

Table 9. The within estimates for some model variants using all plants

Model Variable	(5) Lagged size	(6) Two-year growth	(7) Lagged growth	(8) Growers & decliners	(9) GDP & size
Size		-0.249 (0.003)***	-0.268 (0.003)***	-0.163 (0.003)***	-0.267 (0.003)***
Lagged size	-0.209 (0.003)***				
Age 3–6	-0.009 (0.004)**	-0.022 (0.004)***	-0.014 (0.004)***	-0.020 (0.003)*	-0.020 (0.003)***
Age 7–14	-0.025 (0.005)***	-0.051 (0.004)***	-0.033 (0.005)***	-0.035 (0.004)***	-0.040 (0.004)***
Age 15–	-0.051 (0.006)***	-0.097 (0.005)***	-0.068 (0.006)***	-0.071 (0.005)***	-0.076 (0.005)***
Growth in real GDP	0.938 (0.028)***	0.601 (0.023)***	1.172 (0.028)***	0.276 (0.032)***	0.786 (0.082)***
GDP*size					0.118 (0.022)***
Lagged growth			0.040 (0.004)***		
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	0.713 (0.011)***	0.890 (0.011)***	0.923 (0.012)***	0.671 (0.009)***	0.917 (0.010)***
N of obs.	69980	32422	69980	73901	73901
N of plants	9061	8468	9061	9665	9663
R^2	0.091	0.245	0.130	0.400	0.138

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

Table 10. Human capital effects for young and old plants using both OLS and within estimation

	Young plants		Old plants	
Variable	OLS	Within	OLS	Within
Size	-0.024	-0.507	-0.012	-0.373
	(0.002)***	(0.009)***	(0.002)***	(0.011)***
Age	-0.021	-0.000		
	(0.002)***	(0.009)		
Age 16–29			-0.055	-0.053
			(0.028)**	(0.029)*
Age 30–59			-0.054	-0.065
			(0.028)*	(0.033)**
Age 60–			-0.051	-0.044
			(0.028)*	(0.044)
Relative wages	0.026	0.031	0.028	0.024
	(0.008)***	(0.015)**	(0.011)***	(0.020)
Relative labour productivity	0.028	0.034	0.014	0.013
	(0.003)***	(0.004)***	(0.002)***	(0.004)***
Relative capital intensity	0.008	0.000	0.005	0.007
	(0.001)***	(0.004)	(0.002)***	(0.005)
Relative seniority	-0.028	-0.041	-0.037	-0.052
	(0.005)***	(0.011)***	(0.004)***	(0.009)***
Relative education	0.021	-0.079	-0.033	-0.168
	(0.025)	(0.046)*	(0.030)	(0.046)***
Relative share of women	-0.004	-0.012	-0.003	-0.009
	(0.003)	(0.005)***	(0.004)	(0.007)
Scale economies	0.063	0.005	0.027	0.078
	(0.015)***	(0.051)	(0.009)***	(0.048)
R&D intensity	0.106	0.163	0.070	0.161
	(0.015)***	(0.046)***	(0.020)***	(0.077)**
Constant	0.052	1.624	0.100	1.715
	(0.026)**	(0.060)***	(0.041)**	(0.078)***
N of obs.	15223	15223	11643	11643
N of plants		4015		2393
R^2	0.071	0.279	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.

Table 11. GMM estimates for all plants

Model Dependent: $Size_t$	(1) Pooled OLS	(2) Within	(3) 2SLS DIF	(4) GMM DIF	(5) GMM DIF	(6) GMM DIF	(7) GMM DIF	(8) GMM SYS
$Size_{t-1}$	0.983 (0.001)	0.715 (0.007)	0.939 (0.029)	0.941 (0.028)	0.915 (0.026)	0.846 (0.035)	0.871 (0.031)	1.101 (0.018)
First-order serial correlation	3.017	-25.886	-22.590	-22.757	-21.242	-17.326	-18.684	-23.601
Second-order serial correlation	0.507	-0.046	0.123	0.120	0.114	0.103	0.108	0.119
Sargan (p-value)				0.090	0.006	0.321	0.163	0.000
Instruments			$Size_{t-2}$	$Size_{t-2}$ $Size_{t-3}$	$Size_{t-2}$ $Size_{t-3}$: $Size_1$	$Size_{t-3}$ $Size_{t-4}$	$Size_{t-3}$: $Size_1$	$\Delta Size_{t-2}$ $Size_{t-3}$: $Size_1$

[1] Number of plants: 8045
[2] Number of observations: 63 462
[3] Sample period: 1982–94
[4] Year dummies are included in all estimations.
[5] GMM results are one-step estimates. Heteroscedasticity-consistent standard errors are reported in parentheses. All estimates of α are significant at 1 per cent level.
[6] Test statistics for first-order and second-order serial correlation of the first-differenced residuals (the levels residuals in OLS) are asymptotically standard normal under the null hypothesis of no serial correlation.
[7] Sargan test uses the minimised value of the corresponding two-step GMM estimates (p-value is reported).
[8] Computations were done using the DPD98 program for Gauss (Arellano & Bond, 1991).

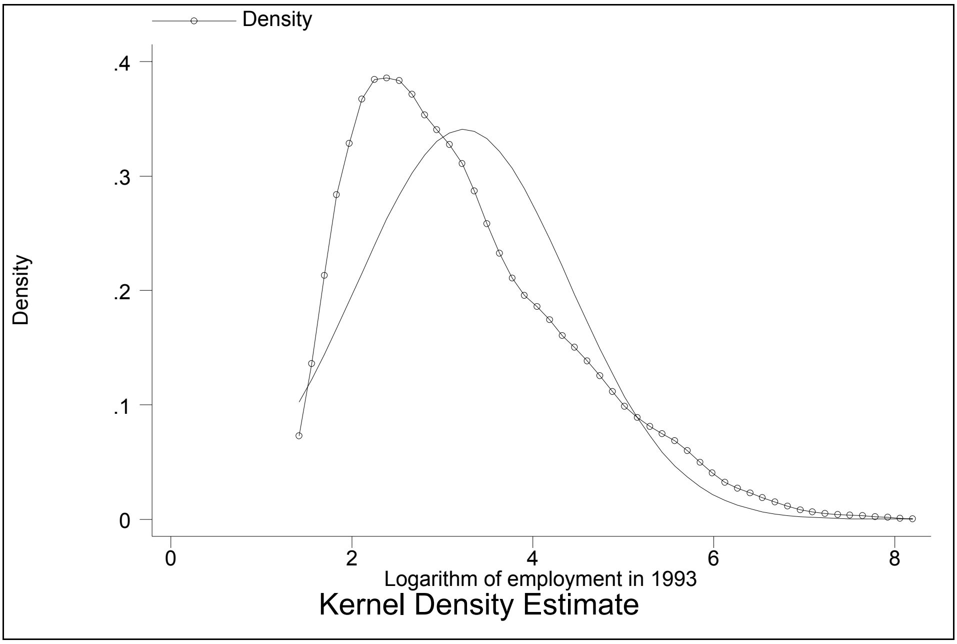

Figure 1. Kernel density estimates of ln(employment) in 1993

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THE DETERMINANTS OF PLANT SURVIVAL IN TURBULENT MACROECONOMIC CONDITIONS

Contents

1 Introduction **2**

2 Empirical findings on the determinants of firm survival **4**

3 Data and non-parametric analysis **8**
- 3.1 Data and definitions 8
- 3.2 The patterns of survival and growth over the cycle 9

4 Semi-parametric analysis of new plant hazard rates **12**
- 4.1 Cox proportional hazards model 12
- 4.2 Discrete-time models with unobserved heterogeneity 18

5 Sectoral differences in the risk of failure **19**

6 Conclusions **22**

A Appendix 1: Cox proportional hazards model **25**

B Appendix 2: Discrete PH models with unobserved heterogeneity **26**

1 Introduction

In recent years, the availability of longitudinal microdata on plants and firms has improved markedly. This has made it possible to identify the actual start-up and closure dates of individual business units and to trace their life cycles. As a consequence, there has been a growing interest in the study of post-entry survival and growth of firms. However, in Finland only a few studies have addressed these questions, and to my knowledge, none of them has considered the determinants of plant survival. Employment growth and firm survival are closely connected. Therefore, regional and industrial policy could benefit greatly from the new knowledge of the firm and industry characteristics determining firm survival. Subsidies and programs could be directed towards those firms that play an important role as employers and have a high likelihood of survival. Traditionally, firm size has been regarded as the most important attribute affecting policy choices, but there are also many other factors that should be taken into account.

The primary purpose of this study is to examine the effect of plant size and various other plant and industry-specific factors on the survival of Finnish manufacturing plants over the period 1981–93. An important aspect is the impact of the macroeconomic environment on the likelihood of survival and employment growth of new plants. The business cycle effects have not received very much attention in the literature, which may be due to the lack of long panel data sets covering strong business cycles. In addition, there are only a few studies on the patterns of plant survival in the service sector. Furthermore, the effects of plant employee characteristics on survival have not been studied much. Due to the availability of a linked employer-employee data set covering the whole business sector, it is also possible to extend this analysis to include both the service sector and the human capital effects.

It is interesting to study whether the hypothesised relationships between explanatory variables and survival hold in turbulent macroeconomic environment. Furthermore, it can be assessed whether the failure probabilities of small and young plants are more sensitive to macroeconomic situation than those of larger and older plants. For this purpose Finland is an excellent case to study because of an exceptionally deep recession experienced by the Finnish economy at the beginning of the 1990s. After a period of overheating in the late 1980s, Finland's gross domestic product decreased by 6.4% in 1991 and the fall continued over the period 1992–93. At the same time the unemployment rate rose dramatically and reached a peak of 16.6% in 1994 (according to the Unemployment Statistics of Statistics Finland). The recession was very deep even in comparison with many other OECD economies, so the findings will be noteworthy.

The principal method of study is the semi-parametric Cox (1972) proportional hazards model. However, because of the annual nature of the data used, a discrete proportional hazards model is also considered. In addition, the effects of unobserved heterogeneity or 'frailty' on the results are taken into account by comparing the findings with two specifications including gamma and normally distributed heterogeneity. The effects of frailty have been mostly neglected in the previous empirical literature on firm survival. Our primary data source is the LDPM (Longitudinal Data on Plants in Manufacturing) of Statistics Finland, which covers basically all Finnish manufacturing plants with at least five employees over the period 1974–94. The LDPM is also available over the period 1995–01 but the sample is smaller, i.e. only plants that belong to firms with at least 20 persons are included. Therefore, these years cannot be included in this analysis, because the break between the years 1994 and 1995 would result in artificially high exit rates. However, further analysis is possible with the Business Register of Statistics Finland covering also the smallest plants and the service sector over the period 1988–2001.

In the theoretical background there are various models of firm growth. The most famous hypothesis of the earliest stochastic models of firm size distribution is Gibrat's law, which states that the firm's expected growth in each period is proportional to the current size of the firm. There are many modifications of Gibrat's law, for example the effects of entry and exit can be incorporated into the model. Earlier empirical findings concerning Gibrat's law are slightly conflicting. Newer models of firm growth based on profit maximisation have also taken into account firm age and survival. Firm survival is affected by a process of selection and adaptation where learning has a central role. Among others Jovanovic (1982), Pakes and Ericson (1998) and Cabral (1995) have created life-cycle models based on learning, which aim at explaining relationships between firm age, size and survival. In these models, entering firms are uncertain about their own efficiency or productivity. After a learning process successful firms decide to continue, whereas the less efficient ones exit. Hence, failure rates are expected to decline with size and age since larger and older firms have more accurate information about their ability and thus more realistic future expectations.

Later empirical studies are often based on the maximisation models and use larger data sets than earlier studies. The most common finding seems to be that the growth rates of new and small firms are negatively related to their initial size (e.g. Dunne & Hughes, 1994, Audretsch, 1995a). Thus, Gibrat's law fails to hold at least for small firms. According to the studies that have taken into account firm age and survival (Evans, 1987; Dunne et al., 1989), the firm's relative growth conditional on survival declines with firm size and age. In addition, the probability of firm survival increases with firm size and age.

In addition to the literature updating Gibrat's law, also another strand of empirical and theoretical literature has evolved, resting on the concept of a product life cycle (Caves, 1998). The emphasis is on the study of industry evolution that is directed by product and process innovations and characterised by periods of shakeouts. Klepper (1996) summarises the regularities concerning the patterns of entry, exit, market structure and innovation over the product life cycle. The demography of organisations and industries has also been studied in the organisational ecology with similar empirical methods, but a different theoretical background (e.g. Carroll & Hannan, 2000).

This paper is organised as follows. Section 2 reviews the empirical literature on post-entry survival and summarises the main findings on plant-specific, industry-specific and macroeconomic factors affecting the likelihood of survival. Section 3 introduces the data sources and definitions and presents the results of the non-parametric analysis. Section 4 provides the findings on the determinants of the hazard faced by Finnish manufacturing plants based on continuous and discrete-time proportional hazards models. In section 5 the analysis is extended to compare the differences in the risk of failure between plants born in manufacturing and services. In addition, human capital effects are considered. Finally, section 6 presents a summary and conclusions.

2 Empirical findings on the determinants of firm survival

In recent years, there has been a growing interest in the study of patterns of post-entry survival and growth. It is difficult, however, to compare empirical findings across countries because data sets, definitions, model specifications and methods of investigation differ considerably. Data sets can be based on statistical surveys, administrative registers or commercial data bases that may have different units of observation (firm or plant) and coverage. Furthermore, there are often minimum size thresholds, below which firms are not included in the survey.

The most typical explanatory variables used in duration models can be grouped into firm-specific, industry-specific and macroeconomic variables. When it comes to firm-specific regressors, one of the most widely studied variables is firm or plant size. The likelihood of survival seems to increase with *current size*, measured by the number of employees (Mata et al., 1995; Disney et al., 2003; Honjo, 2000). However, there are conflicting findings regarding the relationship between *start-up size* and survival. Mata and Portugal (1994) and Audretsch (1995a) find that the likelihood of survival varies positively with firm start-up size. The most common explanation is that the larger the start-up size, the less the entering firms need to grow to attain the industry's optimal efficient size. According to Mahmood (2000), smaller firms may also face more financial constraints in raising capital, which subsequently determines their ability to survive over the critical start-up period. The option of downsizing before exiting is only available to larger firms. Furthermore, large firms may face better tax conditions and be in a better position to recruit qualified labour.

However, there are also opposite findings of a negative relationship between initial size and survival (Mata et al., 1995; Disney et al., 2003). Smaller firms may have the advantage of low overhead costs, and in addition, they require fewer resources for sustenance (Mahmood, 2000). It has also been argued that small firms can overcome disadvantages of size by occupying strategic niches, especially during the mature stage of the product life cycle (Agarwal & Audretsch, 1999). Using data on Portuguese manufacturing plants created during the 1980s, Mata et al. (1995) find that the current size is a better predictor of failure than start-up size. However, the impact of initial size and current size is not independent of the relationship between these two variables, i.e. subsequent growth following entry. Current size has a positive effect on survival, but initial size is negatively related to the likelihood of survival. They explain this counterintuitive result by stating that a plant that has started smaller and therefore experienced faster post-entry growth, has a higher probability of survival.

According to many studies, firm *age* is positively correlated with survival but the effect diminishes over time (e.g. Boeri & Bellmann, 1995; Baldwin et al., 2000).[1] One reason may be that firm age and managerial experience are closely related. The finding of negative duration dependence is also consistent with theories of learning-by-doing as an important factor determining the likelihood of survival (Agarwal & Gort, 2002).[2] *Ownership structure* seems to have a significant, but controversial effect on survival. According to most studies, new plants of existing firms have higher hazard rates (Audretsch & Mahmood,1995; Disney et al., 2003; Wagner, 1999). One explanation is that existing firms may be more constrained by labour market legislation and union agreements than new independent plants (Tveterås & Eide, 2000). However, there are also opposite findings stating that new independent plants have higher hazard rates than new plants of existing firms (e.g. Persson, 1999). According to Tveterås and Eide (2000), it may be easier for a new subsidiary of an existing firm to draw upon human and financial resources from its parent enterprise.

Financial structure of the firm is also a significant determinant of survival. According to empirical findings, higher profitability reduces the hazard faced by new entrants (Tveterås & Eide, 2000; Fotopoulos & Louri, 2000a). Fotopoulos and Louri (2000a) also find that higher commitment in fixed assets increases the likelihood of survival. Furthermore, the greater the debt burden of the firm relative to its assets, the greater the hazard. At the industry level, higher price-cost margins should compensate for size-related cost disadvantages, thereby reducing the risk confronting new establishments, but the empirical findings are conflicting (Honjo, 2000; Audretsch & Mahmood,1995). However, Boeri and Bellmann (1995) find a significant positive relationship between industry profit-to-sales ratio and the likelihood of survival.

So far, there are only a few studies that also include *human capital* variables in the estimations, and the findings are somewhat conflicting. Using data on Swedish manufacturing plants, Andersson and Vejsiu (2001) find some evidence that exit probability increases with average employee age and the share of employees with

[1] Note that with the Cox specification used in this analysis, age cannot be entered directly as an explanatory variable because it is collinear with the baseline hazard.

[2] Some studies also argue that the hazard rate exhibits an inverted U-shaped pattern (Wagner, 1994; McCloughan & Stone, 1998).

technically-oriented education. Persson (1999) also concludes that educational factors are important in explaining survival and growth. There are also many other variables describing human capital that are worth studying, like seniority, work experience and share of females. However, this requires access to linked employer-employee data sets.

The relationship between *capital intensity* and the risk of failure seems to be negative according to some empirical findings (Tveterås & Eide, 2000; Doms et al., 1995). One explanation is that plants with higher capital–labour ratios usually have a lower ratio of variable to fixed costs, i.e. higher degree of sunk costs, which increases the probability of survival. The reason is that sunk costs can be seen as a barrier to exit as well as a barrier to entry. The industry-level capital intensity also seems to be negatively related to the failure rate (Audretsch, 1995a; Agarwal & Gort, 2002). Doms et al. (1995) find that total factor *productivity* is negatively related to failure, indicating that firms close less efficient plants first.[3] In addition, industry-level labour productivity has been found to increase the likelihood of survival (Wagner, 1999; Andersson & Vejsiu, 2001).

Scale economies seem to be an important industry-level determinant of firm survival. The larger the Minimum Efficient Scale (MES) that increases the cost disadvantage faced by sub-optimal entrants, the lower the probability of new firm survival (Audretsch, 1995a). However, in markets where firms smaller than MES constitute a larger proportion of industry population, newer firms may have better chances of survival, but the evidence is scarce (Mata & Portugal, 1994). There is a great deal of empirical evidence suggesting that it is easier to survive in *fast-growing industries*, because entry does not occur at the expense of the established firms' market shares and elevated price-cost margins reduce the cost disadvantage faced by new entrants (Mata & Portugal, 1994; Audretsch, 1995a; Audretsch & Mahmood, 1995). In contrast, firms' lifetimes seem to be shorter in markets with more *entry* due to displacement effects and increased competition (Mata & Portugal, 1994; Honjo, 2000).

Higher rates of *industrial concentration* can lead to retaliatory behaviour against new firms, and hence lower probability of survival. On the other hand, high levels of concentration allow firms to reap higher price-cost margins, which should, in turn, increase the probability of survival. However, since the empirical evidence is also mixed, it is difficult to determine which effect dominates (Baldwin et al., 2000; Wagner, 1994; McCloughan & Stone, 1998).

Audretsch (1995a, 1995b) demonstrates that the probability of survival is lower in industries with a greater amount of *innovative activity*. In highly innovative industries, those firms that successfully innovate will have a greater likelihood of survival, but other firms will be confronted with a lower likelihood of survival.

[3] The finding that firms which will exit in the future are significantly less productive and have lower growth rates of productivity already several years before failure is called the 'shadow of death effect' by Griliches and Regev (1995), who have studied the productivity of manufacturing firms in Israel.

Since the likelihood of any given firm successfully innovating is relatively low, the likelihood of survival confronting a new entrant is also low. However, a highly innovative environment serves as a barrier to survival only within the first few years subsequent to entry.[4] In contrast, Boeri and Bellmann (1995) find a positive relationship between innovative activity and the likelihood of survival in German manufacturing.

Relatively little attention is devoted to the relationship between aggregate economic fluctuations and firm survival. Furthermore, most of these studies do not concentrate on the relationship between plant characteristics and the business cycle effects in explaining survival.[5] *Growth in real GDP* is expected to reduce the number of exits, but the empirical evidence is somewhat mixed. Baldwin et al. (2000) show that there exists a significant, positive relationship between GDP growth and survival. Bhattacharjee et al. (2002) find that macroeconomic instability is a significant determinant of firm exit through both bankruptcies and acquisitions. Audretsch and Mahmood (1995) study the influence of the business cycle on the hazard rates using the *unemployment rate* and the *real interest rate* as proxies for the business cycle. According to their results, the hazard rate for new establishments is higher during macroeconomic downturns, which is indicated by higher unemployment rates. However, interest rates have a negative effect on the hazard, which may be explained by the suggestion that most new firms in the United States are not crucially dependent on external capital. In contrast, Boeri and Bellman (1995) find that exit is not responsive to the business cycle in German manufacturing, even after controlling for industry heterogeneity and displacement effects.

To conclude, both firm-specific variables, especially size, age, ownership, capital and financial structure, and industry-related factors, including scale economies, entry conditions and technological environment, affect the hazard faced by new entrants. Macroeconomic conditions are also important in determining the likelihood of survival. However, further analysis is needed because business cycle effects may not be the same for plants with different characteristics, like size and age. In addition, it remains an open question whether the other hypothesised relationships hold over the strongly evolving business cycle.

[4] Audretsch (1995b) has also studied the effect of technological regime on survival with data on 11 000 U.S. manufacturing firms established in 1976. Under the entrepreneurial regime, where the innovations emanate more from small firms, the hazard rate is shown to be greater than under the routinized regime, where large firms tend to have the innovative advantage.

[5] To my knowledge, only Bhattacharjee et al. (2002) have studied the interaction effects of firm age and various measures of macroeconomic conditions and instability.

3 Data and non-parametric analysis

3.1 Data and definitions

The primary data source used in this study is the Longitudinal Data on Plants in Manufacturing (LDPM) of Statistics Finland, which is available for the period 1974–01 (Ilmakunnas et al. 2001). This data set is based on the Industrial Statistics for the period 1974–94 and on the Statistics on the Structure of Industry and Construction for the period 1995–01. The data is collected by annual surveys. The Industrial Statistics covers, in principle, all Finnish manufacturing plants (or establishments) with 5 or more employees. Smaller plants are also included if their turnover corresponds to the average turnover in firms with 5–10 employees, but there are only a few cases where this condition holds. If a plant falls temporarily below the five-employee cut-off, it is not immediately dropped from the panel. However, over the period 1995–01 the sample is smaller, i.e. only plants that belong to firms with at least 20 persons are included. Therefore, in this study the last year analysed is 1994.[6]

The LDPM contains information on employment, output, value added, wages, capital stock and other plant-level variables. The employment figures represent average employment during the year. The number of hours worked are also reported. The number of employees also includes persons who are, for example, on maternity leave, on annual leave or temporarily laid-off, which may bias some of the results. In this study, plants that have at least 5 employees at least once in their life cycle are included. 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 of Statistics Finland, which also includes the smallest firms and plants. 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. 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, not e.g. headquarters, service units or in the investment phase.

Industry-level information from various other registers and surveys is also used. Information on R&D, imports, exports and output is obtained from the ANBERD (the ANalytical Business Enterprise Research and Development database, OECD) and the STAN (the industrial STructural ANalysis database, OECD) databases covering the whole period under examination. The Business Register and the Employment Statistics of Statistics Finland have been linked to form the PESF (Plant-level Employment Statistics Data on Flows) database, which contains information on job and worker flows in each plant (Ilmakunnas et al., 2001). Churning flows, i.e. the difference between worker turnover and job turnover in the industry,

[6] The results of a corresponding analysis over the period 1987–98 with a size cut-off limit of 20 employees are available upon request. Although it seems that the results are quite sensitive to the time period and the size cut-off limit used, the main findings are rather similar.

can be calculated from the PESF (Burgess et al., 2000a).[7]

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 errors in longitudinal linkages for some years in the late 1970s, plants entering before 1981 are excluded. Problems have been at least partly corrected for but the data is not entirely reliable until 1980. Nevertheless, the fact that we count as entrants only those plants that do not appear in the files during the entire 1974–80 period increases our confidence that entrants really are genuinely new plants in the data. However, because of the cut-off limit, these plants may have existed before the first observation with less than five employees. Entry is thus defined according to the time when the plant reaches the size of five employees.

Exit is defined to cover only those plants that are missing from the database for at least two consecutive years. As a consequence, exits cannot be accurately identified in the last two years of the data. 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 termination of operations are not defined as exits. Changes in ownership and legal status do not affect the plant identification code, but there may be data missing for other reasons, including human errors and changes in sampling criteria. However, permanent relocations from other sectors, e.g. services, cannot be distinguished from 'true' entries or exits. In a majority of the missing cases, a plant is absent for only one year (168 plants). If a plant reappears after two or more years, it is excluded from the data. There were 98 plants (3.1% of the total sample) with this condition.

As a consequence, the final data set consists of ten different cohorts of new plants, covering the period 1981–90, which are tracked up to 1993 (observations in the last year are censored). Because there are some missing values in plant-specific variables, the final sample size varies depending on which variables are included in the estimation, but in most of the estimations there are 2 767 plants. Plants whose industry (at the 4-digit level) has less than 3 plants are excluded from the analysis.

3.2 The patterns of survival and growth over the cycle

In order to choose the most suitable duration model, it is crucial to assess the form of the baseline hazard facing plants. In addition, it is interesting to see whether the dynamics of exit are associated with the cyclical conditions.[8] Does the generally observed pattern of negative duration dependence, i.e. declining hazard, emerge

[7] At the plant level, churning is the difference between worker turnover and the absolute value of the net emploment change.

[8] In the non-parametric analysis exit rates are also calculated for the year 1993 in order to reveal better the effects of recession. However, 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.

despite the strong economic turbulence at the end of the observation period? Figures 1 and 2 present the hazard and survival rates for all cohorts 1981–90 combined.[9] The exit rate for the first interval is 9%, so there are numerous plants that exist in the data for only one year. The hazard rate, i.e. the conditional probability of failure, for the second interval is 11%. In other words, every tenth plant fails in the year following start-up, provided that it has survived thus far. After a slight increase, the hazard rate begins to decrease in the fifth year. In the ninth year it peaks at the 14% level and then monotonically declines until the last interval. Thus, the hazard rate seems to be highly fluctuating. However, if the longer durations are characterised by higher standard errors, it can also be argued that the hazard rate is actually relatively flat.

On the other hand, the cumulative survival rate shows that 35% of the plants do not survive for 4 years, and only 45% still exist after eight years.[10] Less than one-third of the initial population survive for 13 years. Hazard rates might be higher if the plants with less than five employees were included in the analysis. When a plant has grown to having five employees, it may have already passed the most critical period. For example, Mata and Portugal (1994) find that the survival rate is notably higher for firms employing between 20 to 49 employees than for all firms together.

The finding of fluctuating hazard does not correspond to some earlier findings of monotonically decreasing hazard rates (e.g. Mata et al, 1995; Baldwin et al, 2000). However, there are also different results, for example, Wagner (1994) finds that hazard rates tend to increase during the first years and then to decrease non-monotonically afterwards. It is likely that the deep economic crisis at the beginning of the 1990s distorts the results. In addition, when multiple cohorts are combined in a life-table analysis, the assumption is that there are no differences between plants established in different years. Because this is probably not the case, hazard rates are presented separately for different cohorts in Table 1.

When we look at each cohort separately, there still is no clear decreasing pattern of hazard as the plant ages. In the years 1988 and 1989, the risk of failure is relatively low for most cohorts. The hazard rates seem to peak especially during the years 1990–92. Similar pattern is found when the cumulative survival rates are graphed in Figure 3 for cohorts 1985–90. During the first four years the younger cohorts with entry during 1988–90 have experienced a steeper decline in the cumulative survival rates. When we compare these findings with the macroeconomic fluctuations, the conclusion is quite obvious. Average real GDP growth was 2.8% over the period 1981–1986. During the boom period the growth rate rose from 4.3% in 1987 to 4.8% in 1989. Year 1990 was the turning point with −0.3% GDP growth. In 1991 the gross domestic product decreased by 6.4% and

[9] When defining the risk set of plants in each interval, censored observations (plants still existing in 1994) contribute only half of an observation, which is subtracted from the total number of plants entering the interval.

[10] The cumulative survival rates are the survival rates at the end of the interval.

the fall continued over the period 1992–93. Thus, the findings clearly indicate that plant survival is especially sensitive to macroeconomic fluctuations.[11]

In addition, it is interesting to see whether the risk of failure during the recession differs between the younger and older cohorts. Table 1 shows that the hazard rates seem to be slightly higher for the last cohort, which includes plants that have entered closest to the recession. In order to get further information and to control for the fact that hazard rates may in general be higher for young plants, the cumulative survival rates for younger and older cohorts are graphed separately for the boom during 1986–90 and the recession during 1990–94 (Figure 4). These graphs show that during the boom, the cumulative survival rates of different cohorts decline in similar fashion, whereas during the recession the younger the cohort the more rapid the decline in the cumulative survival rate, i.e. the cumulative survival rates converge to some extent. Hence, plants established closer to economic downturns seem to face an increased risk of failure, whereas during a peak the survival patterns of different cohorts are similar.[12] One explanation may be that older firms are more experienced, and thus better equipped to face lower demand. In addition, during the boom financing was relatively easy to arrange and many plants were established with great expectations. However, these plants were presumably less efficient than the average and when faced with recession, many of them did not survive.

In order to shed some light on the effects of recession on the employment performance of different cohorts, the average size of new plants is presented in Table 2. It should be noted that the size averages are probably biased because the Industrial Statistics covers only a fraction of the plants with less than 5 employees. In addition, there has been a strong declining trend in the Finnish manufacturing employment during the entire period of 1980–94. The number of manufacturing employees has fallen 38% from 1980 to 1994 and the average plant size has decreased from 74.2 persons to 60.7 persons. Manufacturing's share of total employment has also fallen steadily, except for the last recession years when total employment decreased considerably.

However, according to Table 2 the average size of the surviving plants increases except for the few recession years when the size decreases for some cohorts. It is also worth mentioning that the average size of beginning cohorts seems to increase over the years. One explanation may be that, due to restructuring, industries with larger average size have become more dominant. It should be noted that increasing average size may simply reflect the fact that smaller plants are more likely to die earlier, i.e. sample selection bias may distort the results. That is why the figures were also calculated for only those plants that survived up to the year 1993 (Table 3). Average size of new entrants clearly increases at start-up when

[11] In the year 1985 the hazard rates are also clearly elevated, but this is probably due to some changes in the plant definitions and the coverage of the Industrial Statistics in the following year. As a result of these changes, the number of plants decreased –6.9% from 1985 to 1986.

[12] Using data on Greek firms Fotopoulos and Louri (2000a, 2000b) have found similar results.

only those surviving for more than a few years are included. Thus, a positive relationship clearly exists between plant start-up size and survival. Moreover, the growth of surviving plants is still considerable, so the finding is not merely a result of sample selection bias.[13] In addition, effects of the recession can still be seen at the beginning of the 1990s.

In order to further investigate whether the growth of new plants is responsive to cyclical factors, employment growth rates for survivors were calculated by dividing the current year's employment for surviving entrants by their birth year employment. Figure 5 illustrates the employment growth rates during the first four years for cohorts 1985–90. In contrast to Boeri and Bellmann (1985), who find that employment performance of various cohorts after entry is not cyclically sensitive, the figure shows that plants born in different cyclical phases have very distinct growth patterns, at least during the first four years of existence. The result holds even after controlling for the sample selection bias.

4 Semi-parametric analysis of new plant hazard rates

4.1 Cox proportional hazards model

Hazard function methods are commonly used in the analysis of duration. The hazard rate is the conditional probability that a plant exits during period $t + \Delta$, given that it has survived until time t, i.e. it measures the risk of failure for a plant during the next year. The hazard function can be defined as follows (e.g. Greene 2000, pp. 939–940):

$$h(t) = \lim_{\Delta \to 0} \frac{\Pr(t \le T \le t + \Delta \mid T \ge t)}{\Delta} = \lim_{\Delta \to 0} \frac{F(t+\Delta) - F(t)}{\Delta S(t)} = \frac{f(t)}{S(t)}, \qquad (1)$$

where $F(t)$ is the cumulative distribution function and $S(t) = 1 - F(t) = Pr(T \geq t)$ is the survival function. When the hazard function slopes upward, distribution is said to exhibit positive duration dependence. The likelihood of failure at time t, conditional upon duration up to time t, is then increasing in t. Negative duration dependence can be defined correspondingly.

Explanatory variables can be included in duration models in many ways. Cox's (1972) semi-parametric proportional hazards (PH) model is a popular method of analys-ing the effect of covariates on the hazard rate, because it does not require any restrictive assumptions regarding the baseline hazard function, which describes the relationship between the risk of failure and survival time, i.e. duration dependence. This is appropriate when the main interest is not in the estimation of the underlying baseline hazard but in the impact of the explanatory variables.

[13] Mata et al. (1995) report similar results with the same kind of analysis of Portuguese manufacturing plants over the period 1983–90.

Furthermore, in this case it seems that the shape of the underlying hazard function may be highly non-monotonic. If the parametric form of the baseline hazard is misspecified, it may bias the coefficient estimates.[14] However, the cost of using a semi-parametric approach is a loss in efficiency, but this is usually not very severe. The Cox model is formulated in Appendix 1.

The proportional hazards specification means that the effect of regressors is to multiply the hazard function by a scaling factor. The Cox method allows the analysis of the duration of a sample of firms belonging to different cohorts and the inclusion of time-varying covariates. The Cox model is used to estimate the effect of various plant and industry-specific covariates on the hazard confronting Finnish manufacturing plants over the period 1981–93 (observations in 1993 are defined as being censored).[15] If there are gaps in the yearly data or missing values in any of the regressors, the plant will be included in the risk pool only in those periods when the data is complete. Missing values of some variables, like the number of employees, could also be imputed on the missing year as the average of the corresponding values in the previous and subsequent year. However, the results do not change much when this method is used.

Start-up size is measured in terms of employment (in logarithmic form) in the initial year. Industry heterogeneity is taken into account by measuring some plant-level covariates in relation to the industry mean, which is measured at the 4-digit industry level using the SIC (Standard Industrial Classification) adopted in 1979 (Tveterås & Eide, 2000). These variables include average hourly wages, labour productivity, price-cost margin, total investment rate and capital intensity in relation to the industry average.[16] The hypothesised relationships of plant size, productivity, profitability and capital intensity with the hazard rate have already been discussed. Higher wages might reflect a greater investment in certain labour-related sunk costs, and thus reduce the risk of failure (Audretsch & Mahmood, 1995). The same kind of argumentation applies to higher investments.

The estimations also include indicator variables identifying plants that belong to multi-unit firms, changes in the ownership structure regarding the number of plants, plants with public ownership and plants with the share of foreign ownership in excess of 50%. Recently, there has been a growing interest in the implications of foreign ownership in various other contexts, e.g. the impact of foreign ownership on productivity. It can be argued that foreign-owned plants possess some superior technological solutions and knowhow, which allows them to outperform domestic plants. Industry-specific variables include scale economies, sub-optimal scale,

[14] When the Weibull and piece-wise constant specifications for the baseline hazard function are used, most of the results do not change much. As an exception, growth in real GDP is no longer significant in the Weibull model. However, the Weibull model assumes a monotonically increasing or decreasing hazard, which most likely is not appropriate for this data.

[15] Plants that exist for only one year are excluded, because these observations may not be entirely reliable.

[16] Capital stock is estimated as the real value of machinery, equipment, transportation equipment, buildings and structures.

market concentration, rate of entry, industry growth, R&D intensity, job turnover and churning.[17] The justification for most of the variables has been discussed earlier. It should be added that the rate of job turnover and churning may also have some importance in predicting the rate of failure. They have been employed only in a few estimations earlier and the results are quite conflicting (Baldwin et al., 2000; Andersson & Vejsiu, 2001; Burgess et al., 2000b).

Export intensity is calculated at the plant level, whereas import intensity is at the industry level. The impact of foreign competition through trade has also been mostly neglected in previous studies. Higher export intensity could increase the likelihood of survival by making a plant less dependent on local business conditions. On the other hand, the plant would be more dependent on foreign market conditions and international competition, which could decrease the probability of survival if the plant was unable to increase its relative efficiency. Higher share of imports might increase the risk of failure through more intense competition and stronger market selection in the domestic markets.

Finally, growth in real GDP is used to capture the macroeconomic fluctuations. Interaction effects with size are included to take into account the fact that macroeconomic conditions may not affect different-sized firms in similar ways. For example, the deterioration in the financial conditions during recession may be more detrimental for smaller plants than for larger ones, because of limited availability of internal financing. In addition, it is easier for large plants to downsize without closing down than for the smaller ones. Furthermore, cohort dummy variables are included to control for the differences between plants entering in different years and to see how the failure rates vary between different-aged plants. More precise definitions of explanatory variables are given in Table 4. Table 5 presents sample description.

The results of estimating the Cox model are presented in Table 6. In all specifications the null hypothesis that all parameters equal zero is rejected on the basis of an overall chi-square test.[18] The first specification includes all the basic regressors employed, whereas equation (2) includes those covariates which seem to have most explanatory power.[19] In specification (3), the explanatory power of start-up size is tested in comparison to current size, but it does not produce a better model. In equation (4) plant size in relation to the industry scale economies is used instead of using size and scale economies separately. Model (5)

[17] R&D figures are available at the 4-digit industry level only for some industries, others are aggregated to the 2- or 3-digit levels, which may distort the results. Churning can be calculated only over the period 1988–93, so an indicator variable is used to describe industries which have higher churning rates than the manufacturing average.

[18] Model diagnostics are discussed in detail in Appendix 2 in Nurmi (2002). The test of proportional hazards by Grambsch and Therneau (1994) implies a possible violation of the proportional hazards assunption. However, the PH assumption is not violated according to the graphical tests performed. Introduction of time-dependent covariate effects, which might mitigate the problem, is left for future analysis.

[19] The robust method of calculating the variance-covariance matrix (Lin and Wei, 1989) with clustering on each plant was also used but the results did not change notably.

concentrates on the effects of ownership changes. Models (6) and (7) investigate further the business cycle effects.

Start-up size has a positive, highly significant effect on the hazard rate, whereas current size has a negative effect on the hazard.[20] However, when initial size is tested separately in equation (3), the sign of the coefficient is negative.[21] Current size seems to be a better predictor of survival than initial size. Model (2) shows that for a 10% increase in current size, the risk of failure is about 4.5% lower. To interpret the coefficients in terms of hazard ratios, they should be exponentiated. For example, the coefficient of current size gives the hazard ratio of 0.637, which means that a one-unit change in current plant size decreases the hazard by 36%. The fact that larger new plants experience a lower risk of failure supports the hypothesis that higher sunk costs and a smaller distance from the industry's optimal size enhance the prospects of survival. Furthermore, the negative and highly significant coefficient of relative size in equation (4) speaks in favour of this explanation.

Higher labour productivity in relation to the industry average increases the likelihood of survival significantly. Furthermore, having a higher price-cost margin than the industry average improves the chances of survival. Relative wages are also negatively related to the hazard rate, and the coefficient is statistically significant in three of the specifications. However, it should be noted that plant size, wages and productivity are to some extent correlated, because smaller plants have been found to have lower wages and labour productivity in relation to the manufacturing average in Finnish manufacturing (Hohti, 2000 and section III of this thesis). Relative investment rate and relative capital intensity turn out to be insignificant, but their signs are negative as expected.[22]

Dummy variables describing ownership status and its changes in model (5) are mainly statistically significant and the results correspond to those of Harris and Hassaszadeh (2000, 2002).[23] Multiplants have a higher risk of failure, which is probably at least partly due to the fact that multi-unit firms can close unprofitable branches rather easily when capacity reductions are needed, whereas the owners

[20] As alternative measures for initial and current plant size the logarithms of the number of employees plus one were used, but these covariates did not yield more significant results.

[21] The negative coefficient for initial size can be explained by following Mata et al. (1995) and reformulating $\beta_1 S_0 + \beta_1 S_1$, where S_0 is the start-up size and S_1 is the current size, as $(\beta_1 + \beta_2) S_0 + \beta_2 (S_1 - S_0)$. According to this expression, the results in model (1) imply that $-0.299 S_0 - 0.897 (S_1 - S_0)$. Hence, the effect of initial size is negative and there is an additional negative effect of growth on the risk of failure.

[22] It is acknowledged that there may be simultaneity problems with some of the coefficients, so model (2) was re-estimated with lagged values of relative wages, relative productivity, relative profitability, relative investment rate, plant level export intensity and multiplant status. The coefficients for lagged profitability and export intensity turned out to be insignificant. However, the coefficients for the main regressors, current size and GDP growth, did not change much.

[23] Disney et al. (2003) have studied the effects of ownership status in more detail by estimating a Cox PH model separately for single and group establishments. They find, for example, that the macroeconomic shock variable is positively related to exits for singles and negative, but insignificant for group establishments.

of independent plants are willing to accept lower rates of return longer without closing a plant.[24] Similarly, plants that have always belonged to a multi-unit firm are more likely to exit.

Plants that change their status from single plant to multiplant have a higher risk of failure. According to Harris and Hassaszadeh (2000), the higher hazard may be due to such changes in ownership structure that result in the rationalisation of the number of plants. Ownership changes in the opposite direction also have a positive, but statistically insignificant coefficient. If the plant has changed its ownership status more than once, the risk of failure decreases. Harris and Hassaszadeh argue that these are probably profitable plants that are involved in many mergers or acquisitions. Public ownership and foreign ownership do not seem to have much effect on the prospects of survival. However, it should be noted that both the share of publicly-owned plants and the share of foreign-owned plants of all plants is only 2%. Harris & Hassaszadeh (2002) find that plants belonging to the foreign-owned sector are less likely to fail. However, the country of ownership has a clear effect on the results.

The MES level of output in the industry has a significant effect on the hazard in two of the models but, in contrast to some previous findings, higher scale economies decrease the risk of failure. High level of scale economies can be considered as a barrier to exit, which may partly explain the results. Other explanatory variables describing industry structure, i.e. sub-optimal scale and industrial concentration, also have a negative effect on the hazard, but the coefficients are not statistically significant. Furthermore, entry rate is not significant and it is highly correlated with the rate of job turnover (0.63). When entry rate was tested separately, it turned out to be positive, but still statistically insignificant. However, in many previous studies entry has been found to exert a negative influence on survival. The coefficient of job turnover is highly significant and positive, in other words, it is harder to survive in industries with high rates of gross job reallocation.[25] In contrast, the hazard rate tends to be lower for plants established in high-growing industries. The level of R&D intensity does not seem to have a significant effect on the hazard rate.

Import penetration has a positive effect on the hazard faced by a plant, i.e. increased import competition in the domestic markets increases the risk of failure. This is in accordance with Jovanovic's (1982) model where more efficient firms replace the less efficient ones. In contrast, the effect of plant-level export intensity on the hazard rate is negative, i.e. if a higher share of plant's output is exported, the likelihood of survival increases. This is probably due to the fact that there is a high correlation between a firm's overall performance and its willingness to export, i.e. good firms become exporters. In addition, during the recession some

[24] According to model (2) the hazard for a multiplant is exp(0.211)=1.23 times the hazard for single plants.

[25] Excess job reallocation (gross job reallocation minus the net employment change) was tested as an alternative to job turnover, but it was less significant and had almost as high correlation with the rate of entry as job turnover.

plants may have survived with the help of higher demand in the export markets.[26] Bernard and Jensen (1999, 2002) have also found that exporting increases the likelihood of survival. In contrast, industry-level export intensity and churning turn out to be statistically insignificant in this analysis. Churning might be more significant as a plant-level variable, but there may also be simultaneity problems with this variable. Nevertheless, Burgess et al. (2000b) have found that high firm-level churning flows are associated with a lower likelihood of survival.

GDP growth is highly significant and negative in all of the specifications suggesting that the risk of failure is considerably increased during macroeconomic downturns. Model (6) includes the interaction of GDP growth with plant size categories. It can be seen that the negative effect of GDP on the risk of failure is the highest for the second smallest size category of plants. In other words, it seems that plants with 10–24 employees have the highest risk of failure during recession. On the other hand, during favourable economic conditions the risk of failure of small plants relative to large ones seems to be reduced. There are significant interaction effects also for other small plant categories, whereas the coefficients are not statistically significant for larger plants with at least 50 employees. Thus, it may be argued that the failure probabilities of small plants are more sensitive to the changing macroeconomic environment, whereas larger plants are hardly affected by the business cycle. However, the differences between size categories are rather small. Other coefficients in equation (6) change only slightly.[27]

The inclusion of cohort dummies in equation (7) does not change other parameter estimates notably (the reference group is the cohort of 1981). The risk of failure has been lower for plants that have started at the beginning of the 1980s, whereas it seems to be somewhat higher for those plants that have started a few years before the oncoming recession. The finding corresponds to the earlier results of the non-parametric analysis. However, only two of the cohort dummies are statistically significant. Finally, a set of regional dummies was included in equation (2), but only one of them turned out to be statistically significant (not reported). The effect of firm location on survival has not been studied much and the earlier findings are slightly conflicting (e.g. Fotopoulos and Louri, 2000b; McCloughan & Stone, 1998).

[26] However, industries with a high share of exports to the eastern markets suffered great losses due to the collapse of the Soviet Union. When interactions of plant's export intensity with industry dummies were included in the estimation, the risk of failure was considerably increased for the textile, wearing apparel and leather industries. Nevertheless, other industries with a negative effect on the hazard rate dominate the results.

[27] When interactions of GDP growth with different plant age categories were included, the effect of GDP on the risk of failure did not vary much over the age categories for the younger plants. However, for the oldest plants (at least 10 years old) the effect of GDP was over three times more negative than for younger plants.

4.2 Discrete-time models with unobserved heterogeneity

Since the data analysed is reported only on annual basis, it may be argued that a discrete model specification would be more suitable.[28] The discrete nature of the data may create a problem of interval censoring. In addition, the presence of many tied events, i.e. multiple subjects in the sample having the event at the same time, can lead to a serious bias in parameter estimates when using the Cox method. In contrast, discrete-time methods can handle ties without introducing bias in the estimates. However, the usual finding is that the results are very similar to the corresponding continuous model.

In addition, it can be argued that some relevant variables are omitted from the analysis either because they are unmeasurable or because their importance is unsuspected. Moreover, measurement errors in observed survival times or regressors may distort the estimates (Lancaster, 1990). The failure to account for the impact of unobserved individual heterogeneity or 'frailty' on the probability of failure may lead to an underestimate (overestimate) of the degree of positive (negative) duration dependence in the baseline hazard. Uncontrolled heterogeneity can also attenuate the magnitude of the estimated effects of the included explanatory variables on the hazard rate. Furthermore, the proportionate effect of a given regressor on the hazard rate is no longer constant and independent of survival time. The usual method for incorporating heterogeneity is to assume a parametric functional form for the pattern of the heterogeneity.

The results for the discrete-time approach are presented in Table 7 using the preferred specification (2) from the previous analysis with the Cox model. The estimation approach used in model (1) is the method by Prentice and Gloeckler (1978), which is similar to the Cox method in that no assumptions about the baseline hazard are made. Conclusions about the effects of frailty are more reliably drawn if a flexible specification for the baseline hazard is used. However, the results may be sensitive to the shape of the distribution chosen, so two alternative distributions are used. A convenient and commonly used distribution for unobserved heterogeneity is the gamma distribution with unit mean and constant variance. A feasible alternative is an inverse normal (Gaussian) distribution, but it is less commonly used in empirical applications. Model (2) is a discrete-time PH model allowing for gamma heterogeneity as proposed by Meyer (1990), whereas model (3) gives the estimates using an inverted normal distribution for unobserved heterogeneity.[29] The econometrics are described in detail in Appendix 2.[30]

When the estimates for the discrete specification without unobserved heterogeneity (1) are compared with the corresponding Cox estimates, most coefficients increase in absolute magnitude and their significance improves. According to the

[28] The figures in the LDPM data are yearly averages, so the exact timing is not known.

[29] Both models (2) and (3) include shared frailty, which allows the observations within the same plant to be correlated.

[30] In future analysis, it will be possible to compare the results with the Cox model allowing for gamma distributed unobserved heterogeneity.

interval-specific baseline hazard estimates (D3-D12, reference group D2), the degree of negative duration dependence increases non-monotonically as the survival time increases. Hence, using a discrete specification does not change these results considerably.

As expected, the estimated coefficients with gamma distributed heterogeneity (2) are larger in magnitude than the corresponding coefficients in the reference model (1). The changes are even larger in model (3) where the frailty term is normally distributed. The significance of the coefficients for relative wages and scale economies increases notably. It should also be noted that the baseline hazard coefficients increase notably for both models including frailty. The improvement in log-likelihood relative to the model (1) is largest for the model (3), but the choice between the gamma and inverse normal specifications is complicated by the fact that the two models are non-nested. The size of the variance of the gamma mixture distribution relative to its standard error suggests that the unobserved heterogeneity is not significant in model (2). The likelihood ratio test of model (2) versus model (1), however, gives the opposite conclusion, but the test is not reliable because these models are also non-nested. The likelihood ratio of $\rho = 0$ suggests statistically significant frailty in model (3).[31]

To summarize, there is some evidence that the unobserved heterogeneity should be taken into account. However, the main conclusions are only strenghtened. Most importantly, allowing for unobserved heterogeneity does not change the findings about the effects of plant size or growth in real GDP on survival. The effects of unobserved heterogeneity should be mitigated and thus estimates more robust, if a flexible baseline specification is used, so the use of a non-parametric baseline hazard specification gets more support. To illustrate some of the results, Figure 6 shows the predicted survival probabilities for different-sized plants implied by the discrete PH model with gamma heterogeneity, when other covariates are evaluated at the sample mean values. It can be seen that the median duration for a small plant with 10 employees is around 6.5 years, whereas for larger plants it is considerably longer (out of sample range).

5 Sectoral differences in the risk of failure

The previous analysis can be extended in various ways by using the Business Register (BR) data of Statistics Finland, which covers in principle all registered employers and enterprises subject to value added tax in Finland annually over the period 1988–2001. Firstly, this data set allows the inclusion of other sectors of the economy besides manufacturing in the analysis. Hence, the differences in the survival rates between manufacturing and services can be studied. Secondly, the BR is available until the year 2001, so the years of recovery after 1993 can

[31] $\rho = \frac{\sigma^2}{\sigma^2+1}$, so it describes the proportion of the total variance contributed by the panel-level variance component.

be included in the analysis. Thirdly, this data set also covers the smallest plants. However, there are some problems with longitudinal linkages due to changes in taxation and statistical practices, which have affected the coverage of especially the smallest plants in the BR. Therefore, in order to produce as reliable a series as possible, only plants with at least three employees are included.

Finally, it is possible to study the effects of human capital on plant survival by using the Plant-level Employment Statistics Data on Average Characteristics (PESA) data set, which has been formed by linking the BR and the Employment Statistics of Statistics Finland (Ilmakunnas et al., 2001). The PESA contains information on the average characteristics of the employees in each plant, including average age, seniority, education and share of women, over the period 1988–2000. However, the data content is much narrower in the BR than in the LDPM, because the BR contains only basic information on plant location, industry, ownership, sales and employment. Subsequently, some of the previously used explanatory variables cannot be calculated for this analysis. The definitions of entry and exit correspond to the ones used in the LDPM data. The analysis includes nine cohorts of new plants covering the period 1989–97, which are tracked up to year 2000 (observations in the last year are censored).[32]

Non-parametric analysis covering the whole business sector reveals that the hazard rate for cohorts 1989–97 is monotonically decreasing, except for the tenth year (not reported). The finding corresponds to the earlier findings of monotonically decreasing hazard rates (e.g. Mata et al, 1995; Baldwin et al, 2000). However, the results are probably affected by the recession, which now biases especially the hazard rates during the first intervals. On the other hand, the cumulative survival rate shows that over half of the plants do not survive for four years, and only 35% still exist after eight years. 29% of the initial population survive for twelve years. Hazard rates are probably higher, because the plants with only a few employees are also included in the analysis. This can be seen especially during the first turbulent years after entry. In addition, there may be substantial differences in the survival patterns across different sectors of the economy. However, when the hazard and survival rates are graphed separately for plants born in manufacturing and services, the differences are quite small (not reported). Manufacturing has lower hazard rates and higher cumulative survival rates for all durations, which is probably due to higher average plant size in manufacturing (17.3 employees) than in services (11.8 employees).

To get some further information, three-year survival rates for all cohorts 1989–97 combined are calculated for different industries at the 2-digit industry level using the SIC adopted 1995 (Table 8). The survival rate is defined as the number of plants surviving in an industry as a percentage of the total number of new plants that were established in that industry. Only industries with at least ten plants are included. For example, only 90 of the 245 plants that entered the wearing apparel industry during the years 1989–97 survived for three years or

[32] Agriculture and public sector are excluded from this analysis.

more. Wearing apparel, textiles and leather as well as construction were among the industries that were hit especially hard by the recession. The three-year survival rate is relatively low also in recycling, other transport equipment and renting industries. As expected, manufacture of paper and pulp as well as radio, television and communication equipment are among the industries with the highest survival rates. Chemicals and insurance seem to be the top survivors of this list. Table 8 also shows that the number of new plants established during the years 1989–97 varies considerably across industries. Over half of the new plants were established within four industries: retail trade, construction, other business activities and wholesale trade. Since mass-entry is often followed by an increased number of exits, which is often called a 'revolving door' phenomenon, it is not surprising that these industries have lower survival rates than the average.

The results of estimating the Cox model separately for plants born in manufacturing and services using the BR data are presented in Table 9.[33] In order to study the effects of macroeconomic conditions on different-sized plants in manufacturing and services, the first model includes some of the earlier covariates and the interactions of GDP growth with plant size categories.[34] One category is added because of the high share of very small plants (having less than 5 employees) in the sample. The results reveal that the negative effect of GDP growth on the risk of failure is most significant for the three smallest size categories in manufacturing, whereas it is significant in all size categories in services. In addition, in services the negative effect is clearly decreasing with plant size implying that cyclical downturns increase the risk of failure more for smaller plants than the larger ones.

Other coefficients correspond rather well to the earlier findings on manufacturing. The effect of plant size on the risk of failure is negative in both sectors, but the absolute effect is higher in services. Belonging to a multi-unit firm increases the risk of failure in manufacturing, but is insignificant for services. Foreign ownership is not significant for manufacturing, whereas in services foreign-owned plants seem to have better chances of survival. In contrast to the earlier findings in this study, industry scale economies (measured with employment) have a highly significant and positive effect on the hazard in all estimations. This result corresponds better to the earlier studies hypothesising that the chances of survival decrease in markets where optimal size is high due to the higher cost disadvantage faced by sub-optimal entrants. The results for industry job turnover and growth correspond to the earlier findings and the effects are similar for services.[35]

In the second model the cohort dummies are included instead of GDP in order

[33] Sample description is available upon request.

[34] Scale economies and industry growth are now defined in terms of employment because output measures are not included in the Business Register. The scale economies variable is divided by 1000.

[35] Somewhat surprisingly, when interactions of GDP growth with different plant age categories were included, the effect of GDP on the risk of failure was negative and decreasing along the age distribution for both sectors.

to compare the hazard rates between plants born during recession and recovery (reference group is cohort 1997). It can be seen that the risk of failure is higher for cohorts born during the years 1989–92, i.e. just before or during the recession. The same pattern is evident both for plants born in manufacturing and services. Controlling for the cohort effects does not change the other coefficients considerably.

The third specification includes variables describing a plant's work force composition relative to the industry average, i.e. relative age of employees, relative seniority measured as the number of months in the firm, relative education measured as the number of schooling years and the relative share of women. Human capital seems to be more important for survival in manufacturing, where all coefficients are significant. Having older or more experienced work force than the industry average seems to increase the risk of failure.[36] Higher level of education and increased share of women also deteriorate the chances of survival. For service-sector entrants, the effects of experience are similar, but education and share of women are no longer significant. It may be argued that plants with a high share of highly-skilled employees are often in the early stages of their life-cycle and engaged in innovative activity and experimentation.[37] Hence, the chances of survival depend on their success in R&D, and the risk of failure is higher. However, plant age is somewhat correlated with the age of employees and their work experience, but this does not seem to show up in the results.

6 Conclusions

In this paper, the survival patterns of new Finnish manufacturing and service sector plants are studied using non-parametric and semi-parametric methods of analysis. The life-table analysis reveals that 35% of manufacturing plants do not survive for 4 years, and after eight years only 45% still exist. In contrast to the findings by Boeri and Bellmann (1995), it is found that the dynamics of exit and employment growth are sensitive to cyclical fluctuations. For example, the hazard rate increases enormously during the deep recession of the 1990s, whereas the employment growth of entering manufacturing plants declines. The results correspond to the Schumpeterian view of creative destruction where recessions are seen as times of 'cleansing'.

However, older manufacturing plants seem to cope better with the unfavorably changing macroeconomic environment. This finding is consistent with the learning models, which predict that older firms are less sensitive to exogenous shocks. In addition, it seems that the business cycle effects have a stronger impact on the risk of failure of small plants than the larger ones. However, there is also strong

[36] Since age and seniority are correlated, they were also tested separately but both remained highly significant anf positive.

[37] Bartel and Lichtenberg (1987) find that the relative demand for educated workers declines with plant age, especially in R&D intensive industries.

evidence in favour of idiosyncratic effects because the business cycle effects do not wipe out all other plant and industry-level effects.

Results from the Cox regression model using data on manufacturing plants suggest that current size is a better predictor of failure than initial size. Larger plants and plants with a smaller distance from the industry's optimal size have a lower risk of failure. The findings suggest that the risk of failure is highest for small plants, which need support especially during the first years after start-up. In addition, new small plants face the highest relative job turnover, which causes costs of unemployment and recruiting (see e.g. Hohti, 2000 and section III of this thesis). However, this can be seen as an unavoidable outcome of the natural process of selection and learning. Hazard rates are also lower for plants with higher productivity, profitability and wages than the industry average. This is in accordance with the cleansing view, according to which the exit of inefficient plants makes room for new ideas and technologies thus improving the industry performance. Plants that belong to firms with more than one plant or which have recently changed their ownership status are more likely to exit. In contrast, if the ownership status has changed more than once, the risk of failure decreases. However, due to possible simultaneity problems, these results should be interpreted carefully and do not necessarily imply causality.

It is easier to survive in fast-growing industries and in industries with a high level of MES. As expected, higher rate of industry job turnover is positively related to the hazard rate. Foreign trade turns out to be an important determinant of survival. Plant-level export intensity has a positive effect on the likelihood of survival, whereas the relationship between industry-level import penetration and survival is negative. In other words, small optimal size, slow growth and a high degree of import competition make the industry more vulnerable and increase the risk of failure faced by new plants.

Further specifications were estimated to account for the potential impact of interval censoring and unobserved heterogeneity on the hazard model estimates. The grouping of time intervals does not seem to introduce serious aggregation bias in the results, because the corresponding continuous and discrete-time duration models provided similar estimates and implications. Including unobserved heterogeneity was important but did not change the main conclusions.

The analysis was also extended to the period 1989–2000 in order to reveal plant survival patterns in the post-recession period and to take into account differences between manufacturing and services. The results show that plant size is a major determinant of the likelihood of survival regardless of data coverage or time period used. As before, especially small plant survival is found to be very sensitive to macroeconomic conditions. Furthermore, the cohorts born before or during the recession have the highest risk of failure in both sectors. There is also some evidence that foreign-owned plants seem to have a lower risk of failure in services. Human capital factors have not been studied much because of data limitations, but they seem to be worthy of more attention. Work force composition turned out to be more crucial in determining the exit probability of manufacturing entrants. In particular, higher relative experience and education of employees seem to increase the risk of failure.

A Appendix 1: Cox proportional hazards model

The Cox regression model can be formally expressed as follows:

$$h(t) = h_0(t)\exp(\beta x'), \tag{2}$$

where $h_0(t)$ is the baseline hazard function at time t, which is estimated when all of the explanatory variables are set to zero, and β is a vector of regression parameters. The use of the partial likelihood approach suggested by Cox does not require that the baseline hazard function has to be specified. To simplify notation, only the case with no time-varying covariates is described. Let $t_1 < t_2 < \ldots < t_k$ represent distinct exit times among n observed survival times. The risk set R_i is defined as the set of plants which have not yet exited prior to time t_i. For every plant j in risk set R_i, $t_j \geq t_i$, the conditional probability that a plant exits at time t_i, given that exactly one exit has occurred at this time, is:

$$\frac{h_i(t)}{\sum\limits_{j\in R_i} h_i(t)} = \frac{\exp(\beta x_i')}{\sum\limits_{j\in R_i}\exp(\beta x_i')}. \tag{3}$$

The baseline hazard function is assumed to be the same for all the observations, and hence it cancels out. The partial likelihood function is obtained by multiplying these probabilities together for each of the k exit times:

$$PL(\beta, x_{1,\ldots,}x_n) = \prod_{i=1}^{k}\left[\frac{\exp(\beta x_i')}{\sum\limits_{j\in R_i}\exp(\beta x_j')}\right]. \tag{4}$$

In the presence of ties, i.e. when there are $m_i \geq 1$ plants exiting at time t_i, Breslow (1974) proposes to maximise the following likelihood function:

$$PL(\beta, x_{1,\ldots,}x_n) = \prod_{i=1}^{k}\left[\frac{\exp(\beta s_i')}{\left(\sum\limits_{j\in R_i}\exp(\beta x_j')\right)^{m_i}}\right], \tag{5}$$

where s_i is the vector sum of covariates of the m_i plants. Then the partial log-likelihood is:

$$\ln PL(\beta, x_{1,\ldots,}x_n) = \prod_{i=1}^{k}\left[\beta s_i' - m_i \ln\sum_{j\in R_i}\exp(\beta x_j')\right]. \tag{6}$$

Maximisation of the partial likelihood yields estimators of β with properties similar to those of the usual maximum likelihood estimators, such as consistency and asymptotic normality, regardless of the actual shape of the baseline hazard function. The relative lack of precision (efficiency) for the PL estimates in comparison to the ML estimates due to the loss of information is expected to decrease with an increase in the sample size. A negative (positive) coefficient indicates that the risk of failure at a moment in time is reduced (increased). The above formulation of the Cox regression model can be easily extended to allow for time-varying covariates which are used in this study.[38]

B Appendix 2: Discrete PH models with unobserved heterogeneity

It may be more appropriate with annual data to recognise that the underlying continuous durations are only observed in discrete time intervals:

$$[0 = a_0, a_1), [a_1, a_2), [a_2, a_3), ..., [a_{k-1}, a_k = \infty). \tag{7}$$

The discrete-time formulation follows the Prentice-Gloeckler (1978) model. A gamma mixture distribution to summarize unobserved heterogeneity is incorporated as proposed by Meyer (1990).[39] Covariates may vary between time intervals but are assumed to be constant within each of them.

When the proportional hazards form is assumed for the hazard function, the continuous time survivor function takes the form:

$$S(t, x_{it}) = \exp\left[-\int_0^t h(\tau, x_{it})d\tau\right] = \exp\left\{-\exp\left[x_{it}'\beta + \log(H_t)\right]\right\}, \tag{8}$$

where $H_t = \int_0^t h_0(\tau)d\tau$ is the integrated baseline hazard at t. The probability of exit in the interval j for plant i is $prob\,\{T \in [a_{j-1}, a_j)\} = S(a_{j-1}, x_{it}) - S(a_j, x_{it})$, and the survivor function at the beginning of the jth interval is $prob\,\{T \geq a_{j-1}\} = S(a_{j-1}, x_{it})$. The conditional probability of exit in the jth interval is thus given by:

$$\begin{aligned} h_j(x_{it}) &= prob\,\{T \in [a_{j-1}, a_j) \mid T \geq a_{j-1}\} \\ &= 1 - \left[S(a_j, x_{it})/S\left(a_{j-1}, x_{it}\right)\right]. \end{aligned} \tag{9}$$

In the discrete case the survivor function can be rewritten as:

$$S(a_j, x_{it}) = \exp[-\exp(x_{it}'\beta + \delta_j)], \tag{10}$$

where $\delta_j = \log(H_{it})$ for $j = 1, ..., k$. The corresponding discrete-time hazard in the jth interval is:

$$h_j(x_{ij}) = 1 - \exp[-\exp(x_{ij}'\beta)\gamma_j] \text{ with } \gamma_j = \int_{a_{j-1}}^{a_j} h_0(\tau)d\tau. \tag{11}$$

[38] In the preliminary analysis, non time-varying covariates, defined according to the first years following start-up, were used and the findings were fairly similar.

[39] Stata program 'pgmhaz' by Stephen Jenkins is used for implementation. I would like to thank Tomi Kyyrä for first suggesting this program.

To simplify, all intervals are now assumed to be of unit length, in this case one year. Hence, the recorded duration for each plant i corresponds to the interval $[t_i - 1, t_i)$. The baseline hazard may be assumed to take on a non-parametric form that allows a separate effect for each duration interval. Alternatively, γ_j can be described by some semi-parametric or parametric function. Let us define an indicator variable $y_{it} = 1$ if plant i exits the state during the interval $[t-1, t]$ and $y_{it} = 0$ otherwise. The log-likelihood can be written in sequential binary response form:

$$\log L = \sum_{i=1}^{n} \sum_{j=1}^{t_i} \left\{ y_{ij} \log h_j(x_{ij}) + (1 - y_{ij}) \log \left[1 - h_j(x_{ij})\right] \right\}, \tag{12}$$

which is easy to estimate as a complementary log-log model.

To incorporate a gamma mixture distribution for unobserved or omitted individual heterogeneity, the instantaneous hazard rate specification is changed as follows:

$$h_{it} = h_0(t) u_i \exp(x_{it}'\beta) = h_0(t) \exp[x_{it}'\beta + \log(u_i)], \tag{13}$$

where u_i is a gamma distributed random variate with unit mean and constant variance σ^2. A crucial assumption is that u_i is distributed independently of x and t. The discrete-time hazard function corresponding to (9) is:

$$h_j(x_{ij}) = 1 - \exp\{-u_i \exp(x_{ij}'\beta)\gamma_j\}. \tag{14}$$

Plants having a completed spell during the interval are identified using a censoring indicator $c_i = 1$, and those still remaining in the state, i.e. having a right-censored spell, are identified using $c_i = 0$. The likelihood function turns out to be:

$$\log L = \sum_{i=1}^{n} \log \left\{ (1 - c_i) A_i + c_i B_i \right\}, \tag{15}$$

where

$$A_i = \left[1 + \delta^2 \sum_{j=1}^{t_i} \exp\left[x_{ij}'\beta + \theta(j) \right] \right]^{-\delta^{-2}}, \text{ and} \tag{16}$$

$$\begin{aligned} B_i &= \left[1 + \delta^2 \sum_{j=1}^{t_i - 1} \exp\left[x_{ij}'\beta + \theta(j) \right] \right]^{-\delta^{-2}} - A_i, \text{ if } t_i > 1 \\ &= 1 - A_i, \text{ if } t_i = 1, \end{aligned} \tag{17}$$

where $\theta(j)$ is a function describing duration dependence in the hazard rate. Instead of the gamma mixing distribution, a commonly used alternative is to include an inverse normal (Gaussian) distribution to describe unobserved individual heterogeneity.

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SECTION V: THE DETERMINANTS OF PLANT SURVIVAL

Table 1. Hazard rates of new plants

Cohort	Year 1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
1981	0.11	0.08	0.10	0.08	0.11	0.08	0.08	0.09	0.11	0.11	0.13	0.13	0.08
1982		0.08	0.07	0.07	0.13	0.09	0.09	0.07	0.06	0.15	0.17	0.14	0.07
1983			0.09	0.10	0.13	0.07	0.08	0.04	0.05	0.12	0.20	0.11	0.10
1984				0.10	0.12	0.08	0.09	0.06	0.10	0.12	0.15	0.14	0.07
1985					0.13	0.08	0.12	0.07	0.09	0.11	0.13	0.11	0.10
1986						0.08	0.15	0.08	0.05	0.10	0.20	0.11	0.10
1987							0.08	0.06	0.11	0.19	0.19	0.10	0.12
1988								0.09	0.13	0.15	0.14	0.13	0.06
1989									0.13	0.19	0.16	0.15	0.08
1990										0.15	0.19	0.22	0.13

Table 2. Average size of new plants

Cohort	Year 1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
1981	21.25	24.27	25.76	27.35	29.98	31.88	33.02	35.55	37.82	39.16	36.76	36.59	36.70	39.97
1982		19.01	20.41	21.15	22.45	24.66	25.93	26.81	27.27	27.41	26.79	26.28	27.18	29.35
1983			20.33	22.80	24.63	27.29	28.55	30.81	31.56	32.73	33.04	34.79	36.42	41.66
1984				22.76	24.06	25.61	26.73	26.18	26.74	27.29	27.49	27.76	28.90	32.94
1985					29.04	37.40	40.25	43.61	46.39	47.58	46.75	47.52	48.57	55.51
1986						30.21	32.83	41.09	42.48	45.80	42.48	44.64	50.34	65.59
1987							30.18	32.58	35.24	37.17	38.27	39.07	40.45	44.97
1988								30.16	34.79	36.11	36.82	35.54	36.49	38.48
1989									42.72	45.78	43.69	45.32	47.80	53.20
1990										34.43	36.27	37.90	43.19	48.64

Table 3. Average size of new plants surviving at least until 1993

Cohort	Year 1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
1981	26.48	30.51	32.17	33.20	38.83	41.55	40.84	43.56	44.41	44.86	42.96	39.18	36.70	39.97
1982		25.58	27.06	27.37	29.16	29.94	30.68	31.62	32.22	31.85	29.70	27.89	27.18	29.35
1983			25.89	29.07	31.23	34.52	35.67	37.33	38.36	39.84	38.09	37.14	36.42	41.66
1984				27.44	28.09	29.95	31.74	31.81	31.91	32.08	31.07	29.09	28.90	32.94
1985					37.66	50.68	53.99	56.09	58.43	56.52	52.99	50.51	48.57	55.51
1986						30.99	33.82	47.38	48.15	50.83	50.03	47.63	50.34	65.59
1987							42.56	45.30	47.29	47.85	44.90	41.03	40.45	44.97
1988								39.95	43.90	42.32	40.23	37.76	36.49	38.48
1989									59.46	56.64	54.25	50.59	47.80	53.20
1990										41.17	41.59	43.08	43.19	48.64

Table 4. Explanatory variables

Variable	***Description***
Start-up size	Logarithm of the number of employees at start-up
Current size	Logarithm of the number of employees
Relative size	Value of gross real output / Industry MES
Relative wages	(Wages / Hours worked) / Industry average hourly wages
Relative labour productivity	(Value added / Hours worked) / Industry average labour productivity
Relative price-cost margin	((Value added – Wages – Materials) / Value added) / Industry price-cost margin
Relative capital intensity	Capital-labour ratio / Industry average capital-labour ratio
Relative investment rate	(Gross investments / Gross output) / Industry average investment rate
Plant's export intensity	Exports / Gross output in the plant
Public ownership	Dummy variable with value one for public ownership
Foreign ownership	Dummy variable with value one for plants in which more than 50% of the equity is held by non-Finnish residents
Currently multiplant	Dummy variable with value one for plants owned by a multiplant firm
Continuously multiplant	Dummy variable with value one for plants belonging to a multiplant firm throughout the period observed
Becomes multiplant	Dummy variable with value one if a single plant becomes multiplant
Becomes single plant	Dummy variable with value one if a multiplant becomes a single plant
Multiple ownership changes	Dummy variable with value one for plants that change ownership status more than once
Scale economies	Mean size of the largest plants in each industry accounting for one half of the industry value of gross real output
Sub-optimal scale	Proportion of industry output in plants smaller than MES (Comanor & Wilson, 1967)
Concentration	Herfindahl index for gross output
Entry rate	Number of entrants / Total number of plants in the industry
Rate of job turnover	(Gross job creation + Gross job destruction) / Average number of jobs in the industry (Davis et al., 1996)
Industry growth	(Change in industry real value added in two consecutive periods) / Average real value added
R&D intensity	R&D expenditures/number of employees in the industry
Churning	(Worker flow – Job turnover) / Average number of jobs in the industry (average over the years 1988–93), dummy=1 if higher than manufacturing average
Import penetration	Imports / (Gross output + imports – exports) in the industry
Growth in real GDP	Relative change in the real gross domestic product
Cohort dummies	Dummy variables for different entry years (reference group is the first cohort COH81)

Table 5. Sample description

Covariates	N	Mean	Std	Min	Max
Start-up size	18486	2.68	0.90	0.69	6.90
Current size	18657	2.82	0.93	0.00	7.28
Relative size	18743	0.28	0.75	0.00	24.46
Relative wages	18641	0.88	0.28	0.00	11.26
Relative labour productivity	18641	0.98	0.89	0.00	52.67
Relative price-cost margin	18612	0.00	0.06	-5.18	0.15
Relative capital intensity	17968	0.00	0.00	0.00	0.22
Relative investment rate	17940	0.00	0.08	0.00	6.62
Plant's export intensity	18613	0.10	0.52	0.00	28.61
Public ownership	18749	0.02	0.14	0.00	1.00
Foreign ownership	18749	0.02	0.15	0.00	1.00
Currently multiplant	18749	0.16	0.37	0.00	1.00
Continuously multiplant	18749	0.12	0.32	0.00	1.00
Becomes multiplant	18749	0.01	0.09	0.00	1.00
Becomes single plant	18749	0.01	0.08	0.00	1.00
Multiple ownership changes	18749	0.02	0.16	0.00	1.00
Scale economies	18748	0.61	0.80	0.05	9.02
Sub-optimal scale	18748	0.08	0.03	0.01	0.31
Concentration	18748	0.05	0.06	0.01	0.87
Entry rate	18748	0.03	0.03	0.00	0.94
Rate of job turnover	18748	0.18	0.08	0.02	1.77
Industry growth	18748	0.00	0.14	-0.94	0.97
R&D intensity	18749	0.68	1.07	0.02	9.17
Churning	18749	0.53	0.50	0.00	1.00
Import penetration	18749	0.30	0.23	-1.43	1.24
Growth in real GDP	18749	0.01	0.03	-0.06	0.05

It should be noted that some variables are scaled for presentation purposes:
scale economies is measured in terms of 100 000 000 Finnish marks. R&D intensity is divided by 10 000, whereas relative price-cost margin, relative investment rate and relative capital intensity are divided by 1 000.

SECTION V: THE DETERMINANTS OF PLANT SURVIVAL

Table 6. Empirical results with the Cox regression model

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Start-up size	0.598		-0.135				
	(0.064)***		(0.039)***				
Current size	-0.897	-0.451			-0.445	-0.454	-0.465
	(0.061)***	(0.039)***			(0.039)***	(0.039)***	(0.039)***
Relative size				-1.081			
				(0.153)***			
Relative wages	-0.235	-0.182	-0.454	-0.322	-0.188	-0.181	-0.163
	(0.121)*	(0.118)	(0.125)***	(0.122)***	(0.118)	(0.118)	(0.119)
Relative labour productivity	-0.416	-0.445	-0.419	-0.294	-0.441	-0.445	-0.463
	(0.058)***	(0.058)***	(0.059)***	(0.059)***	(0.058)***	(0.058)***	(0.059)***
Relative price-cost margin	-0.781	-1.080	-1.028	-0.790	-1.062	-1.067	-1.118
	(0.306)**	(0.317)***	(0.307)***	(0.301)***	(0.317)***	(0.320)***	(0.326)***
Relative capital intensity	-31.903						
	(24.736)						
Relative investment rate	-3.510	-5.709	-5.338	-6.748	-5.810	-5.365	-6.073
	(4.040)	(4.548)	(4.325)	(4.503)	(4.546)	(4.646)	(4.788)
Plant's export intensity	-0.414	-0.355	-0.681	-0.479	-0.358	-0.350	-0.341
	(0.166)**	(0.161)**	(0.169)***	(0.162)***	(0.160)**	(0.161)**	(0.161)**
Public ownership	-0.154						
	(0.247)						
Foreign ownership	-0.014						
	(0.224)						
Currently multiplant	0.142	0.211	0.091	0.090		0.206	0.227
	(0.087)	(0.082)**	(0.085)	(0.082)		(0.082)**	(0.083)***
Continuously multiplant					0.289		
					(0.089)***		
Becomes multiplant					0.722		
					(0.276)***		
Becomes single plant					0.441		
					(0.364)		
Multiple ownership changes					-1.068		
					(0.318)***		
Scale economies	-0.049	-0.056	-0.100		-0.058	-0.056	-0.065
	(0.050)	(0.045)	(0.048)**		(0.045)	(0.045)	(0.046)
Sub-optimal scale	-0.425						
	(0.396)						
Concentration	-0.655						
	(0.597)						
Entry rate	-0.336						
	(1.247)						
Rate of job turnover	1.133	1.210	1.160	1.471	1.193	1.185	1.160
	(0.429)***	(0.341)***	(0.344)***	(0.329)***	(0.343)***	(0.342)***	(0.343)***
Industry growth	-0.856	-0.955	-0.947	-0.947	-0.957	-0.956	-1.267
	(0.227)***	(0.217)***	(0.218)***	(0.209)***	(0.218)***	(0.218)***	(0.200)***

SECTION V: THE DETERMINANTS OF PLANT SURVIVAL

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R&D intensity	-0.038						
	(0.037)						
Churning	0.071						
	(0.069)						
Import penetration	0.444	0.299	0.248	0.094	0.289	0.300	0.289
	(0.189)**	(0.121)**	(0.123)**	(0.120)	(0.121)**	(0.121)**	(0.122)**
Growth in real GDP	-3.526	-3.753	-4.296	-4.108	-3.681		
	(0.917)***	(0.873)***	(0.874)***	(0.861)***	(0.873)***		
GDP * size 1 (less						-3.525	
than 10 employees)						(1.158)***	
GDP * size 2						-4.703	
(10–24 employees)						(1.245)***	
GDP * size 3						-4.089	
(25-49 employees)						(2.089)*	
GDP * size 4						3.175	
(50-99 employees)						(3.627)	
GDP * size 5						-3.785	
(100-249 employees)						(5.480)	
GDP * size 6 (at						-1.276	
least 250 employees)						(12.027)	
Cohort 1982							-0.200
							(0.096)**
Cohort 1983							-0.221
							(0.121)*
Cohort 1984							-0.085
							(0.114)
Cohort 1985							-0.089
							(0.138)
Cohort 1986							0.076
							(0.142)
Cohort 1987							0.023
							(0.120)
Cohort 1988							0.039
							(0.142)
Cohort 1989							0.047
							(0.144)
Cohort 1990							0.001
							(0.159)
N (plants)	2724	2767	2724	2767	2767	2767	2767
Log likelihood	-9734.8	-9943.3	-9844.2	-9970.4	-9932.5	-9941.0	-9945.7
LR statistic	500.0***	410.9***	281.1***	340.6***	432.6***	415.5***	406.1***

Standard errors in parantheses.
***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table 7. Empirical results with discrete proportional hazards models and unobserved heterogeneity

Variable	Continuous PH model (Cox)	(1) Discrete PH model	(2) With gamma heterogeneity	(3) With normal heterogeneity
D3		0.029	0.130	1.086
		(0.090)	(0.099)	(0.151)***
D4		0.039	0.245	1.709
		(0.094)	(0.119)**	(0.192)***
D5		-0.121	0.159	1.925
		(0.103)	(0.143)	(0.218)***
D6		-0.101	0.261	2.281
		(0.110)	(0.169)	(0.244)***
D7		-0.289	0.138	2.349
		(0.125)**	(0.195)	(0.272)***
D8		-0.252	0.222	2.595
		(0.132)*	(0.213)	(0.301)***
D9		0.091	0.633	3.189
		(0.121)	(0.226)***	(0.325)***
D10		-0.292	0.298	2.944
		(0.148)**	(0.257)	(0.358)***
D11		-0.283	0.373	3.140
		(0.166)*	(0.288)	(0.383)***
D12		-1.352	-0.595	2.352
		(0.324)***	(0.422)	(0.491)***
Current size	-0.451	-0.483	-0.606	-1.181
	(0.039)***	(0.039)***	(0.060)***	(0.092)***
Relative wage	-0.182	-0.207	-0.288	-0.657
	(0.118)	(0.119)*	(0.143)**	(0.210)***
Relative labour	-0.445	-0.469	-0.481	-0.533
productivity	(0.058)***	(0.059)***	(0.064)***	(0.082)***
Relative price-cost	-1.080	-2.214	-2.712	-4.548
margin	(0.317)***	(0.788)***	(1.151)**	(1.489)***
Relative investment	-5.709	-7.121	-7.365	-8.602
rate	(4.548)	(3.970)*	(4.398)*	(5.253)
Currently multiplant	0.211	0.226	0.313	0.559
	(0.082)**	(0.083)***	(0.109)***	(0.187)***
Plant's export intensity	-0.355	-0.353	-0.397	-0.635
	(0.161)**	(0.161)**	(0.189)**	(0.264)**
Scale economies	-0.056	-0.049	-0.081	-0.184
	(0.045)	(0.045)	(0.055)	(0.081)**
Rate of job turnover	1.210	1.304	1.546	1.924
	(0.341)***	(0.340)***	(0.396)***	(0.511)***
Industry growth	-0.955	-1.043	-0.930	-0.741
	(0.217)***	(0.219)***	(0.233)***	(0.281)***
Import penetration	0.299	0.328	0.526	0.925
	(0.121)**	(0.121)***	(0.171)***	(0.270)***
Growth in real GDP	-3.753	-4.018	-5.754	-11.091
	(0.873)***	(0.881)***	(1.124)***	(1.435)***
Constant		-0.687	-0.301	-1.074
		(0.152)***	(0.214)	(0.294)***
Ln(variance of gamma σ^2)			-0.068	
			(0.355)	
LR-test: model (2) vs. model (1)			16.4***	
LR-test: $\rho = 0$				50.2***
N (plants)	2767	2742	2742	2742
Log likelihood	-9943.3	-4342.2	-4334.0	-4317.1
Wald statistic	410.9***	502.0***		338.9***

Standard errors in parantheses.
***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table 8. Survival rates by industry (all cohorts 1989–97 combined)

SIC	Industry (manufacturing 15–37)	N	Survival rate after three years
18	Wearing apparel	245	0.367
37	Recycling	14	0.429
35	Other transport equipment	179	0.436
71	Renting of machinery and equipment etc.	327	0.456
17	Textiles	194	0.464
45	Construction	7152	0.481
70	Real estate activities	1705	0.482
50	Sale, repair and maintenance of motor vehicles	2429	0.489
20	Wood	774	0.496
52	Retail trade	6601	0.497
10	Mining of coal and lignite	120	0.500
14	Other mining and quarrying	119	0.504
55	Hotels and restaurants	3640	0.519
15	Food and beverages	622	0.523
51	Wholesale trade	5177	0.524
36	Furniture	533	0.525
34	Transport equipment	104	0.529
19	Leather	71	0.535
64	Post and telecommunication	2503	0.539
74	Other business activities	6063	0.560
26	Other non-metallic mineral products	364	0.563
65	Financial intermediation	545	0.563
22	Publishing and printing	905	0.569
67	Activities auxiliary to financial intermediation	115	0.574
72	Computer and related activities	1098	0.594
29	Machinery and equipment n.e.c.	1098	0.600
41	Collection, purification and distribution of water	18	0.611
62	Air transport	44	0.614
30	Office machinery and computers	26	0.615
28	Fabricated metal products	1390	0.617
27	Basic metals	74	0.622
60	Land transport	2635	0.627
63	Supporting transport activities, travel agencies	858	0.632
61	Water transport	102	0.637
31	Electrical machinery	222	0.644
32	Radio, television and communication equipment	163	0.644
25	Rubber and plastics	254	0.646
73	Research and development	82	0.695
33	Medical instruments etc.	207	0.705
21	Pulp and paper	119	0.714
40	Electricity, gas etc.	202	0.767
24	Chemicals	137	0.781
66	Insurance and pension funding	191	0.791

Table 9. Comparison of manufacturing and services using the Cox regression model

	Business cycle effects		Cohort effects		Human capital effects	
Variable	Manufacturing	Services	Manufacturing	Services	Manufacturing	Services
Current size	-0.636 (0.033)***	-0.791 (0.020)***	-0.651 (0.032)***	-0.696 (0.017)***	-0.700 (0.038)***	-0.722 (0.024)***
Foreign ownership	-0.254 (0.156)	-0.196 (0.053)***	-0.214 (0.156)	-0.166 (0.053)***	-0.253 (0.176)	-0.197 (0.066)***
Currently multiplant	0.310 (0.052)***	-0.023 (0.020)	0.288 (0.052)***	-0.029 (0.020)	0.374 (0.066)***	0.041 (0.028)
Relative age of employees					0.566 (0.157)***	0.553 (0.074)***
Relative seniority					0.262 (0.063)***	0.142 (0.023)***
Relative education					0.629 (0.209)***	0.087 (0.104)
Relative share of women					0.035 (0.021)*	0.023 (0.014)
Scale economies	1.095 (2.657)***	4.617 (0.310)***	1.162 (0.265)***	4.877 (0.289)***	1.504 (0.293)***	5.391 (0.360)***
Rate of job turnover	0.773 (0.212)***	0.962 (0.081)***	0.671 (0.213)***	1.014 (0.081)***	0.524 (0.294)*	0.665 (0.119)***
Industry growth	-1.157 (0.234)***	-0.699 (0.108)***	-1.385 (0.220)***	-0.805 (0.105)***	-1.241 (0.305)***	-0.407 (0.147)***
GDP * size 1 (less than 5 employees)	-2.982 (0.736)***	-4.202 (0.329)***				
GDP * size 2 (5–9 employees)	-9.418 (0.882)***	-9.089 (0.435)***				
GDP * size 3 (10–24 employees)	-7.983 (1.413)***	-4.289 (0.837)***				
GDP * size 4 (25–49 employees)	-3.461 (2.864)	5.047 (1.831)***				
GDP * size 5 (50–99 employees)	-5.120 (4.766)	19.915 (2.531)***				
GDP * size 6 100–249 employees)	-11.982 (7.024)*	34.678 (3.141)***				
GDP * size 7 (at least 250 employees)	28.893 (8.490)***	46.273 (5.516)***				
Growth in real GDP					-5.561 (0.779)***	-7.417 (0.388)***
Cohort 1989			0.750 (0.096)***	0.707 (0.044)***		
Cohort 1990			0.473 (0.101)***	0.505 (0.046)***		
Cohort 1991			0.550 (0.106)***	0.375 (0.049)***		
Cohort 1992			0.435 (0.109)***	0.364 (0.050)***		
Cohort 1993			0.098 (0.104)	0.091 (0.049)*		
Cohort 1994			0.122 (0.108)	0.092 (0.049)*		
Cohort 1995			0.138 (0.108)	0.140 (0.048)***		
Cohort 1996			0.196 (0.109)*	0.181 (0.049)***		
N (plants)	5988	25453	5988	25453	5764	20002
Log likelihood	-21852.8	-116394.5	-21851.0	-116469.7	-13423.5	-61805.5
LR statistic	857.5***	3335.3***	861.0***	3184.9***	614.6***	2117.1***

Standard errors in parantheses. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

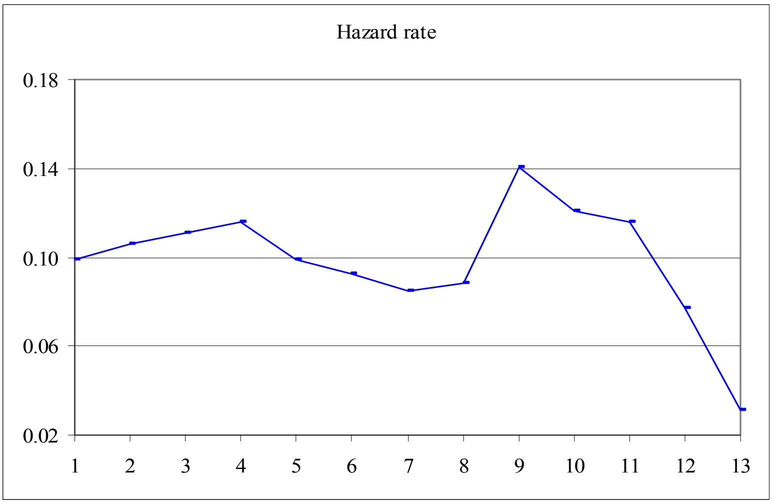

Figure 1. The hazard rates of new plants (all cohorts 1981–90 combined)

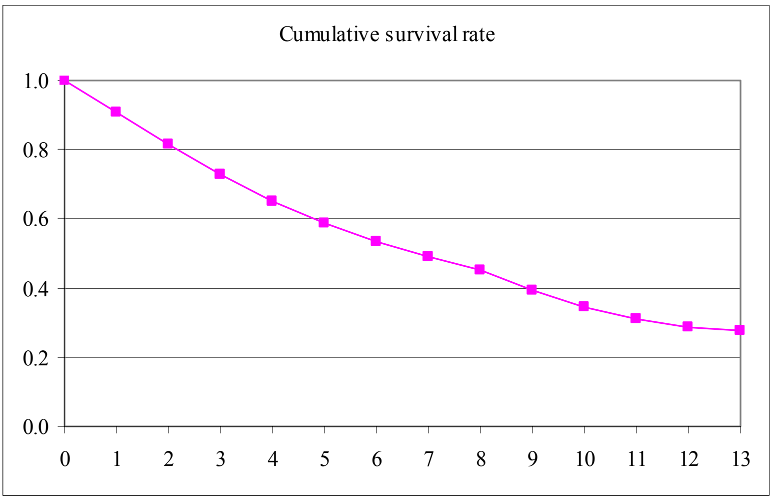

Figure 2. The survival of new plants (all cohorts 1981–90 combined)

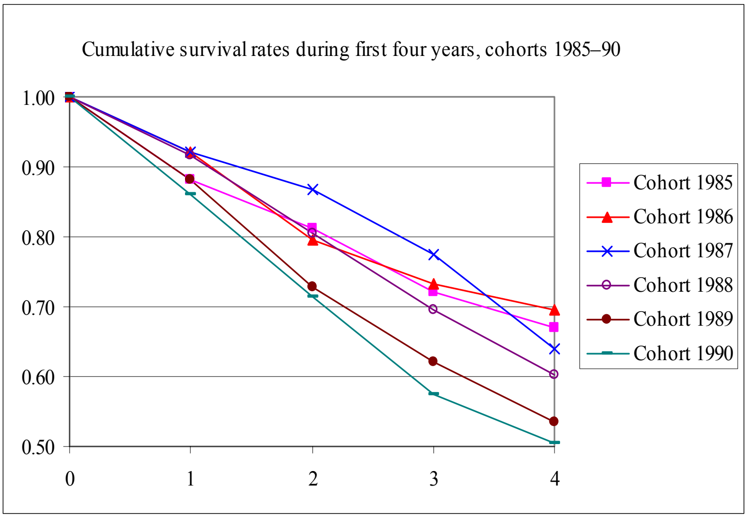

Figure 3. The survival of new plants during first four years (cohorts 1985–90)

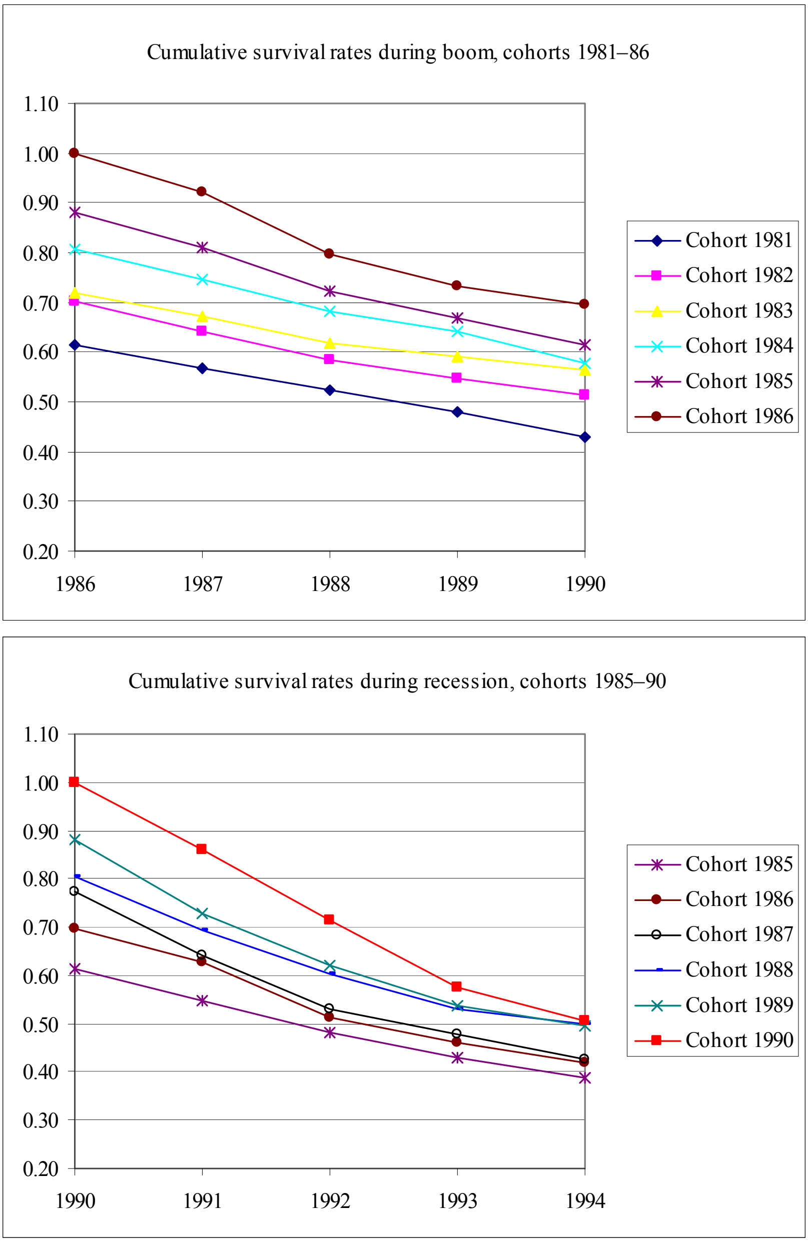

Figure 4. The survival of different-aged cohorts during boom and recession

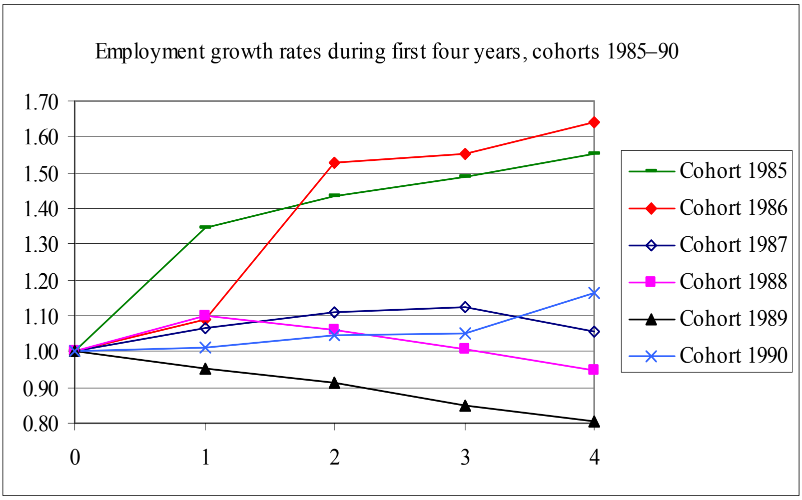

Figure 5. Employment growth of new plants during first four years (cohorts 1985–90)

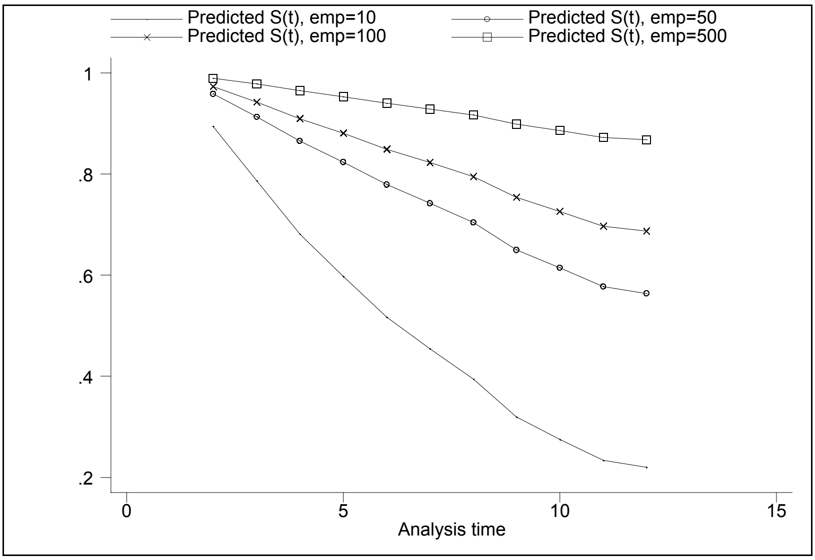

Figure 6. Predicted survival functions by plant size for the discrete PH model with gamma heterogeneity

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