PELLERVON TALOUDELLISEN TUTKIMUSLAITOKSEN
RAPORTTEJA Nro 197

PELLERVO ECONOMIC RESEARCH INSTITUTE
REPORTS No. 197

GROWTH OF NEW FIRMS:

EVIDENCE FROM FINLAND 1996-2003

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Helsinki 2006

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ISBN 952-5594-20-3 (NID)
ISBN 952-5594-21-1 (PDF)
ISSN 1456-3215

Helsinki 2006

PREFACE

Increasing the establishment of new firms and the growth of existing enterprises is an explicit goal of the Finnish economic and industrial policy. Lack of growth-oriented firms is argued to be one of the main obstacles to economic growth and increase in employment. New firms are also often seen as an important source of innovations. Yet, little is actually known about the growth processes of individual firms and the determinants of firm growth. Are there any common characteristics among successful business firms and how do the challenges faced by new firms differ from mature firms? Increasing the knowledge on these questions increases our understanding in planning support measures and policies in order to foster rapid growth.

This study summarizes what is known about firm growth both theoretically and empirically and investigates growth processes of the Finnish firms by applying a large data set covering the whole business sector between the years 1996 and 2003. It aims to identify both firm and industry level determinants affecting the performance of firms.

This research is part of the ProACT research program 2001-2005 on innovation policy funded jointly by Tekes, the Finnish Funding Agency for Technology and Innovation, and the Ministry of Trade and Industry. Pellervo Economic Research Institute and the author would like to thank Tekes for financing this research project and Satu Nurmi and Juha Honkkila from the Research Laboratory of the Statistics Finland for helping with the formation of the research data.

Helsinki, May 2006

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ANSSI RANTALA. 2006. GROWTH OF NEW FIRMS: EVIDENCE FROM FINLAND 1996-2003. Pellervo Economic Research Institute No. 197. 119 p. ISBN 952-5594-20-3 (NID), ISBN 952-5594-21-1 (PDF), ISSN 1456-3215.
Abstract: This study investigates the growth process of new firms. After reviewing the theoretical literature on firm growth and the empirical evidence, an empirical study on the growth of new firms in the Finnish economy is carried out by applying a large firm-level panel data set covering the whole business sector between the years 1996 and 2003. The results indicate that, in general, small firms grow faster than their larger counterparts. However, by spitting up the data by various birth types, it turns out that new firms with a larger founding team grow faster than smaller firms, which are founded by just one entrepreneur, or without a single entrepreneur or worker. The so-called spin-off firms, whose work force comes mainly from one existing large firm, also perform well. The human capital of the entrepreneur, or of the founding team of entrepreneurs and workers, is found to affect the performance of the firm during the early years of its existence. Both previous leadership or management experience and tertiary education have a positive and statistically significant effect on the growth process. Subjective innovation survey data is used as a measure of innovation activity of the new firms. It turns out that innovative firms do not display higher growth rates than other firms.
Keywords: *Firm growth, new firms, Finland, entrepreneurship, human capital, panel data.*

ANSSI RANTALA. 2006. UUSIEN YRITYSTEN KASVU: TULOKSIA SUOMESTA VUOSILTA 1996-2003. Pellervon taloudellisen tutkimuslaitoksen raportteja nro 197. 119s. ISBN 952-5594-20-3 (NID), ISBN 952-5594-21-1 (PDF), ISSN 1456-3215.
Tiivistelmä: Tässä tutkimuksessa tarkastellaan uusien yritysten kasvua. Ensin luodaan katsaus sekä teoreettiseen että empiiriseen kirjallisuuteen. Sen jälkeen tutkitaan uusien yritysten kasvua Suomessa laajan, koko yrityssektorin kattavan yritystason paneeliaineiston avulla vuosina 1996-2003. Tulosten mukaan yleisesti pätee, että pienet yritykset kasvavat suuria yrityksiä nopeammin. Jakamalla aineisto yritysten syntytavan mukaan luokkiin havaitaan kuitenkin, että uudet yritykset, joiden perustajajoukko koostuu useammasta henkilöstä kasvavat nopeammin kuin ne yritykset, joissa on vain yksi perustaja tai ei yhtään päätoimista yrittäjää tai työntekijää. Ns. spin-off –yritykset, joiden perustajat tulevat pääosin yhdestä yrityksestä, kasvavat myös ripeästi. Perustajajoukon henkinen pääoma vaikuttaa myös myönteisesti yrityksen menestymiseen ensimmäisten vuosien aikana. Sekä aikaisempi yrittäjyys- ja johtamiskokemus että korkea-asteen koulutus vaikuttavat tilastollisesti merkittävällä tavalla yritysten kasvuun. Uusien yritysten innovaatiotoiminnan mittarina tutkimuksessa käytetään innovaatiokyselyiden aineistoja. Osoittautuu kuitenkin, että innovatiiviset yritykset eivät kasva muita yrityksiä nopeammin.
Asiasanat: *Yrityksen kasvu, uudet yritykset, Suomi, yrittäjyys, henkinen pääoma, paneeliaineisto*

CONTENTS

EXTENDED ABSTRACT

This study investigates the growth process of new firms. After reviewing the theoretical literature on firm growth and the empirical evidence, an empirical study on the growth of new firms in the Finnish economy is carried out by applying a large panel data set covering the whole business sector between the years 1996 and 2003.

The results of the empirical study using Finnish data suggest that firm growth is not a purely random process. There are both firm and industry level determinants, which according to econometric analyses conducted, do affect the performance of the firm. First of all, the size of the firm does matter for growth. Small firms grow faster than their larger counterparts. The birth type of the firm has an impact on growth as well. Artificial new firms, which are founded as a result of a restructuring of some existing firms, display higher growth than real new firms when the size of the new firms is controlled for. If the birth types are further split up into finer groups, it turns out that real new firms, which have a larger founding team grow faster than smaller firms, which are founded by just one entrepreneur, or without a single entrepreneur or worker. The so-called spin-off firms, whose work force comes mainly from one existing large firm, also perform well. Irrespective of the birth type, limited liability firms outperform other legal forms in growth.

The human capital of the entrepreneur, or of the founding team of entrepreneurs and workers, is found to affect the performance of the firm during the early years of its existence. Both previous leadership or management experience and tertiary education have a positive and statistically significant effect on the growth process. Tertiary education is not found to have a more pronounced effect in the knowledge-based industries, as is sometimes argued, but there is some evidence that the composition of education matters. The results suggest that in the knowledge-based industries, both technical and business oriented higher tertiary education matter for firm performance, but in the other sectors only business administration education boosts new firm growth.

It is also studied how innovations affect growth at the firm level. Subjective innovation survey data is used as a measure of innovation activity. It turns out that innovative firms do not display higher growth rates

than other firms. In fact, the subsequent growth performance is weaker among the firms which announce to be innovative during the first years of their existence. It is also tested, whether product and process innovations have different effects on the subsequent growth. Somewhat surprisingly, it is the product innovators, and not process innovators, which grow slower than other firms in terms of employment. All in all, innovations do not seem to foster growth at the firm level in this study.

Innovation surveys provide direct evidence on the output of innovation activities. New firms are of very small size, and linking the research data and the innovation surveys conducted by Statistics Finland revealed that young firms were not well represented in the surveys. The rapid growth of a firm can, however, be interpreted as a measure of its innovation output. Fast-growing new firms which are able to take over market share from incumbent firms have most likely succeeded in creating new ways to produce goods and services more efficiently than before. This interpretation of the results of this study suggests that, irrespective of the industry, founders with relevant work experience in the same industry, and founders with leadership experience and good educational background are most likely to create dynamic and innovative new firms. The results apply to a large population of firms and are hence representative of the whole population of Finnish business firms.

All in all, the results of the study seem to suggest that high education and management experience contribute to the growth of new firms, but a few caveats are called for. The results of the econometric analyses can be interpreted also as strengthening the perception that new firm growth is a process which displays a rather high level of variation among firms. In addition, the econometrical models do not capture the growth process very well, and most of the variation is not explained by the model variables. Even tough there are interesting interactions e.g. between the education of the founding team and firm growth, as well as between the previous management experience and growth, it must be remembered, that the fit of the models do not change much when these variables are introduced.

LAAJENNETTU TIIVISTELMÄ

Tutkimusaineisto ja –menetelmät

Tässä tutkimuksessa tarkastellaan uusien yritysten kasvuprosesseja. Ensin luodaan katsaus sekä teoreettiseen että empiiriseen kirjallisuuteen. Sen jälkeen tutkitaan uusien yritysten kasvua Suomessa laajan, koko yrityssektorin kattavan yritystason paneeliaineiston avulla vuosina 1996-2003.

Tutkimuksessa hyödynnetään Tilastokeskuksen yritys- ja yksilötason rekisteriaineistoja. Tutkimusaineiston rungon muodostaa Yritysrekisterin mukaan vuonna 1996 syntyneet uudet yritykset, joita on noin 30 000. Samoja yrityksiä seurataan aina vuoteen 2003 tai niiden poistumiseen saakka. Tutkimusaineiston kokoamisessa erityistä huomiota kiinnitetään aidosti uuden yritystoiminnan ja yritysjärjestelyjen kautta syntyneiden "epäaitojen" uusien yritysten erottelemiseen. Mm. OECD:n piirissä tehdyt kansainväliset vertailututkimukset viittaavat siihen, että uusien yritysten kasvusta saa hyvin erilaisen kuvan, jos epäaitoja yrityksiä ei ole poistettu aineistosta.

Uudet yritykset jaetaan aitoihin ja epäaitoihin yrityssyntymiin hyödyntämällä Tilastokeskuksen yhdistettyä työnantaja-työntekijäaineistoa, jossa on vuosittain mukana periaatteessa kaikki suomalaiset työikäiset henkilöt (16-70 vuotiaat) ja runsaasti tietoja heidän taustastaan. Henkilökohtaisten tietojen lisäksi aineistossa on henkilön työnantajan yritystunnus, mikä mahdollistaa uusien yritysten ja niiden henkilökunnan tietojen yhdistämisen. Jäljittämällä uusien yritysten perustajien edellisen vuoden työnantajat voidaan arvioida onko kyse aidosta uudesta yrityksestä, yritysjärjestelystä tai puhtaasti hallinnollisesta tapahtumasta, kuten esimerkiksi yritysmuodon muutoksesta, joka aiheuttaa usein uuden yritystunnuksen syntymisen yritysrekisteriin. Mikäli uuden yrityksen henkilökunta koostuu suureksi osaksi jonkun toisen edellisenä vuotena Yritysrekisteristä löytyvän yrityksen henkilökunnasta, tai joku yritys on luovuttanut merkittävän osan työntekijöistään uudelle yritykselle, katsotaan, että yritystoiminta ei ole aidosti uutta, vaan kyseessä on yritysjärjestelyn kautta syntynyt "epäaito" uusi yritys.

Kaikista vuonna 1996 syntyneistä uusista yrityksistä aidoiksi voidaan demografisen menetelmän perusteella luokitella noin 96 % ja epäaidoiksi vain 4 %. Epäaitoja uusia yrityksiä on siten melko pieni määrä, mutta niiden tunnuslukujen vertailu aitoihin uusiin yrityksiin antaa viitteitä siitä, että kyseessä on selvästi erilaiset yritysjoukot. Aidot uudet yritykset ovat huomattavasti pienempiä kuin epäaidot uudet yritykset. Mediaaniyrityksessä on vain 0,5 henkilöä töissä kokopäiväiseksi muutettuna, ja työllisten määrän keskiarvokin on vain hieman yli yhden henkilön. Epäaito uusi mediaaniyritys on sitä vastoin lähes kolmen henkilön suuruinen, ja keskiarvo on lähes 40 henkilöä. Joukossa on siten myös varsin suuria yrityksiä.

Tutkimuksen empiirisessä analyysissä ilmenee, että yritysten kasvua ei voi kuvata satunnaisena polkuna. Tutkimuksessa estimoidaan vuonna 1996 Suomessa syntyneille yrityksille, joita seurattiin aina vuoteen 2003 tai niiden poistumiseen saakka useita erilaisia kasvuyhtälöitä. Estimoinneissa käytetään aineiston yhdistettyä poikkileikkaus- ja aikasarjaominaisuutta hyödyntäviä paneeliestimaattoreita, joiden avulla voidaan kontrolloida kasvuun vaikuttavia havaitsemattomia yrityskohtaista tekijöitä.

Tulokset

Tutkimuksen empiirisen analyysin mukaan sekä yrityskohtaiset että toimialakohtaiset tekijät vaikuttavat yrityksen kasvuun. Ensinnäkin, yrityksen koko vaikuttaa sen kasvuun. Pienet yritykset kasvavat nopeammin kuin suuret yritykset; tulosten mukaan yrityksen koon kasvaminen 10 prosentilla alentaa yrityksen vuotuista kasvua 1-7 prosenttiyksikköä. Myös yrityksen syntytapa vaikuttaa kasvuun. Epäaidot yritykset, jotka syntyvät yritysjärjestelyjen tuloksena kasvavat aitoja uusia yrityksiä nopeammin, kun yritysten koon vaikutusta kasvuun kontrolloidaan. Jakamalla aineisto edelleen yritysten syntytavan mukaan tarkemmin eri luokkiin havaitaan kuitenkin, että uudet yritykset, joiden perustajajoukko koostuu useammasta henkilöstä kasvavat nopeammin kuin ne yritykset, joissa on vain yksi perustaja tai ei yhtään päätoimista yrittäjää tai työntekijää. Ns. spin-off –yritykset, joiden perustajat tulevat pääosin yhdestä yrityksestä, kasvavat myös ripeästi. Yrityksen syntytavasta riippumatta rajoitetun vastuun yhtiöiden, eli osakeyhtiöiden, kasvu on keskimäärin noin 25 prosenttiyksikköä nopeampaa kuin muun yhtiömuodon omaavien yritysten.

Perustajajoukon henkinen pääoma vaikuttaa myönteisesti yrityksen menestymiseen ensimmäisten vuosien aikana. Sekä aikaisempi johtamiskokemus että korkea-asteen koulutus vaikuttavat tilastollisesti merkittävällä tavalla yritysten kasvuun. Aikaisempi johtajakokemus lisää keskimääräistä kasvua 12-37 prosenttiyksikköä, ja korkeakoulutus 19-27 prosenttiyksikköä. Korkea-asteen koulutuksen merkitys ei ole tietoon perustuvilla aloilla suurempi kuin muilla toimialoilla. Sitä vastoin koulutuksen suuntauksella näyttää olevan erilainen merkitys tietoon perustuvilla aloilla. Näillä aloilla sekä teknillisellä että kaupallisella koulutuksella on positiivinen yhteys yrityksen kasvuun, mutta muilla toimialoilla vain kaupallinen koulutus edistää uuden yrityksen kasvua.

Tutkimuksessa selvitetään myös, miten innovaatiot vaikuttavat yrityksen kasvuun yritystasolla. Subjektiivisia innovaatiokyselyitä käytetään yritysten innovaatiotoiminnan tuotoksen mittarina. Osoittautuu, että innovaatioita tehneet yritykset eivät kasva muita yrityksiä nopeammin. Itse asiassa kolmen ensimmäisen vuoden aikana innovoineet yritykset kasvavat muita yrityksiä hitaammin. Kun tutkitaan tuote- ja prosessi-innovaatioita erikseen, havaitaan hieman yllättäen, että tuoteinnovaatioita tehneet yritykset kasvavat muita yrityksiä hitaammin, mutta prosessi-innovaatioita tehneet yritykset eivät erotu muista yrityksistä. Tutkimuksen tulokset viittaavat siihen, että innovaatiot eivät edistä kasvua yritystasolla.

Innovaatiokyselyt tarjoavat suoraa näyttöä innovaatiotoiminnan tuotoksesta. Uudet yritykset ovat hyvin pieniä, ja tutkimusaineiston yhdistäminen Tilastokeskuksen innovaatiokyselyihin paljasti, että uudet yritykset eivät ole hyvin edustettuina näissä kyselyissä. Yrityksen nopeaa kasvua voidaan kuitenkin pitää innovaatiotoiminnan tuotoksen mittarina. Nopeasti kasvavat uudet yritykset, jotka onnistuvat valtaamaan markkinaosuuksia markkinoilla jo toimivilta yrityksiltä ovat todennäköisesti onnistuneet kehittämään uusia tapoja tuottaa tuotteita ja palveluita aikaisempaa tehokkaammin. Näin tulkittuna tutkimuksen tulokset viittaavat siihen, että riippumatta toimialasta uuden yrityksen perustajat, joilla on työkokemusta samalta toimialalta, ja joilla on aikaisempaa johtajakokemusta ja hyvä koulutus todennäköisimmin pystyvät luomaan dynaamisia ja innovatiivisia uusia yrityksiä, jotka kasvavat ripeästi. Tutkimuksen tulokset perustuvat laajaan aineistoon ja ovat siten hyvin edustavia koko taloutta ajatellen.

Tutkimuksen tulokset viittaavat yleisesti siihen, että korkea koulutustaso ja johtamiskokemus vaikuttavat uuden yrityksen menestymiseen myönteisesti. Muutama varaus liittyen tulosten tulkintaan on kuitenkin paikallaan. Ekonometriset analyysit osoittavat, että uusien yritysten kasvu vaihtelee hyvin paljon yrityksestä toiseen. Lisäksi, suuri osa vaihtelusta ei selity tutkimuksessa käytettyjen muuttujien vaihtelulla. Vaikka koulutuksella ja johtamiskokemuksella näyttäisi olevan positiivinen yhteys yrityksen kasvuun, on kuitenkin muistettava, että estimoitujen mallien selitysasteet eivät juuri kasva, kun muuttujat lisätään kasvuyhtälöön.

1 INTRODUCTION

In the public policy debate an often heard claim is that the lack of growth-oriented firms is one of the main obstacles to economic growth and prosperity in a society. It is also often argued that new firms and new entrepreneurs could contribute to the fall in the unemployment rate by employing the available labour reserves. Yet very little is actually known about the growth processes of individual firms and the determinants of firm growth in the Finnish economy. Are there any common characteristics among successful business firms, and what kind of support measures and policies, if any, foster rapid growth?

The challenges faced by new firms may differ at various stages of development from a business idea to a successful mature firm. The birth process requires new ideas, new products and processes and other innovative activity. The post-entry growth stage demands new managerial and organizational skills as firms have to handle the increased production volume. Understanding the post-entry performance of firms is important because it increases our knowledge on the selection process of markets which enables some firms to survive and grow, while others stagnate and ultimately exit. Hence, it is valuable for the policy-making process to get more knowledge about the factors affecting the birth and growth processes of new firms.

New firms have an important role in the resource allocation process both within and between the industries. The true importance of the new firms comes about through the increase in their market share. It is unlikely that the number of new firms would have a notable impact on the functioning of the industries and on the economy as a whole, if they are very small relative to the incumbent firms. Hence, in order to obtain a broader picture of the importance of new firms, it is important to look beyond the entry process, and study the growth of the new firms more closely.

The importance of new firms in innovation is also often mentioned in the debate. New firms are seen as an important source of innovations, which enhance the overall productivity growth in the economy. Successful new firms, which take over market share from the incumbents, have most likely managed to create new kinds of products and services. Therefore, new firm growth can be interpreted as an indicator of innovation output. It is difficult to get any information on the innovativeness of small and new firms especially at the service sector, and by studying growth it is possible to capture at least some features of the innovation process.

The aim of the study is twofold. The first goal is to summarize what is known about firm growth both theoretically and empirically in the field of economics. The research on firm growth has not been theory driven as is often the case in economics, but it has over the decades developed in an interplay of empirical and theoretical contributions. After reviewing the earlier contributions, an empirical investigation on growth processes of the Finnish firms is carried out by applying a large data set covering the whole business sector between the years 1996 and 2003.

The results of the empirical study using Finnish data suggest that firm growth is not a purely random process. There are both firm and industry level determinants, which according to econometric analyses conducted, do affect the performance of the firm. First of all, the size of the firm does matter for growth. Small firms grow faster than their larger counterparts. The birth type of the firm has an impact on growth as well. Artificial new firms, which are founded as a result of a restructuring of some existing firms, display higher growth than real new firms when the size of the new firms is controlled for. If the birth types are further split up into finer groups, it turns out that real new firms, which have a larger founding team grow faster than smaller firms, which are founded by just one entrepreneur, or without a single entrepreneur or worker. The so-called spin-off firms, whose work force comes mainly from one existing large firm, also perform well. Irrespective of the birth type, limited liability firms outperform other legal forms in growth.

The human capital of the entrepreneur, or of the founding team of entrepreneurs and workers, is found to affect the performance of the firm during the early years of its existence. Both previous leadership or management experience and tertiary education have a positive and statistically significant effect on the growth process. Tertiary education is not found to have a more pronounced effect in the knowledge-based industries, as is sometimes argued, but there is some evidence that the composition of education matters. The results suggest that in the knowledge-based industries, both technical and business oriented higher tertiary education matter for firm performance, but in the other sectors only business administration education boosts new firm growth.

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2 FIRM GROWTH IN ECONOMICS LITERATURE

The growth of firms has mostly been absent from economics textbooks. In the traditional neo-classical analysis firms are just black-boxes, and all that is needed is a production function which tells how inputs are combined to produce output. Standard microeconomics textbook analysis says nothing about the dynamics of the industry structure. There is no role for the entrepreneur or for the evolution of the size of the firm.

Entry process of new firms is seen as an equilibrating force, so that in markets were firms are able to earn excess rents, new firms enter and will drive profits to zero. In declining industries the exit of some incumbent firms will increase the profits so that in equilibrium excess rents are zero. This traditional view is at odds with the large evidence on the industry dynamics, which clearly shows that entry and exit in an industry are highly correlated, that is, entry and exit are taking place in the same industries at the same time.[1] In order to explain this continual turnover, economists have relied on models that emphasize producer heterogeneity and market selection.

The importance of new firms and entrepreneurs has quite recently been highlighted in the so-called Schumpeterian growth theory, which, in the spirit of Joseph Schumpeter, emphasizes the role of "creative destruction" in economic development.[2] Entrepreneurs are the key players in the process of increasing productivity. They constantly try to innovate and bring new products to the market, which would make their rivals' products obsolete and hence force them to exit from the market place. New firms are important in this process of creative destruction, because they develop innovations, and the entry threat forces the incumbent firms to innovate as well in order to survive in the competition (Aghion and Howitt, 2005; Aghion et al., 2004 and 2005).

The entry of new firms fosters productivity growth, as new firms drive old firms out from the markets. The large number of new firms may not, however, be a sufficient threat to the incumbent firms, if the new firms do not survive and grow fast enough. Provided that a considerable fraction of all

[1] For empirical evidence, see e.g. Brandt (2004).
[2] See Aghion and Howitt (1992 and 1998) for a comprehensive presentation of the Schumpeterian growth theory.

new firms exits shortly after the entry, a phenomenon which was called a "revolving door" by Audretsch (1995b) emerges.

The traditional microeconomic and macroeconomic analyses were silent about the growth processes of firms. Therefore, it is not surprising that the research of firm growth has been, and to a large extent still is, mostly empirically oriented. Sutton (1997) describes the development of the literature as a "continual interplay between theoretical modelling and empirical evidence, and a shift of focus in terms of the empirical regularities which seem to be of primary interest to researchers."

3 STOCHASTIC GROWTH MODELS OF THE FIRM

3.1 Gibrat's law of proportional effect

The literature on the growth of firms was initiated in 1931, when Robert Gibrat's book *Inégalités Économiques* was published. Gibrat (1931) was the first to present a formal model of the evolution of firm size over time. He launched "the law of proportional effect", which stated that the expected increase in firm size is proportional to the current size of the firm.

The proportional effect and its implications for the size distribution of firms can, following Sutton (1997), be illustrated with a simple example. Denoting the size of the firm at time *t* by x_t and letting the random variable ε_t denote the proportionate rate of growth between period *t-1* and *t*, one obtains

$$x_t - x_{t-1} = \varepsilon_t x_{t-1} .$$

Hence, it follows that x_t is determined by the starting size of the firm, x_0, and all previous and the current period shocks

$$x_t = (1+\varepsilon_t)x_{t-1} = x_0(1+\varepsilon_1)(1+\varepsilon_2)...(1+\varepsilon_t).$$

Assuming that the time period is short, and hence ε_t is small, one can justify the use of the approximation $\varepsilon_t \approx \log(1+\varepsilon_t)$. By taking logs from the above expression one obtains

$$\log x_t \approx \log x_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_t .$$

If the shocks ε_t are independent with mean *m* and variance σ^2, it follows that in the limit as $t \to \infty$ and hence the impact of the term $\log x_0$ becomes smaller, the distribution of $\log x_t$ is approximated by a normal distribution with mean *mt* and variance $\sigma^2 t$. The limiting distribution of x_t is hence lognormal, and the variance of the distribution increases over time.

Gibrat (1931) applied this new "law" to the French establishment level data from the late 19th and early 20th century. He was able to show that the size distribution was indeed close to the lognormal distribution in various industries. These findings were thus consistent with the theoretical prediction of the law of proportional effect. Gibrat's stochastic growth model has remained as a benchmark and a starting point for studies of firm growth and industry evolution.

3.2 Implications of Gibrat's law for the growth of firms

Gibrat's law has three main propositions. First, firms of different size classes have the same average proportionate growth. In other words, size does not matter for growth. Second, the dispersion of growth rates about the common mean is the same for all size classes. The variation of growth should hence be the same for small and large firms. Third, there is no serial correlation (positive or negative) in growth rates. Previous growth performance should not affect current performance so that e.g. rapid growth in the past does not predict rapid (or slow) growth in the future.

In addition, the law of proportional effect has some rather interesting consequences on the growth patterns of firms. Namely, under Gibrat's law the size of the firm follows a random walk (possibly with a drift), which means that unexpected shocks have permanent effects on the size of the firm. The current size of the firm is the sum of all previous shocks to the size. Hence, the growth process cannot be described as a deterministic trend with some fluctuations caused by random shocks around that trend. The growth process is thus difference stationary and not trend stationary. Provided that the size of the firm follows a random walk, the growth process is path dependent. As the shocks are unpredictable, it will be impossible to forecast the size of the firm in some point in time in the future.

Another implication of Gibrat's law is that firm growth rates are expected to idiosyncratic. If the shocks faced by various firms are independent of each other, the growth rate of the economy as a whole, or the growth rate of that particular industry, should not affect the evolution of an individual firm. Therefore, the past or present performance of other firms or the aggregate economy should not provide any information on the growth prospects of a given firm. History dependency of the growth process is hence limited to the firm's own history.

3.3 Further developments and evidence of the stochastic firm growth model

The interest in the growth of firms revived in the 1950s and 1960s, when both theoretical and empirical work, which extended and challenged Gibrat's law started to appear. The interest of these early empirical contributions was to test Gibrat's law, that is, to see whether the growth rate is independent of size. The basic equation to be tested is of the form

$$gr_t = \alpha + \beta \log x_{t-1} + \varepsilon_t ,$$

where gr_t is the growth rate and x_{t-1} is the size of the firm. Hart and Prais (1956) investigated the growth of the quoted companies in the UK between the years 1885 and 1950. Their statistical analysis of the market valuation the firms gave support to Gibrat's law. Small and large firms seemed to grow at the same rate, except for the time period from 1939 to 1950, when the growth of the small firms outperformed that of the large ones.

Hart and Prais (1956) also noted among the first that the entry and exit process may be important for the concentration of an industry. Entry of new firms into the industry will offset the general tendency for concentration to increase over time implied by Gibrat's law. Their policy recommendation was hence straightforward: maintaining favourable conditions for free entry of new firms is important for restricting the concentration which could ultimately lead to a monopoly.

Simon and Bonini (1958) formalized the role of the entry process on the size distribution of firms. They argued that on the theoretical grounds Gibrat's law is plausible, if one assumes constant returns to scale, at least above some threshold minimum size. Provided that unit costs are constant, small and large firms should on average have the same chances of growing or shrinking in proportion of their current size. Simon and Bonini showed that assuming Gibrat's law and a constant entry rate yields a constant steady-state skew size distribution of firms called Yule-Simon distribution.

In addition to theoretical considerations, Simon and Bonini (1958) provide empirical support to Gibrat's law by studying the growth of the 500 largest industrial corporations in the US between the years 1954 and 1956. Their findings are broadly similar to the ones from the UK presented by Hart and Prais (1956). The frequency distributions of percentage changes in the firm size are quite similar for small, medium sized and large firms approximating normal distributions with equal means and standard deviations. In other words, the size of the firm does not affect the growth performance. However, "small" firms in the sample are not actually small, since only 500 largest firms in the US are studied.

Hymer and Pashigian (1962) applied a somewhat larger data set than Simon and Bonini (1958) covering the one thousand largest manufacturing firms in the US from 1946-1955. They found that the growth rate of assets is not related to firm size, but the variance of growth is negatively related to size. Hymer and Pashigian (1962) were the first to tackle the problem with failing companies. In order to calculate growth one obviously needs to observe the size of the firm at least in two points in time. The problem with failing firms can be solved by accepting only those firms in to sample which survive, and hence can be observed also at the end of the time period. This simple procedure can, however, bias the results, if small firms are more likely disappear than large ones. Hymer and Pashigian (1962) applied another method, namely firms which were dissolved during the time period were given a growth rate of minus 100 per cent.

Further evidence of Gibrat's law was provided by Hart (1962) using four rather small data sets form the UK. The data were from various industries, quoted and unquoted companies, and before and after the Second World War. None of the data sets analyzed showed any statistically significant relationship between the growth of firm profits and size of the firm. The variability of the growth was found to be positively related to size in one data set, negatively in another data set, and no relation was detected in the two remaining data sets.

Mansfield (1962) tested Gibrat's law with US data containing practically all firms, large and small, in steel, petroleum and rubber tire industries from 1916 to 1957. The coverage of the data is hence much better than in the other early studies, where the large firms were strongly over-represented. However, the number of observations is rather limited.

Mansfield was the first to study the impact of sample censoring on the empirical results concerning the validity of Gibrat's law. He pointed out that Gibrat's law can be formulated in three different ways depending on the treatment of the exiting firms.

The first case is that the size of the firms exiting from the sample before the observation period ends is regarded as zero and hence the growth rate becomes minus 100 per cent. This was the approach chosen by Hymer and Pashigian (1962). Mansfield (1962) finds that in general this version of Gibrat's law fails to hold and interprets that the reason is that small firms are more likely to exit. The second case is that Gibrat's law holds for those firms which do not exit during the observed time period. This version was assumed e.g. in Hart and Prais (1956). Gibrat's law is still rejected in most cases. Small firms seem to grow faster than large firms, and the variance of growth rates is higher for smaller firms. The third case is the one proposed by Simon and Bonini (1958), which states that Gibrat's law holds only for firms exceeding the minimum efficient size in the industry, and not exiting during the observation period. Restricting the analysis to this group of larger firms do yield support for Gibrat's law. The growth of firms becomes independent of size, but the variance is still linked negatively the size.

The stochastic model of firm growth can be questioned on theoretical grounds, because it is not based on maximization behaviour of rational agents and hence it does not explain why firms' growth process evolves as observed. Sutton (1997) points out, however, that criticising the stochastic models on the grounds of lacking maximization behaviour misses the target. One can construct a maximizing model of the firm, where each market consists of a sequence of equal sized and independent business opportunities which arise over time. A simple way to present this idea is to consider an "island" model, where there are a number of isolated island markets, each of which can support only one establishment. An optimizing model would result in one firm entering each market, but be silent about the selection mechanism that chooses the particular firm from the set of potential entrants.

The island model will produce the law of proportional effect only if one assumes that the probability of an existing firm to seize the upcoming business opportunity is proportional to the current size of the firm. According to Sutton (1997), the real problem of the traditional stochastic approach to firm growth is not in the absence of maximizing behaviour, but in the reliance on Gibrat's law. If one abandons the assumption that the probability to expand to a new market is positively related to the size of the firm, the model yields no predictions about the relationship between firm size and growth. Some later contributions have also relied on Gibrat’s law. A prime example is Lucas' (1978) influential theoretical model of the size distribution of firms, which assumes Gibrat's law in order to prove the existence and uniqueness of equilibrium.

Hart and Oulton (1996) have stressed that superimposed upon all the systematic forces of firm growth is a large stochastic factor: storms and floods, earthquakes, wars, terrorism, change of government, stock exchange bubbles, health scares and a multitude of other random effects will influence a firm’s growth. The resulting growth process seems to be purely random, because these stochastic shocks will outweigh the systematic forces in so many cases.

4 MAXIMIZING MODELS OF FIRM GROWTH AND INDUSTRY EVOLUTION

4.1 Stylized results

Starting from the 1980s, new empirical findings brought about by research conducted with new firm level data sets revealed a bunch of new "stylized results" or "statistical regularities", as Geroski (1995) and Sutton (1997), respectively, called them.[3] Accumulating empirical evidence on the evolution of firms and industries suggested that small firms seemed to grow faster than large ones, and that the growth of young firms outperformed that of older firms. These studies will be reviewed in more detail in Chapter 5.

Most studies did concentrate on the size and age effects on growth. The reason for this rather narrow focus is related at least to two things. Firstly, in order to test Gibrat's law one needs to take the size aspect into account. Secondly, the lack of high quality data, which includes information on various characteristics of the firm and of the entrepreneur and the workers, forced the researchers to focus on the size and age variables, which were available in many data sets. Doms et al. (1995) noted that the studies treat producer size and age as proxies for efficiency differences that could arise from either observed or unobserved differences in managerial ability, production technologies, and experience.

4.2 Passive learning models

Jovanovic (1982) was the first to construct an optimizing model of firm behaviour based on learning, which is consistent with the observed behaviour. In his model, the firms are uncertain about their productivity when entering the market. In particular, the production costs are random and they differ among firms. The entering firm does not know the mean of its cost distribution, which Jovanovic calls the firm's "true cost". The distribution of true costs among firms is, however, known to all potential entrants. In each time period, firms observe their efficiency, and based on

[3] Other useful surveys include e.g. Caves (1998), Geroski (2000) and Audretsch (2003).

this new piece of information they update their beliefs about their relative efficiency. The model is sometimes called the "passive", or Bayesian, learning model of firm growth. The outcome of the model is that efficient firms are likely to grow and survive, whereas inefficient firms will eventually decline and fail. As the costs are random, this selection mechanism is "noisy", and some truly inefficient firms may well prosper some time and some efficient firms may fail. Lippman and Rumelt (1982) also based their model on the idea of uncertain costs upon entry. The uncertainty is, however, resolved right after the entry has taken place.

Jovanovic's model of learning implies that firms will choose to enter the market with a lower size than would be considered optimal. This is due to the uncertainty about their relative efficiency, which ultimately determines their faith in the market place. Young and small firms hence tend to grow fast.

The passive learning model of Jovanovic emphasizes selection as the driving force behind firm and industry evolution. Obviously, this "survival of the fittest" idea is not the whole story behind the evolution of firms, but it quite nicely captures the idea of uncertainty on the supply side of the market. Hopenhayn (1992) develops an equilibrium theory of industry dynamics with entry, exit and firm growth based on a similar set up as in Jovanovic. Hopenhayn's version is a simplified one, as the firms do not engage in Bayesian learning as they know the distribution of the productivity shocks.

Cabral (1995) shows that small firms may grow faster than large ones, provided that capacity and technology choices involve some degree of sunkness. Sunk costs refer to investments for which the value is lost in case of exit. As in Jovanovic (1982), the firms learn about their efficiency only in participating in the market and make investment decisions based on the arriving information. The model is more stylized than in Jovanovic (1982). Small firms are assumed to have a lower probability of survival. Hence smaller entrants are likely to invest more gradually than larger entrants, if investment costs are proportional to capacity and are sunk in case of exit. This strategy yields a higher expected growth rate for small firms over some transitional time period, since large entrants are close to or at the optimal level already at the time of entry. Sunk capacity costs are necessary for producing size and growth relationship in Cabral's model. Without the sunk costs, expected growth is independent of size, but the expected growth of surviving firms is actually decreasing with size.

4.3 Active learning models

Another strand of the learning literature emphasizes the "active" learning of the firms instead of the "passive" learning discussed above. Ericson and Pakes (1995) construct an industry equilibrium model where firms or entrepreneurs actively explore their economic environment and try to enhance their profit opportunities through investment in research and exploration-type processes. The outcome of the investment is uncertain and stochastic, and the firm’s success depends also on the success of the other firms in the industry, and on the competitive pressure coming from outside the industry and though entry of new firms.

The model captures the heterogeneity among competing firms and the idiosyncratic nature of the evolution of firms' fortunes. The passive learning approach emphasizes the selection mechanism, albeit a noisy one, which sorts firms to efficient and successful and inefficient and failing ones. The active learning approach highlights the competitive pressure which forces firms to struggle to maintain profits and survive. The knowledge stock of the aggregate economy grows over time, and this new knowledge is embodied in the new entrants to the industry.

Each incumbent firm has to make a decision whether to continue or to exit the industry, and provided that it decides to stay, it has to decide how much to invest into R&D. If the expected present value of the future net cash flow generated by optimal investment path is less than the liquidation value of the firm, it is optimal to exit. The potential entrant firms weight the expected profits after entry against the cost of entry. Potential entrants have an addition source of uncertainty, as they do not know their relative efficiency upon entry.

In Ericson and Pakes (1995), the industry is in a dynamic equilibrium when all firms have rational expectations, that is, all firms have the correct understanding about the mechanisms generating the evolution of industry structure including the true distribution of all future states of the world. In this kind of setup, firm entry and exit are equilibrium phenomena, which are observed taking place simultaneously in an industry. The industry structure is in a state of flux all the time. Firms' paths will be truly idiosyncratic, and there is no general pattern how firms grow after entering the industry. All firms will eventually die due to the competitive pressure, but the life-cycles may be very different from each other. Starting from an identical position, some firms may explore and be successful for an extended period of time, whereas others may fail quite fast despite the efforts.

4.4 Industry and firm specific human capital

Rossi-Hansberg and Wright (2005) build a model of firm size dynamics, where the size dependence of growth is related to the accumulation of industry specific human capital in the presence of industry specific productivity shocks. Assuming that returns to human capital at the firm level and at the industry level are diminishing, an abundance of human capital leads to low rates of return and slower accumulation of human capital. In industries, where the stock of human capital is low, the rate of return is high and hence also the rate of accumulation. The process of human capital accumulation is mean reverting. This implies that the evolution of firm size displays mean reversion, as firms respond to changes in factor prices. Small firms then tend to grow faster than large ones and Gibrat's law does not hold. The deviation from Gibrat's law is larger in industries, which use physical capital more intensely and human capital less intensely. At the aggregate level this means that sectoral differences in growth patterns between e.g. service sectors and manufacturing are potentially large.

4.5 R&D, innovations and knowledge capital

Griliches and Klette (2000) present a quality ladder model of firm growth where R&D investment and stochastic innovations are the engines of growth. In their model, the firms in the industry compete with differentiated products, and each firm upgrades the quality of its products through a stochastic R&D process in order to prevent other firms to overtake its product line. The R&D investment increases the probability of innovation, that is, a new and improved product. Rival firms may participate the R&D race for the improved product by paying a sunk entry cost. The optimal R&D investment is then determined by zero profit condition, that is, expected profits from participating the race must be in balance with the sunk entry cost.

Firm's expected output and profits are increasing in the product quality, which gives incentives to invest more in R&D. However, making further product improvements becomes more difficult and costly as the product quality is improved. Griliches and Klette (2000) develop results concerning the growth process of the firm assuming that these effects cancel out each other so that the size of the firm does not affect its R&D intensity. This also implies that in equilibrium the probability of a successful innovation is independent of size. As each innovation is assumed to contribute to the output growth at the same rate, Gibrat's law of the proportional effect holds under these assumptions.

Another theoretical model of innovating firms with implications to growth is provided by Klette and Kortum (2004), who focus on the role of knowledge capital in innovation process. The appearance of new innovations is stochastic and depends on the current R&D investment and the accumulated knowledge capital. They analyze the evolution of an industry characterized by multi product firms. Innovation is a new product, which is introduced to the market. The size of the firm is simply the total number of products. The growth of the firm is hence determined by its innovation intensity and the intensity of creative destruction, which is the rate at which firms lose products to the competing firms.

The firm's knowledge capital refers to all the skills, techniques and know-how which are employed in the innovation process. The modelling strategy concerning knowledge capital is very simple, namely the number of products in the firm’s production. The number of products is also the cumulative sum of all previous innovations by the firm, which are not superseded from the market by rival firms.

The optimal R&D policy for the firm in the model relates the R&D expenditure proportionally to the accumulated knowledge capital, which yields constant innovation intensity. Hence, the growth of the firm is independent of the size and Gibrat's law holds. Provided that the growth rate is conditioned on survival, that is, if only surviving firms are taken into account, then the growth rate is decreasing in size for small firms. For large firms, the probability of survival is high anyway and Gibrat's law is a good approximation of large firm growth. Another contribution on innovation and firm growth is Klepper and Thomson (2005), where the role of various goods is replaced by submarkets.

5 EMPIRICAL STUDIES OF FIRM GROWTH

5.1 Firm, entrepreneur and industry characteristics

The interest in firm growth was revived in the 1980s, when new data sets started to become available. The standard approach is to insert new explanatory variables into the stochastic growth model. The new variables are usually related to the characteristics of the firm or of the industry where the firm operates. The firm level variables are such as size, age, legal form, ownership structure, sector, location, etc.

Storey (1994) emphasizes that the growth of the small firm depends on three components: the starting resources of the entrepreneurs, the firm, and the strategy, which all are needed in the growth process. The empirical studies on firm growth usually focus on the firm characteristics. Much less work is done on the other two components. The resources of the entrepreneurs include, for example motivation, education, management experience, prior self-employment experience, the size and composition of the founding team, prior sector experience, training, age, etc. The strategy includes matters such as technological sophistication, exporting, management training, workforce training, new products, competition, management recruitment, external equity etc. Obviously, knowledge about many of the factors mentioned is not easily available, and collecting such information requires that surveys are conducted.

The theoretical contributions reviewed above were inspired by new empirical evidence on firm performance, which started to accumulate in the early 1980s. Empirical work was made possible by new firm-level data sets, which started to become available. Most of the data sets applied in the early studies of the 1980s consist of firms in the manufacturing sector. Service sector data sets have become available much later. Another shortcoming in the early studies was that the firms included in the data sets were relatively large ones. New data sources, such as register based data, have solved also this problem.

The most common measure of size and growth in the empirical literature is employment. Sometimes also turnover or total assets are used. There are, however, very few contributions, where two or more growth measures are used and comparisons are made.[4] As Sutton (1997) points out, this is actually quite surprising, since it is not obvious that the results are independent of the choice of the measure.

5.2 Size and age effects

Most of the empirical studies of firm growth focus on the size and age effects. On the one hand, the aim of these studies is to test Gibrat's law. On the other hand, the age effect is related to learning and selection arguments of the theoretical literature.

Hall (1987) addresses an econometric problem called sample selection bias, which is a potential problem in firm growth equations. In order to study growth at the firm level, information on size is required both at the beginning of the period and at the end of the period. If small firms with slow or negative growth are more likely to disappear from the sample than larger firms, then small fast growing firms will be over-represented in the final sample, and due to the sample selection bias the negative impact of size on growth is over-estimated. The sample selection can be taken into account by estimating a probit equation for survival jointly with the growth equation using maximum likelihood. The results show, however, that sample selection does not explain the size-growth relationship in Hall's sample. This result comes out from practically all studies of firm growth.[5] There is thus strong empirical evidence that sample selection is not behind the size effect of firm growth.

Hall (1987) presents evidence on firm employment growth from publicly traded firms in the US manufacturing sector. The data covers only large companies. Only 1 per cent of the firms in the US manufacturing are included, but their total employment is around 90 % of all employment in the manufacturing sector. The results show that small firms tend to grow faster than the large ones. Also, the variance of growth rates is larger for small firms.

Another early contribution to the "new" empirical literature on firm growth is by Evans (1987a), who, in addition to the size dependence, studies

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[4]See e.g. Heshmati (2001), where employment, turnover and assets are used as dependent variables.

[5] See e.g. Hall (1987), Evans (1987a, 1987b), Wagner (1994), Dunne and Hughes (1994), Almus and Nerlinger (1999), Heshmati (2001) and Nurmi (2004).

also the possible age dependence of firms' employment growth. Evans's firm level data is drawn from a database consisting of most of the firms in the US manufacturing sector and it covers the years 1976-82. Very small firms are though underrepresented, as the data is collected by a credit rating agency.

In reporting the results Evans (1987a) splits the data into two parts based on their age. The data set contains precise information on the age of the firms only for firms younger than 7 years. The older firms are divided into 3 age groups. Evans's main results are that firm growth is decreasing in size when age is controlled for, and that growth is decreasing in age when size is controlled for. The departures from Gibrat's law are decreasing with size, but do not go away. The age dependence of growth is consistent with the passive learning model of Jovanovic (1982) discussed above.

For the group of young firms selection bias is controlled for by estimating a selection equation, but the results remain the same as in the OLS estimation. It is noteworthy that sample selection bias does not seem to be a problem even among the young firms, where the reported exit rate of the firms is a lot higher than among the older firms.

In a companion paper Evans (1987b) uses a slightly different data set which covers all firms from 100 manufacturing industries in 1976-1980. Evans estimates growth and survival equations separately for each industry to study the robustness of the results obtained from pooled data. The industry level results are consistent with earlier findings. The negative relationship between growth and size holds for 89 industries out of 100, and the negative relationship between growth and age holds for 76 industries.

Evans (1987b) studies also the impact of firm size and age on the variability of growth. Firm age is negatively related to the variability of growth in 80 industries and firm size is negatively related to the variability of growth in 85 industries. The age and size of the firm are found to be positive related to survival in both studies by Evans.

Dunne, Robert and Samuelson (1989) study also the growth of firms in the US manufacturing sector. Their data stretches over the period 1967-1982 and includes over 200 000 plants that entered in 1967, 1972 or 1977 to the Census of Manufactures. They apply grouping techniques to study the growth process. Observations are grouped into cells based on firm and industry characteristics such as firm size, age, year of observation, industry, ownership status and initial size. The mean growth rate, the variance of the growth rate and the exit rate are calculated for each cell, and it is examined how these measures vary across cells.

The empirical method applied in Dunne at al. (1989) is free from distributional assumption and it allows nonlinearity in the growth measures. Hence, it escapes the problem of separating sample selection, heteroscedasticity, and nonlinearity in the estimation, which is problematic in the method of Hall (1987) and Evans (1987a, 1987b). The downside of the grouping method is the loss of information. Also, the idea that exit is paralleled with a growth rate of -1 is somewhat unsatisfactory.

Despite the different method, the empirical results of Dunne et al. (1989) are well in line with the results obtained in Hall and Evans. The age and the current size of the firm are negatively related to the failure rate. When only successful plants are analyzed the age and size effects of growth are negative. The mean growth rates are negative for large and old plants in the single-plant firms, whereas for multi-plant firms the mean growth rates are always positive (with one exception). The variance of the growth rates declines both with age and size.

When the focus is shifted to the whole sample including the failing plants which are attached with the growth rate of -100 per cent, the results change somewhat. The growth of the single-unit plants is still decreasing in size, because the decline in the growth rate of the successful plants with increased size is stronger than the concurrent decrease in the failure rate. For multiunit plants the relation between expected growth and size is on average positive. For age effects using the whole sample no clear pattern emerged. The size and age effects on the variance of growth rates are found to be similar with the sample including only the successful firms, that is, the variance is decreasing in the size and the age of the firm. Further evidence on the negative effects of firm size and age on firm growth in the US is provided by Audretsch (1995a, 1995b).

5.3 Size and age effects in other countries

Wagner (1992) tests Gibrat's law with a data set with some 7 000 manufacturing establishments from Germany for 1978-1989. The smallest establishments are excluded from the sample since the size threshold is 20 employees. Wagner did not find any size effect of growth, and hence Gibrat's law seems to hold. In another study, Wagner (1994) focuses on new firms which entered the German manufacturing industries in 1979-1982 and follows them until 1990. The probability of failure is found to increase during the first few years and decline (non-monotonically) afterwards. Wagner didn't find any size effects on employment growth and hence Gibrat's law seems to hold in this data set as well. Harhoff et al. (1998) did, however, find evidence that small firms grow faster than large ones with a German data containing around 11 000 firms observed between years 1989 and 1994 from all sectors of the economy. Almus and Neringer (2000) focus on new firms, which were established between 1989 and 1994 in the German manufacturing sector. The size of the data set varies between years from around 800 firms up to over 4000. As in Wagner, the estimation was done for three year intervals to minimize the survivor bias. Gibrat's law was rejected in all cases. Small firms were found to grow faster than large ones. Almus and Nerlinger (2000) apply a German manufacturing data to study the growth of new firms. Their data consist of approximately 20 000 new independent firms established between 1989 and 1996. Size is negatively related to growth and Gibrat's law is thus violated.

Empirical evidence from the UK is provided by Dunne and Hughes (1994), who look at both the quoted and unquoted UK companies in the period 1975-1985. The data includes over 2 000 firms, which all survived the period 1975-1980 and their performance is followed until 1985 or until exit. Some 25 % of firms employ less than 500 people. The size and growth measure in the study is net assets. For surviving firms the mean growth rate is much higher for smaller firms and levels off after a certain threshold. This suggests that size matters for growth for small firms. The variance of growth rate is found to decrease monotonically with size.

Dunne and Hughes (1994) estimate the growth equation separately for 19 industries to investigate whether the size-growth relationship is a product of aggregation bias. If some industries are characterized by rapid overall growth and have below average firm size, the result of the analysis of all industries taken together may show a negative relationship even though within individual industries no such relationship exists. Estimation results reveal that in most industries, and for the firm population as a whole, size of the firms is negatively related to growth, and aggregation bias thus do not explain the observed pattern. Age is found to be negatively related to growth in the whole sample, but at the industry level most of the coefficients are negative but insignificant.

Hart and Oulton (1996) provide more evidence on firm growth from the UK. Their data of some 87 000 independent companies over the period 1989-1993 contains relatively more small firms than that of Dunne and Hughes (1994). Hence, the lower tail of the size distribution of firms is better represented in the data, and the role of small firms as job generators can be assessed more accurately.

Hart and Oulton (1996) focused on testing Gibrat's law and their regression included only lagged size and industry and time dummies. The results concerning the surviving firms only in terms of employment, sales and asset growth are clear. Small firms outperformed bigger firms and hence Gibrat's law is violated. Especially, firms with less than 8 employees grew faster than other firms. Among the larger firms size does not seem to affect growth. The explanatory power the model decreases sharply as larger firms are excluded from the sample. This implies that there is more turbulence in the growth process at the lower end of the size distribution. Hart and Oulton (1996) conjecture, like Simon and Bonini (1958) earlier, that small firms below the minimum efficient scale grow faster because they experience decreasing average costs of production. Once the turning point is reached the average cost curve flattens

Kumar (1985) investigated the size effect and persistence of growth with a UK data from 1960-1976 with five year intervals. The data set included around 1 700 firms. A notable difference with earlier studies is that the data set contained also a limited range of service industries such as wholesale, retail and transport. Services were, however, analyzed separately form manufacturing industries only in case of acquisition growth. Five different variables were used as the size and the growth measures of the firm. The results were not sensitive to the choice of the measure. In all cases small firms had a higher average growth than large firms.

Mata (1994) investigates new firm growth in Portuguese manufacturing with a data set consisting of around 550 new firms which entered the markets in 1983 and employed at least 10 workers. Their performance is followed until 1987 or until they exit. The impact of size on growth is found to be negative. Mata (1994) applies panel data estimation techniques, and finds strong evidence of the firm specific fixed effects. The absolute value of the size coefficient in the growth equation increases by the factor of 25 when fixed effect results are compared with the pooled OLS results. The direction of the bias in OLS estimation suggests that the firm specific intercepts are positively correlated with size. Mata (1994) interprets the unobserved firm-specific effect to be related to e.g. management characteristics of the firm.

Mata (1994) also tests the idea raised already by Simon and Bonini (1958) and Mansfield (1962) that Gibrat's law holds only for firms above some threshold size. This is done by increasing the minimum number of employees in the firms accepted to the data first from 10 to 15, then from 15 to 20 until 100 is reached, and estimating the growth equations for each new data set. In the pooled data the size coefficient becomes insignificant at 30 employees and turns positive at 45 employees, albeit it is never significantly positive. When the same estimation is carried out with firm dummies, the coefficient remains quite stable until 90 employees, and then drops by a half.

Persson (2004) analyzes the growth performance of the new Swedish establishments which have survived at least seven years. The growth measure is the average growth of employment during that period. Persson finds that the start-up size affects negatively to subsequent growth of the establishment, that is, Gibrat's law does not hold.

Heshmati (2001) contains annual observations around 8 000 micro and small firms (1-100 employees) from Sweden covering the period 1993-1998. Firm growth is measured with three different variables: employment, sales and assets. The employment growth estimation results using pooled OLS and random effects method show that Gibrat's law is rejected. The coefficient of the current size is negative and the coefficient of the squared size is positive. His analysis implies that the relationship between size and growth is nonlinear so that for firms large enough size can be positively related to growth. Evaluated at the sample mean the size elasticity of growth is negative. The relationship between age and growth is also nonlinear in a similar fashion. The coefficient of age is negative, whereas the coefficient of age squared is positive. Again, the age elasticity of growth is negative at the sample mean.

Yasuda (2005) studies the employment growth performance of some 14 000 manufacturing firms form Japan. The firms were first observed in 1992 and again in 1998. Only firms with more than 50 employees were included in to the data set. The results repeat the observed pattern. Size and age are negatively related to growth. Honjo's (2004) study focuses on some

3 500 Japanese new manufacturing joint-stock companies, which entered the markets between 1992 and 1996, and were followed until year 2000. Also in this study, size is negatively related to subsequent sales growth.

5.4 Persistence of growth

Chesher (1979) pointed out another way how firm growth can deviate from Gibrat's law. Growth rates may be positively serially correlated so that above average growth is often followed by high growth, and low growth is followed by below average growth. Chesher (1979) studied the UK firm sample of 183 companies existing between 1960 and 1969, which were classified as "commercial" and "industrial". The size of the firms is measured by capital employed. Size is found to be unrelated to growth, but growth is positively serially correlated, that is, growth seems to be persistent. Kumar (1985) also found statistically significant impact of persistence in growth in the UK firm data, but Dunne and Hughes (1994) did not find any evidence supporting the hypothesis. Wagner (1992) detected persistence in the growth process with a German data, whereas Almus and Neringer (2000) did not. Audretsch et al. (2004) also test Gibrat's law by testing whether growth is autocorrelated using Dutch hospitality sector data. In most of the cases Gibrat's law can not be rejected and the autocorrelation coefficients are rather small and even negative.

5.5 The role of innovations, R&D and technology in firm growth

An early contribution on innovations and firm growth is by Mansfield (1962), who showed that firms which have succeeded in producing major innovations do grow faster in terms of turnover than other firms. Van Reenen (1997) pointed out that the direction of the effect of innovation on employment growth at the firm level is, however, a priori ambiguous. Usually, a distinction is made between process and product innovations. The impact of product innovations on firm employment is likely to be positive, as the new product will generate new demand. However, in the spirit of Schumpeter, the new good may drive out old products of the innovation firm as well, and the total expansion in labour demand will be reduced. The impact of innovations on firm growth is less clear in case of process innovations. Provided that the process innovation is of the labour-saving type, the direct effect on employment is negative. The indirect effect comes through the demand channel, as lower production costs tend to lower the product prices and thus boost the product demand. This in turn will stimulate labour demand and employment. The magnitude of the indirect effect depends on the price elasticity of demand and on the competition at the product market.

Van Reenen (1997) finds with UK manufacturing data comprising of some 600 listed companies between 1976 and 1982 that commercialized innovations do have a positive and lasting impact on employment. Niefert (2003) studies the impact of patenting activities on firm growth with a German data consisting of some 1 400 new firms founded between 1990 and 1997, which were followed until 1999 or until exit. The results show that patenting activity enhances employment growth, and that the number of patents is not as important as the very act of performing patenting activities.

Audretsch (1995a) studies the role of innovation activity at the industry level on the employment growth of new firms using biannual data from the U.S. manufacturing covering the years 1976-1986. The data consist of around 2 500 new firms which were established in 1976 and survived to 1986. He finds large differences in the relative growth of new firms across industries. He argues that different technological regimes explain the variation in growth rates.

Audretsch states that an industry where scale economies are not present, "corresponds to what has traditionally been referred to as an industry with no or only low barriers to entry. In such an industry, firms with low or even no growth will not be forced to exit out of the industry as a result of any cost disadvantages, so that, on average, lower mean growth rates should tend to be observed in industries exhibiting only a trivial degree of scale economics". He goes on and argue that "what have traditionally been considered to pose as barriers to entry actually serve as barriers to survival". The technological regime thus shapes the observed growth rates of surviving entrants. Audretsch (1995a) focuses on the surviving firms in the growth analysis. Entry and survival barriers at the industry level are measured with scale economies and product differentiation, which is enabled by innovative activity.

The minimum efficient scale of production is measured Audretsch (1995a) as the mean size of the largest plants in each industry accounting for one-half of the industry value of shipments. In order to measure the relative importance of innovative activity in the industry, the total innovation rate is defined as the total number of innovations recorded in a certain year divided by industry employment. The small firm innovation rate is defined as the number of innovations contributed by firms with fewer than 500 employees divided by small firm employment

Audretsch (1995a) considers various lengths of time of observation. The short-run growth of new firms is defined as stretching from 1976 only to 1978, whereas the long-run growth of the surviving firms is measured by looking the growth rate between years 1976 and 1986. He also looks at the performance of the firms still operating in 1984-86, which he calls adolescent firms.

The results show that the start-up size of the firm is negatively related to growth both in the short run and in the long run. What is interesting in the results, is that for adolescent firms size do not affect growth. Industry growth also boosts firm growth, albeit the effect is statistically rather weak. Scale economies also affect positively during the first two years, but later (1976-86) the coefficient becomes insignificant. Both the total innovation rate and the small firm innovation rate have positive coefficients, but only the latter is significant in the long-run growth investigation. For adolescent firms innovation measures do not appear to affect growth.

In a companion paper Audretsch (1995b) and in Audretsch and Mahmood (1994) the same data is used and the analysis is augmented with capital intensity as an explanatory variable. It turns out that capital intensity increases growth in the short-run (the first two years), but the effect vanishes as the period of observation is extended.

Baldwin and Rafiquzzaman (1995) test empirically whether the passive learning, natural selection model by Jovanovic (1982) or the active learning model brought about by Ericson and Pakes (1995) describes better the evolution of Canadian industries. They focus on the post-entry performance of firms that enter an industry by constructing new plant, that is, they focus on the so-called Greenfield entrants.

Baldwin and Rafiquzzaman (1995) followed the entrants of the years 1971-1982 in the Canadian manufacturing until 1989. Their method for separating the two types of learning is simple. The population of entrants is divided into two groups. The first group consists of firms which did not survive the first ten years and the second of firms which were still in operation after ten years. These two groups were approximately of equal size. The performance of the two groups relative to the average incumbent firm in terms of firm size, labour productivity, wages and profitability is then compared at birth, which in this case means the first three years. Same measures of performance are also calculated for the firms surviving to early adolescence, that is, until the age of ten years. Industries where the difference in performance measures of the two groups are substantial at birth and where the survivors make little progress in improving their performance relative to incumbents are characterized as natural selection industries. Those industries where the two groups do not differ at birth, but where the survivors improve their relative performance are dominated by active, or evolutionary, learning.

The natural selection process seems to be in force, as in general the relative performance measures, such as labour productivity, wages and profitability of the surviving entrants exceeds that of the exiting entrants and the improvement in performance of the surviving firms is limited. In particular, labour productivity of the surviving entrants relative to incumbents did not improve at all during the ten first years. By contrast, in the size variable successful entrants do grow and contribute to the growth of the relative size of the firm. But, the successful firms are bigger than exiting firms already at birth.

Multivariate analysis is used to further study the determinants of post-entry growth of entry cohorts at the industry level. Selection is at work when the relative growth of the entrant cohort is considered. The relative size at birth of survivors to exiting firms contributes positively to growth. The analysis also shows that the learning factor is important for growth, namely the growth of labour productivity of the survivors relative to incumbents fosters growth. In industries were the minimum efficient scale is high, the growth of entrants, both all and surviving, is also higher. Somewhat surprisingly the growth of the industry does not affect the growth of the entrants. The explanation seems to be that industry growth fosters entry significantly. The share of R&D personnel is not related to entrant growth.

Doms, Dunne and Roberts (1995) study the role of technology use in the performance of US manufacturing plants. Their data of around 6 000 firms is merged from register data and survey data on the advanced technology use and covers the years 1987-1991. The producer heterogeneity in technology comes from two sources. The differences in plant-level capital-labour ratio and in the type of the manufacturing technologies adopted are investigated.

The use of advanced technology use may affect the performance of the firm through many ways. The most obvious effect is the direct effect on the productivity growth of the firm. The second possibility, and perhaps more interesting, is that the use of advanced technologies may serve as a proxy for unobserved managerial ability. Provided that the firms with the most able management are also the most able to exploit advanced production technologies, then the same firms are most likely to adopt the new technology and to outperform others due to their efficiency advantages.

The capital-labour relationship is positively related to growth and labour productivity, and total factor productivity contribute to plant employment growth. Advanced technology use in 1988, such as CAD systems, robots, laser technology, computer networks, etc. is found to foster growth monotonically.

Baldwin and Johnson (1999) provide some evidence from new firm innovativeness and growth in the Canadian business sector. Their data consists of firms born between the years 1983 and 1986, which are surveyed in 1993. They show that fast-growing firms are more likely to innovate than slower growing firms. Their analysis is, however, purely descriptive.

Almus and Nerlinger (2000) focus on new firms, which were established between 1989 and 1994 in the German manufacturing sector. The analysis was carried out separately for firms in the technology intensive branches and for the non-technology intensive branches, where the break-down was made based on the R&D-intensity of the industry with 3.5 per cent expenditure share of the turnover as a threshold. The results did not, however, show any differences between the industries, and Gibrat's law was rejected in all cases.

Yasuda (2005) shows that R&D expenditure per employee has a statistically significant impact on firm growth. In particular, R&D dummy variable has a positive sign and is significant in the whole sample. Also in the sub sample, where all firms have positive R&D spending, R&D affects growth positively.

Almus (2002) studies the determinants of fast-growing firms in Eastern and Western Germany. Employment is used the growth measure. The data consists of around 2000 new firms established between the years 1990 and

1993 both in manufacturing and service sectors. Somewhat surprisingly, firms in technology intensive manufacturing sectors, that is, R&D-intensity is over 3.5 % of the turnover, or in knowledge-intensive business services did not seem to have better changes of being fast-growers.

5.6 Entry type and growth

The type of entry and subsequent performance of the firm has been investigated in some studies, but growth has seldom been the performance measure in question. This is likely due to the fact that the theoretical framework applied in the contributions is quite often sociology-based organizational ecology or evolutionary economics, which emphasize the survival of the organization as the performance measure.[6] Geroski (2000) has argued that "organizational ecologists have a very narrow conception of organizational performance, namely survival: either an organization survives or it does not, and that is about all there is to it". Geroski goes on and states that "although populations are homogeneous in the eyes of organizational ecologists, in reality they are not. Firms differ in size (for a start), and this means that some have outgrown others, probably because they have generated enough profits (or have engineered a sufficiently rich cash flow) to finance the investments needed to outgrow their rivals. This is an interesting and important part of the evolutionary process, and to make any progress with it, one needs to look at performance measures such as growth rates or profitability. Survival is interesting, but it is just not rich enough to describe the experiences that firms go through as their markets change and develop over time."

Klepper (2002a) studies the evolution of market structure in the US automobile industry in the 20th century and classifies all firms into four categories according to their backgrounds. Experienced firms diversified into cars from other industries. Experienced entrepreneurs, who had ran firms in other industries and founded new car firms were called de novo firms. Spin-offs were firms initiated by one or more persons who had previously worked for some automobile firms. The rest of the firms were called inexperienced firms. Klepper (2002a) shows that even though diversifying firms on average

[6] Carroll and Hannan (2000) provide a comprehensive treatment of the organization ecology approach to the evolution of firms and industries.

outperformed de novo entrants in terms of survival, spin-offs outperformed all firms and eventually dominated the industry. Carroll et al. (1996) showed that, as in Klepper (2002a), diversifying firms, which are called de alio firms, outlasted de novo entrants in the US automobile industry, and that among the de alio firms the ones coming from bicycle and carriage manufacturers outperformed the others. This also points to the direction that previous experience does matter. Klepper and Simons (2000) show that firms' experience prior to entry do affect the performance in the US television producer industry. Firms that diversified from radio manufacturing had longer survival, higher innovation rates and greater market shares. Further evidence on the importance of prior experience is provided by Klepper (2002b), where, in addition to television and automobile manufacturers, also tires and penicillin producers were analyzed. Also Dunne et al. (2003) find that prior experience has an effect on the survival of the firms for seven different manufactured products in 181 geographic markets in the U.S. over the 1963-1997 period.

Persson (2004) utilizes a linked employee-employer data from Sweden, which covers all new establishments, that is, around 80 000 of them, in Sweden in 1987 and 1988. The establishments are followed up to 1995 or until exit. The general problem with register data is that it is difficult or impossible to distinguish genuine, or real, firm or establishment births and deaths from artificial ones. New firms and establishments appear in the official registers not only due to the creation of new business ventures, but also because of mergers and acquisitions, dispersals of existing firm to many firms, outsourcing and administrative changes such as changes in the legal form of the firm. Persson applies a demographic method to separate real births from artificial ones. The main idea is to use the information of the register-based employment statistics data on the employees of the firm to make the separation. If, for example, a majority of the employees in some new firm have the year before worked in some other firm which exited from the data, the entry is not considered as a real one.[7]

Persson's (2004) results show that new Swedish establishments which are born because of a merger have lower growth than genuinely new establishments. New establishments due to a dispersal also have lower growth but the difference is not statistically significant.

[7] More discussion about the demographic method will be in Chapter 7, where it is applied to the Finnish data.

Mata, Portugal and Guimaraes (1995) present descriptive analysis on the impact of entry type on the post-entry evolution of Portuguese manufacturing plants. They classify entrants into two main groups which are further divided into two sub-groups. Plants which are established by new entering firms are labelled as de novo entrants. These are further divided to single plant entrants and to plants belonging to a new firm which enters the markets with several plants, that is, multi-plant entrants. The plants initiated by already established firms are divided to ones whose parent firm is already operating a plant in the same industry, which are called experienced entry, and to those whose parent company is not operating in that particular industry, which in turn are labelled as diversified entry.

They find that de novo entrants, both single plant and multi-plant, grow considerably. For example, the cumulative growth rate for single plants established in 1983-1984 and followed until 1990 is over 100 per cent. Also experienced entrants display growth, but the rate is much lower. Diversified entrants, by contrast, stayed approximately at the same size during the whole time period. The size of the average entrants in each class is, however, quite different. De novo plants are much smaller having about seven employees. Experienced entrants have over 30 workers and diversified entrants employ around 20 workers on average

Kumar (1985) was able to separate acquisition growth from internal growth. Acquisition growth is defined as expenditure on acquisitions of new subsidiaries as a proportion of opening size measured by net assets. For the whole data set the sign of the effect of size on acquisition growth changed from positive to negative between the time periods 1960-1971 and 1966-1976. For the manufacturing industry the impact is significantly negative for the whole period. The dispersion of growth by acquisition was found to be negatively related to size.

Baldwin (1995) studied the impact of mergers on firm growth with Canadian plant-level data from the 1970s. The results show that mergers do have "real" effects. In most cases, the market share of the plants, that is, both for the acquired and the old plants, increase. Profitability and productivity increases in most cases as well. The spin-offs did lost market share and their performance was not boosted after they were divested.

McGuckin and Nguyen (2001) investigate the impact of ownership changes on the subsequent employment growth. Their plant level data covers around 105 000 plants in the US manufacturing for the period 1977-

1987. They find that those around 16 000 plants which went through an ownership change during the period did growth significantly faster than those whose owners stayed the same. In particular, those plants which were acquired did grow faster than plants belonging to a firm which did not acquire any new plants. Moreover, the plants which were owned by an acquiring firm over the whole period did not experience weaker employment growth than plants belonging to a firm which did not acquire any new plants. In other words, there is no evidence that the employment growth in the acquired plants did come from the exiting plants of the acquiring firms.

Mata and Portugal (2004) study to performance of foreign owned new firms relative to domestic ones in Portugal. In case of foreign entry, they are able to distinguish between those firms which proceed by creating a new firm and those that acquire an already existing business. The firms have entered the market between 1983 and 1989. There were over 120 000 entrants during the period, of which about 1 per cent were foreign firms. The data is panel data and firms were followed until 1990 or exit. The results show that foreign entrants are much larger in terms of employment than the domestic ones at the time of entry. The subsequent growth rates differ so that foreign greenfield entrants grow much faster than domestic firms, but foreign acquisition firms grow slower than domestic firms, albeit the difference is not statistically significant.

Further evidence on the impact of birth type on the subsequent growth performance of the firm is provided by OECD studies by Schreyer (2000) and Brandt (2004). Both studies suggest that whether or not artificial new firms can be separated from real births may have substantial effects on the results. In particular, Brandt's (2004) results related to Finland are especially interesting. She compares the growth performance of the new firms with two data sets. The first is the one utilized in the OECD firm-level data project, and the second is the Eurostat data consisting of new firms in the Business Register. The notable difference in these two data sets is that in the Eurostat data artificial new firms are excluded from the data, whereas in the OECD data all new firms, including the ones which are due to restructuring, are in the data set. In addition, the smallest firms are excluded from the OECD data. The results concerning the growth performance during the first couple of years are rather different in the two data sets. In the OECD data the two year employment gain is around 10 per cent, whereas in the Eurostat data the gain is around 65 per cent.

5.7 Legal form of the firm

The legal form of the firm can also be linked to post-entry performance. Harhoff et al. (1998) hypothesizes that the entrepreneur's choice of the legal form can reflect her attitude towards the risk of failure and her assessment of the riskiness of the projects undertaken by the firm. Harhoff et al. (1998) actually finds support for this hypothesis, whereas Almus (2002) concludes that the legal form of the firm do not affect the probability of being a high-growth firm.

5.8 Industry effects

Most of the empirical studies on firm growth use only the data from manufacturing sector, even though its share of output and employment is continuously shrinking. Evidence from the service sector is scarce. A notable exception is Harhoff et al.(1998), where the data covers all major sectors of the German economy. Harhoff et al. (1998) estimate employment growth equations separately for manufacturing, construction, trade and service sector firms. Their results concerning the size effect are very similar across industries, and they conclude that 'the regularity of the size-growth relationship points to important underlying economic mechanisms applicable beyond the narrow confines of the manufacturing sector.

Audretsch et al. (2004) test Gibrat's law in the Dutch hospitality sector covering hotels, camping sites, restaurants and cafeterias. The data covers the years 1987-1991 and the firms are observed annually. Following Mansfield (1962) they create three data sets. One includes all firms in the data, and exiting firms are given the growth rate of -100 per cent. The second one contains only the firms which survived the whole period. The third data set includes only the large surviving firms. Gibrat's law is tested by dividing the data by size and growth into quartiles and then it is tested whether firm growth rates are equally distributed across the size classes.

The results show that size and growth are independent in the Dutch hospitality sector when only surviving firms and surviving large firms are analyzed. In the first case Gibrat's law is rejected. Thus, it seems that in this narrow sub-sector of services size does not matter for growth.

5.9 The role of human capital in firm growth

The role of human capital on the performance of the firm has not attained much interest in the economics literature. Bosma et al. (2004) divide human capital investment into three categories: general, industry-specific and entrepreneurship-specific investment. General human capital is applicable in all professions and activities, and is often proxied by variables such as the age of the entrepreneur or the founding team, high education and experience as an employee. Industry-specific human capital is accumulated by experience in the particular industry, and it loses part of its value outside the particular industry. The entrepreneurship-specific investments include prior experience in business ownership and experience in activities relevant to business ownership, such as leadership experience. Entrepreneurship-specific investment in turn loses part of its value outside entrepreneurial environment.

Storey (1994) reviewed 17 studies focusing on the role of education on firm growth. In nine studies it was found that the impact was positive. Almus (2002) studies the determinants of fast-growing firms in Eastern and Western Germany. Employment is used as the growth measure. The data consists of around 2000 new firms established between the years 1990 and 1993 both in manufacturing and services. The results indicated that for Western Germany the firms established by entrepreneurs with a PhD had the highest probability to grow fast and the firms established by people with a university degree had also significantly higher chances of owning firms that become fast-growers.

The use of linked employer-employee data enables the investigation of the human capital effects on growth. Persson (2004) found with a Swedish data that the educational level of the work force affects the growth rate positively, so that establishments employing personnel with university degree grow faster. The age of the employees also affects growth, so that if the work force is very young, that is, under 25 years old, or quite old, that is, over 59 years, growth rate seems to be higher. Colombo and Grilli (2005) studied the growth performance of around 400 new technology-based Italian firms. They detected also the positive impact of high education on firm growth.

Bosma et al. (2004) study the role of human capital in the performance of new business start-ups. Their data covers approximately 2 000 Dutch entrepreneurs from all industries who started their firms in 1994. The performance of the firms was followed until 1997. They consider profits, survival and cumulative full-time equivalent employment as performance measures. Employment generation was boosted by experience as an employee, but high education was not found to have any impact on employment growth.

Honjo (2004) provides also evidence on the impact of general human capital on new firm turnover growth in the Japanese manufacturing. Firms where the entrepreneur possesses a technical college or a university degree are found to grow faster than other firms.

In addition to the level of education, there is some evidence that the field of education may affect the performance. Almus and Nerlinger (1999) found that especially technical skills have a positive impact on growth in high-tech, in medium high-tech and in low-tech manufacturing sectors, whereas business skills are found to affect growth only in the low-tech firms. Colombo and Grilli (2005) suggest, somewhat surprisingly, that in the knowledge-based sector business and law studies boost growth, whereas technical and science education do have a smaller and statistically rather weak impact.

Entrepreneurial human capital is also found to affect growth in some studies. Storey (1994) reviews the earlier evidence, which shows that in four studies the impact is positive, in six cases no relation is found and in one contribution the impact is even negative. In Bosma et al. (2004), prior experience of business ownership affects positively on the profits and employment generation, albeit the coefficient of employment is statistically insignificant. Leadership experience is not found to have any impact on employment growth. Colombo and Grilli (2005) do find a positive relation between new firm growth and both managerial experience of the founding team and the previous entrepreneurial experience. Bosma et al. (2004) look also at the industry experience, which affects employment growth of the Dutch start-up firms positively.

Quite interestingly, Bosma et al. (2004) report that those entrepreneurs who indicated at the start-up year that one of their goals was to achieve employment growth actually did generate more employment than others. Likewise, those who indicated that high incomes were one of their motives to start up a firm did generate more profits than others.

Bosma et al. (2004) also studied whether the role of human capital is more pronounced in the knowledge intensive industries such as the ICT industry and business services. They did not, however, find any industry effects supporting this hypothesis.

Almus and Nerlinger (1999) found that firms established by teams instead of a single person grow faster in the low-tech sectors. Almus (2002) did not, however, establish a connection between the size of the initial team of founders and the probability of being a high-growth firm.

5.10 Location and firm growth

Heshmati (2001) studies the impact of various regional variables and firm growth with a Swedish data. Regional human capital effects are investigated by including municipality level variables, such as the ratio of people unemployed to the number of vacancies, average length of education of the unemployed, the percentage of people having higher education, and measures of regional development support for entrepreneurs. The variables characterizing the regional labour market can be thought to be important for expansion opportunities especially in regions with low industrial concentration. Access to labour with appropriate education is expected to have positive effects on growth opportunities. The regional and labour market variables do also matter for firm performance. The average length of education of the people registered as unemployed affect growth negatively, whereas the fraction of working age population with higher education and the ratio of people unemployed to the number of vacancies affect growth positively. Regional development support to promote entrepreneurial activities did not affect growth.

Audretsch and Dohse (2004) link the employment growth of new technology firms to geographic location. Knowledge of the locational impact on firm performance is rather limited. The so-called New Economic Geography literature studies the forces of agglomeration of economic activity at the aggregate level, and a related literature has investigated the role of agglomerative externalities in case of the growth of cities.[8] The analysis of

[8] See e.g. Fujita, Krugman and Venables, 1999 for a comprehensive treatment of the New Economic Geography approach. Glaeser et al. (1992) and Rosenthal and Strange (2003) study the growth of cities.

the benefits of spatial concentration goes back at least to Marshall (1920), who argued that cities enhance productivity by allowing for labour market pooling, input sharing and technological spill-overs. Marshall described how knowledge spills over within a geographically bounded space "…inventions and improvements in machinery, in processes and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas." Glaeser et al. (1992) also argue that spatial aspect is important for knowledge spill-overs because "after all, intellectual breakthroughs must cross hallways and streets more easily than oceans and continents."

An important finding in this literature is that agglomerations of economic activity seem to affect economic growth positively. It is, however, much less clear how agglomeration of economic activity affects growth at the micro level. Audretsch and Dohse (2004) focus on small technology intensive manufacturing firms, as knowledge activities are thought to benefit more from spatial concentration than non-knowledge activities. Audretsch and Dohse (2004) apply a straightforward approach and augment a very standard empirical firm growth equation with location-specific variables to find whether location matters for firm growth. A firm which is located in an agglomeration has better access to knowledge resources and to knowledge spill-overs. Hence, their performance should exceed the average performance, and the impact of location should affect the performance more in knowledge intensive industries.

The data used in Audretsch and Dohse (2004) consists of new technology firms that were publicly listed on the Neuer Markt in Germany between the years 1997-2002.[9] The regional breakdown is based on the 97 German planning regions. The knowledge resources of the region is captured by a dummy variable, which gets the value 1 in top 20 per cent of the regions with the highest fraction of workers with academic education. The results indicate that regional human capital does strengthen the growth performance of the firms statistically significantly. The results give also support to the hypothesis that agglomerations are more important for knowledge intensive industries. When the sample is divided into two sub-

[9]The Neuer Markt, launched in 1997 by Deutsche Boerse, the German stock exchange, was Europe's most important growth stock market and Europe's closest equivalent to the Nasdaq. It was closed in June 2003 and the firms are listed on other indices of Deutsche Boerse.

samples consisting of high and low knowledge sectors, human capital variable is significant and positive only in high knowledge sector. Audretsch and Dohse (2004) test also whether the presence of venture capital firms in the region boost firm growth, but the coefficient is insignificant and of the wrong sign, that is, negative in all estimations.

6 FINNISH EVIDENCE ON FIRM GROWTH

Finnish evidence on the determinants of firm growth is scant. Hohti (2000) uses establishment-level data from Finnish manufacturing sector during the period 1980-1994. The smallest establishments are missing from the data, since only a tiny fraction of establishments with less than five employees are covered in the Industrial Statistics of Statistics Finland. The data on job flows is calculated from the Employment Statistics. The data is divided into size categories and the growth rate of employment is measured by applying the arithmetic mean of annual growth rates and the compound interest method. The sorting of the firms into various size categories is based either on the current size or on the average size of establishment over the observation period. The overall growth rate of establishments during the period is clearly negative being around three per cent annually.

Different methods give rather different results concerning the impact of establishment size on growth. When the current size is used as the classification measure, small establishments seem to have more negative net employment change rate than large establishments. When the average size of the establishment during the observation period is used, the relationship between size and growth disappears. When the compound interest method is used, the large establishments seem to have more negative employment change than smaller establishments. Hence, the analysis does not provide unambiguous results concerning the impact of size on the growth of the establishments. Hohti's results can be seen to shed light on the growth of firms as well, since only about seven per cent of the firms in the data consist of more than one establishment.

Maliranta (2003) studies the net employment change in the Finnish manufacturing sector between the years 1990-1997. The data sources are the same as in Hohti (2000), extended with plant-level variables such as labour productivity, R&D and capital intensity, plant age, wage level and wage dispersion. The average labour characteristics, such as education, job tenure, age and the share of females are also considered. The data contains some 1 700 plant observations per year which cover around a half of the total manufacturing employment in Finland. The analysis contains only continuing plants.

In Maliranta's (2003) study, the impact of the plant size on the employment growth is clearly positive. Larger plants thus grow faster than smaller ones, and plant size is not converging. Labour productivity is found to increase employment growth, but R&D intensity does not affect employment growth when industry effects are controlled for. Plant age does not seem to have any impact on employment growth, but one needs to bear in mind that productivity is controlled for.

Ilmakunnas and Maliranta (2005) study job flows with a much larger data set containing around 220 000 plant-year observations in the Finnish business sector between the years 1991 and 1997. The data set thus covers not only manufacturing, but also the whole service sector and construction. The empirical results show that, as in Maliranta (2003), larger firms grow faster than small ones. One explanation for this might be the exceptional time period covered in the study, namely the great depression of the 1990s and the recovery phase after the slump. The age effect is clearly negative, which implies that older plants grow slower than younger ones. Labour productivity, measured by sales per employee, is found to boost employment growth.

Kangasharju (2000) focuses on the small firms in the Finnish business sector between years 1988-1995. Most of the firms in the data of some around 26 000 firms have less than 50 employees. The analysis consists of surviving firms only. In addition to firm related variables, the data set contains information on the characteristics of the entrepreneur, such as the age, education level and gender. The growth variable in the study is the turnover of the firm. The turnover variable has five size classes and the growth of the firm is determined by changes in the size class. The determinants of firm growth probability are therefore analyzed with logit models.

Kangasharju (2000) do not test any size effects. New firms which survive the first year do have a higher growth probability than more mature firms. The industry of the firm is also found to affect the growth probability. In the manufacturing sector and in construction growth is higher than in the wholesale and retail trade. The lowest growth probability is found in the other service sectors.

The characteristics of the entrepreneur also affect firm performance. The youngest entrepreneurs have the highest growth probability. Educational level is also found to have a monotonic impact on growth so that the higher the education, the faster is growth.

The business cycle swings do affect firm performance so that during the recession the growth probabilities go down in all sectors. However, it seems that the effects of the variables considered in the study on firm performance do not change a lot along the business cycle. This suggests that the empirical studies on the determinants of firm growth may not suffer greatly of any biases due to a particular business cycle phase at the time period under study.

Nurmi (2004) tests Gibrat's law directly, and investigates also other determinants of firm growth such as age and human capital effects as well as macroeconomic factors. The data covers Finnish manufacturing firms between the years 1981-1994. The size threshold, as in Hohti (2000) is five employees. There are around 80 000 plant-year observations and close to 10 000 different plants in the data. The average employee characteristics of the plants are linked from the Employment Statistics which contains the plant and firm codes for each worker.

Nurmi (2004) reports results separately for young and old plants, because the plant age in the older cohorts can not be determined with certainty. The young plants are born after 1974 and their age is known. However, the "birth" takes place when the plant reaches the five employee threshold. The new plant in the data can thus be an old plant which was just smaller earlier. The estimation methods applied in the study include pooled OLS and the within-transformation, which enables that plant level heterogeneity is taken into account.

The analysis focuses on the surviving firms only, but in this kind of panel data set with annual observations the selection bias can be expected to be of limited importance. The growth interval is only one year and hence the exit rate is rather low being around seven per cent.

For the young firms the size and age are negatively related to growth. The squared terms of size and age are both positive indicating that the adverse impact on growth levels off with size and age. The interaction term between size and age is also positive suggesting that the growth rate decreases with size more slowly in case of older firms, and with age more slowly in case of larger plants.

Plants with higher wages, higher labour productivity and higher capital intensity than the industry average grow faster. Industry characteristics do also affect growth so that in those industries where R&D intensity is high and scale economics are present is growth also faster.

The impact of human capital on plant growth is taken into account by adding the average employee characteristics into the model. Somewhat surprisingly, in the plants where the employees are less experienced than on average in the industry, is growth higher. Other human capital variables studied, that is, relative education and relative share of women does not show as strong relationships as the experience variable. Education variable is not significant, and the sign is positive in OLS but negative in within estimation.

For older plants Nurmi's results are broadly similar to the results obtained for young plants. Size is still negatively related to growth. The age effect is not clear. In most model specifications growth seems to be higher for older plants, which are over 30 years old. Relative seniority still hinders growth and education also has a negative impact.

In addition, Nurmi (2004) tests the impact of macroeconomic fluctuations for plant growth. As expected, the growth in real GDP boosts plant employment growth. The interaction term of size and GDP growth is positive. It means that the impacts of business cycle fluctuations on plant growth are more pronounced for large firms.

Kangasharju and Pekkala (2002) provide evidence of the impact of education on the growth probabilities of firms run by self-employed. Their data covers the years 1990-1995 and focuses on the very smallest firms. The highest education level with 13 years or more of education is found to increase the growth probability of the firm.

7 THE DATA OF THE EMPIRICAL STUDY OF THE GROWTH OF NEW FIRMS IN FINLAND

7.1 Firm-level data sources

The data set used in the empirical study concerning new firm growth in the Finnish economy is combined from various firm-level and individual-level data bases of Statistics Finland. The main source of firm-level data is the Business Register, which contains practically all existing and actively functioning firms in the Finnish business sector. In order have data in the Business Register, the firm must have either at least 0.5 employees or turnover exceeding a certain threshold, which was around 9 000 euros in 1996.

The employment data in the Business Register is announced as full-time equivalent employment, which means that the employment figures are adjusted for part-time workers. For example, if there are three employees, but each of them works only half-time, the total employment of the firm is 1.5 employees. Therefore, the data suits exceptionally well for the study of new firms, which very often are small. A common problem in the empirical studies of firm size and growth concerning small firms is that one person firms can only grow bigger, but not shrink without exiting. This potential source of bias does not exist in this data source.

The basic information concerning the firms is drawn from the annual Business Register files. In addition to the employment data, other variables include the encrypted enterprise code, the turnover of the firm in nominal terms, the legal form of the firm and the Standard Industrial Classification code at the five-digit level.

Data on innovation activities of the new firms is obtained from innovation surveys carried out by Statistic Finland. The first survey used consists of the years 1996-1998. There were around 3 000 firms in the original data. The data contains information on the innovation output of the firm divided to product and process innovations. The other innovation survey used is the so-called Community Innovation Survey 3 (CIS 3), which was commissioned by the European Commission and was carried out by Statistics Finland. The CIS 3 is about the innovation output of the firms between the years 1998-2000.

A third source of innovation activity data is the so-called R&D panel data compiled in Statistics Finland from various R&D surveys between the years 1986-2003. It includes knowledge on the innovation inputs, i.e. the costs related to the R&D activities. The number of firms in the data varies from year to year. During the period in question, there are up to 3 000 firms annually in the data set.

7.2 Individual-level data sources

The data concerning the personnel of the firms is obtained from the so-called FLEED (Finnish Longitudinal Employer-Employee Data) formed by the Research Laboratory of Statistics Finland. The individual-level information content and coverage of the FLEED corresponds to the "effectiveness data" of the Population Statistics unit of Statistics Finland. In principle, all Finnish citizens aged 16-70 living in Finland are included in the annual data set. The time span of the data stretches from 1988 to 2003. The unit of observation in the FLEED is the individual. In addition to personal information, such as the encrypted personal identification number, education, age, employment status, profession, incomes and socio-economic status, the data set contains encrypted firm and establishment codes, which can be used in linking the firms and their personnel. A person can have only one firm code attached to herself, so that firm code should reflect the primary source of income.

The encrypted firm codes in the FLEED are important in the current study, because they allow the so-called demographic method to be applied in the sorting of new firm births to real and artificial births. The new firm is classified as a real birth, if it creates its business from scratch, and not by buying an existing establishment or business line from some existing firm. New firms created by restructuring of the existing firms, like merger and acquisition activity, are classified as artificial births.

The demographic method uses knowledge on the previous employers of the personnel of the new firm so that new firms sharing a large fraction of workers with some already existing firm can be discriminated from real births. Obviously, the demographic method is not a water-proof method to separate real and artificial births, but at least the most obvious cases can be excluded.

7.3 Choice of the base year of the investigation

As the aim of this study is to investigate the growth of new firms, it is important to choose a long enough time span so that growth can be observed and assessed. On the other hand, the "great depression" of the 1990s was a very exceptional time period in Finish economic history. The GDP dropped around 14 per cent and unemployment rose from three per cent to reaching almost 20 per cent between the years 1991 and 1994. It is hence quite likely that the behaviour of the firms during that period does not reflect the behaviour of the firms during more tranquil times. Another matter which guided the selection of the research data was the fact that by choosing all firms from one year it is possible to calculate the birth rate of new firms and to get a full picture of the birth process in the whole economy. Yet another reason is related to the data available on the socio-economic status of the individuals. This variable is available for the 1990s only for years 1990, 1993 and 1995.

The year 1996 was chosen as the starting point of the growth analysis. The firms born in 1996 can be followed until 2003, which is currently the last year available in the Business Register. Seven years is a relatively long time period when firms are in question. Namely, only around half of the firms are still in operation after seven years. In 1996, the economy had already recovered from the depression and the GDP growth was fairly rapid at around four per cent. Hence, the impact of the depression period on the firm birth process should not be extremely strong. This choice of the base year makes it possible to observe the socio-economic status of the employees three times in the early 1990s. The work experience of the employees can be observed in year 1990, that is, already before the depression, which can be important, as the other two observations are from the depression era. Some people with e.g. management experience may have become unemployed during the depression, but still possess managerial or entrepreneurial human capital.

7.4 Definition of firm birth

In the first phase of the formation of the research data, all new firm codes in 1996 were extracted from the Business Register. The firm code was labelled as being new if the code did not appear in the Business Register in 1995 or 1994. The latter condition was applied in order to separate re-activations of old firms from new firms. In 1996, the total number of firms in the Business Register was 212 914. Of these firm codes, 30 466 were new in a sense that the codes did not appear in 1995 or 1994 in the Business Register.

In total, there were 3 700 141 persons in the FLEED in 1996. When the FLEED was linked to these new firm codes, we found 73 227 persons, who had one of these firm codes as a primary employer in 1996. It was found, however, that only 13527 firms did have persons attached to them, and so there were 16 939 firms without a single individual as a worker or as an entrepreneur.

The FLEED in 1995 was linked to the new firm codes in 1996 in order to find out the origin of the work force of all the new firms. In total, there were 3 692 029 persons in the FLEED in 1995. This exercise revealed that even though all firm codes were new in the Business Register in 1996, there were 12 289 persons with one of the new firm codes already in 1995. This property applied to 5645 firm codes, which were deleted from the data based on the observation that they were not born in 1996. Similarly, there might be firms which appear in the Business Register first time in some year after 1996, but which have the first entries in the FLEED in 1996. These firms should actually be included in the data set, but this was not done in this study. One reason for ignoring these firms is that for the study of growth, firm's size in terms of employment or turnover is needed, but as the firm does not exist in the Business Register in 1996, this piece of information is not available.

After deleting these firms there were 7882 firms with 56 720 persons attached to them left in the data. The discrepancy between the employment figures comes from the fact that also those persons were deleted, who did not have the same firm code in 1995 and 1996, but were attached to one of those firms in 1996 where at least one person did have the same firm code. The total number of employees in each of the old firms existing in 1995 from which the employees moved to the new firms was calculated from the FLEED in 1995. This knowledge in needed in the sorting of new births.

7.5 Demographic method for firm births

Each individual-level observation in the FLEED contains information about the new firm code in 1996 and the old firm code in 1995. Some of the individuals obviously do not have a firm code in 1995, as persons may have been unemployed or outside the labour force.

Firm births are divided to seven categories based on the fraction of personnel shared with old existing firms. Let n_i describe the total number of workers in a firm existing in 1995, and n_j is the total number of workers in a new firm in 1996. The number of workers moving from firm i to a new firm j is given by n_{ij}.

Using the above defined variables and the fractions n_{ij}/n_i and n_{ij}/n_j derived from them, one can define the following demographic events.

1) Genuine birth: $n_{ij}/n_i<=0.6$ and $n_{ij}/n_j<=0.6$ for all i and j, or $n_i=1$ and and $n_{ij}/n_j<=0.6$ for all i and j,
2) Genuine birth with one person: $n_i=/1$ (not equal to one) and $n_{ij}=n_j=1$ for all i and j
3) Spin-off: $n_{ij}/n_i<=0.1$ and $n_{ij}/n_j>0.6$ and $n_j>=2$ for all i and j
4) No staff: $n_j=0$
5) Transfer: $n_{ij}/n_i>0.6$ and $n_{ij}/n_j>0.6$ for all i and j
6) Dispersal: $0.1<n_{ij}/n_i<=0.6$ and $n_{ij}/n_j>0.6$ for all i and j
7) Merger: $n_{ij}/n_i>0.6$ and $n_{ij}/n_j<=0.6$ for all i and j

The first four events are classified as real births and the last three as artificial births. It should be noted that genuine births with one person attached to the firm include all new firms founded by one person except the case where one person moves from one person firm to another, which is classified as a transfer.

Spin-off firms are separated from dispersals and classified as real births, because otherwise all new firms where the founders, or a large fraction of them, are coming from the same firm would be classified as dispersals no matter how large the old firm is. In the above classification of spin-off, the group of people moving from the old firm to the new firm is not allowed to constitute more than 10 per cent of the old firm's work force.

The same new firm can share workers with several old firms, and hence it can have more than one birth classification attached to it. For example, let us consider a new firm in 1996 with 10 employees which shares seven employees with a firm of 10 employees existing in 1995. In addition, there is another firm with three workers in 1995 which gives all three of them to the new firm. The first case attached to a new firm is labelled as a business transfer, and the latter case as a merger. It is reasonable, however, to attach only one birth class to each of the new firms. In the above example the more natural choice is the transfer. The following hierarchical order is applied in the study.

1) Transfer exceeds all other forms of birth
2) Dispersal (can not co-exist with the transfer, exceeds the merger because over 60 per cent of the personnel comes from a single firm)
3) Spin-off (exceeds the merger, and can not co-exist with the dispersal or the transfer)
4) Merger (exceeds the genuine birth)
5) Genuine with one person, mutually exclusive with the genuine birth
6) Genuine birth

7.6 The existence of various birth types

Table 1 illustrates the number of new firms in 1996 in various birth categories and the average size of the firms in terms of employment and turnover. In total there are thus 23 802 real births and 1 019 artificial births. The total number of new firms is hence 24 821. About 95 per cent of the new firms can be classified as real births, and only 5 per cent are artificial births.

Table 1 shows that new firms are very small on average in Finland. The median real new firm has only 0.5 employees, and the arithmetic mean is 1.2 employees. The mean size being bigger than the median size implies that the size distribution is skewed to the right, i.e. there are a lot of small firms and a smaller stock of larger firms. The artificial new firms are much larger. The median firm has around 3 employees and the mean is close to 40 employees. The artificial births have even more skewed distribution than the real births.

Table 1. New firms in 1996 in the Finnish business sector

		Employment		Turnover 1996 EUR	
	Number of firms	Mean Size	Median Size	Mean Size	Median Size
Genuine	1 940	4.9	2.2	1 034 376	126 814
Genuine one	4 798	1.0	0.8	64 011	31 619
No staff	16 939	0.8	0.4	68 387	21 864
Spin-off	125	17.2	4.9	3 324 816	396 924
Real births in total	23 802	1.2	0.5	163 340	26 237
Transfer	674	12.8	1.5	1 658 824	90 485
Dispersal	239	44.7	4.8	13 296 640	393 392
Merger	106	178.0	6.5	54 044 952	289 535
Artificial births in total	1 019	37.5	2.8	9 837 791	151 874
All new firms	24 821	2.7	0.6	560 515	27 415

By looking at various birth types one observes that some new firms which are outcomes of restructuring, especially dispersals and mergers, must be very large, as the average sizes are much bigger than the median sizes of firms. These figures are affected by restructuring in the forest industry in 1996. There are actually a handful of new firms in the data which have thousands of workers.

It is possible to calculate the birth rate in the aggregate economy based on these figures. Defining the birth rate as the number of real births relative to the number of firms in the Business Register during the year yields a birth rate of 11.7 per cent. However, there are 3 466 new firms in the 1996 new firm data which do not survive until 1997. Most of these firms are real births, and only 125 firms are artificial births. Hence, following the Eurostat procedure of excluding these firms from business dynamics data, we are left with 20 336 real births and a birth rate of 9.6 per cent. In Eurostat (2004), enterprise birth rates are provided for Finland from year 1998 onwards. Earlier data is not available, but the birth rate in our calculations is quite close to the birth rate from 1998 in the Eurostat data, which is 8.5 per cent.

7.7 The panel data

The new firms can be followed annually by linking the annual Business Register data between the years 1996 and 2003 to the 24 821 firm new codes of year 1996. This gives 130 196 annual firm observations to the time-series cross-section data, i.e. panel data, which forms the core of the research data.

The focus of the study is in the growth of firms, which is measured with annual employment growth and with annual turnover growth in real terms. Hence, those observations which lack either one of these variables in any observation year, or have zero values, are deleted. This procedure leaves 116 169 observations in the data.

Some industries are excluded from the sample, such as agriculture and fishing (SIC codes A and B), mining and quarrying (C), electricity, gas and water supply (E), public administration and defence, compulsory social security (L), private households employing domestic staff and undifferentiated production activities of households for own use (P), extra-territorial organizations and bodies (Q) and industry unknown (X). After this operation there are 110 068 observations in the sample.

The growth of firms is observed and measured annually. Therefore, firms with missing year observations are excluded from the sample. The number of new firms in the research data is 18 181 and there are 94 389 firm-year observations. For some purposes the survivor panel, i.e. the data set containing only those firms which survive until 2003, will be used. There are 7996 survivor firms in the data. In most of the analyses the focus is in employment growth, but some results concerning turnover growth are also presented.

7.8 The birth type by industry

New firms are grouped to different industries in Table 2a.[10] Manufacturing is further divided into four sub-groups based on the R&D intensity of the industry. The break up follows the OECD (2005) classification, where manufacturing industries are grouped into high-tech, medium high-tech, medium low-tech and low-tech industries, and knowledge-intensive business services are separated from other services.

By inspecting the division of birth types over industries, the first observation is that almost ¾ of the new firms are in the service sector. Only

[10] The number of firms in Tables 2a and 2b is smaller than the total amount of firms in the research data, that is, 18 181 firms, because one-year firms are excluded from the sample due to the fact that it is impossible to calculate any growth measures for them.

about 10 per cent are manufacturing firms and around 15 per cent of the firms are in construction industry. Table 2b reveals that there is surprisingly little variation between the industries in the grouping of births into various birth types. The order of the five most common birth types is the same in all industries.

The fraction of the firms without a single person attached to them varies between 49 % and 64 % and is hence the most common birth type in all industries. The second most common way of birth is a genuine new firm with only one person. The fraction of these firms ranges from 16 % to 36 %. The third most common birth type in all industries is a genuine new firm with more than one person. On average, there firms comprise around 10 % of all new firms, and the fraction varies from 5 % to 13 %.

Another observation, which becomes evident by looking at the data, is that new firms which are outcomes of the restructuring of existing firms, that is, artificial births, are more common in the manufacturing industries, and especially in the high-tech and medium high-tech industries. The number of observations in total is, however, quite limited in these sectors.

Table 2a. *New firms in various industries*

	High-tech	Medium high-tech	Medium low-tech	Low-tech	Const.	Knowledge int.serv.	Oth. pers. services	Trade, hot.&rest. and transp.	Total
Genuine	9	29	57	110	256	257	87	769	1 574
Genuine one	18	48	89	190	520	627	577	1 475	3 544
No staff	38	177	242	633	1 315	1 877	900	3 945	9 127
Spin-off	3	5	3	6	6	30	2	46	101
Transfer	6	20	19	40	67	73	39	284	548
Dispersal	4	11	13	12	29	37	6	90	202
Merger	0	4	6	7	10	16	2	36	81
Total	78	294	429	998	2 203	2 917	1 613	6 645	15 177

Table 2b. *The fraction of birth types in various industries*

	High-tech	Medium high-tech	Medium low-tech	Low-tech	Const.	Knowledge int.serv.	Oth. pers. services	Trade, hot.&rest. and transp.
Genuine	0.12	0.10	0.13	0.11	0.12	0.09	0.05	0.12
Genuine one	0.23	0.16	0.21	0.19	0.24	0.21	0.36	0.22
No staff	0.49	0.60	0.56	0.63	0.60	0.64	0.56	0.59
Spin-off	0.04	0.02	0.01	0.01	0.00	0.01	0.00	0.01
Transfer	0.08	0.07	0.04	0.04	0.03	0.03	0.02	0.04
Dispersal	0.05	0.04	0.03	0.01	0.01	0.01	0.00	0.01
Merger	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.01
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

8 DESCRIPTIVE STATISTICS OF SURVIVAL AND GROWTH

8.1 The survival of new firms

In order to get a broad picture of the performance of new firms, it is important to look at the survival chances of new firms. Growth figures between some time periods can be obtained only for surviving firms, and hence it is important to obtain information about the disappearing firms as well. This study uses one year growth intervals, which is the shortest time span allowed by the data applied. This choice the interval also minimizes the possible survivor bias in the growth estimates, as only a relatively small fraction of firms do not survive to the end of the period.

Table 3. *Survival and the evolution of the average size of the new firms*

	1996	1997	1998	1999	2000	2001	2002	2003
All new firms	18 181	15 177	13 146	11 421	10 306	9 476	8 686	7 996
Average size	3.21	3.92	4.44	4.99	5.32	5.67	5.87	6.25
Survival rate	1.00	0.83	0.72	0.63	0.57	0.52	0.48	0.44
Hazard rate		0.17	0.13	0.13	0.10	0.08	0.08	0.08
Real births	17 305	14 346	12 381	10 723	9 659	8 865	8 119	7 466
Average size	1.31	1.66	2.01	2.29	2.56	2.49	2.66	2.78
Survival rate	1.00	0.83	0.72	0.62	0.56	0.51	0.47	0.43
Hazard rate		0.17	0.14	0.13	0.10	0.08	0.08	0.08
Artificial births	876	831	765	698	647	611	567	530
Average size	40.57	43.05	43.74	46.46	46.63	51.89	51.76	55.11
Survival rate	1.00	0.95	0.87	0.80	0.74	0.70	0.65	0.61
Hazard rate		0.05	0.08	0.09	0.07	0.06	0.07	0.07

Table 3 shows the basic information on new firm growth and survival in the research data. When all new firms are investigated, that is, births are not sorted out to real and artificial ones, one observes that the probability of firm death, i.e. the hazard rate, is relatively high during the early years, but decreases over time. This is a standard result in the literature.[11] After five years around one half of the firms are still in operation.

The average size of the surviving firms increases also over time. This does not yet, however, provide any evidence on the growth of the firms. If there is a selection process, in which small firms are the ones to exit, then the average firm size can increase over time even though individual firms do not.

When the real births are separated from the artificial ones, it becomes evident how differently these two classes of new firms behave. The artificial births are much larger than the real births, and the hazard rates are much lower during the whole observation period. The average size of the surviving firms is also increasing at a slower pace (Table 3). Where only half of the real births survive the first five years, the artificial firms display is surviving rate of 70 per cent. After seven years still around 60 per cent of the artificial firms are up and running (Figure 1a and 1b).

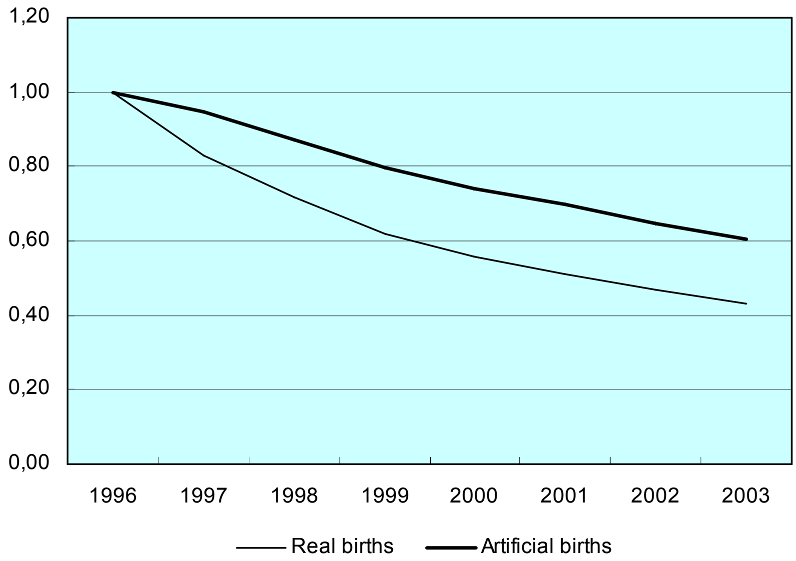

Figure 1a. *The survival of real and artificial births*

[11] See e.g. Mata et al. (1995), Mata and Portugal (2004) and Persson (2004).

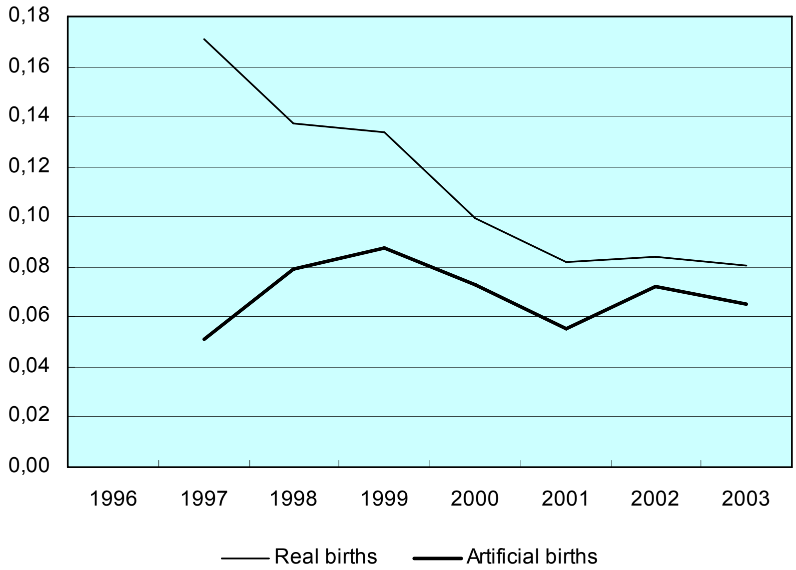

Figure 1b. *The hazard rate for real and artificial births*

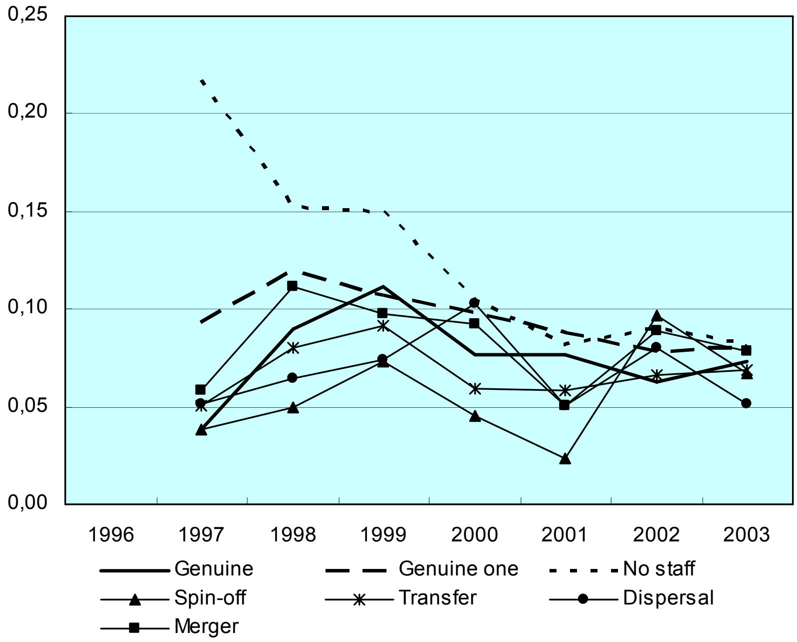

Figure 2. *The hazard rate by birth type*

Based on Figure 1b, one is temped to argue that real new firms phase a very high probability of exit during the early years of their life. This is not, however, the whole story. When real and artificial births are further divided based on the demographic method presented above, it turns out that the high hazard rate of the real births derives solely from no staff class, which dominates other real birth types in numbers (Figure 2). The evolution of the hazard rates of the other real births resembles the shape of the hazard rates of the artificial births, so that the probability of exit first increases and then decreases over time.

The evolution of the average size follows quite a similar pattern in various birth types. All real births display a rather brisk growth in average size, and also the dispersals grow rather rapidly even though the average size of these firms is quite large. Firms established by mergers do show the slowest increase in the average size in relative terms. It should be kept in mind that these figures can be an artefact of the selection process, where smaller firms exit from the markets.

Table 4. *Survival and the evolution of the average size of the new firms by birth type*

	1996	1997	1998	1999	2000	2001	2002	2003
Genuine	1 637	1 574	1 433	1 273	1 175	1 085	1 017	943
Average size	5.10	6.53	7.74	8.77	9.55	8.21	8.43	8.73
Survival rate	1.00	0.96	0.88	0.78	0.72	0.66	0.62	0.58
Hazard rate		0.04	0.09	0.11	0.08	0.08	0.06	0.07
Genuine one	3 910	3 544	3 120	2 785	2 512	2 291	2 112	1 940
Average size	0.99	1.06	1.32	1.44	1.61	1.67	1.71	1.73
Survival rate	1.00	0.91	0.80	0.71	0.64	0.59	0.54	0.50
Hazard rate		0.09	0.12	0.11	0.10	0.09	0.08	0.08
No staff	11 653	9 127	7 732	6 576	5 887	5 406	4 915	4 513
Average size	0.74	0.84	0.99	1.10	1.23	1.31	1.39	1.46
Survival rate	1.00	0.78	0.66	0.56	0.51	0.46	0.42	0.39
Hazard rate		0.22	0.15	0.15	0.10	0.08	0.09	0.08
Spin-off	105	101	96	89	85	83	75	70
Average size	17.75	20.22	21.89	24.10	25.41	27.04	34.77	36.80
Survival rate	1.00	0.96	0.91	0.85	0.81	0.79	0.71	0.67
Hazard rate		0.04	0.05	0.07	0.04	0.02	0.10	0.07
Transfer	577	548	504	458	431	406	379	353
Average size	11.68	13.10	14.17	14.00	14.17	14.89	15.40	15.21
Survival rate	1.00	0.95	0.87	0.79	0.75	0.70	0.66	0.61
Hazard rate		0.05	0.08	0.09	0.06	0.06	0.07	0.07
Dispersal	213	202	189	175	157	149	137	130
Average size	48.89	56.43	58.83	64.52	61.89	79.07	83.59	86.29
Survival rate	1.00	0.95	0.89	0.82	0.74	0.70	0.64	0.61
Hazard rate		0.05	0.06	0.07	0.10	0.05	0.08	0.05
Merger	86	81	72	65	59	56	51	47
Average size	213.75	212.34	211.08	226.54	243.14	247.83	236.39	268.54
Survival rate	1.00	0.94	0.84	0.76	0.69	0.65	0.59	0.55
Hazard rate		0.06	0.11	0.10	0.09	0.05	0.09	0.08

8.2 The growth of new firms

The selection argument can be studied by comparing the evolution of mean size of the surviving firms to all firms. Figures 3a and 3b show that selection is indeed affecting the average size of the firms over time. Both in real and artificial new firm classes the survivors are larger already at birth.

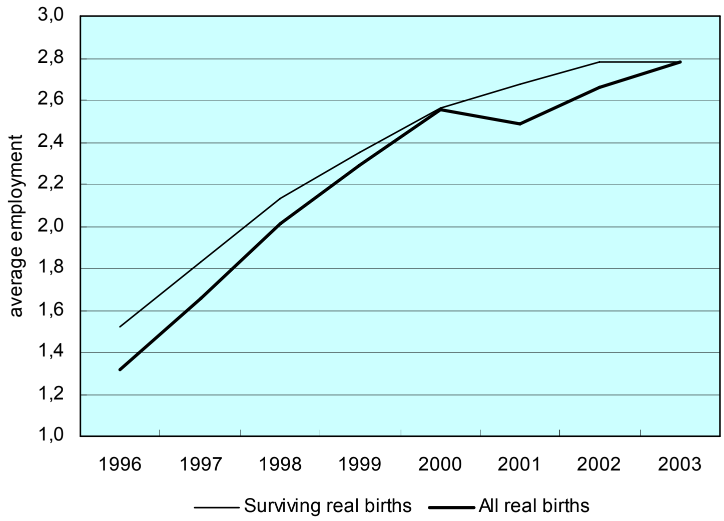

Figure 3a. *The evolution of average size among real births*

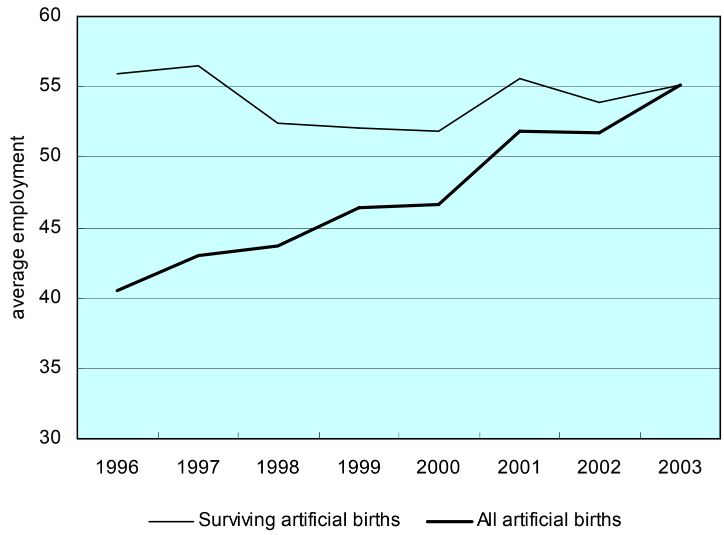

Figure 3b. *The evolution of average size among artificial births*

The difference is not, however, so noticeable in real births as it is in case of artificial ones. In fact, the surviving artificial new firms do not grow at all during the observation period. The real births which survive grow rather rapidly and they on average almost double their size in seven years. It is important to notice that this is univariate analysis, where the characteristics of the firms are not controlled for. In order to assess the effect of birth type on firm growth properly, regression analysis is called for.

Table 5. *The evolution of average size among various birth types*

	1996	1997	1998	1999	2000	2001	2002	2003
Genuine surviving	943	943	943	943	943	943	943	943
Average size	4.21	5.66	6.66	7.46	8.19	8.61	8.71	8.73
Genuine all	1 637	1 574	1 433	1 273	1 175	1 085	1 017	943
Average size	5.10	6.53	7.74	8.77	9.55	8.21	8.43	8.73
Genuine one surviving	1 940	1 940	1 940	1 940	1 940	1 940	1 940	1 940
Average size	1.07	1.19	1.43	1.55	1.72	1.75	1.78	1.73
Genuine one all	3 910	3 544	3 120	2 785	2 512	2 291	2 112	1 940
Average size	0.99	1.06	1.32	1.44	1.61	1.67	1.71	1.73
No staff surviving	4 513	4 513	4 513	4 513	4 513	4 513	4 513	4 513
Average size	0.85	0.93	1.11	1.22	1.35	1.41	1.45	1.46
No staff all	11 653	9 127	7 732	6 576	5 887	5 406	4 915	4 513
Average size	0.74	0.84	0.99	1.10	1.23	1.31	1.39	1.46
Spin-off surviving	70	70	70	70	70	70	70	70
Average size	21.02	25.37	27.08	28.02	28.49	30.12	36.16	36.8
Spin-off all	105	101	96	89	85	83	75	70
Average size	17.75	20.22	21.89	24.1	25.41	27.04	34.77	36.8
Transfer surviving	353	353	353	353	353	353	353	353
Average size	14.78	15.8	16.01	15.65	15.35	15.38	15.28	15.21
Transfer all	577	548	504	458	431	406	379	353
Average size	11.68	13.10	14.17	14.00	14.17	14.89	15.40	15.21
Dispersal surviving	130	130	130	130	130	130	130	130
Average size	58.78	67.82	66.49	67.79	68.19	86.3	85.94	86.29
Dispersal all	213	202	189	175	157	149	137	130
Average size	48.89	56.43	58.83	64.52	61.89	79.07	83.59	86.29
Merger surviving	47	47	47	47	47	47	47	47
Average size	356.98	331.27	287.2	281.83	280.66	272.44	254.82	268.54
Merger all	86	81	72	65	59	56	51	47
Average size	213.75	212.34	211.08	226.54	243.14	247.83	236.39	268.54

When real and artificial births are further divided, it turns out that the evolution of firm size is fairly similar within all real new firms so that surviving firms really grow over time (Table 5). The artificial new firms display more heterogeneous developments. In all three sub-groups the average size of the firms grows, but only in dispersal class the surviving firms do grow as well. That is, in dispersal class, the increase in the average size is mostly due to real growth, whereas in transfer, and in merger class in particular, the observed growth in the average size is due to the selection process where smaller firms disappear. In merger class, the surviving firms actually shrink quite considerably.

8.3 Employment generation

Another way to summarize the survival and the growth of new firms is to look at the employment generation of the whole cohort of new firms. This is done in Table 6, where the first three rows display the total employment first for all firms, and then for real and artificial births. These figures reflect the total employment of the 1996 born firm cohort in each observation year. There are two effects in work. First, the number of firms goes down as the time elapses and so the employment decreases as well. Provided that the existing firms do grow over time, should the negative impact of the exits on the employment generation be moderated or even reversed.

First by looking at all firms, it is revealed that the impact of the exiting firms on employment is so strong that excluding the first year after birth, the total employment declines every year. Three years after the birth the total employment of the 1996 firm cohort is below the start-up year figure, and after seven years the employment has gone down by about 14 per cent. The evolution of total employment is not so gloomy, if only real births are considered. The total employment first rises and falls below the start-up year only after five years.

The opposite effects of firm exits and growth becomes clear when the same analysis is conducted for the firms which survive until the end of the seven year observation period. This is presented in the last three rows in Table 6. The surviving firms do grow on average. The employment in the surviving firms increases over 20 per cent in seven years. The breakdown to real and artificial births is quite revealing. The surviving artificial new firms do not grow at all during the observation period, whereas the real births display a rather rapid growth. The surviving real births increase their employment by over 50 per cent in three years, and over 80 per cent in the first seven years. So, on average, the surviving real new firms do grow quite rapidly.

Table 6. *Employment generation of the new firm cohort of 1996 in the seven year period*

	1996	1997	1998	1999	2000	2001	2002	2003
All new firms	58 286	59 545	58 393	56 983	54 865	53 767	50 974	49 944
Real births	22 749	23 767	24 936	24 553	24 695	22 063	21 628	20 737
Artificial births	35 537	35 778	33 457	32 431	30 170	31 704	29 346	29 207
All surviving firms	40 970	43 605	43 738	45 111	46 617	49 423	49 280	49 944
Surviving real births	11 335	13 641	15 944	17 530	19 142	19 968	20 736	20 737
Surviving artificial births	29 635	29 964	27 794	27 581	27 474	29 455	28 543	29 207

8.4 The growth of survivors

The average growth figures presented above describe the development of the average firm in each birth type. They do not, however, tell anything about the distribution of growth among various birth types. Figure 4 shows the distribution of growth among real new births and artificial new births. These figures are based on the 7996 surviving firms, i.e. firms which stay alive the whole observation period from 1996 until 2003.

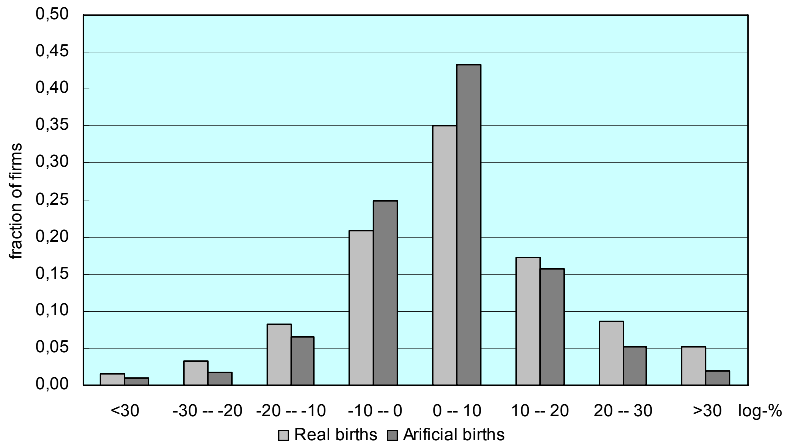

Figure 4. *Distribution of average annual growth rates among real and artificial new firms*

The average annual growth rate in the whole data is 4.6 % in log per cent.[12] The distributions of growth rates are quite symmetric, in particular in case of the real births. The most common growth class is between 0-10 per cent annual growth both in real and artificial new firms. If a firm grows at an annual rate of 10 per cent for seven years, it will double its size. The second largest group in both birth types contains, however, firms which display growth between -10-0 per cent. This implies that a relatively large fraction of new firms do shrink during the first seven years.

Really fast growing firms are more prevalent among the real births. Close to 15 per cent of the real new firms grow over 20 per cent annually, i.e. they almost quadruple their size in seven years. Among the artificial births, only around seven per cent of the firms reach the average growth rate of over 20 per cent.

Inspecting the growth distributions more closely one observes that it is not just the smallest real new firms which are likely to grow fast (Table 7). In addition to the no staff class, the genuine class has also around 15 per cent of high-growth firms with a growth rate over 20 per cent. In genuine one class and in spin-off class the fraction is somewhat smaller. Among the artificial new firms the fraction of high-growth firms lies between 4 and 7 per cent.

Table 7. *Distribution of average annual growth rates among various birth types*

	Genuine	Genuine one	No staff	Spin-off	Transfer	Dispersal	Merger
<30	0.01	0.01	0.02	0.00	0.01	0.02	0.00
-30 -- -20	0.03	0.03	0.04	0.01	0.02	0.02	0.02
-20 -- -10	0.06	0.08	0.09	0.04	0.08	0.04	0.06
-10 -- 0	0.22	0.21	0.21	0.16	0.23	0.31	0.21
0 -- 10	0.34	0.39	0.33	0.49	0.46	0.35	0.45
10 -- 20	0.20	0.18	0.17	0.21	0.13	0.21	0.21
20 -- 30	0.09	0.07	0.09	0.04	0.05	0.05	0.04
>30	0.06	0.03	0.06	0.04	0.02	0.02	0.00

[12] The log per cent is defined as the difference of the log size of the firm. Unlike the standard per cent growth rates, log per cent figures are symmetric so that the average growth rates are not biased.

The above analysis describes the average growth of the firms across time. It thus hides the time pattern of growth at the firm level completely. Table 8 illustrates the evolution growth in the whole seven year period both for real and artificial births. The first observation from table 8 is that growth rates tend to decline over time. For real births growth is strongest in the second year, whereas the artificial firms display the highest growth already during the first year. For both firm types the growth rate declines quite rapidly. It must be kept in mind, however, that during the last years of the observation period growth in the macro economy was relatively weak, which partly explains the modest performance at the firm level as well. The second observation is that the variation of growth rates across firms is highest during the first years of existence, and then it stabilizes at a lower level. This levelling phase takes somewhat longer in case of real births. The third observation is that the variation of growth across firms is greater among real births than among artificial new firms.

Table 8. *The evolution of average growth and the variation of growth over time*

Real births	1997	1998	1999	2000	2001	2002	2003
Mean	0.113	0.166	0.065	0.053	-0.009	-0.006	-0.049
Std dev.	0.727	0.556	0.460	0.420	0.386	0.407	0.443
Min	-3.401	-2.89	-2.565	-3.611	-3.892	-2.862	-3.219
Max	3.638	4.779	3.332	2.526	3.497	3.161	3.332
N	7466	7466	7466	7466	7466	7466	7466

Artificial births	1997	1998	1999	2000	2001	2002	2003
Mean	0.181	0.074	0.016	-0.014	0.003	-0.005	-0.024
Std dev.	0.532	0.373	0.268	0.305	0.288	0.279	0.286
Min	-2.303	-2.996	-1.609	-2.088	-1.956	-2.079	-1.292
Max	3.982	2.251	1.159	1.386	1.273	1.798	2.747
N	530	530	530	530	530	530	530

9 ECONOMETRIC EVIDENCE ON FIRM GROWTH: FIRM-LEVEL CHARACTERISTICS

The descriptive statistics presented in the previous chapters hinted that firm growth is a complex phenomenon, which is probably affected by a host of factors. By just looking at the descriptive figures, one can not isolate the impact of various effects on the growth process. Some firms grow and prosper, while others fail and ultimately die. In order to assess the importance of various factors, we estimate firm growth equations with the panel data, which formation was explained above.

In most analyzes employment will be used as the independent variable. Employment growth is chosen, because the employment generation ability of the firms is at the heart of the public discussion about the proper enterprise and entrepreneurship policy. In addition, the quality of the employment data should be very high, as all the data is in full-time equivalent employment, which captures the changes in employment with precision also in the lower tail of the size distribution.

Some basic formulations will, however, be estimated also with firm turnover as an independent variable. To anticipate the results, it turns out that growth processes of employment and turnover are quite similar at the firm level. Qualitatively the results are almost identical. Those factors which have an effect on employment growth do foster the growth of turnover as well. This is actually quite expected, as the positive correlation between annual employment and turnover growth at the firm level is relatively high, the Pearson correlation coefficient being around 0.60.

9.1 Estimation methods used in the study

The empirical evidence on firm growth is obtained by estimating growth equations with both ordinary least squares (OLS) and with panel data methods which make use of the combined time series cross section feature of the data set. We will apply both the so-called random-effect method and the fixed-effect method.[13] The reason behind the use of the panel data

[13] See e.g. Baltagi (1999) for discussion about various panel data estimation techniques.

techniques is to take the unobserved heterogeneity into account. Provided that the firms do differ in their growth potential, and that these differences can not be explained by the dependent variables, the OLS parameter estimates will be biased.

Most estimations are carried out with a randomly drawn sub-sample of the total research data set, which contains a one fifth of the original data set firms and has 15 015 year observations.[14] The data set was restricted due to computational limitations when using the TSCS procedure of the SAS/ETS estimation package. In some cases it was, however, possible to use the whole research data.

Table 9 illustrates the descriptive statistics of the sample applied in the statistical analyses. All size variables and the age variables are in natural logs, and the dependent variables, that is, employment growth and turnover growth are defined as the first difference of the size variables in logs. The mean of the dummy variables can be used to calculate how large a fraction of the observations does belong to that particular class. For example, the mean of the artificial-dummy tells that around 7 per cent of the observations do belong to this class.

[14] The panel data methods require that there are at least two growth observations for each firm. This implies that only firms which survive until the end of year 1998 are included in the estimations. The research data used in the analyses is a random sample of the 13 146 firms which are still in operation in 1998 (see Table 3).

Table 9. ***Descriptive statistics of the sample used in the analyses***

	N	Mean	Std dev.	Min	Max
Growth, employment	15015	0.024	0.543	-3.807	4.644
Growth, turnover	15015	0.057	0.511	-5.559	4.852
Size, employment	15015	-0.028	1.197	-2.306	7.055
Size, turnover	15015	6.688	1.301	2.294	15.072
Age	15015	1.116	0.648	0.000	1.946
Industry growth, employment	15015	0.035	0.128	-0.835	6.128
Industry growth, turnover	15015	0.072	0.171	-0.819	6.634
Top 5 share, employment	15015	0.194	0.171	0.044	0.970
Top 5 share, turnover	15015	0.254	0.188	0.043	0.982
Median size, employment	15015	0.058	0.405	-1.609	4.550
Median size, turnover	15015	11.240	0.629	9.878	16.071
GDP growth	15015	3.834	1.735	1.000	6.200
Artificial	15015	0.067	0.250	0.000	1.000
Genuine	15015	0.103	0.305	0.000	1.000
Genuine one	15015	0.254	0.435	0.000	1.000
No staff	15015	0.571	0.495	0.000	1.000
Spin-off	15015	0.005	0.070	0.000	1.000
Transfer	15015	0.048	0.213	0.000	1.000
Dispersal	15015	0.014	0.119	0.000	1.000
Merger	15015	0.005	0.073	0.000	1.000
High-tech	15015	0.006	0.074	0.000	1.000
Medium high-tech	15015	0.021	0.145	0.000	1.000
Medium low-tech	15015	0.033	0.179	0.000	1.000
Low-tech	15015	0.068	0.252	0.000	1.000
Construction	15015	0.150	0.357	0.000	1.000
Knowledge services	15015	0.189	0.391	0.000	1.000
Other services	15015	0.113	0.317	0.000	1.000
Knowledge-based	15015	0.216	0.411	0.000	1.000
Limited liability	15015	0.526	0.499	0.000	1.000
Employer	15015	0.013	0.112	0.000	1.000
Self-employed	15015	0.101	0.301	0.000	1.000
Upper management	15015	0.039	0.193	0.000	1.000
Supervisor	15015	0.059	0.236	0.000	1.000
Same industry	15015	0.096	0.297	0.000	1.000
Lower tertiary	15015	0.040	0.195	0.000	1.000
Higher tertiary	15015	0.029	0.169	0.000	1.000
Doctorate	15015	0.001	0.037	0.000	1.000
Technical tertiary	15015	0.011	0.098	0.000	1.000
Business tertiary	15015	0.012	0.105	0.000	1.000
Science tertiary	15015	0.004	0.065	0.000	1.000

9.2 Firm size, age and growth

We will first address the question how firm size and firm age are related to growth. As reviewed in Chapters 3 and 5, the simplest formulations of firm growth have traditionally included only firm size as an explanatory variable in the growth equation. This model is then applied to assess whether Gibrat's law holds or not. If the size of the firm is unrelated to growth, that is, the parameter coefficient estimate of the size variable does not statistically significantly deviate from zero, then the expected growth rate of all the firms is the same. Hence, small firms do not grow any faster or slower than their larger counterparts. If, however, the coefficient is significantly negative, small firms do outperform the large ones. This kind of result obviously could have implications for public policy, e.g. it could be argued that support measures should be targeted to small firms which have more growth potential than larger firms. It should be remembered, however, that as Hart and Oulton (1996) argue "it would be unwise to base any employment policy on the faster average growth of small firms until we establish why the smallest companies enjoyed such rapid growth in the period".

The most parsimonious model estimated from the data is presented in Table 10. Firm growth is measured both in employment growth and in turnover growth, which is deflated with the Consumer Price Index (CPI). Growth is in both cases measures by the difference of the log size of the firm. The independent variables include the size of the firm, the age of the firm, industry growth rate, the share of the largest five firms in the three-digit industry level, the size of the median firm in the industry defined at the three-digit level, and GDP growth rate.

The estimation method is a pooled OLS, which implies that the panel data property of the data is ignored. Even though the focus of the study is in employment growth, some results for turnover growth will also be presented. In turnover growth estimations, the size variable is turnover, and not employment. Likewise, all industry variables used are related to turnover in the turnover growth estimations. E.g. the industry growth variable is the growth of the industry turnover in real terms and not the industry employment growth. To anticipate the results, it turns out that employment and turnover growth processes do not display large differences. This is not surprising after observing that the correlation between employment and

Table 10. *The OLS estimates of employment and turnover growth*

	OLS estimation Employment Growth		OLS estimation Turnover Growth	
Intercept	0.000		0.018	
	0.028		0.076	
Size	-0.089	***	-0.062	***
	0.004		0.004	
Age	-0.029	**	-0.117	***
	0.012		0.012	
Industry growth	0.194	***	0.127	***
	0.036		0.036	
Top 5 share	-0.030		0.015	
	0.027		0.021	
Median size	0.106	***	0.050	***
	0.012		0.007	
GDP growth	0.012	***	0.000	
	0.004		0.004	
N of obs.	15015		15015	
Wald test	119.2	***	144.4	***
R^2	0.046		0.055	

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

turnover growth at the firm level is relatively high; the Pearson correlation coefficient being around 0.60 in the data.

In both growth estimations size and age affect growth negatively and the coefficients are statistically significant at the 5 per cent level. This is obviously consistent with the selection model of Jovanovic (1982) reviewed in Chapter 4. This is also in line with the empirical evidence from both abroad and from earlier Finnish studies reviewed in Chapters 5 and 6.

Industry level variables are also found to have an effect on the growth performance of firms. Industry growth rate measured with employment growth or with turnover growth at the three-digit industry level boosts growth also in case of new firms. The employment or turnover share of the five largest firms at the industry is added to the model in order to capture the impact of concentration of the industry on new firm growth. The expected sign of the coefficient is ambiguous. It may well be so that in an industry which is dominated by a few large firms, there are market niches for smaller firms. Hence, firms are not forced to grow in order to survive, and growth can be slow. The effect of concentration can, however, be of the opposite direction. If the smaller firms in an industry are sub-contractors of the bigger companies, it may well be so that the new firms need to grow rapidly in order to be big enough to get contracts with the large firms. In this regression model, the share of the largest firms turns out to be insignificant.

The third industry variable is the median size of the firms in the industry. This variable is included in the model to capture the impact of size on the efficiency of the production. If the median firm in a certain industry is relatively large, it is assumed that the minimum efficient scale of the production is large as well. Quite often the minimum efficient scale is defined as the mean size of the firms producing a half of the industry turnover. In our case, where the analysis focuses on the new firms, the median size of the firms is assumed to be a better indicator of the required size for efficient production. The median size variable seems to be working as expected, as the coefficient is positive and highly significant in both estimations.

The potential impact of business cycles on the growth performance is captured by the GDP growth variable. In the employment equation, the coefficient of the GDP growth variable is positive and significant, whereas in the turnover equation the coefficient is insignificant.

It seems that there are both firm-specific and industry-specific determinants of firm growth, and that the macroeconomic environment also affects the firm performance. Hence, firm growth is not a purely random process. The explanatory power of the model is, however, quite weak. The coefficient of determination, that is R^2, is only around 0.05. This is not, however, an exceptionally low value in large data sets. Similar results have been obtained e.g. by Heshmati (2001) and Nurmi (2004).

9.3 The impact of firm heterogeneity

The pooled OLS estimates presented above do not take into account the possible firm-specific effects, which are not captured by the independent variables. The OLS estimates are unbiased only if the intercept is the same for all firms. Therefore, in what follows we apply panel data estimation methods, which can yield unbiased estimates of the independent variables in the presence of firm heterogeneity. We apply both the random effects estimator and the fixed effects estimator. The random effects estimator is the more efficient one, but it may give inconsistent estimates. The fixed effect estimator is always consistent, but it is generally not as efficient as the random effects estimator. The fixed effect estimator is also called the least squares dummy variable (LSDV) estimator, as it is an OLS estimation ran with firm dummies.

The fixed effect estimator has its limitations. It can not be applied in a situation where some of the independent variables within the unit of observation, i.e. the firm, are constant over time. This is actually the case in this study e.g. when the role of the firm birth type, previous management experience and education in the firm growth process are investigated. Therefore, in these cases only the random effect estimates will be presented.

In Table 11, the pooled OLS estimates of the employment growth equation in Table 10 are reproduced in order to make the comparison of different estimation methods easier. The second column displays the results of the random effects estimation. The random effects estimates are, however, unbiased only if the firm specific effects are uncorrelated with the independent variables. This can tested by a Hausman test (Hausman, 1978), which tests whether the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator. The Hausman test clearly rejects the null hypothesis that the random effects estimates are the same as the consistent fixed effect estimates. This implies that the fixed effect estimator should be used.

Table 11. *OLS, random effects and fixed effect estimates of employment growth*

	OLS estimation Employment grow th	Random Effects Employment grow th	Fixed Effects Employment grow th
Intercept	0.000	-0.067 **	
	0.028	0.032	
Size	-0.089 ***	-0.505 ***	-0.661 ***
	0.004	0.007	0.008
Age	-0.029 **	-0.003	0.015
	0.012	0.010	0.011
Industry grow th	0.194 ***	0.108 ***	0.086 ***
	0.036	0.032	0.033
Top 5 share	-0.030	-0.174 **	-0.469 ***
	0.027	0.071	0.138
Median size	0.106 ***	0.396 ***	0.385 ***
	0.012	0.025	0.035
GDP grow th	0.012 ***	0.009 **	0.008 **
	0.004	0.004	0.004
N of obs.	15015	15015	15015
N of cross sections		2462	2462
Time series lenght		7	7
Wald test	119.2 ***		
R^2	0.046	0.295	0.479
Hausman test (m value)		1645.4 ***	
F test for no fixed effects			3.92 ***

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

The fixed effect estimates are the consistent ones, and thus they can be used to assess the possible biases in the OLS and random effect estimators. In the third column, the F-test with the null hypothesis of no firm-specific fixed effects is clearly rejected. This further strengthens the case for fixed effects. To sum up, there are firm-specific fixed effects, which are correlated with the independent variables. Hence, both OLS and random effect estimates are inconsistent. Also, the explanatory power of the model improves considerably when fixed effects are included.

Looking at the estimated coefficients, one observes that even though the Hausman test suggests that the random effects estimator is biased, the parameter estimates of the random and fixed effect estimators are quite close to each other in most cases and the same coefficients are statistically significant. On the contrary, the OLS estimates deviate much more from the fixed effect estimates. The random effects estimates may not, after all, be much biased.

When the panel data property of the data set is taken into account, most of the coefficients get larger in absolute terms. The parameter estimate of the size, for example, decreases from around -0.09 to -0.50 in random effects and to -0.66 in fixed effects. Similar results are obtained in Nurmi (2004) in a data set consisting of young plants in the Finnish manufacturing sector between the years 1981-1994, and in Mata (1994) with a data set of new Portuguese manufacturing firms in the years 1983-1987. In Nurmi (2004), the parameter estimate for the size variable decreases from -0.02 to -0.51 when the OLS estimates are compared with the fixed effect estimates. In the Portuguese case the OLS coefficient is -0.02, and random and fixed effect coefficients are -0.08 and -0.57, respectively. Mata (1994) interprets this result to show that the growth potential of larger firms is actually higher than that of the smaller firms. In other words, the firm-specific effect is positively correlated with the size of the firm, so that if all firms were of the same size (which they obviously are not), those firms which are indeed larger would grow faster.

The effect of firm size to growth seems to be quantitatively quite large. Taking the estimates at face value implies that an increase in the size of the firm in terms of employment by 10 per cent would, ceteris baribus, reduce the growth rate by 0.9-6.6 per cent.

10 THE FIRM BIRTH TYPE AND GROWTH

The descriptive statistics presented in Chapter 8 hinted that the performance of the firm is strongly affected by the birth type. Especially, the growth performance of the real and artificial new firms seemed to follow quite different paths. In this chapter, the impact of birth type is studied more closely. First, the data set is split up into two sub-samples, one consisting of the real births and the other consisting of the artificial new firms. This is done in order to find out whether the impact of the independent variables on growth depends on the birth type. After that, the data is divided further into seven sub-samples presenting each birth type defined earlier. In this investigation, we use the original large data of some 13 000 firms for all artificial births and for spin-offs, because the number of observations in the research sample is quite limited in these birth types.

In Table 12, both employment and turnover growth are estimated separately for real and artificial births. The size coefficient is larger in absolute terms for real new firms in both estimations. Small real births thus grow faster relative to large firms than artificial births of the same size.

The age variable is somewhat puzzling, since it indicates that the impact of age is stronger for artificial firms than real new firms both in terms of employment and turnover growth. Following Jovanovic (1982), one would expect, however, that it is the real births, which engage in learning and that the successful new firms would grow fast. Artificial new firms should have much better knowledge about their own efficiency and the market conditions, and therefore their start-up size should be closer to the optimal size and they should not display such a rapid growth. It is also noteworthy that age affects more negatively on the turnover growth than on the employment growth. Industry growth affects significantly only to the real births, and the median size of the firms has a stronger effect on the real births.

Table 12. *OLS estimates of employment and turnover growth by birth type*

	Real births OLS estimation Employment growth	Real births OLS estimation Turnover growth	Artificial births OLS estimation Employment growth	Artificial births OLS estimation Turnover growth
Intercept	-0.023	0.079	0.219 ***	0.050
	0.030	0.081	0.078	0.230
Size	-0.105 ***	-0.073 ***	-0.030 ***	-0.028 ***
	0.005	0.005	0.009	0.009
Age	-0.022 *	-0.111 ***	-0.101 ***	-0.166 ***
	0.013	0.012	0.034	0.042
Industry growth	0.205 ***	0.132 ***	0.136	0.058
	0.038	0.031	0.153	0.201
Top 5 share	-0.042	0.006	-0.043	0.051
	0.028	0.022	0.082	0.085
Median size	0.102 ***	0.050 ***	0.076 ***	0.045 **
	0.014	0.008	0.023	0.021
GDP growth	0.014 ***	0.003	-0.016	-0.035 **
	0.004	0.004	0.011	0.014
N of obs.	14006	14006	1009	1009
Wald test	126.1 ***	145.8 ***	5.3 ***	5.7 ***
R^2	0.051	0.059	0.031	0.033

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

The pooled OLS estimates do not make use of the panel data quality of the data, and they are not consistent in the presence of firm heterogeneity. In Tables 13a and 13b, the employment growth equations for real and artificial births, respectively, are estimated with random effect and fixed effect estimators. It turns out again that the random effect estimates are much closer to the fixed effect estimates that the pooled OLS estimates. Hence, it seems to be possible to rely on the random effect estimates even though the Hausman test clearly rejects the null hypothesis that the firm-specific effects are uncorrelated with the independent variables.

Table 13a. *OLS, random effects and fixed effect estimates of employment growth for real births*

	OLS estimation Employment growth		Random Effects Employment growth		Fixed Effects Employment growth	
Intercept						
	0.030		0.032			
Size	-0.105	***	-0.511	***	-0.665	***
	0.005		0.007		0.008	
Age	-0.022	*	0.005		0.020	*
	0.013		0.011		0.011	
Industry growth	0.205	***	0.123	***	0.091	***
	0.038		0.033		0.034	
Top 5 share	-0.042		-0.217	***	-0.486	***
	0.028		0.070		0.143	
Median size	0.102	***	0.370	***	0.405	***
	0.014		0.026		0.037	
GDP growth	0.014	***	0.010	***	0.009	**
	0.004		0.004		0.004	
N of obs.	14006					
N of cross sections			2462		2462	
Time series lenght			7		7	
Wald test	126.1	***				
R^2	0.051		0.297		0.480	
Hausman test (m value)			1559.9	***		
F test for no fixed effects					3.86	***

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

The coefficient of the size variable for the real births is -0.66 in the consistent fixed effect estimation and -0.51 in the random effect estimation. The corresponding coefficients for the artificial births are -0.55 and -0.40. The difference is thus not very large. The age variable is still puzzling, as the coefficient in case of real new firms turns to positive and is even weakly significant in the fixed effect estimation. When the artificial births are considered, the effect is still negative and significant at the 5 per cent level. Otherwise the results are in line with the OLS estimates. The industry variables have a more pronounced impact on the real new firms, and the most coefficients are larger in absolute terms compared with the OLS results.

Further evidence on the impact of firm birth type on the subsequent performance is provided in Tables 14a and 14b, where all seven previously classified birth types are analyzed separately. Due to low number of observations in the research sample, data on spin-offs, transfers, dispersals and mergers are taken from the total research data of some 13 000 firms.

Table 13b. *OLS, random effects and fixed effect estimates of employment growth for artificial births*

	OLS estimation Employment growth		Random Effects Employment growth		Fixed Effects Employment growth	
Intercept	0.219	***	0.497	***		
	0.078		0.110			
Size	-0.030	***	-0.397	***	-0.555	***
	0.009		0.024		0.029	
Age	-0.101	***	-0.089	***	-0.066	**
	0.034		0.028		0.029	
Industry growth	0.136		-0.101		-0.101	
	0.153		0.136		0.141	
Top 5 share	-0.043		0.453		0.054	
	0.082		0.286		0.486	
Median size	0.076	***	0.296	***	0.184	**
	0.023		0.068		0.086	
GDP growth	-0.016		-0.011		-0.010	
	0.011		0.010		0.010	
N of obs.	1009					
N of cross sections			166			
Time series lenght			7			
Wald test	5.3	***				
R^2	0.031		0.248		0.482	
Hausman test (m value)			97.3	***		
F test for no fixed effects					4.42	***

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Table 14a. *Employment growth estimation for genuine, genuine one, no staff and spin-off classes*

	Genuine Random Effects Employment growth	Fixed Effects Employment growth	Genuine one Random Effects Employment growth	Fixed Effects Employment growth
Intercept	0.436 ***		-0.005	
	0.089		0.054	
Size	-0.409 ***	-0.537 ***	-0.532 ***	-0.673 ***
	0.020	0.023	0.014	0.015
Age	-0.060 **	-0.039	0.020	0.027
	0.029	0.030	0.019	0.020
Industry growth	0.363 ***	0.332 ***	0.182 **	0.161 **
	0.119	0.124	0.075	0.080
Top 5 share	0.068	-0.933 **	-0.421 ***	-1.099 ***
	0.199	0.435	0.116	0.249
Median size	0.218 ***	0.215 **	0.252 ***	0.351 ***
	0.069	0.106	0.044	0.062
GDP growth	0.013	0.012	0.003	0.002
	0.011	0.011	0.007	0.007
N of obs.	1554	1554	3809	3809
N of cross sections	266	266	656	656
Time series lenght	7	7	7	7
R^2	0.284	0.479	0.300	0.475
Hausman test (m value)	143.6 ***		397.9 ***	
F test for no fixed effects		3.75 ***		3.71 ***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

	No staff Random Effects Employment growth	Fixed Effects Employment growth	Spin-off Random Effects Employment growth	Fixed Effects Employment growth
Intercept	-0.303 ***		0.502 ***	
	0.042		0.139	
Size	-0.530 ***	-0.680 ***	-0.275 ***	-0.440 ***
	0.009	0.010	0.030	0.038
Age	0.019	0.025 *	-0.080 *	-0.053
	0.015	0.015	0.041	0.042
Industry growth	0.104 ***	0.058	-0.297	-0.264
	0.039	0.040	0.203	0.218
Top 5 share	-0.181 **	-0.167	0.488 *	-0.160
	0.081	0.190	0.261	0.593
Median size	0.338 ***	0.450 ***	0.134 *	0.056
	0.032	0.051	0.074	0.108
GDP growth	0.013 **	0.011 **	0.001	0.001
	0.005	0.005	0.015	0.015
N of obs.	8570	8570	587	587
N of cross sections	1529	1529	95	95
Time series lenght	7	7	7	7
R^2	0.303	0.484	0.178	0.402
Hausman test (m value)	957.5 ***		51.5 ***	
F test for no fixed effects		3.66 ***		3.16 ***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Table 14b. *Employment growth estimation for transfer, dispersal and merger classes*

	Transfer				Dispersal				Merger			
	Random Effects		Fixed Effects		Random Effects		Fixed Effects		Random Effects		Fixed Effects	
	Emp. growth		Emp. growth		Emp. growth		Emp. growth		Emp. growth		Emp. growth	
Intercept	0.487	***			0.447	***			0.943	***		
	0.066				0.104				0.177			
Size	-0.489	***	-0.648	***	-0.312	***	-0.489	***	-0.333	***	-0.533	***
	0.015		0.017		0.022		0.028		0.040		0.053	
Age	-0.070	***	-0.043	**	-0.074	**	-0.049		-0.148	***	-0.103	**
	0.017		0.017		0.029		0.030		0.044		0.046	
Industry growth	0.242	***	0.241	***	0.139		0.139		-0.133		-0.051	
	0.081		0.084		0.139		0.145		0.200		0.210	
Top 5 share	0.167		-0.420		0.852	***	1.381	***	0.271		-0.022	
	0.177		0.293		0.232		0.403		0.383		0.718	
Median size	0.334	***	0.212	***	0.185	***	0.112		0.211	**	0.055	
	0.048		0.058		0.069		0.098		0.086		0.118	
GDP growth	-0.010	*	-0.009		0.005		0.007		-0.013		-0.011	
	0.006		0.006		0.010		0.011		0.016		0.016	
N of obs.	3028				1119		1119		422		422	
N of cross sections	503				188		188		72		72	
Time series lenght	7				7		7		7		7	
R^2	0.309		0.484		0.192		0.451		0.221		0.453	
Hausman test (m value)	307.1	***			119.0	***			32.4	***		
F test for no fixed effects			4.22	***			3.86	***			3.26	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

The real new firms excluding the spin-offs do share some characteristics (Table 14a). The impact of size is relatively strong in all three classes. Industry growth is a significant factor for genuine and genuine one classes, whereas a large median size boosts growth in all birth types. The concentration of the industry hinders growth in genuine and genuine one classes, but the relationship is weaker in the no staff class. Spin-offs seem to be rather different from the other real births, as only size variable is significant, and displays a lower value relative to the other birth types.

In artificial births, the transfers behave differently from the other two births types, that is, dispersals and mergers. (Table 14b) This is not surprising, as business transfers are much smaller than the other artificial new firms on average. The size variable affects more strongly, as well as industry growth and median size of the firms. Dispersals and mergers display the lowest coefficient values for the size variable among all birth types. For mergers, the industry variables and the GDP growth do not affect growth significantly, but age is negatively related to growth.

To sum up, the performance of the real new firms seem to be much more influenced than the artificial new firms by the external conditions in the industry and in the economy as a whole. The size of the firm has generally a stronger negative effect on growth than in the artificial births. The age of the firm does not, at least during this rather short observation period of 7 years, clearly affect the growth performance. The artificial births, and especially dispersals and mergers, are not much influenced by the external factors. The impact of size on growth is somewhat weaker, but the negative age effect is present. In particular, the new firms formed by mergers do display a clear time pattern, were the growth slows down when the firm ages.

The results indicate that there are differences in the behaviour between various birth types, but in most cases, these differences appear as rather small in estimated coefficients so that the signs of the coefficients are the same between the birth types. Hence, we can quite safely use the combined data and assess the growth differences between the birth types by introducing dummy variables for each type. This is done in Table 15 where the variable "Artificial" gets a value one for all artificial births and the reference group is the real births.

Table 15. *Employment growth estimation for the whole data*

	OLS estimation Emp. growth	Random Effects Emp. growth	OLS estimation Emp. growth	Random Effects Emp. growth
Intercept	-0.009	-0.113 ***	0.153 ***	0.578 ***
	0.028	0.032	0.031	0.053
Size	-0.097 ***	-0.517 ***	-0.126 ***	-0.548 ***
	0.004	0.007	0.005	0.007
Age	-0.028 **	-0.001	-0.023 *	0.005
	0.012	0.010	0.012	0.010
Artificial	0.120 ***	0.694 ***		
	0.015	0.059		
Genuine one			-0.160 ***	-0.639 ***
			0.016	0.053
No staff			-0.211 ***	-0.862 ***
			0.016	0.049
Spin-off			0.212 ***	0.768 ***
			0.044	0.220
Transfer			-0.028	-0.070
			0.019	0.080
Dispersal			0.045	0.267 **
			0.031	0.128
Merger			0.018	0.413 **
			0.060	0.197
Industry growth	0.197 ***	0.109 ***	0.201 ***	0.108 ***
	0.036	0.032	0.036	0.031
Top 5 share	-0.032	-0.181 **	-0.033	-0.185 ***
	0.027	0.071	0.027	0.070
Median size	0.104 ***	0.381 ***	0.101 ***	0.347 ***
	0.012	0.025	0.012	0.025
GDP growth	0.012 ***	0.009 **	0.011 ***	0.009 **
	0.004	0.004	0.004	0.004
N of obs.	15015		15015	
N of cross sections		2686		2686
Time series lenght		7		7
Wald test	108.6 ***		80.8 ***	
R^2	0.048	0.302	0.061	0.318
Hausman test (m value)		1464.6 ***		1017.6 ***

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

The results indicate that the artificial births do grow faster than real new firms. This may seem strange at first sight, since from the descriptive analysis in Figure 3 it became evident that real new firms did indeed display higher relative growth rates than the artificial ones. That result did not, however, take into account that the other characteristics of the firms also differ. Most importantly, the artificial births are much larger than the real births, and as was already pointed out, the size has a negative impact on the growth performance. The correct interpretation of the positive coefficient of the Artificial-dummy is that given the other characteristics, such as the size, the artificial new firms do grow faster than the real new firms.

In the third and the fourth column of Table 15, the reference group is the genuine class. Excluding spin-offs which display the highest coefficient, other real births do grow much slower than genuine class. The smallest ones, which are founded without a single person attached to them in the Employment Statistics, display the largest negative coefficient among real new firms. Mergers and dispersals grow faster than the genuine class, whereas the transfers do not differ significantly from the genuine class.

The quantitative impact of the birth type dummy variables is substantial in many cases. For example, the parameter estimates for the artificial-dummy range from 0.120 to 0.694, which implies that other things equal, the growth rate of an average artificial new firm is 12.0-69.4 percentage points higher than that of a real new firm. The observed differences in the growth rates between different birth types are obviously not as large. As Figure 4 in Chapter 8.4 revealed, the growth distributions, and hence the average growth performance, did not differ much between real and artificial new firms. The explanation lies in the "other things equal" assumption. Artificial firms are much larger than real firms, as displayed e.g. in Table 1 in Chapter 7.6. As the negative impact of the size variable on growth is quite substantial, artificial new firms display stronger growth performance than their size would suggest.

11 MANUFACTURING, CONSTRUCTION AND SERVICE INDUSTRIES

The bulk of the international evidence on determinants of firm growth comes from manufacturing industries. The main reason for this is data availability. Manufacturing industries have been much better represented in commercial data sets, which have been collected by rating agencies, financiers such as banks, etc. The production of official statistics has also been more advanced in the industrial sector than in trade and services. In Finland, the manufacturing sector employs only around one quarter of the total employment in the business sector. Thus, in order to get a full picture of the firm growth in the economy, one should pay attention to the other sectors as well. In particular, from the public policy perspective in which the growth of employment is a primary target, the role of the service sector is essential.

First we assess the growth process in manufacturing, in construction and in services by splitting up the data and estimating the employment growth equations separately for each of them. It has sometimes been argued that services are "different" from manufacturing in a sense that the size of the firm does not matter for growth, or that the minimum efficient scale of production is very small.[15]

The estimation results presented in Table 16 do not give much support to this hypothesis. The size coefficients are indeed quite similar. In fact, it seems more like that the construction industry is different and manufacturing and services display quite similar patterns. The most obvious difference between service and manufacturing sectors is that the concentration of the industry affects negatively to growth in services, whereas in manufacturing the impact is positive, but statistically insignificant. In the service sector there seems to be market niches even though a few large firms dominate the markets. It could be argued that in the manufacturing the concentration forces small firms to grow to be able to act as sub-contractors to the large companies. This did not, however, come clearly out of the data in case of manufacturing. On the contrary, there is some evidence on the role concentration in the construction sector. In the sub-sectors dominated by a few large firms do also the new firms grow rapidly. The coefficient is large but only weakly significant in the fixed effect

[15] See e.g. Audretsch et al. (2004).

estimation. The coefficient of age is also significant in construction, and quite interestingly, the sign of the effect is positive.

Table 16. *Employment growth estimation for manufacturing, construction and services*

	Manufacturing		Construction		Services	
	Random Effects	Fixed Effects	Random Effects	Fixed Effects	Random Effects	Fixed Effects
	Emp. Growth	Emp Growth	Emp. Growth	Emp Growth	Emp. Growth	Emp Growth
Intercept	-0.194 *		-0.358 ***		-0.065 *	
	0.116		0.125		0.036	
Size	-0.558 ***	-0.697 ***	-0.503 ***	-0.679 ***	-0.497 ***	-0.650 ***
	0.018	0.020	0.018	0.022	0.008	0.009
Age	-0.001	0.008	0.084 ***	0.118 ***	-0.014	0.001
	0.029	0.029	0.032	0.034	0.012	0.012
Industry growth	0.207 ***	0.152 *	0.606 **	0.514 *	0.081 **	0.081 **
	0.080	0.082	0.285	0.298	0.035	0.036
Top 5 share	0.103	0.113	1.494 ***	1.821 *	-0.219 ***	-0.738 ***
	0.192	0.291	0.546	0.950	0.084	0.159
Median size	0.417 ***	0.340 ***	0.471 ***	0.387 ***	0.397 ***	0.404 ***
	0.058	0.083	0.120	0.140	0.030	0.041
GDP growth	0.003	-0.003	0.022 **	0.023 **	0.009 **	0.008 *
	0.010	0.011	0.010	0.011	0.004	0.004
N of obs.	1921	1921	2249	2249	10845	10845
N of cross sections	337	337	392	392	1899	1899
Time series lenght	7	7	7	7	7	7
R^2	0.359	0.527	0.274	0.448	0.291	0.478
Hausman test (m value)	208.8 ***		243.7 ***		1180.8 ***	
F test for no fixed effects		4.78 ***		3.29 ***		3.9 ***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

12. TECHNOLOGY AND KNOWLEDGE, LEGAL FORM AND REAL BIRTHS

The descriptive analysis and the preliminary econometrical evidence in the previous chapters included all new firms. Now, we drop the artificial ones and concentrate on the real births. In this chapter, we look more carefully at the different kind of industries and birth types in order to better understand what kind of firms seem to be performing well. In addition, the role of the legal form of the firm is assessed.

12.1 Industry effects

A special attention is paid to the technology and knowledge intensive sectors. It is evident that all sectors exploit new technology and knowledge to some extent, but some sectors are more intensive in either producing or in using new knowledge.

The manufacturing sector will be divided into four sub-sectors based on the R&D intensity of the two or three digit level industry. The classification is based on the OECD classification, in which the industries are divided into high-technology, medium-high-technology, medium-low-technology and low-technology based on their R&D expenditures divided by production and R&D expenditures divided by value added (OECD, 2005).

The service sector is also divided into three groups in order to separate knowledge intensive services from other services. The knowledge services are based on the OECD classification and include post and telecommunications, finance and insurance and business services excluding real estate activities (OECD, 2005). The class "other services" include other private services such as hairdressing, laundry services, recreational services, etc. and education and health services. The last two could well be added to the knowledge intensive services, but they are often excluded from the analysis altogether, because a large faction of the production is produced by the public sector. The reference group in the estimation is retail and wholesale trade, hotels and restaurants and transportation.

Later in Chapter 14, where the role of education is investigated, the data is divided into two sub-samples. The first contains technology and knowledge-based industries, which consist of high-technology and medium-high-technology manufacturing and knowledge-intensive services, and the second contains all other industries.

The first and the second column of Table 17 present random effects estimates of the role of birth type and industry separately. The reference groups are the genuine class and the trade and transportation class, respectively. The fixed effect estimates are not presented, because that method can not be applied when there are time invariant independent variables in the equation to be estimated. The OLS results will also be omitted, but it should be noted that the pooled OLS results are qualitatively very similar to the random effect results. Also, earlier analysis in Chapter 9 hinted that even though the Hausman test seems to reject the independence of firm-specific effects from the independent variables, the parameter estimates are quite close to the consistent estimates.

In the third column, the birth type and industry is analyzed together. The reference group is now a genuine new firm in the trade, hotels and transportation sector. The birth type story remains unchanged so that firms which started with zero or one person grow slower, and spin-offs grow significantly faster than firms in the genuine class. All the manufacturing sector dummies have insignificant coefficient estimates, but knowledge services and other personal services do seem to grow faster than the trade sector firms.

Table 17. *Employment growth estimation for real births: industry and birth type effects*

	Random Effects Emp. growth		Random Effects Emp. growth		Random Effects Emp. growth	
Intercept	0.574	***	-0.186	***	0.497	***
	0.051		0.036		0.053	
Size	-0.547	***	-0.513	***	-0.550	***
	0.007		0.007		0.007	
Age	0.012		0.004		0.012	
	0.011		0.011		0.011	
Genuine one	-0.640	***			-0.645	***
	0.050				0.050	
No staff	-0.863	***			-0.869	***
	0.046				0.047	
Spin-off	0.768	***			0.771	***
	0.206				0.206	
High-tech			0.060		0.022	
			0.189		0.186	
Med. high-tech			-0.025		0.012	
			0.105		0.104	
Med. low-tech			-0.006		0.067	
			0.081		0.080	
Low-tech			-0.050		-0.035	
			0.060		0.059	
Construction			0.182	***	0.185	***
			0.042		0.041	
Knowledge services			0.097	**	0.134	***
			0.038		0.038	
Other Services			0.133	***	0.152	***
			0.047		0.046	
Industry growth	0.122	***	0.112	***	0.110	***
	0.032		0.033		0.032	
Top 5 share	-0.216	***	-0.148	*	-0.157	**
	0.069		0.076		0.075	
Median size	0.329	***	0.387	***	0.344	***
	0.026		0.027		0.026	
GDP growth	0.010	***	0.010	***	0.010	***
	0.004		0.004		0.004	
N of obs.	14006		14006		14006	
N of cross sections	2462		2462		2462	
Time series lenght	7		7		7	
R^2	0.316		0.298		0.318	
Hausman test (m value)	1050.3	***	1528.1	***	1015.9	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

12.2 Legal form of the firm

The legal form of the new firm may affect the subsequent growth performance, because the choice of the legal form may reflect the entrepreneur's perceptions of the riskiness of the project. Limited liability firms can pursue riskier projects with high returns in case of success, whereas unlimited liability firm's operations may be constrained by the entrepreneur's fear of losing all or a considerable part of one's wealth in case of failure. Limited liability firms may also have a better access to financial and other resources.

Table 18 reveals that indeed limited liability firms display higher growth rates even when the birth type is controlled for. Quantitatively, the impact is substantial, as on average the growth rate of limited liability firms is over 25 percentage points higher than that of other legal forms. This finding is in line with Harhoff et al. (1998), were limited liability firms were also found to grow rapidly with a German data. The higher growth rate of limited liability firms does not come about because e.g. larger new firms with rapid average growth, such as genuine class firms, are more often limited liability firms.

A priori one could also argue that limited liability firms may grow slower than others, since firms may start as unlimited liability firms, but later change their legal status to limited liability, e.g. when the ownership base is widened. This kind of new firms are not really new, and thus they may already have past the rapid growth phase. On the other hand, new owners may have been taken in because the firm has plans to expand its operations, and the growth performance of such new firms may be strong. These problems do not arise in our data, as such new firms are labelled as artificial and hence they do not show up in the data used in Table 18.

__Table 18.__ Legal form of the firm and employment growth

	Random Effects Emp. growth		Random Effects Emp. growth	
Intercept	0.5738	***	0.37535	***
	0.051		0.0531	
Size	-0.5474	***	-0.55035	***
	0.00704		0.00706	
Age	0.01215		0.01169	
	0.0106		0.0106	
Genuine one	-0.64022	***	-0.53552	***
	0.0498		0.0491	
No staff	-0.86278	***	-0.80821	***
	0.0464		0.0451	
Spin-off	0.76827	***	0.75794	***
	0.2057		0.1987	
Limited liability			0.26587	***
			0.0257	
Industry growth	0.12185	***	0.12253	***
	0.0321		0.0321	
Top 5 share	-0.21627	***	-0.20466	***
	0.069		0.0672	
Median size	0.32925	***	0.31699	***
	0.0255		0.0251	
GDP growth	0.01005	***	0.01001	***
	0.00384		0.00384	
N of obs.	14006		14006	
N of cross sections	2462		2462	
Time series lenght	7		7	
R^2	0.3161		0.317	
Hausman test (m value)	1050.25	***	1036.8	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

13 MANAGEMENT EXPERIENCE AND GROWTH

In addition to a business idea, the start-up of a new firm usually requires time, financial resources, courage and a lot of effort from the entrepreneur or from the whole founding team, which may comprise of the entrepreneur and paid workers as well. After the initial start-up phase, the possible growth of the firm involves new challenges to the management. It is not self-evident that the skills needed in the birth process are the same which are needed in the growth process. The management of an expanding firm need to pay attention to human resource management, to new organizational arrangements suitable for larger scale of production etc.

In this chapter, we investigate the impact of entrepreneurship specific human capital, i.e. previous management or leadership experience of the founding team on the subsequent growth performance of the new firm. The information on previous management experience is obtained from the FLEED, where each individual's occupation and socio-economic status is reported in the years 1990, 1993 and 1995. We utilize this information by introducing dummies for the experience as an employer, self-employed, upper management and as a supervisor. These classes of work experience are intended to capture such skills which could be assumed to be important for managing a growing firm. Former employers have already run a company with employees. Self-employed have experience of running a business, and have therefore experience of setting up and doing business. The downside of former self-employment experience may be that these people can be accustomed to work alone, and do not even aspire for growth. Upper management experience, such as the managing director, chief financial officer, or human resource manager experience, could be assumed to be very important in the growth phase. Supervisor experience as a general leadership experience can also be important in the growth process.

Each experience dummy gets a value of one provided that at least one person of the founding team possesses such experience in any observation year, i.e. in 1990, 1993 or 1995. Obviously, the data on leadership experience can be obtained only if the matching of the firm-level data with FLEED yielded a positive number of employees, i.e. firms in no staff class have all the management experience dummies set to zero by definition.

Previous leadership experience can be found in a relatively large fraction of the new firms. In particular, at least one founder with former self-employment experience is found in one fourth of the new firms of which data on personnel is available. Experience as an employer is found only in 3 per cent of the firms, but close to 10 per cent of the firms possess upper management experience and almost 15 per cent of the firms have at least one person with supervisory experience.

In addition to management experience, we look at the importance of immediate industry experience on the growth. The same industry dummy gets a value one if at least one member of the founding team comes to the new firm directly from a plant which has the same three-digit industry code in 1995 as the new firm in 1996. The plant is chosen to the observation unit instead of the firm, since it is assumed to better describe of industry where the founding team member was employed. In large multi-plant firms the industry codes of plants and the firm may differ.

We apply the same methodology as in the previous chapter by first presenting the estimation results without controlling the birth type (column 2) and then with birth types (column 3). The reference group consists of all other occupation backgrounds and unknown occupation.

By inspecting the second column of Table 19 one is attempted to conclude that all kinds of management and leadership experience contribute positively to firm growth. Upper management and employer experience display the highest coefficients, and both supervisor and self-employment coefficients are positive and highly significant.

However, the picture changes considerably when the birth type is controlled for. All coefficients become smaller, and only upper management and supervisor coefficients remain statistically significant. This can be interpreted as reflecting the fact that people with management experience are more likely to start spin-offs and genuine class firms, which display higher growth rates than the other birth types. It is also noteworthy, that previous upper management experience, and not e.g. self-employment experience, is found to be important for a firm's success. Likewise, the immediate industry experience, which can be seen as an alternative way to classify spin-offs, is found to be positively related to growth.

By inspecting the third column in Table 19 one obtains that the growth rate of the firms where the founding team possesses upper management experience is about 37 percentage points higher than in firms where no-one has any management of entrepreneur experience. Immediate industry experience in turn adds some 13 percentage points to the growth rate of the firm.

Table 19. *Management experience and employment growth*

	Random Effects		Random Effects		Random Effects	
	Emp. growth		Emp. growth		Emp. growth	
Intercept	0.574	***	-0.205	***	0.467	***
	0.051		0.033		0.061	
Size	-0.547	***	-0.533	***	-0.550	***
	0.007		0.007		0.007	
Age	0.012		0.009		0.013	
	0.011		0.011		0.011	
Genuine one	-0.640	***			-0.565	***
	0.050				0.054	
No staff	-0.863	***			-0.753	***
	0.046				0.057	
Spin-off	0.768	***			0.570	***
	0.206				0.210	
Employer			0.404	***	0.188	
			0.143		0.143	
Self-employed			0.256	***	-0.022	
			0.049		0.054	
Upper management			0.633	***	0.373	***
			0.090		0.092	
Supervisor			0.347	***	0.119	*
			0.071		0.072	
Same industry			0.429	***	0.130	**
			0.056		0.061	
Industry growth	0.122	***	0.124	***	0.123	***
	0.032		0.032		0.032	
Top 5 share	-0.216	***	-0.238	***	-0.238	***
	0.069		0.070		0.069	
Median size	0.329	***	0.357	***	0.328	***
	0.026		0.026		0.026	
GDP growth	0.010	***	0.010	***	0.010	***
	0.004		0.004		0.004	
N of obs.	14006		14006		14006	
N of cross sections	2462		2462		2462	
Time series lenght	7		7		7	
R^2	0.316		0.308		0.318	
Hausman test (m value)	1050.3	***	1248.1	***	1016.6	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

14. EDUCATION AND GROWTH

This chapter investigates the role of the general human capital of the founding team on the firm performance. We introduce three education dummies into the growth equation: lower tertiary education, higher tertiary education, and doctorate, which includes the licenciate degrees as well. The other lower education and unknown education act as the reference group. As in the management experience case, the data on education can be obtained only if the matching of the firm-level data with FLEED yielded a positive number of employees, i.e. firms in no staff class have all the education dummies set to zero by definition.

Highly educated personnel may be better suited to manage the growth of the firm. In particular, in the technology and knowledge-based industries highly educated founding team of the firm may have an advantage in producing new knowledge and utilizing the existing knowledge. Therefore, the impact of tertiary education should be more pronounced in those industries.

Higher education is not a particularly common feature among the founding teams of new firms. In around 9 per cent of the firms at least one of the founding team possesses a lower tertiary degree, and a higher tertiary degree is found in 7 per cent of the new firms. At least one doctorate or a licenciate degree is in less than 1 per cent of the firms.

We also look at the composition of tertiary education by separating technical and science graduates and business administration graduates from other university graduates. This enables us to assess the relative importance various educational fields on firm performance. It may be so that technical education is important in the technology intensive manufacturing, whereas the impact of business administration skills may be particularly valuable at the service sector.

In Table 20, the second column reports the estimation results for firm growth when the education variables are included. It is found that both lower and higher tertiary education do affect firm growth positively and are statistically highly significant. The doctorate dummy has a coefficient estimate which is of the same size, but is not significant.

When the birth type is controlled for in the third column, the lower and higher tertiary education dummies are still significant, but the parameter estimates are much smaller. The doctorate dummy is of the same size as before, but is still insignificant. The quantitative impact of tertiary education is marked. Lower tertiary education adds little less than 20 percentage points to the growth rate of the firm, and higher tertiary education over 25 percentage points relative to firms with no tertiary education.

Somewhat different results are obtained when the industries of the new firms are controlled for in Table 21. Lower and higher tertiary education display significant positive coefficient, whereas the doctorate dummy is insignificant. But, the size of the coefficients is unchanged.

Table 20. *Education, birth type and employment growth.*

	Random Effects Emp. growth		Random Effects Emp. growth		Random Effects Emp. growth	
Intercept	0.574	***	-0.143	***	0.489	***
	0.051		0.032		0.056	
Size	-0.547	***	-0.520	***	-0.549	***
	0.007		0.007		0.007	
Age	0.012		0.006		0.012	
	0.011		0.011		0.011	
Genuine one	-0.640	***			-0.589	***
	0.050				0.052	
No staff	-0.863	***			-0.778	***
	0.046				0.051	
Spin-off	0.768	***			0.538	**
	0.206				0.213	
Lower tertiary			0.602	***	0.185	**
			0.088		0.091	
Higher tertiary			0.564	***	0.265	***
			0.098		0.099	
Doctorate			0.573		0.579	
			0.480		0.475	
Industry growth	0.122	***	0.124	***	0.123	***
	0.032		0.033		0.032	
Top 5 share	-0.216	***	-0.237	***	-0.220	***
	0.069		0.070		0.069	
Median size	0.329	***	0.366	***	0.329	***
	0.026		0.026		0.026	
GDP growth	0.010	***	0.010	***	0.010	***
	0.004		0.004		0.004	
N of obs.	14006		14006		14006	
N of cross sections	2462		2462		2462	
Time series lenght	7		7		7	
R^2	0.316		0.302		0.317	
Hausman test (m value)	1050.3	***	1425.6	***	1026.8	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Table 21. *Education, industry and employment growth*

	Random Effects Emp. grow th		Random Effects Emp. grow th		Random Effects Emp. grow th	
Intercept	-0.143	***	-0.186	***	-0.200	***
	0.032		0.036		0.036	
Size	-0.520	***	-0.513	***	-0.522	***
	0.007		0.007		0.007	
Age	0.006		0.004		0.006	
	0.011		0.011		0.011	
Low er tertiary	0.602	***			0.614	***
	0.088				0.088	
Higher tertiary	0.564	***			0.562	***
	0.098				0.099	
Doctorate	0.573				0.522	
	0.480				0.480	
High-tech			0.060		0.052	
			0.189		0.188	
Med. high-tech			-0.025		-0.064	
			0.105		0.105	
Med. low -tech			-0.006		0.001	
			0.081		0.081	
Low -tech			-0.050		-0.041	
			0.060		0.059	
Construction			0.182	***	0.191	***
			0.042		0.042	
Know ledge services			0.097	**	0.036	
			0.038		0.038	
Other services			0.133	***	0.111	**
			0.047		0.047	
Industry grow th	0.124	***	0.112	***	0.115	***
	0.033		0.033		0.033	
Top 5 share	-0.237	***	-0.148	*	-0.171	**
	0.070		0.076		0.076	
Median size	0.366	***	0.387	***	0.380	***
	0.026		0.027		0.026	
GDP grow th	0.010	***	0.010	***	0.010	***
	0.004		0.004		0.004	
N of obs.	14006		14006		14006	
N of cross sections	2462		2462		2462	
Time series lenght	7		7		7	
R^2	0.302		0.298		0.303	
Hausman test (m value)	1425.6	***	1528.1	***	1397.0	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

We investigate further the interaction of tertiary education and technology and knowledge-based industries. We do this by estimating the growth equation with education variables separately for knowledge-based industries and for other industries. The number of persons with doctorate degrees is very limited in the data set. Therefore we utilize the larger data set and form a sub-sample of the knowledge-based industries in order to get more observations with doctorate degrees.

Quite interestingly, the impact of tertiary education is very different in the knowledge-based industries than in other industries. By comparing the first and the second columns in Table 22, it becomes evident that especially the doctorate education is important in the knowledge-based sectors, but not in the other industries. The sizes of the coefficients of lower tertiary, higher tertiary and doctorate education are in the opposite order in the two industry clusters. In the knowledge-based sectors, higher tertiary education has a higher coefficient than lower tertiary education, and doctorate education has even larger coefficient. In addition, all parameter estimates are highly significant. For other sectors, the order is the other way around, and doctorate education has an insignificant coefficient.

The impact of industry concentration on new firm growth seems to be very different in the knowledge-based sectors than in other sectors. The effect is clearly positive in the knowledge-based sectors, but negative in the other sectors. This may be explained by the importance of firm networks in the knowledge-based industries. In order to participate in the cooperation with the large firms e.g. as a sub-contractor, the firm needs to attain a certain size relatively fast.

To gain some insight on the role of the composition of the tertiary education on firm growth, we introduce three more education dummies to the previous growth equation: technical, science and business administration dummies, which get the value one when at least one member of the founding team has either higher tertiary or doctorate degree in the above mentioned fields. The purpose of this exercise is to assess whether all kinds of tertiary education is equally important or not, and to detect whether the impact of these three fields are similar in knowledge-based and in other sectors of the economy.

Table 22. *Education and employment growth in the knowledge-based industries*

	Knowledge-based industries Random Effects Emp. growth		Other industries Random Effects Emp. growth	
Intercept	-0.151	***	-0.134	***
	0.035		0.037	
Size	-0.520	***	-0.520	***
	0.007		0.008	
Age	-0.022	**	0.016	
	0.012		0.012	
Lower tertiary	0.482	***	0.687	***
	0.065		0.130	
Higher tertiary	0.523	***	0.547	***
	0.061		0.152	
Doctorate	0.723	***	0.289	
	0.197		0.670	
Industry growth	0.050		0.188	***
	0.031		0.047	
Top 5 share	0.264	***	-0.332	***
	0.072		0.082	
Median size	0.451	***	0.348	***
	0.036		0.029	
GDP growth	0.003		0.010	**
	0.004		0.004	
N of obs.	13510		10934	
N of cross sections	2413		1923	
Time series lenght	7		7	
R^2	0.299		0.300	
Hausman test (m value)	1193.4	***	1162.6	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Studying the column 2 in Table 23 reveals that in the other than knowledge-based sectors, it is the business administration education, which matters the most for firm growth. Both higher tertiary and doctorate dummies turn insignificant, and the doctorate coefficient even becomes negative. The story is quite different for knowledge-based industries. All technical, science and business administration education have positive and significant coefficients, whereas the higher tertiary dummy turns insignificant. The doctorate dummy also shrinks in size, but remains weakly significant. These results suggest that in the knowledge-based industries, both technical and business oriented tertiary education matter for firm performance, but in the other sectors only business administration education boosts new firm growth. The role left for other kinds university degrees is more limited in both industry clusters.

Table 23. *Composition of tertiary education and employment growth*

	Knowledge-based industries Random Effects Emp. growth		Other industries Random Effects Emp. growth	
Intercept	-0.149	***	-0.133	***
	0.035		0.037	
Size	-0.522	***	-0.520	***
	0.007		0.008	
Age	-0.022	*	0.016	
	0.012		0.012	
Lower tertiary	0.445	***	0.601	***
	0.065		0.135	
Higher tertiary	0.135		0.280	
	0.109		0.191	
Doctorate	0.409	*	-0.509	
	0.211		0.755	
Technical tertiary	0.472	***	0.224	
	0.131		0.396	
Business tertiary	0.408	***	0.796	**
	0.129		0.346	
Science tertiary	0.412	**	0.309	
	0.176		0.697	
Industry growth	0.050		0.186	***
	0.031		0.047	
Top 5 share	0.260	***	-0.332	***
	0.072		0.082	
Median size	0.449	***	0.346	***
	0.036		0.029	
GDP growth	0.003		0.010	**
	0.004		0.004	
N of obs.	13510		10934	
N of cross sections	2413		1923	
Time series lenght	7		7	
R^2	0.300		0.300	
Hausman test (m value)	1169.7	***	1155.4	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

15 INNOVATION ACTIVITY AND GROWTH

At the public policy discussion, innovations are often linked with high-growth firms. As reviewed in Chapter 5.5, there is some evidence that innovations at the industry level boost firm growth, and that R&D expenditure at the firm level also foster growth.

We utilize the innovation survey conducted by the Statistics Finland in 1999, which covers the years 1996-1998. The time period in question suits very well for our purposes, since the survey years are the first three years of our new firm data set. The innovation survey is similar to the Community Innovation Surveys (CIS), which have been carried out by the European Union for four times up till now. This survey was conducted between the CIS II (1994-1996) and CIS III (1998-2000).

There are pros and cons in using the innovation surveys as the data source for firm level innovation. On the positive side is the fact that they give direct information on the innovation output. Other measures of innovation activity, such as R&D expenditure measure actually the inputs of innovation process, but tell nothing about the output. Patent data can also be utilized, but patents are more like intermediate inputs than innovation output. In addition, many innovations get never patented. This is the case especially in process innovations.[16] The survey data applied contains also information about the type of the innovation, that is, whether it is a product or a process innovation. The problem with the innovation survey data is that they contain only subjective data on the existence of innovations. The perceptions of the respondents about innovations may vary between individuals and industries.

The data set used in this chapter is different from the data applied in other chapters. The innovation survey data with around 3 000 firms is combined with the large research data set of around 13 000 new firms, instead of the sub-sample applied earlier. This results in a rather small data set of 104 firms and 648 observations. Of these firms, 72 announced in the survey that they had either product of process innovations.

Three interrelated measures of innovation activity at the firm level are applied. The first measure is an innovation dummy, which gets a value one if

[16] See Audretsch (2003) for discussion about the problems with various innovation indicators.

the firm has reported either product of process innovations in the innovation survey, and a value zero otherwise. These new firms have thus innovated at some point of time during the first three years of their existence. The two other measures focus on the product innovations and the process innovations separately. It may well be so that these two kinds of innovations do have different impacts on the performance of the firm.

Table 24 presents the results of the basic formulation studied in earlier chapters augmented with the innovation activity dummy variable. The size coefficients in the OLS estimation are somewhat smaller in absolute terms than in the larger research data used previously. The age variable has, however, much stronger negative effect on growth. What is notable is that the innovation activity displays negative coefficients both in employment and in turnover growth estimations. The effect is statistically significant only in the turnover growth estimation.

Table 24. *Innovation activity and employment and turnover growth*

	OLS estimation Emp. growth	OLS estimation Turnover growth
Intercept	0.482 ***	0.413
	0.174	0.319
Size	-0.042 **	-0.071 ***
	0.017	0.019
Age	-0.235 ***	-0.404 ***
	0.068	0.070
Innovation activity	-0.048	-0.134 **
	0.054	0.057
Industry growth	0.076	0.127 ***
	0.132	0.049
Top 5 share	-0.155	-0.260 **
	0.120	0.117
Median size	0.029	0.096 ***
	0.033	0.031
GDP growth	0.012	-0.026
	0.022	0.024
N of obs.	648	648
Wald test	10.51 ***	17.49 ***
R^2	0.103	0.161

Heteroskedasticity robust (White, 1980) standard errors below the parameter estimates
Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

When the employment growth equation is estimated with random effect estimator in the column 1 of Table 25, the age variable becomes insignificant. The parameter estimate of the innovation activity variable increases in size, and becomes weakly significant. The columns 2 and 3 present estimation results in a case where the innovation activity is split up to product and process innovations. It seems that product innovations do have a negative impact on growth, but that process innovations do not affect growth adversely.

If we include only the knowledge-based industries in the investigation, the results remain unchanged. The size of the sample shrinks further, so that there are less than 450 observations and 71 firms, of which 50 announces to be innovative (see Table 26).

In the above analysis, the birth type and the industry of the firms were not controlled for. In the second column of Table 27, we examine the impact of total innovation activity when the birth type is controlled for. The innovation activity coefficient turns insignificant, but remains negative. Different birth types display a similar pattern as in the larger research data. Genuine firms with one or zero persons grow much slower than larger real new firms. The spin-offs have the highest parameter coefficient, but it is statistically insignificant. In column 3, the industry of the firm is controlled for. Innovation activity coefficient is still significantly negative. Two manufacturing industries, medium-high-technology and low-technology industries stand out from the other sectors as having higher firm growth. This result is different from the larger research data, where construction and service industries had faster growth.

All in all, innovations do not seem to foster growth at the firm level in this study. We experimented also with other innovation data sets, as well as with a data set including R&D expenditures by combining these with our research data of new firms born in 1996. The CIS III data set, which covers the years 1998-2000 and the R&D-panel covering the years 1985-2003 compiled in the Research Laboratory of Statistics Finland were utilized, but the outcome of these exercises were in line with the reported ones. Innovations and innovation input measured with R&D expenditure had statistically insignificant impact on firm growth, and most of the coefficients were actually negative.[17]

[17] These results are omitted.

Table 25. *Product and process innovations and employment growth*

	Random Effects Emp. growth		Random Effects Emp. growth		Random Effects Emp. growth	
Intercept	0.997	***	1.034	***	0.778	***
	0.252		0.243		0.214	
Size	-0.397	***	-0.400	***	-0.391	***
	0.029		0.029		0.029	
Age	-0.066		-0.064		-0.068	
	0.057		0.057		0.057	
Innovation activity	-0.353	*				
	0.200					
Product innovation			-0.427	**		
			0.194			
Process innovation					-0.125	
					0.189	
Industry growth	0.133		0.136		0.130	
	0.148		0.148		0.148	
Top 5 share	-0.239		-0.232		-0.190	
	0.329		0.328		0.328	
Median size	0.080		0.076		0.080	
	0.075		0.075		0.076	
GDP growth	0.012		0.013		0.013	
	0.019		0.019		0.020	
N of obs.	648		648		648	
N of cross sections	104		104		104	
Time series lenght	7		7		7	
R^2	0.312		0.314		0.309	
Hausman test (m value)	55.31	***	53.24	***	58.66	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Table 26. *Product and process innovations and employment growth in the knowledge-based industries*

	Random Effects Emp. growth		Random Effects Emp. growth		Random Effects Emp. growth	
Intercept	0.908	***	0.960	***	0.674	***
	0.277		0.276		0.233	
Size	-0.379	***	-0.383	***	-0.372	***
	0.034		0.034		0.033	
Age	-0.014		-0.013		-0.016	
	0.063		0.063		0.063	
Innovation activity	-0.344					
	0.212					
Product innovation			-0.409			
			0.211	**		
Process innovation					-0.109	
					0.202	
Industry growth	0.122		0.126		0.119	
	0.144		0.144		0.144	
Top 5 share	-0.536		-0.552		-0.473	
	0.346		0.346		0.345	
Median size	0.159		0.150		0.156	
	0.107		0.107		0.108	
GDP growth	0.032		0.032		0.032	
	0.022		0.021		0.022	
N of obs.	438		438		438	
N of cross sections	71		71		71	
Time series lenght	7		7		7	
R^2	0.329		0.330		0.325	
Hausman test (m value)	35.59	***	34.19	***	38.55	***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

Table 27. *Innovation activity, industry effects and employment growth*

	Random Effects Emp. growth	Random Effects Emp. growth	Random Effects Emp. growth
Intercept	0.997 ***	1.425 ***	0.646 *
	0.252	0.285	0.361
Size	-0.397 ***	-0.437 ***	-0.415 ***
	0.029	0.030	0.030
Age	-0.066	-0.050	-0.060
	0.057	0.056	0.057
Innovation activity	-0.353 *	-0.149	-0.369 **
	0.200	0.205	0.204
Genuine one		-0.738 ***	
		0.277	
No staff		-0.888 ***	
		0.236	
Spin-off		0.253	
		0.305	
High-tech			0.390
			0.454
Med. high-tech			1.002 **
			0.427
Med. low-tech			0.600
			0.517
Low-tech			0.950 **
			0.409
Construction			0.046
			0.720
Knowledge services			0.384
			0.324
Other services			0.411
			0.611
Industry growth	0.133	0.146	0.158
	0.148	0.146	0.148
Top 5 share	-0.239	-0.419	-0.497
	0.329	0.328	0.366
Median size	0.080	0.070	0.048
	0.075	0.075	0.077
GDP growth	0.012	0.012	0.013
	0.019	0.019	0.019
N of obs.	648	648	648
N of cross sections	104	104	104
Time series lenght	7	7	7
R^2	0.312	0.335	0.322
Hausman test (m value)	55.31 ***	31.44 ***	45.83 ***

Statistically significant at the 1 (***), 5 (**) and 10 (*) per cent level

16 CONCLUDING REMARKS

The performance of firms is affected by numerous factors. As Hart and Oulton (1996) have stressed, there is obviously a large stochastic factor: storms and floods, earthquakes, wars, terrorism, change of government, stock exchange bubbles, health scares and a multitude of other random effects will influence a firm's growth. These stochastic shocks will outweigh the systematic forces in so many cases that the resulting growth process may seem to be largely random. This research has attempted to assess the existence and impact of several systemic factors, which can be thought to affect growth. The results of the study suggest that firm growth is not a purely random process, but that there are indeed determinants, which affect the growth process of the firm and are statistically and economically significant.

The study identified both firm and industry level determinants, which according to econometric analyses conducted, do affect the performance of the firm. First of all, the size of the firm does matter for growth. Small firms grow faster than their larger counterparts. The birth type of the firm has an impact on growth as well. Being an artificial new firm, which is founded as a result of a restructuring of some existing firms, actually boost growth, when the size of the firms is controlled for. If the birth types are further split up into finer classes, it turns out that the real new firms, which have a larger founding team grow faster than smaller firms, which are founded by just one entrepreneur, or without a single entrepreneur or worker. The so-called spin-off firms also perform well. Limited liability firms outperform the other legal forms.

Quite expectedly, the growth of the industry boosts growth also for the new firms. The service sector does not seem to be "different" from manufacturing and construction industries in terms of the size effect on growth, as argued e.g. by Audretsch et al. (2004). The median size of the firms at the industry, which is used as a proxy for a minimum efficient scale of production, affects positively on new firm growth in all three main business sectors. There are, however, interesting differences on the impact of concentration on new firm performance. Namely, in the service sector the share of the 5 largest firms affects growth negatively, whereas in construction the impact is positive and in manufacturing concentration does not matter for growth. When the data is grouped based on knowledge intensity, it turns out that in knowledge-based industries, which include knowledge intensive business services, the impact of concentration is positive. The impact of industry level characteristics on new firm growth thus seems to depend on the nature of the industry, e.g. the prevalence of firm networks and sub-contacting varies from industry to industry.

The human capital of the entrepreneur, or of the founding team, is found affect the performance of the firm during the early years of its existence. Both previous leadership or management experience and tertiary education have a positive and statistically significant effect on the growth process. Tertiary education is not found to have a more pronounced effect in the knowledge-intensive industries, but there is some evidence, that the composition of education matters. The results suggest that in the knowledge-based industries, both technical and business oriented higher tertiary education matter for firm performance, but in the other sectors only business administration education boosts new firm growth.

It was also studied, how innovations affect growth at the firm level. Subjective innovation survey data was used a measure of innovation activity. It turned out that innovative firms no not display higher growth rates than other firms. In fact, the subsequent growth performance is weaker among the firms which announce to be innovative during the first years of their existence. It is also tested, whether product and process innovations have different effects on the subsequent growth. Somewhat surprisingly, it is the product innovators, and not process innovators, which growth slower than others in terms of employment. Hence, innovations do not seem to foster growth at the firm level in this study.

Innovation surveys provide direct evidence on the output of the innovation activities. New firms are of very small size, and linking the research data and the innovation surveys conducted by Statistics Finland revealed that young firms were not well represented in the surveys. The rapid growth of a firm can, however, be interpreted as a measure of its innovation output. Fast-growing new firms which are able to take over market share from incumbent firms have most likely succeeded in creating new ways to produce goods and services more efficiently than before. This interpretation of the results of this study suggests that, irrespective of the industry, founders with relevant work experience in the same industry, and founders with leadership experience and good educational background are most likely to create dynamic and innovative new firms. The results apply to a large population of firms and are hence representative of the whole population of Finnish business firms.

All in all, the results of the study seem to suggest that high education and management experience contribute to the growth of new firms, but a few caveats are called for. The results of the econometric analyses can be interpreted also as strengthening the perception that new firm growth is a process which displays a rather high level of variation among firms. In addition, the econometrical models do not capture the growth process very well, and most of the variation is not explained by the model variables. Even tough there are interesting interactions e.g. between the education of the founding team and firm growth, as well as between the previous management experience and growth, it must be remembered, that the fit of the models do not change much when these variables are introduced.

By highlighting the large variance of performance among new firms, and the quite limited understanding of the possible sources of this variance, this piece of research can be interpreted to warn against policies, which attempt to "pick the winners" at the early stage of the birth and growth processes of firms. As long as the public sector does not have any information advantage over the private agents on the success probabilities of individual firms, there is a high risk that narrowly targeted support measures are not allocated in an efficient way. Hence, it seems reasonable to focus on such policies which provide stability and support the development of business condition equally for all firms, including the new ones. Such policies, or "framework conditions", have been advocated e.g. Schreyer (2000) in case of high-growth firms and Brandt (2004) in the case of new firm births. Schreyer (2000) depicts nicely the idea of framework conditions by stating that "…what follows for policy is the importance of supporting the functioning of the search process, through appropriate institutional, legal and administrative framework conditions. If specific action is taken in support of firms, it should be to help them to find out about the viability of their goods and services but not to help them with the goods and services themselves. Policies with "framework" character are of fundamental importance – their main focus lies in fostering the working of markets and in removing unnecessary obstacles to the creation, expansion, development and exit of firms."

Brandt (2004) discusses about the framework conditions, which enhance the experimentation and search processes for new firms. Product and labour market regulation may constitute direct or indirect barriers to the entry of new firms. Aghion and Howitt (2005) also argue that the competition policy in Europe has been focused too much on the competition between incumbent firms, but neglected the competition effect coming through entry of new firms. Excessively stringent bankruptcy laws which prevent from taking second changes after a failed business venture, or employment protection regulation, which make it very costly for firms to exit the market of reduce their size when the operations turn out not to be profitable, should also be avoided. Barriers to exit can become also barriers to entry, and barriers to growth as well. A well functioning education system also contributes to the development of favourable business conditions by providing high-skilled labour and managerial and entrepreneurial skills for firms. All in all, flexible and transparent institutions supporting market entry and growth of new firms and exit of failed firms are of vital importance for innovative and well functioning business sector, and hence for the economic growth and the prosperity of the society.

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