UNIVERSITY OF SUSSEX

SPRU - SCIENCE AND TECHNOLOGY POLICY RESEARCH

INDUSTRIAL DYNAMICS AND TECHNOLOGICAL STRUCTURE OF THE PAPER AND PULP INDUSTRY

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DECLARATION

I HEREBY DECLARE THAT THIS THESIS HAS NOT BEEN AND WILL NOT BE, SUBMITTED IN WHOLE OR IN PART TO ANOTHER UNIVERSITY FOR THE AWARD OF ANY OTHER DEGREE.

ALFONSO CRUZ NOVOA

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To Claudia

... y una mañana fresca se apareció,
no se anunció, serena, no hizo promesas,
sencillamente llegó y se quedó.
Pablo Milanés

Alfonso Cruz Novoa
Santiago, Septiembre 2011

UNIVERSITY OF SUSSEX

Alfonso Cruz Novoa - Doctor of Philosophy

THESIS TITLE

Industrial Dynamics and Technological Structure of the Paper and Pulp Industry

SUMMARY

This thesis investigates the existence and form of association between the technological structure of one of the most highly capital-intensive industries in the world, the paper and pulp (p&p) industry, and its dynamic behaviour in terms of market growth and development. Industrial structure issues are particularly relevant in highly capital-intensive sectors because they reflect the influence of economies of scale and changing patterns of entry and exit.

The thesis draws upon two related bodies of literature: the dynamics of industrial structure, and heterogeneity within industry. It uses a quantitative hypothesis-deductive method and two panel databases. The first of these databases identifies key characteristics of the world's 150 largest p&p firms during the period 1978-2000, accounting for two-thirds of world output. The second dataset contains annual production capacity for the entire population of US p&p companies during the period 1970-2000. The US is the largest producer and consumer of p&p, accounting for one-third of world output.

The main findings are as follows. Firstly, we demonstrate that p&p firms' growth is not a 'random walk' process, a generalization referred to in the literature as Gibrat's law. Nor is there a linear relation between growth and size distribution or between time and growth rates. We find that size, technology and time matter. Secondly, we demonstrate that this departure from Gibrat's law is due to the existence of three distinctive technological configurations or strategic groups of firms: 'Large & Diversified', 'Medium & Specialized', and 'Small & Very Specialized', which show persistently heterogeneous growth performance. In contrast with the findings in most of the recent empirical literature that shows smaller firms growing faster within the industry size distribution, the medium & specialized p&p companies show systematically the highest rates of growth. Thirdly, patterns of p&p firm survival and technological adoption behaviour over the last three decades are identified and related to the principal technological advances during the period, i.e. the very rapid increase in paper machine operating speed.

The research contributes to the literature by providing robust new empirical evidence of the persistence over time of an intra-industry technological structure that systematically influences the heterogeneous performance of firms with different technological configurations and whose origins are linked to firms' growth processes (industrial dynamics) in the p&p industry.

ABBREVIATIONS

AF&PA	American Forest and Paper Association
ANOVA	Analysis of Variance
Btu	British Thermal Unit. (British energy unit equivalent to 252.2 calories)
corr	corrugated medium
CPBIS	Center for Paper Business and Industry Studies
ctfs	coated freesheet paper
ctgw	coated grownwood paper
EU	Europe
FAO	Food and Agriculture Organization
FPL	Forest Products Laboratory
FPL-UW	Forest Products Laboratory-University of Wisconsin
G-7	Group of seven industrialized nations of the world (U.S., France, Germany, Italy, Japan, United Kingdom, Canada)
GDP	Gross Domestic Product
gp	graphic paper
grms/m2	Grams per square meter
HHI	Herfindahl-Hirschman Index
IO	Industrial organisation
JV	Joint Venture
kg	Kilogram
kraft	kraft paper
L	Large
liner	liner board
M&A	Mergers & Acquisitions
NAFB	North American Fact Book
N.Am.	North America
m.	million
mp	market pulp
mppb	market pulp + paper + board
n	number
n/i	no information
news	newsprint
nm	number of mills
OLS	ordinary least squares
P&B	Paper & Board
PP&B	Pulp, Paper & Board
PPI	Pulp & Paper International Magazine
PPNAFB	Paper & Pulp North American Fact Book
R&D	Research & Development
RBV	Resource based view
recb	recycled board
ROCE	Return on capital employed
ROI	Return on capital invested
S	Small
sbb	solid bleach board

SE	:	Standard Error
SIC	:	Standard Industrial Classification
SPPR	:	Scandinavian Paper and Pulp Report
special	:	specialty papers
st.dev.	:	standard devistion
th.	:	thousand
tissue	:	tissue paper
tonnes	:	metric tonnes
ucfs	:	uncoated freesheet paper
ucgw	:	uncoated grownwood paper
US	:	United States
US$	:	United States dollar
USDA	:	United States Department of Agriculture
USEPA	:	United States Environmental Protection Agency
VL	:	Very Large
VS	:	Very Small
v/s	:	versus
W	:	World
# obs.	:	number of observation

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CHAPTER 1

INTRODUCTION

This introductory chapter is organized in three sections. Section 1.1 provides the background to the investigation and discusses the research problem. Section 1.2 explains the research approach, the methodologies and data used to investigate the three research questions posed in Chapter 3. Section 1.3 provides a brief outline of the thesis chapters.

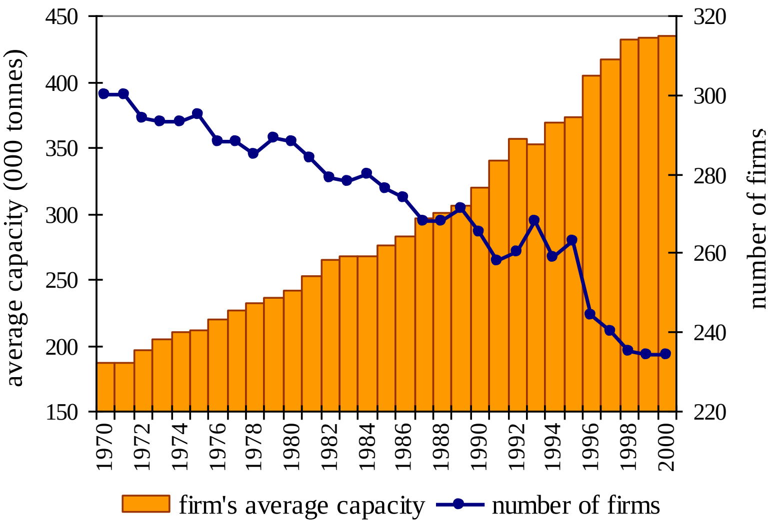
1.1 Background and research problem

The research problem is concerned with the existence and form of association between the technological structure of one of the most highly capital-intensive industries in the world, i.e. paper and pulp (p&p), and its dynamic behaviour in terms of market growth and development. Industry structure is particularly relevant in studies of highly capital-intensive sectors due to the features they exhibit, such as strong economies of scale.

The large-scale production from high capital-intensive industries is considered by numerous industrial organization scholars as an important entry barrier to new firms (Eaton and Lipsey 1979; Lieberman 1987). Some have argued that companies invest in excess capacity with the specific purpose of creating entry barriers (Wenders 1971; Spence 1977; Spulber 1981) and as a consequence we would expect less firm mobility in these types of sectors. However, Dosi et al. (1997) argue that both entry and exit rates are important forces that shape the dynamics of even high capital intensive sectors.

The p&p industry has for long been considered to be a ‘mature’, ‘homogenous’ and rather ‘static’ sector and perhaps because of this, has proved less interesting for the investigation of issues related to changes in industrial structure or the role of technology in influencing these changes. However there are several reasons why the p&p industry should be considered appropriate for an investigation of the dynamics of industrial structure and the forces behind it. Firstly, it is one of the most capital-intensive sectors in the world. In the US average annual investment in the p&p industry is US$16,000 per employee, four times the average for all industry (Carrere and Lohmann 1996). Secondly, since the early 1980s the global p&p industry has exhibited an interesting dynamism that has changed its structural composition (Zavatta 1993; Wait 1994; Diesen 1998). It has undergone a major transformation that has changed its size distribution and increased its concentration at the global level. While in 1978 the top 20 firms produced 25% of total output, in 2000, this had risen to almost 40%. In the US, the largest p&p producer and consumer in the world, the number of firms has decreased from 300 in 1970 to 234 in 2000, while average production capacity has increased from 187,000 to 434,000 tonnes (see Figure 1.1).[1]

Figure 1.1 Number of firms and average capacity in the US p&p industry

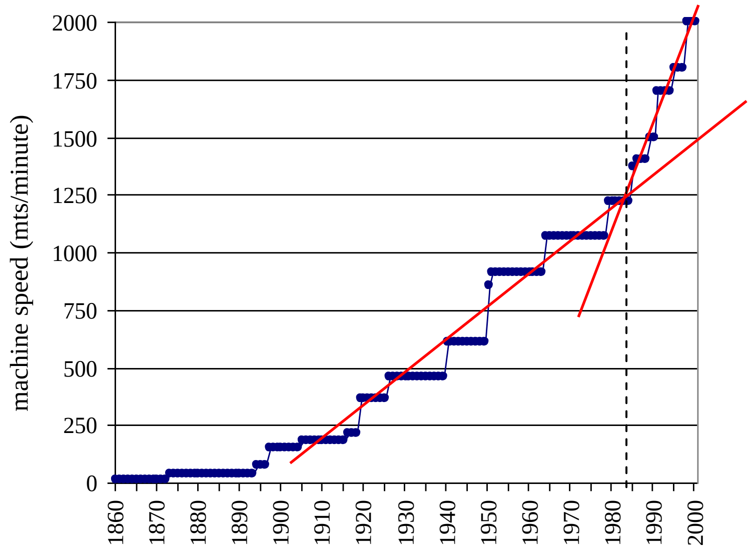


Thirdly, the industry exhibits very significant differences in the size of firms, which vary from small single product firms with 2,000 tonnes/year capacity, to very large and diversified firms with annual production capacity of 12 million tonnes/year (6,000 times larger than the smallest firm). Industrial dynamics type questions are interesting in this sort of industrial context where important and systematic heterogeneity in firm size

[1] Total US p&p industry capacity has also almost doubled from 60 m. to 105 m. tonnes during the period 1970-2000 (see Chapter 2).

persists over time. Fourthly, since the mid 1980s the p&p industry has experienced significant technological advances which might have affected its structure and dynamics. One of its most important technological features is the operating speed of the p&p machines (Mardon, Vyse et al. 1991; Davy 1997; Haunreiter 1997). Figure 1.2 depicts the world technology frontier.

Figure 1.2 Paper machine operation speed technology frontier, 1860-2000



Note: This curve corresponds to newsprint and printing & writing papers technology classes
Source: Own elaboration from Michael van Dijk DPhil Thesis data (Dijk 2005)

The curve in Figure 1.2 shows a sort of exponential increase in p&p machine speeds with a possible inflection point in the mid 1980s,[2] influenced strongly by the introduction of automatic process control. These technological changes allowed important increases in production scale and productivity,[3] but at considerably higher costs. It could be argued that the rapid technological changes that occurred in paper machines since the mid 1980s have driven at least part of the p&p industry dynamics observed during this period. This argument would support the hypothesis of the significant effects of technological progress on industry structure (Brock 1981; Kamien and Schwartz 1982; Abernathy, Clark et al. 1983; Baldwin and Scott 1987) and reject the assumption made by classical industrial organization authors who downplay this effect (Mason 1939; Bain 1968).

[2] There was also an inflection point around 1910.
[3] E.g. the increased speed and breadth of state-of-the-art newsprint machines increased the scale of production from 75,000 to more than 350,000 tonnes per year in the period 1960-2000 (Haunreiter 1997).

In the context of the dynamism and technological changes in the capital intensive p&p industry, we would expect patterns to emerge in relation to the growth, entry and exit of the firms investigated in this thesis. On the other hand, the dynamics of p&p industry structure have been somewhat overlooked by academic analysis.[4] This is surprising considering the relevance of concentration in high capital-intensive sectors. However, it is precisely this lack of research interest that enables us to test several hypotheses relating to capital intensive industries that should increase our understanding, essential for an appreciation of modern industrial activity since an increasing number of industries are becoming capital intensive (Clark 1923).

1.2 Research approach, methods and data

The empirical investigation in this thesis is based on a panel of firm, industry and country level data drawn from two databases. The first contains information on the key characteristics of 150 largest world p&p firms during the period 1978-2000. At the global level, there are more than 1,000 p&p companies located in about 100 different countries across all five continents. Because of the fragmented and regional nature of the industry, the 150 largest firms, which account for two-thirds of world output, are an appropriate representation of the global industry.

The second dataset contains data on the annual production capacity of the entire population of US p&p companies for the period 1970-2000, including capacity data for the 13 principal p&p technological classes. The US is by far the largest producer and consumer of pulp, paper and board, accounting for approximately one-third of world production and consumption.

To answer the three research questions formulated and explained in Chapter 3, the thesis uses a quantitative hypothesis-deductive approach and specific statistical and econometric tools. For the investigation of Gibrat's law or the 'random-walk' hypothesis (first research question), a dynamic econometric model is applied that takes

[4] I made an extensive and detailed search of the research on this industry on the central topic of this thesis (see Chapter. 3). I can confirm that there has been little academic research on the dynamics of industry structure in the p&p sector or the role of technology in influencing these dynamics.

account of the several econometric problems often present in dynamic analysis such as serial correlation, heteroskedasticity, sample selection bias and non-linearity. To respond to the second research question that demonstrated that random-walk does not apply due to the existence of technological configurations of firms, a cluster analysis is used in order to group and test the different clusters of firms and their specific technological characteristics and persistent heterogeneous performance.

To analyse the third research question, which involves patterns of firms survival and technology adoption, ‘transition matrixes’ are constructed that show firms’ entry, exit and movements in terms of their sizes, within a specific period of time. Thus, we can identify how many firms have entered and exited and whether the size of the incumbent firms has changed or stayed the same during each period analysed. To study the patterns and determinants of firms’ survival, a general hazard model that allows for different explanatory variables to vary within the study period is applied. The ‘hazard function’ is a statistical technique determining the conditional probability that a firm exits the industry in time t, given that it was subject to the risk of exit during the past time t. Both a semi-parametric model (the Cox Proportional Hazard) and a parametric distribution (Weibull) are used to model the data.

In the absence of direct data on the acquisition of new machinery, we created a threshold variable at the level of the firm’s technology class, per decade, in order to identify the lumpy annual capacity changes. The firms that adopted new capital equipment tend to have very high relative annual capacity growth in the specific technology class; thus, this constitute an appropriate index of adoption and is used as an instrumental variable for analysing patterns of technology adoption.

1.3 Outline of the thesis

The thesis is organized in eight chapters. After this ‘Introduction’, Chapter 2 ‘Industry Context’ provides a general understanding of the main characteristics of the p&p industry and its technological and economical evolution since the 1970s at both global level and US levels. Chapter 3 ‘Research Questions and Literature Review,’ reviews the most relevant research on the p&p industry and the remaining gaps; introduces the three research questions; and reviews the three bodies of literature most closely related to the research questions: the dynamics of firm growth, the nature of firm technological configurations (heterogeneity within industries, strategic groups), and firms' technology adoption decisions. Chapter 4 'The Data,' describes the data and data sources used in this study, and the variables employed in the analysis.

Chapter 5 'Firm Growth and Firm Size Distribution within the Paper and Pulp Industry,' presents the research addressing the first research question. It describes in depth the statistical methods used to conduct a robust analysis of the dynamic growth process of p&p firms during the period 1970-2000 considering the specific econometric problems that affect dynamics analyses of this type. The chapter discusses the limitations of the stochastic approach (Gibrat's law) which has been widely used to model the growth process in firms. It presents the empirical finding associated with p&p firms and discusses the main conclusions.

Chapter 6 'Technological Configuration of the Paper and Pulp Industry,' focuses on the second research question. It investigates the technological configuration (strategic groups) of p&p firms within the industry and presents a comparative analysis of the growth-rate performance among strategic groups. It presents the quantitative method used for this purpose, the analysis and main results.

Chapter 7 'The Effects of Technology Advances on Paper and Pulp Industry Dynamics' focuses on the third research question. It studies the patterns and determinants of p&p firm survivals (and its complement, patterns and determinants of p&p firms that exit the industry) on the one hand and patterns of technology adoption behaviour on the other. This chapter contributes to the industrial dynamics empirical literature by providing evidence of the existence of survival and technology adoption patterns in one of the world's most capital intensive industries from year 1970 to 2000 when the p&p industry had important structural changes.

Chapter 8 'Conclusions' summarizes the research problem, the aims and the background to the thesis. The main findings are presented along with their theoretical and empirical implications. The contribution of this thesis to the literature is described. The limitations of this investigation are discussed and directions for future investigation in the field are suggested.

CHAPTER 2

INDUSTRY CONTEXT

This chapter provides an overview of the main features of the global and US p&p industries during the periods 1978-2000 and 1970-2000 respectively. Within this industrial context, it highlights questions related to their dynamics and technological structure which are worthy of investigation for three reasons. First, in spite of its mature, homogenous and rather static image, the industry has shown a dynamism that is not common for sectors based on natural resources that uses capital and energy intensive processes (Zavatta 1993; Wait 1994; Diesen 1998). After the mid 1980s the industry experienced a major transformation (Ghosal and Nair-Reichert 2007), which changed its global structural composition and increased its global concentration. While in 1978 the top 20 firms accounted for 25% of total output, in 2000, this rose to almost 40%, which is a significant increase considering the fragmented characteristics of the industry.

Second, since the mid 1980s the industry has made significant technological advances such as the acceleration of paper machines operation speed (see Figure 1.2). The strategic responses of firms to these technological opportunities have been diverse and have produced diverse outcomes such as wide variations in growth-rates over time. Third, there is a significant variability in firm size even among the world's 150 largest companies. The size of the largest firm in year 2000 in terms of p&p sales is 192 times the size of the bottom 150 firms and 164 times in terms of their total p&p output. The availability of a range of structural and performance panel data from the world's largest p&p firms over 23 years and the entire population of US p&p companies over 30 years allows us to test different hypotheses proposed by the dynamics of industrial structure literature.

At world level, there are over a thousand p&p companies located in more than a hundred different countries across the world. Because of the fragmented and regional nature of the industry, we choose to concentrate on the largest 150 firms, which account for two-thirds of world output. At country level, the US is by far the largest producer and consumer of pulp, paper and board, accounting for approximately one-third of world production and consumption. We study the population of US p&p companies since this allows investigation of the entire firm size distribution, including medium and small size companies, and its dynamics.

The chapter is organized in four sections. Section 2.1 describes the p&p making process, including a review of historical developments and the main technologies involved. Sections 2.2 and 2.3 summarize the basic features of the global and US p&p industries, provide descriptive analyses of their structure and dynamics, and raise some interesting questions related to industrial dynamics and technological structure literatures. Section 2.4 summarizes and concludes the chapter.

2.1 The pulp and paper making process

2.1.1 Historical Development

The Chinese invented the first paper making process in the first century AD, and the practice extended to other Asian countries in succeeding centuries. The process was unknown in the western hemisphere until the 12th century when it was introduced in Europe. During the next seven centuries paper was produced, sheet by sheet, through a hand operated process using different recycled fibrous raw materials such as rags, rope, fishnets (Georgia-Tech 2006). This slow and expensive process and the scarcity of the raw materials limited the growth and diversification of the industry output until in the 19th century Nicholas-Louis Robert, a Frenchman, came up with the idea of mechanizing the hand made paper production process. Robert worked as an inspector in the Essonnes paper mill, a French paper company employing manual methods which was owned by Leger Didot. In 1798 Robert created a prototype of the first paper machine able to produce a continuous sheet of paper and on 18 January 1799 it was patented (Haunreiter 1997).

The patent rights were sold to Leger Didot who took this paper machine design to England and with financial support from Henry and Sealy Fourdrinier, made some improvements and created what was known as the Fourdrinier paper machine which was patented in 1806. This new equipment revolutionized the industry (Zavatta 1993) making possible a great increase in output and transforming paper making into a continuous-process industry. In the years that followed, the paper making machine diffused rapidly across Europe resulting in the collapse of many traditional handmade-paper mills. The first Fourdrinier machine in the US was imported from England in 1827 (Georgia-Tech 2006).

In spite of the new paper production capacity and reduced production costs, the price of the paper remained high because of the scarcity of rags, the main raw material for paper manufacture. This provided motivation for increased efforts to find and experiment with alternative raw materials. In the mid 19th century, wood pulp became a viable and convenient substitute for rag pulp resulting in a significant reduction in paper production costs during the second half of the century (Tremblay 1994). A low cost and fast growing industry began to satisfy the rapidly growing demand for paper and board during the latter half of the 19th century.

2.1.2 The modern pulp and paper making process

The modern p&p industry is based on three main, strongly connected, productive activities: cultivation of forest resources, pulp production (extraction of cellulose fibres), and paper and board products production (Figure 2.1). Pulp is the primary raw material for paper production. Excluding its water content, wood is comprised of roughly 50% cellulose, 30% lignin and 20% oils and other substances. The lignin binds the cellulose fibres into a structure or matrix. Broadly speaking, papermaking involves the removal of cellulose from the lignin matrix, and formation of the fibres into a web of paper. Pulping is the process by which the cellulose fibre is extracted from the wood. Papermaking is the process that transforms the pulp into paper, using one piece of equipment, the paper machine. Figure 2.2 depicts the steps involved in the paper production process. P&p making can be either vertically integrated in one mill or separated across two mills. The pulp that is supplied for sale to non-integrated paper mills is referred to as ‘market pulp’ in the specialized literature.

Figure 2.1 Paper and pulp basic productive activities

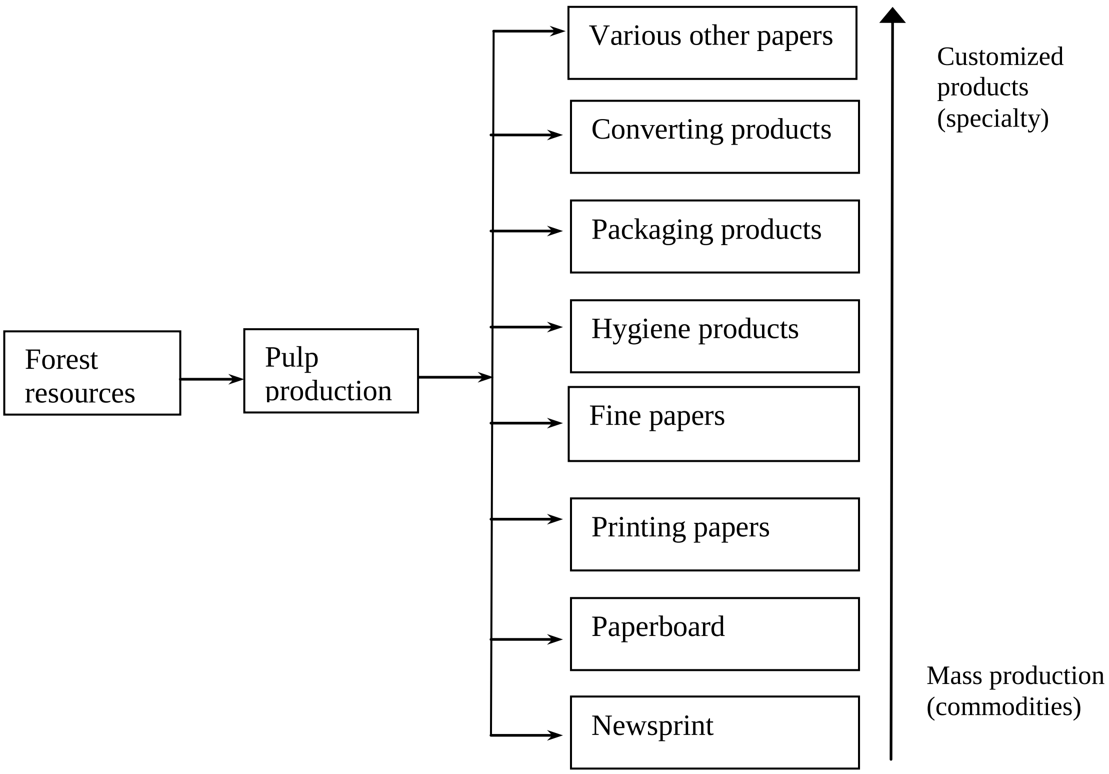
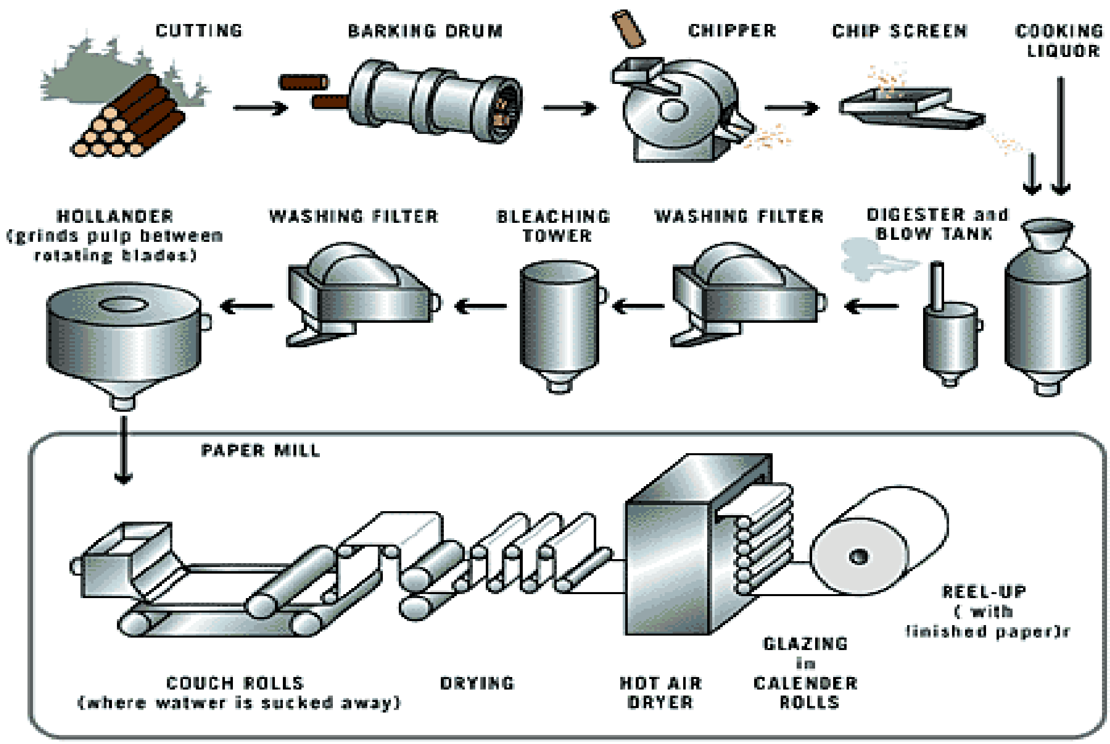


Figure 2.2 Pulp and paper production process



Source: http://www.hytechcontrols.com/images/Pulp-And-Paper-Process.jpg

Forestry resources

The first basic stage in the p&p production chain comprises the growing and harvesting of forests. The key economic variables in this stage are speed of growth of the trees, which defines their cost, and fibre quality. Pulp is the basic raw material for the production of paper and paperboard which are the basis for all the other paper products. Paper and pulp mills fibre inputs can come from several sources: local forests and plantations; fibre in the form of market pulp sometimes produced at a distance from the mills; and recycled fibre. Virgin fibre production involves management of forest plantations, harvesting of the wood, and transportation to the mill.

Pulping processes

The second basic stage in the p&p production process is pulp making. Once the wood arrives at the mill, it has to be debarked and then the wood is ground directly into pulp through a mechanical process, or converted into chips for thermo-mechanical pulping or chemical pulping. In the paper production process, pulp represents up to 70% of the production cost, depending on the type of product and type of process used. Pulp plants generally operate at near to 100% production capacity. There are different techniques for pulping. The three most important processes are: chemical, mechanical and recycled fibre which are explained briefly below.

- Chemical pulping

Chemical pulping (also called kraft pulping) turns the wood chips into pulp. This is the main pulping method used worldwide (approximately 48% of world pulp capacity). Wood chips are 'cooked' in a chemical solution at high temperature and pressure, in order to remove the lignin and extract useful cellulose fibres from the raw material. Pulp fibres then are produced in both unbleached and bleached form. The fibres are washed before going on to a bleaching stage and then either dried for shipping as market pulp or pumped to an integrated paper machine. Bleached chemical pulp is used to make bright white paper suitable for long storage.

The main disadvantage of the chemical processes compared to the mechanical process is wood yield. While the former yields between 45% and 55% of pulp output per unit of fibre input (the rest of the fibre dissolves and is used to produce energy for the pulp mill power plant), mechanical processes yield between 88% and 98%. Nevertheless, the chemical process is technically and economically superior to the mechanical process, mainly because it generates better quality pulp and is more energy efficient.

- Mechanical pulping

Mechanical pulping represents less than 20% of world pulping capacity. Machinery replaces chemicals in this process. The fibres are physically separated either on a large rotating grindstone (stone ground-wood pulping) or by passing heated wood chips through rotating discs (thermo-mechanical pulping). Both processes require a large input of electrical energy. Though the yield is higher than for chemical processes, the pulp produced is weaker, because the mechanical action tends to break the fibres. This pulp is also more prone to discoloration and less suitable for bleaching. For these reasons mechanical pulps are limited to a thinner range of end-uses such as news print.

- Recycled pulps.

Recycled fibre represents 36% of world pulping capacity. Its use has increased because of environmental concerns. However, there is a limit to the number of times recycled fibre can go through the production-use-collection loop. Four or five times around the cycling loop are considered the maximum, so there will always be a need for virgin pulp fibre. Most of the complexity of recycling paper involves the removal of inks, adhesives and other impurities. The resulting products from recycled fibres are normally lower quality than those produced from virgin fibre.

Paper making process

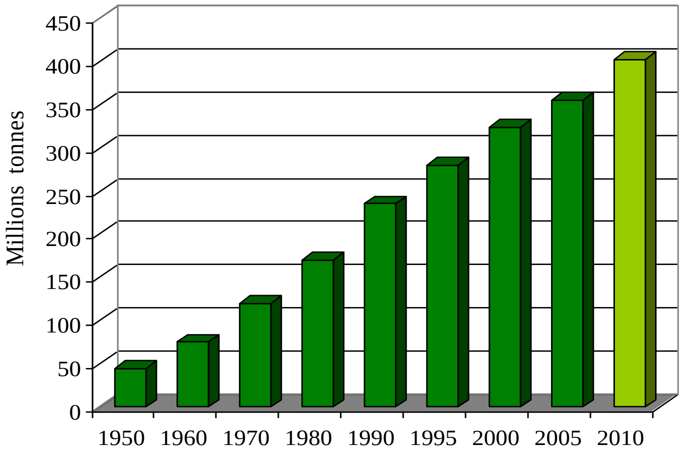
The third basic stage in the p&p production chain is paper making which essentially is a filtration process conducted in a single paper machine using pulp. The generic paper machine has seven distinct sections: the head box, wire section (wet end), press section, drying section, size press, calender, and reel-up. The paper making process starts with a suspension of pulp fibres, fillers and chemicals, dispersed evenly on to a rapidly-moving wire mesh, which allows the water to drain away by gravitational force, leaving a sheet of moist pulp. Pressure and heat are applied to this fibre web to produce paper. Generally a paper machine produces uncoated paper, but a coating can be applied to the surface of base paper using an on-machine coater or off-machine coater. The heavier the coating, the higher the print quality of the paper.

The paper making stage comprises a variety of products referred to in the industry as 'grades'[5] or 'technological classes'. These technological classes go from standardized commodities such as newsprint or paperboard, to highly specialized and customized products such as sanitary paper, specialty papers or packaging, where differentiation and market orientation play a key competitive role. New products derived from pulp fibre are continuously being developed to fill new niche market needs.

2.2 The global pulp and paper industry

The p&p industry historically is a fragmented region-based industry sector. In physical terms, it is one of the largest industries in the world. It accounts for about 2.5% of the world's industrial production (UNIDO 1993), across about 100 countries in the five continents. Since 1950, world paper and board output has increased more than five-fold, from 45 million tonnes in 1950 to 324 million tons in 2000 (see Figure 2.3), with an average annual compound growth rate of more than 4%.[6]

Figure 2.3 World paper consumption, 1950-2010



Sources: FAO Statistics 2006. PPI 2001.
Data from year 2010 are Jaakko Pöyry prognosis, 2000.

[5] 'Grades' is the term that the specialized p&p literature uses to refer to the different types of p&p products or technological classes such as pulp, newsprint, graphic papers, tissue, special and industrial papers, linerboard, corrugated medium, solid bleached board, etc.
[6] E.g. in 2007 world wheat production was 607 million tonnes (http://faostat.fao.org) and world sugar production was 160 million tonnes (http://www.fao.org/docrep).

World consumption is forecast to continue to increase because demand for paper is strongly correlated to population growth, higher literacy levels, and expansion of dynamic sectors such as information systems and services, and growth in world trade.

2.2.1 Basic characteristics of the global p&p industry

The p&p industry can be characterized by five key technological and economic features which have influenced the structure and dynamics of the global industry (Carrere and Lohmann 1996; Herbert-Copley 1998; Norberg-Bohm and Rossi 1998; Dijk 2005). These five key features are: 1) capital and scale intensive; 2) energy intensive; 3) cyclical market behaviour; 4) technology absorber (supplier dominant); 5) environmental impact, all of which are analysed in the following part of this subsection.

Capital and scale intensive

The p&p industry ranks among the most scale and capital intensive manufacturing sectors (Nilsson, Larson et al. 1996). In the US, the p&p industry's annual average investment is US$ 16,000 per employee, four times the country's manufacturing average (Carrere and Lohmann 1996). This high capital and scale intensity creates strong entry and exit barriers. Initial capital costs and on-going investments require large-scale financing. The investment needed for the construction of a state of the art chemical pulp plant with capacity production of 1,000 tonnes per day is more than US$ 1 billion. The cost of a state of the art paper machine of maximum width and speed is over $300 million US dollars and its production capacity is over 400,000 tonnes/year.

The economy of scale of a paper mill is determined by the speed and width of its paper machine. The dominant factor since the early 1980s has been speed rather than width. The problems related to increased width are the dramatic increase that would be required in the diameter of the machine roll - an exponential factor of 3. Thus manufacturers of paper machinery have restricted it width to a maximum of 10 m because of this technical constraint. The maximum speed of a newsprint machine in 1955 was approximately 400 metres per minute and in 2004 had increased by a factor of more than 6 to 2,500 metres per minute.

Energy intensity

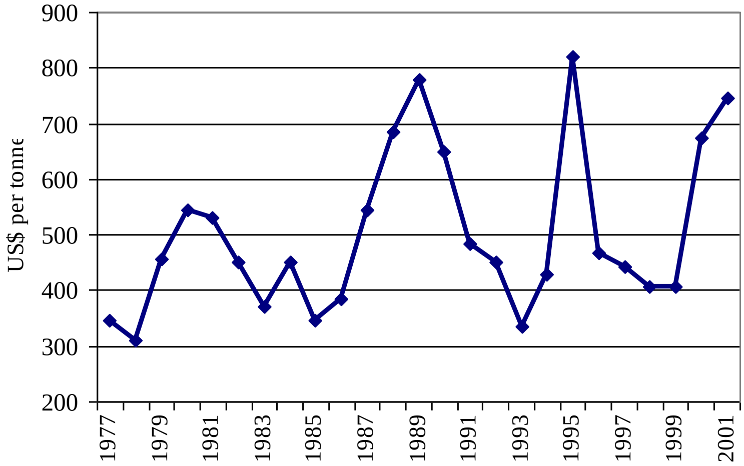
The p&p industry is one of the world's most energy intensive sectors. Pulp, paper, and paperboard mills account for about 12% of total manufacturing energy use in the US contributing about 9% to total US manufacturing carbon dioxide emissions (U.S. EIA 1997). Energy and environmental concerns, manifest in changing market demands and more stringent environmental regulations, are among the most important drivers of technological change in the p&p industry.

The sector has made significant efforts to reduce total energy use since the 1973 energy crisis and has increased the fraction of energy provided from self-generated biomass resources. The energy intensity of the US p&p industry has declined from 42.2 million Btu per tonne of output in 1972, to 26.2 million Btu per tonne of output in 2002 (Ruth, Davidsdottir et al. 2000). This efficiency improvement has been achieved through incremental technological improvements and innovations, retirement of less efficient facilities, and better housekeeping practices.

Cyclical market behaviour

An important feature of the p&p industry is its highly cyclical nature, characterized by important fluctuations in the international prices of its main commodity products. In the 1990s the international market price of pulp has varied from US$300 to more than US$800 per tonne, with shorter and more pronounced cycles compared with previous decades (Figure 2.4). This characteristic market behaviour is the result of fluctuating demand which is highly correlated to world economic activity and a supply side that cannot adjust immediately to the changes in demand because of the high economies of scale and capital intensive nature of production units. In periods of high demand and high prices new high capacity production units with state of the art technology usually comes into operation. The economies of scale of the new plants produce over capacity resulting in a fall in international prices. The cyclical nature of the industry means that investment is risky and can potentially result in large losses for investors. Because of this cyclicality, historically large firms have coordinated informally in order to achieve a better balance between supply and demand and to maintain or increase prices (Lilja and Moen 2003).

Figure 2.4 International price of market pulp



Source: Paperloop 2008 (http://www.risiinfo.com)

Incremental and continuous technological innovations

In spite of its relatively low-tech image the p&p industry is technology intensive.[7] Its knowledge formation and technical development is often characterized by strong links among related sectors and institutions including equipment providers, project-engineering firms, industrial automation, chemical suppliers, energy utilities, customers, research institutes and universities, regulators, etc. Through these interactive relationships, firms exploit advanced research and advanced technologies. Together, these constitute an industry cluster, in which inter-sectoral complementarities and related knowledge flows drive technical change (Autio, Deitrichs et al. 1997).

Increased scale and complexity in p&p production processes has led to specialization and a technology shift towards capital goods supplier firms. This is evident in the low R&D intensity of the p&p industry as a whole (Laestadius 1998a); the industry is considered an absorber rather than a generator of new technologies. In terms of Pavitt's (1984) taxonomy, it would be classified as a 'supplier dominated industry'. Since the early 1980s industry R&D efforts have been oriented towards process innovations that promote energy efficiency, address environmental concerns and increase scale through improved speed and greater size of production systems.

[7] Laestadius (1998a) suggests that the OECD's aggregate science and technology indicators are not reliable for a deeper understanding of R&D activities in p&p technology or for their classification of a low tech sector.

P&p technology falls into three categories. First, there is straightforward transfer of technology developed outside the p&p industry cluster such as power generation and electrical drive technology. Second, there is technology that is adapted for use in the p&p industry with some changes, for example control systems with modified sensors, and screening and cleaning technologies. Third, there is p&p specific technology such as devices for control and optimization of the manufacturing process, and the development of new paper based products.

In Chapter 1 we pointed to operating speed as being one of the most important technological features of paper machines (Mardon, Vyse et al. 1991; Davy 1997; Haunreiter 1997). During the 1980s the introduction of automatic process control technologies increased significantly the speed of paper machines which is reflected by the inflection point in Figure 1.2. These technological changes increased the scale of production and productivity very rapidly, but also increased costs considerably. Have these significant technological changes affected the structural dynamics of the p&p industry? Are there patterns of p&p firms' entry, exit and growth associated with these innovations? These are relationships worthy of investigation in order to increase our knowledge of the relevant effect of technological progress on the dynamics of industry structure, as several scholars have argued (Kamien and Schwartz 1982; Abernathy, Clark et al. 1983; Baldwin and Scott 1987), rejecting the assumptions made by classical industrial organization authors who downplay this effect (Mason 1939; Bain 1968).

Environmental sensitivity

Environmental aspects are a fundamental dimension of sectoral tendencies since the p&p industry is ranked among the top five in terms of quantities of toxic materials generated per unit of output (Herbert-Copley 1998). Since the early 1970s most of the developed countries have introduced strict environmental policies pushing the industry to invest significantly to reduce its environmental impact. There is a clear priority to develop environmentally friendly products and process technologies in order to reduce effluent emissions through the re-utilization of all process sub-products. The long term aim is a closed system operation, with no effluents, and thus no contamination. Concern for the environment has promoted the development of new technologies on the one hand, and pushed additional regulation to increase the use of recycled fibre on the other.

The utilization of recycled fibre has increased significantly and it is expected to continue to do so. In the US, the total paper and paperboard recovered has grown from 8.4 million tonnes and 25% recovery in 1961 to 51.0 million tonnes and a 51% recovery in 2005. Recovering of newsprint grade was 70% in 2005 (AF&PA 2006).

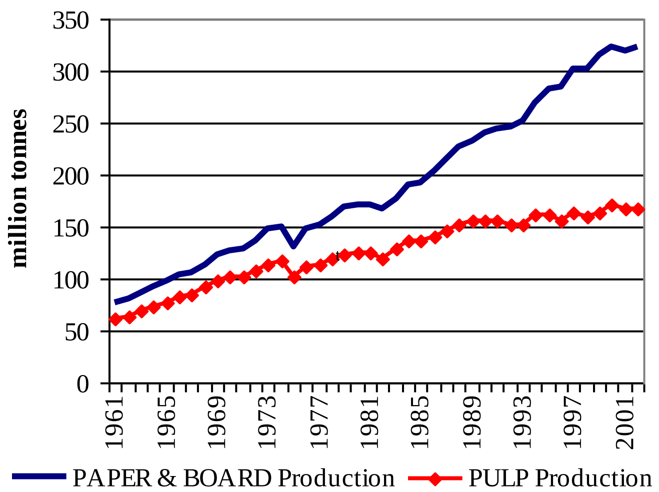
2.2.2 Structure and dynamics of the global pulp and paper industry

Industry structure is understood as the number and size distribution of the firms that populate an industry, thus it comprises variables such as number of sellers and buyers, sellers' and buyers' size distribution, barriers to entry and exit, mobility barriers, diversification, vertical integration, etc. (Carlton and Perloff 2004). The purpose of this subsection is to provide a brief understanding of the global p&p industry structure and its dynamics during the period 1978-2000.

<u>The production side</u>

World p&p production is located in more than 1,000 companies in some 100 countries across the five continents. There are approximately 9,000 pulp mills and 14,000 paper mills worldwide, of which about 8,000 pulp mills and 10,000 paper mills are located in China. Most are small with less than 1 th.tonnes per year output, operate using old technology and are oriented to the domestic market. Figure 2.5 shows the evolution of world paper and board production and pulp production over a 40 year period.

Figure 2.5 World production of pulp and paper & board



Source: FAO Databases (http://www.fao.org/forestry/site/databases/en/)

In spite of the fact that p&p are produced by a large number of countries, there is a significant concentration of the production in the developed countries. Tables 2.1a and 2.1b show the 20 largest country producers of paper and board and pulp in the period 1960 to 2000. In 2000, ten countries: USA, Japan, China, Canada, Germany, Finland, Sweden, France, South Korea and Italy accounted for 74% of world paper and board output. In pulp production, the top ten countries accounted for 82% of total output.

Table 2.1a World's top 20 paper and board producers (m. tonnes and %), selected years

	Country	1960		1970		1980		1990		2000	
1	USA	31.1	42	47.6	37	56.8	33	71.5	30	85.8	26
2	Japan	4.5	6	13.0	10	18.1	11	28.1	12	31.8	10
3	China	1.9	3	3.8	3	5.6	3	13.7	6	30.9	10
4	Canada	7.8	11	11.3	9	13.4	8	16.5	7	20.8	6
5	Germany	3.4	5	5.5	4	7.6	4	12.8	5	18.2	6
6	Finland	2.0	3	4.3	3	5.9	3	9.0	4	13.5	4
7	Sweden	2.2	3	4.4	3	6.2	4	8.4	4	10.8	3
8	France	2.6	4	4.1	3	5.2	3	7.0	3	10.0	3
9	South Korea	32	0	0.3	0	1.7	1	4.5	2	9.3	3
10	Italy	1.5	2	3.4	3	4.9	3	5.7	2	9.1	3
11	Brazil	0.5	1	1.1	1	3.4	2	4.8	2	7.2	2
12	Indonesia	0.0	0	0.0	0	0.2	0	1.4	1	6.9	2
13	UK	4.1	6	4.9	4	3.8	2	4.9	2	6.6	2
14	Russia	3.2	4	6.7	5	8.7	5	10.7	4	5.2	2
15	Spain	0.3	0	1.1	1	2.6	2	3.4	1	4.8	1
16	Taiwan	0.2	0	0.4	0	1.5	1	3.3	1	4.5	1
17	Austria	0.6	1	1.0	1	1.6	1	2.9	1	4.4	1
18	Mexico	0.4	1	0.9	1	1.9	1	2.9	1	3. 9	1
19	India	0.3	0	0.9	1	1.1	1	2.3	1	3.9	1
20	Netherlands	1.1	1	1.6	1	1.7	1	2.7	1	3.3	1
	WORLD	74.4	100	129.3	100	171.0	100	239.5	100	324.2	100
	North America	38.9	52	58.9	46	70.2	41	88.0	37	106.6	33
	Europe	25.6	34	45.2	35	59.0	35	78.2	33	100.1	31
	Asia	7.9	11	20.6	16	32.3	19	59.8	25	99.4	31
	Latin America	1.7	2	3.7	3	7.7	5	10.8	5	14.8	5
	Africa	0.3	0	0.9	1	1.7	1	2.7	1	3.3	1

Notes: Countries are ranked according to 2000 figures; % of world's shares
Source: FAO Databases (http://www.fao.org/forestry/site/databases/en/)

During the early 1990s a new structure of international supply of p&p began to emerge. New low cost country providers of p&p began to occupy significant positions in the world market. Many of these producers are located in the southern hemisphere, e.g. Brazil, Chile, South Korea Republic, Indonesia, New Zealand, etc. (Carrere and Lohmann 1996). These countries have a natural cost advantage in the production of pulp because of their abundant natural resources and because the rotation time for pulpwood is less than half compared with northern hemisphere countries. Nevertheless, the traditional northern hemisphere companies have maintained their competitiveness based on several strategies: shift to higher value added products, process and product technological innovations, and vertical integration.

Table 2.1b World's top 20 pulp producers (m. tonnes and %) in selected years

	Country	1960		1970		1980		1990		2000	
1	USA	21.9	37	38.3	36	46.0	35	57.2	35	56.9	31
2	Canada	10.1	17	16.6	16	20.2	15	22.8	14	26.9	14
3	China	0.8	1	2.7	3	4.3	3	10.0	6	17.2	9
4	Finland	3.7	6	6.2	6	7.2	5	8.9	5	11.9	6
5	Sweden	5.0	8	8.1	8	8.7	7	9.9	6	11.5	6
6	Japan	3.5	6	8.8	8	9.8	7	11.3	7	11.4	6
7	Brazil	0.3	1	0.9	1	3.5	3	4.5	3	7.5	4
8	Russia	3.2	5	6.7	6	8.4	6	10.1	6	5.9	3
9	Indonesia	0.0	0	0	0	0.0	0	0.7	0	4.1	2
10	India	0.1	0	0.6	1	0.8	1	1.0	1	2.6	1
11	France	1.2	2	1.8	2	1.8	1	2.2	1	2.5	1
12	Norway	1.5	3	2.2	2	1.5	1	2.2	1	2.5	1
13	Chile	0.1	0	0.4	0	0.8	1	0.8	0	2.3	1
14	South Africa	0.6	1	0.8	1	1.0	1	1.9	1	2.3	1
15	Germany	1.6	3	1.8	2	2.0	2	2.7	2	2.2	1
16	Portugal	0.1	0	0.4	0	0.9	1	1.4	1	1.8	1
17	Austria	0.5	1	0.9	1	1.2	1	1.5	1	1.8	1
18	Spain	0.2	0	0.7	1	1.3	1	1.5	1	1.8	1
19	New Zealand	0.3	0	0.6	1	1.1	1	1.3	1	1.6	1
20	Poland	0.5	1	0.7	1	0.9	1	0.6	0	0.9	0
	WORLD	60.0	100	107.2	100	132.0	100	162.6	100	186.2	100
	North America	33.0	55	54.9	51	66.3	50	80.0	49	83.8	45
	Europe	21.0	35	34.9	33	40.1	30	45.6	28	46.7	25
	Asia	5.2	9	14.3	13	18.1	14	27.3	17	41.1	22
	Latin America	0.8	1	2.2	2	5.9	4	7.3	4	11.8	6
	Africa	0.1	0	0.9	1	1.6	1	2.4	1	2.8	2

Source: FAO Databases (http://www.fao.org/forestry/site/databases/en/)
Notes: Countries are ranked according to year 2000 figures; % of world's shares

At firm level there have been important changes during the period 1975-2000. Tables 2.2 and 2.3 compare the world's 20 largest companies for both periods: firm production scale increased by three times; the concentration ratio of the top 20 firms increased from 23% to 39%; the concentration ratio of the top 10 firms increased from 14% to 26%. While in 1975, the 20 largest firms were in only four countries, in 2000 the top 20 firms were in nine countries. Five of the top 10 firms in 1975 were still in operation in 2000 and six of the top 20 firms survived to year 2000.

Table 2.2 World's 20 largest paper and board producers in year 2000 (m. tonnes)

Rank	Company	mppb production[1]	mp production	p&b production	mppb C-ratio[2]	Location of head quarter
1	International Paper	16.8	2.3	14.4	0.05	USA
2	Stora Enso	14.0	1.1	13.0	0.08	Finland
3	Georgia-Pacific	13.2	1.7	11.6	0.12	USA
4	Nippon Unipac Holding	8.3	0.4	8.0	0.14	Japan
5	UPM-Kymmene	8.3	0	8.3	0.17	Finland
6	Smurfit-Stone Container Co	7.9	0.5	7.4	0.19	USA
7	Weyerhaeuser	7.7	2.3	5.4	0.21	USA
8	Oji Paper	7.2	0.1	7.1	0.23	Japan
9	Abitibi-Consolidated	6.9	05	6.4	0.25	Canada
10	Mondi International	6.4	0.4	6.0	0.26	SAfrica
11	Sappi	5.9	1.0	4.9	0.28	SAfrica
12	Fort James Corporation	4.9	0.2	4.7	0.29	USA
13	Norske Skogindustrier	4.8	0.7	4.1	0.31	Norway
14	Svenska Cellulosa (SCA)	4.8	0.3	4.5	0.32	Sweden
15	Asia Pulp&Paper Company	4.4	0.4	4.0	0.33	Singapore
16	Bowater Inc.	4.3	0.9	3.4	0.34	USA
17	M-real	4.2	0	4.2	0.36	Finland
18	Jefferson Smurfit Group	3.9	0	3.9	0.37	Ireland
19	Kimberly-Clark	3.8	0	3.8	0.38	USA
20	Mead	3.7	0.1	3.6	0.39	USA

[1]Firms are ranked according to mppb production. [2]Concentration of largest firms over world output.
Source: adapted from PPI magazine - September 2001 issue

Table 2.3 World's 20 largest paper and board producers in year 1975 (m. tonnes)

Rank	Company	mppb Production[1]	mp Production	p&b Production	mppb C-Ratio[2]	Location of head quarters
1	International Paper	5.4	0.6	4.8	0.04	USA
2	Weyerhaeuser	2.4	0.8	1.6	0.05	USA
3	Crown Zellerbach	2.0	0.1	1.9	0.07	USA
4	St. Regis	2.0	0.1	1.9	0.08	USA
5	Bowater Corp.	1.8	0.3	1.5	0.09	England
6	Abitibi-Consolidated	1.7	0.1	1.7	0.10	Canada
7	Mead	1.7	0.4	1.3	0.11	USA
8	Georgia-Pacific	1.6	0.4	1.3	0.12	USA
9	Great Northern Nekoosa	1.6	0	1.5	0.13	USA
10	Westvaco	1.6	0	1.6	0.14	USA
11	MacMillan Bloedel	1.5	0.3	1.2	0.15	Canada
12	Union Camp	1.5	0	1.5	0.16	USA
13	Container Corp. of America	1.4	0	1.3	0.17	USA
14	Scott Paper	1.4	0	1.4	0.18	USA
15	Jujo Paper	1.3	0.2	1.1	0.19	Japan
16	Oji Paper	1.3	0	1.3	0.20	Japan
17	Consolidated Bathurst	1.1	0.1	1.0	0.21	Canada
18	Continental Forest Ind.	1.1	0.1	1.1	0.21	USA
19	Reed International	1.1	0.2	1.0	0.22	England
20	Daishowa Paper	1.1	0	1.1	0.23	Japan

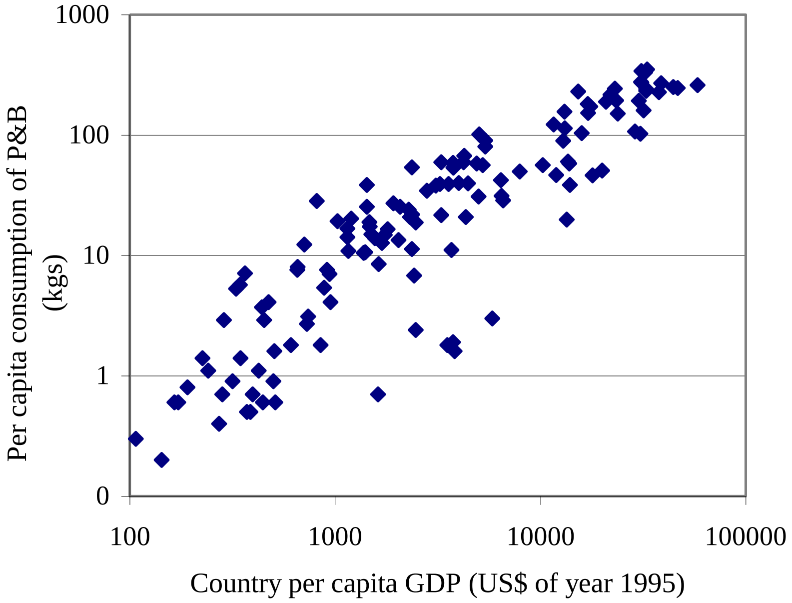
[1]Firms are ranked according to mppb production. [2]Concentration of largest firms over world output.
Source: adapted from PPI magazine - September 1976 issue

<u>The demand side</u>

Both the volume and sophistication of demand have grown. Both aspects have contributed to increasing market segmentation and continuous development of new paper related products, especially in relation to the use of new process technologies and new process control systems. At the same time, in the main consumer countries, preference for non-contaminated products and processes has increased considerable. Aggregate demand for p&p at country level is highly correlated to the degree of economic development (Diesen 1998). Figure 2.6 shows this correlation, comparing per capita consumption of paper and board with countries' per capita GDP. We can conclude from these data that global consumption of paper products in their different forms will continue to grow in succeeding decades.

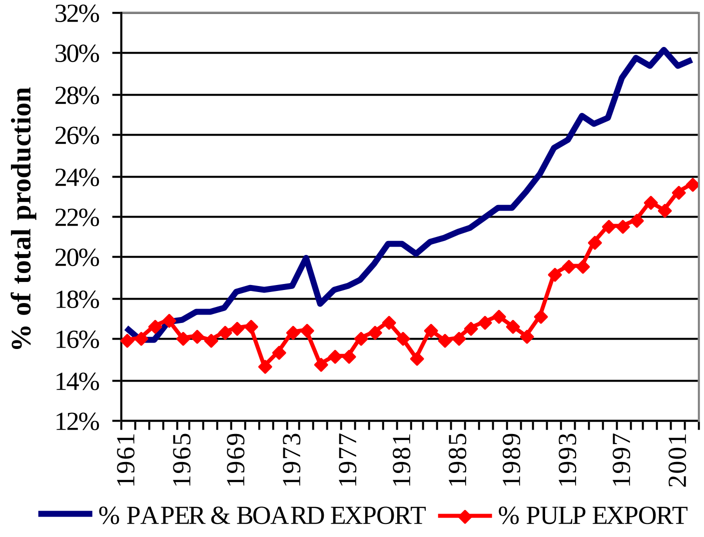
International trade in pulp and paper products has increased gradually since mid 1970s (see Figure 2.7). Imports of market pulp increased from 14% in 1975 to 24% of total output in 2000, and imports of paper products have increased steadily to reach more than 30% of world output in year 2000.

Figure 2.6 Per capita consumption of paper and board versus country per capita GDP (data of 135 countries in year 2007)



Source: Own elaboration. Data taken from PPI Annual Review, July 2008 & International Energy Annual 2008, World Population and GDP. www.eia.doe.gov/emeu/iea/popgdp.html

Figure 2.7 World imports of paper & board and pulp, period 1961-2003



Source: FAO Database (http://www.fao.org/forestry/site/databases/)

Entry, exit and mobility barriers

There are three main sources of entry barriers to this sector. First the large initial capital investment needed to capture the benefits of scale economies; second, the need for easy access to forest resources, so far, the most important raw material for the p&p industry; third, the need to manage and control the complex and expensive production process and operate at full capacity. These entry barriers have led to two important characteristics in this sector. First, the amounts of resources needed to implement productive plants are very large and therefore require strategic financing of investment. Second, the direction and rhythm of technical change depends on the interactions among project engineering and capital goods firms, and firm's internal knowledge of the production process and forest activity.

The most important exit barrier is the highly industry-specific character of most of the capital equipment used in the p&p production process. This equipment cannot be transferred to production activities in other sectors. Mobility barriers are present, but somewhat less important than entry and exit barriers. With an investment of between one third and one half of the cost of a new paper machine, firms have the possibility to adapt or rebuild older machines usually designed to produce a specific range of products in order to produce products in a different product category. This allows firms some flexibility to move from one market segment to another.

Integration of p&p firms

As explained in Section 2.2, p&p production historically has been characterized by a three-stage structure: forestry resources, pulp plants and paper plants. According to the degree of vertical integration, firms can be categorized in four main groups:

- *Fully integrated production.* Forest resources and p&p product firms are co-owned and usually co-located. Thus, trees go to pulp production, which goes directly to the paper mills.
- *Backwards-integrated production.* Forest resources and pulp production units based on virgin fibre are co-owned and co-located, but separated from paper production which is usually located closer to final paper markets. This type of production is usually called ‘market pulp’ and is common in the Latin American countries.
- *Forward-integrated production.* P&p firms are co-owned but the trees are purchased from third parties. This structure prevails in the Scandinavian countries.
- *Non-integrated production.* This is the case of firms that own only pulp or paper production facilities but not both.

Mergers and acquisitions

An acquisition occurs when one company gains a controlling ownership share in another company. Acquisitions can be achieved in a variety of ways, including using retained earnings to purchase the majority voting shares in another company. From a legal point of view, the company that is bought ceases to exist and the acquiring company ‘swallows’ the acquired business. Mergers occur when two firms negotiate an arrangement to combine and form a single new company.

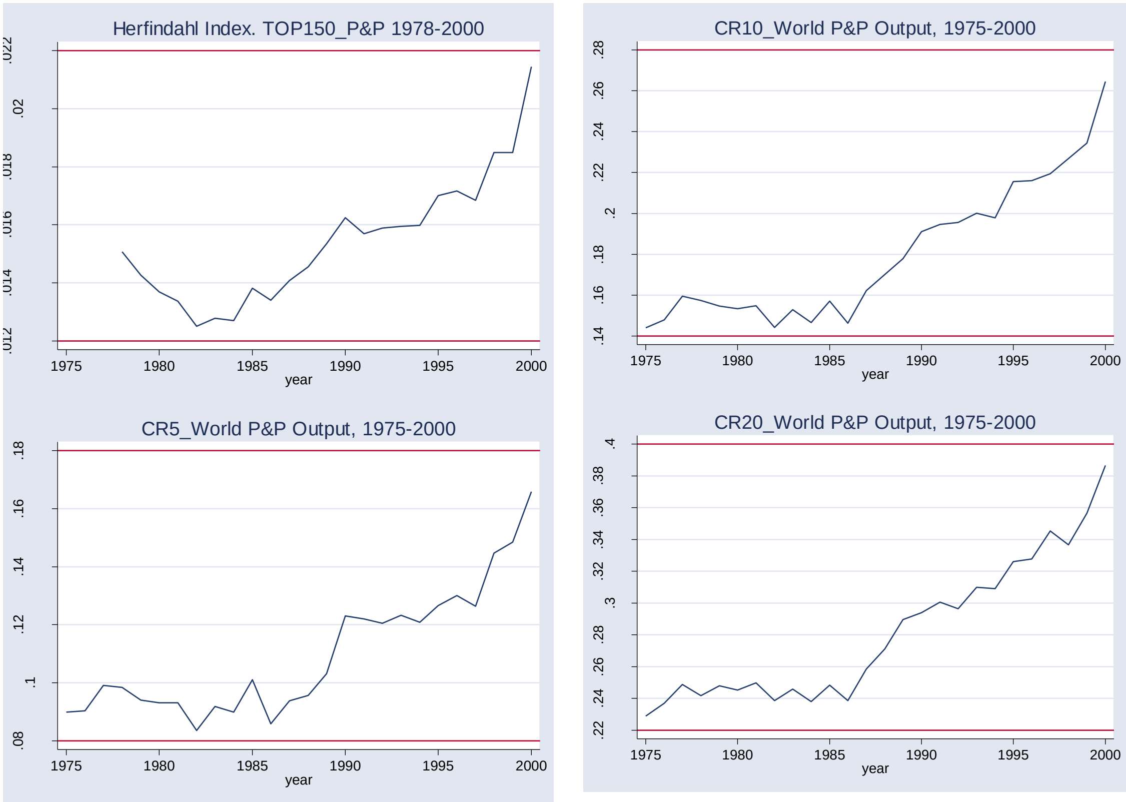
In a merger, both companies’ stocks are surrendered and new stock is issued. For instance Stora and Enzo, two large Scandinavian p&p firms, merged in 1998 to create StoraEnzo, which is one of the largest paper producers in the world. Two Finnish p&p firms - United Paper Mills and Kymmene – merged in 1995 to create UPM-Kymmene. Horizontal mergers occur when two companies in direct competition share the same product lines and markets. Vertical mergers happen when a customer and company or a supplier and a company merge. Mergers and acquisitions provide a fast means to enlarge the stock of capital and market position than other forms of investment and may result in increased market power.

Since the early 1990s M&A increased in the global p&p industry especially among the largest firms. They provide an important way for firms to augment their production capacity and thus to grow and globalize. Several of the largest firms have acquired other large and medium sized firms thereby increasing the industry concentration.

Dynamics of the global p&p industry

Our access to production data for the world's 150 largest p&p firms over 28 years allows us to study the evolution of seller concentration across a considerable time period. Figure 2.8 shows the evolution of the Herfindahl indexes of the 150 largest p&p firms, accounting for more than 70% of the world output, during the period 1978-2000. There has been a steady increase in industry concentration since the mid 1980s. A similar tendency of increasing global p&p industry concentration appears when using concentration ratios C5, C10 and C20 for the period 1975-2000.

Figure 2.8 Concentration performance of the global p&p industry 1975-2000



Source: Annual Review PPI Magazine, years 1976 to 2001

2.3 The US p&p industry

We also analyse the population of US p&p firms over a 30 year period from 1971 to 2000 which allow an examination of the complete size distribution. In subsection 2.3.1 we present the main characteristics of the US p&p industry and in subsection 2.3.2 we discuss the 13 disaggregated p&p technology classes or grade commodity categories. This allows us to study the technological behaviour and performance of the relevant p&p markets,[8] which in this industry are contingent on the type of output.

2.3.1 Main characteristics of the US p&p industry

The US is by far the world's largest paper producing and consuming country. In 2000 production of pulp, paper and paper board was 143[9] million tonnes, about 28% of world output. The second largest paper producing and consuming country is China with 48 million tonnes or 9% of world output (FAO Database). In 2000 US per capita consumption of paper and board products was 331 kg, the third highest in the world after Finland and Belgium.[10] The p&p industry is an important branch of US manufacturing. It accounts for about US$100 billion, is the ninth largest manufacturing sector in the US, and accounts for nearly 5% of the US manufacturing sector's contribution to GDP (PPNAFB 1999, p.2).

The significant technological advancement in the global p&p industry in 1970-2000 led to capital investment of US$ 8-15 billion per year in the US sector in the 1980s and 1990s (AF&PA 2000). As a consequence the industry is among the most modern in the world and one of the most capital-intensive manufacturing sectors in the US (USEPA 2000, p. 4A-8) measured as average investment per employee. Table 2.4 presents some summary statistics for the US p&p industry during 1970-2000. It shows a growing industry that displays a tendency towards larger and fewer firms and mills over the years resulting in a steadily higher level of concentration. Despite this increased concentration, many smaller firms continue to exist. In 2000, there were 675 p&p mills

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[8] One way to identify relevant markets is to compare cross-elasticity of demand. Firms (and their specific types of outputs) with high demand cross-elasticity are considered to be in the same market. Firms (and their specific types of outputs) with low demand cross-elasticity are considered to be in different markets.
[9] This figure is derived from the 86 m. tonnes of paper and board products and 57 m. tonnes of pulp.
[10] In 2000, Finland had the highest per capita consumption of paper and paper board products at 352 kg followed by Belgium at 341 kg.

and 234 firms. International commerce also shows a steady increase in 1970-2000. Exports grew from 8.6% to 16% of market pulp, paper and board production while imports increased from 18% to 25% of market pulp, paper and board production.

Table 2.4 The US p&p industry, 1970-2000

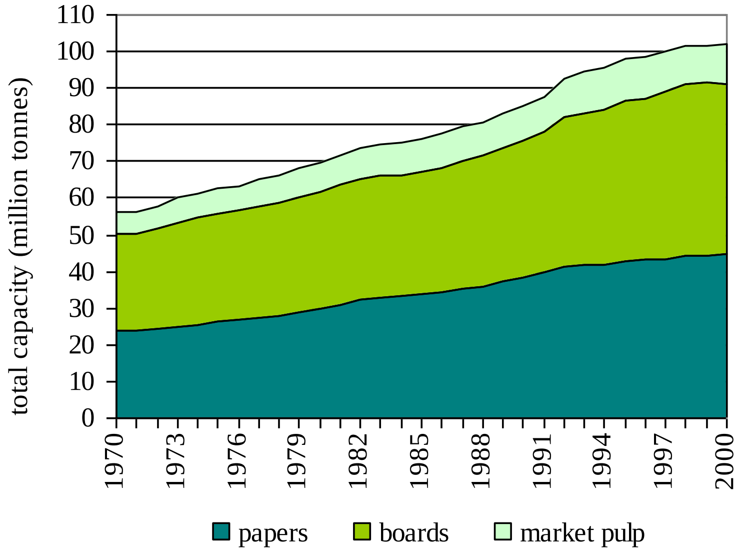
Characteristic	1970	1980	1990	2000
Annual industry capacity (m.tonnes):				
Pulp	41.7	53.0	59.4	62.9
Market Pulp	5.7	8.0	9.1	10.6
Paper & Board	50.4	61.6	75.8	91.3
Annual production (m.tonnes):				
Pulp	38.3	46.0	57.2	57.0
Market Pulp	n/i	5.9	8.0	7.8
Paper & Board	47.6	56.8	71.5	85.5
Total number of firms:	300	288	265	234
number of single grade firms	199	197	177	155
% of single grade firms	66%	68%	67%	66%
Total number of mills:	1,122	860	752	675
Pulp mills	313	248	214	176
Paper & board mills	809	612	538	499
Exports (m.tonnes)	4.5	7.0	10.2	14.7
Imports (m.tonnes)	9.3	11.5	15.9	22.8
Firm's capacity (m.tonnes):				
Average	0.19	0.24	0.32	0.43
Standard Deviation	0.43	0.54	0.79	1.16
Maximum capacity	4.90	5,197	7.27	12.24
Mill's capacity (m.tonnes):				
Pulp mill average capacity	0.13	0.21	0.28	0.36
Paper & Board mills average cap.	0.08	0.10	0.14	0.19
Production/capacity ratios:				
Pulp	0.92	0.87	0.96	0.91
Paper & Board	0.87	0.92	0.94	0.91

Source: Own elaboration, data taken from Paper Loop Annual Review several years, North American Profile several years, FAOSTAT

Capacity Trends

Figure 2.9 depicts US annual production capacity for papers, boards and market pulp from 1970 to 2000. Annual average growth capacity increased by 3.0%. The annual rate of increase in capacity started to decelerate during the 1990s. Paper and board products comprises approximately 45% each of the total industry capacity in year 2000 while market pulp comprises 10%. Market pulp comprises only 15% of total US pulp capacity in 2000 because of integrated mills. Most imported pulp comes from Canada.

Figure 2.9 The US Annual Production Capacity of Market Pulp, Paper & Board



Source: FPL-UW database

Capacities expanded through the construction of new mills (greenfield mills) or the installation of new machines or improvement to existing machines in existing mills. At the same time, capacity declined when mills were closed or when some machines were taken out of production. This dynamic process is shown in Table 2.5.

Table 2.5 Number & % of US p&p mills by production capacity in 1970 and 2000

capacity range	1970		2000	
(th.tonnes)	# of mills	% of mills	# of mills	% of mills
<100	383	66%	244	49%
100-200	96	17%	79	16%
200-300	42	7%	48	10%
300-400	29	5%	24	5%
400-500	15	3%	30	6%
>500	14	2%	72	14%
total	579	100%	497	100%

Source: Peter J. Ince, United States Paper, Paperboard, and Market Pulp Capacity Trends by Process and Location, 1970–2000.

Smaller mills in year 1970 producing less than 100 th.tonnes represented 66% of the total; in year 2000 they represented 49%. Large mills in 1970 with more than 500 th.tonnes capacity represented 2% of the total (14 mills), in 2000 they represented more than 14% (72 mills). During the three decades studied many smaller mills closed and new large mills started up; thus, total capacity expanded even though there was an absolute decline in the total number of mills and firms.

Firm strategy

Faced with growing domestic and international competition, US p&p firms have sought to achieve greater economies of scale based on major capital investments (e.g. in newer and faster paper machines). Table 2.6 lists the ten largest firms in terms of total production capacity in 1970 and 2000. We can see that there is a significant increase in firm size and level of industry concentration.

Table 2.6 Top ten US firms in market pulp, paper & board capacity, 1970 and 2000

Annual capacity year 1970			Annual capacity year 2000		
Firm	(million tonnes)	(%)[a]	Firm	(million tonnes)	(%)[a]
International Paper Co.	3.9	7.1	International Paper	10.8	10.4
Georgia–Pacific Corp.	2.6	4.4	Georgia–Pacific Corp.	6.9	6.6
Crown Paper Corp.	2.4	4.3	Smurfit–Stone Corp.	6.7	6.5
St Regis Paper Co.	2.0	3.5	Weyerhaeuser Co.	5.0	4.8
Weyerhaeuser Co.	1.9	3.4	Abitibi–Consolidated In.	4.3	4.1
Kimberly–Clark Corp.	1.6	2.8	Mead Corp.	3.3	3.2
Union Camp Corp.	1.3	2.3	Temp–Inland Inc.	3.2	3.1
Great Northern Paper In.	1.3	2.3	Westvaco Corp.	3.0	2.9
Scott Paper Co.	1.2	2.2	Willamette Industries In.	2.9	2.8
Container Corp. America	1.1	2.1	Fort James Corp.	2.9	2.8
Top 10 US firms	19.3	34.4	Top 10 US firms	49.1	47.2
Total US in 1970	56.1		Total US in 2000	103.8	

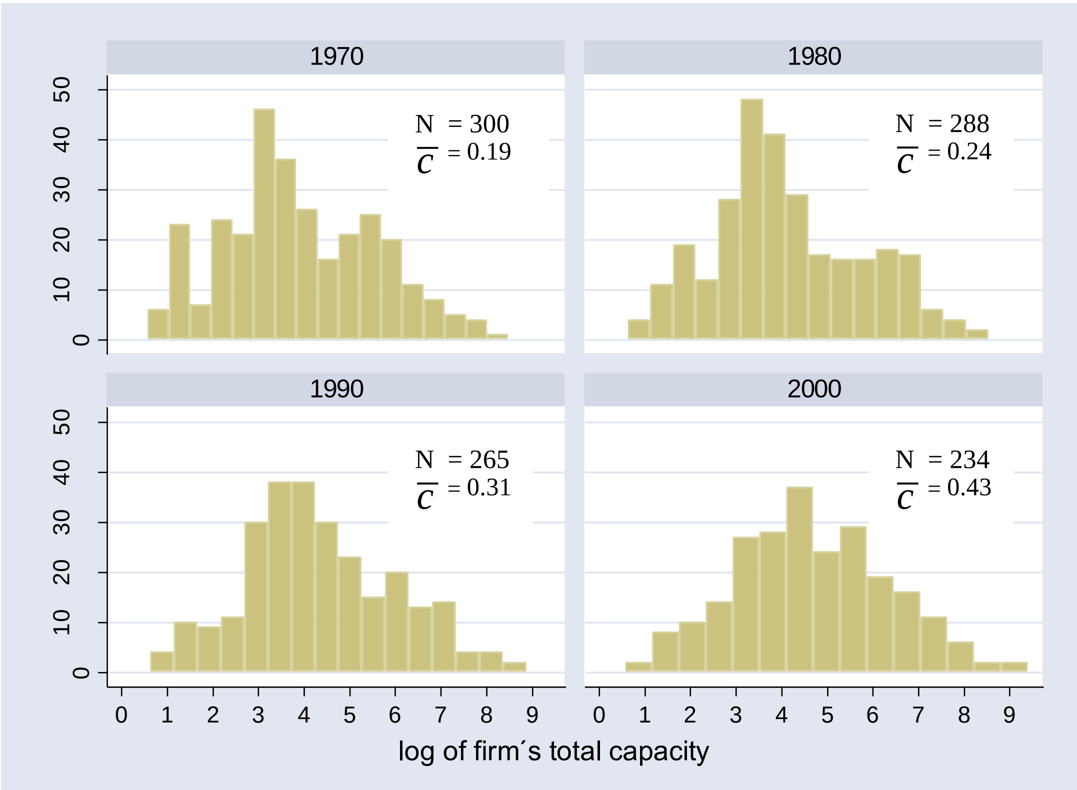
[a] *Percentage of total US capacity,* *Sources: NAFB years 1971 and 2001*

2.3.2 Structure and dynamics of the US p&p industry

Size distribution of the US p&p firms

To get a first understanding of the firm size distribution in the US p&p industry in 1970-2000, we conduct a descriptive analysis of firm's annual production capacity as a proxy for firm size. Figure 2.10 shows the size distribution curves for four selected years. The shapes of the histograms suggest that the size distributions for the first three years 1970, 1980 and 1990 have more than one hump; however this shape tends to flatten out in 2000, where the distributions suggest log-normality. This pattern is confirmed by two normality tests done for each year, shown in Tables 2.7 and 2.8. Neither skewness nor kurtosis are significant in year 2000 which is confirmed by the Shapiro-Wilk W test. The size distribution is not stationary; rather it shows an interesting dynamism over the years, which be analyzed in greater detail in Chapter 7.[11]

Figure 2.10 Size distribution curve of US p&p firms for four selected years



Source: FPL-UW database. N is the number of firms per year.
$\bar{c}$ is the annual average production capacity per company in million tonnes.

Table 2.7 Skewness/Kurtosis tests for Normality

year	N	Skewness	Kurtosis	adj chi2(2)	Prob>chi2
1970	300	0.076	0.005	10.08	0.006**
1980	288	0.012	0.063	8.95	0.011**
1990	265	0.043	0.355	5.00	0.082*
2000	234	0.272	0.434	1.84	**0.399**

*variable used: log(capacity), * significant at 10% level, ** significant at 5% level*

[11] To calculate skewness and kurtosis in the distributions, we estimated the following equations:

$$Skewness(c) = \frac{1}{N\sigma^3}\sum_{i=1}^{N}(c_i - \bar{c})^3 \qquad Kurtosis(c) = \frac{1}{N\sigma^4}\sum_{i=1}^{N}(c_i - \bar{c})^4 - 3$$

where c is the vector of capacity data, N the number of observations, $\bar{c}$ the mean of the capacity data and σ the standard deviation of the capacity data. A skewness measure of 0 indicates a perfectly symmetric distribution. A kurtosis measure of 0 indicates that the distribution is perfectly mesokurtic.

Table 2.8 Shapiro-Wilk W test for Normality

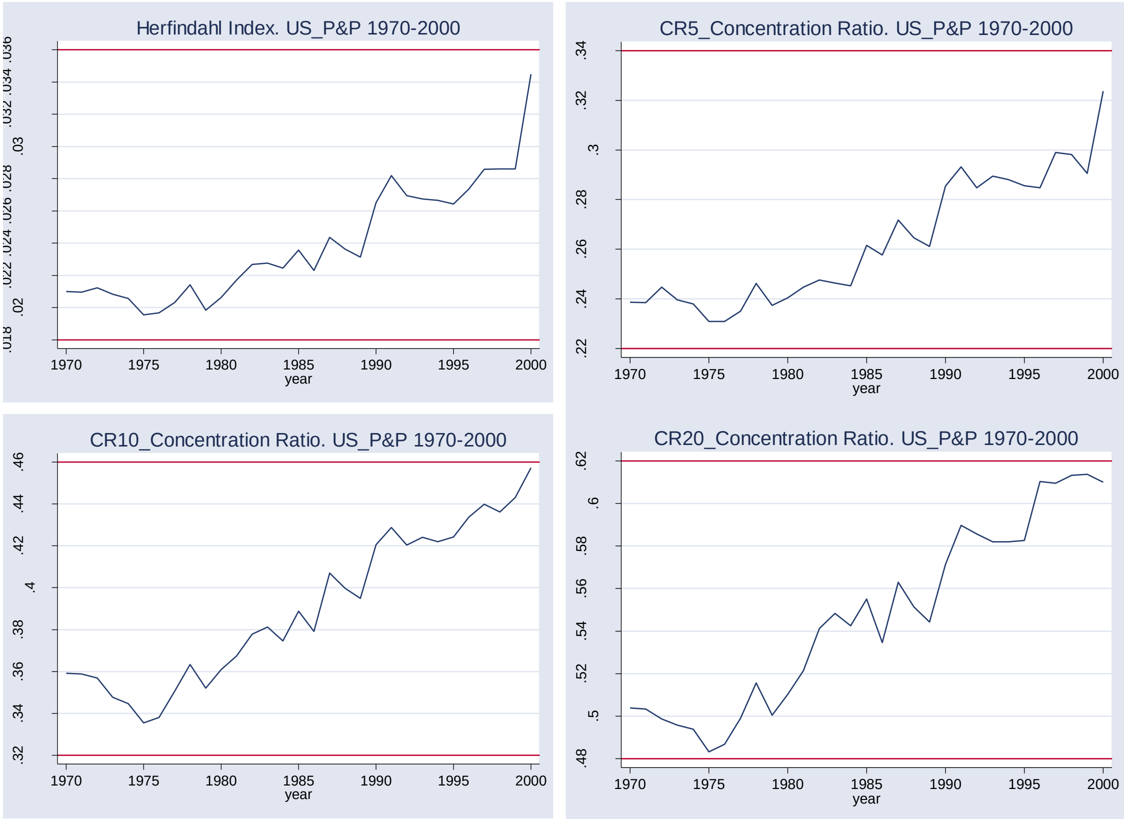
year	N	W	V	z	Prob>z
1970	300	0.982	3.739	3.096	0.001**
1980	288	0.978	4.477	3.512	0.000**
1990	265	0.987	2.464	2.105	0.018**
2000	234	0.995	0.857	-0.359	**0.640**

*variable used: log(capacity), * significant at 10% level, ** significant at 5% level*

<u>Dynamics of the US p&p industry</u>

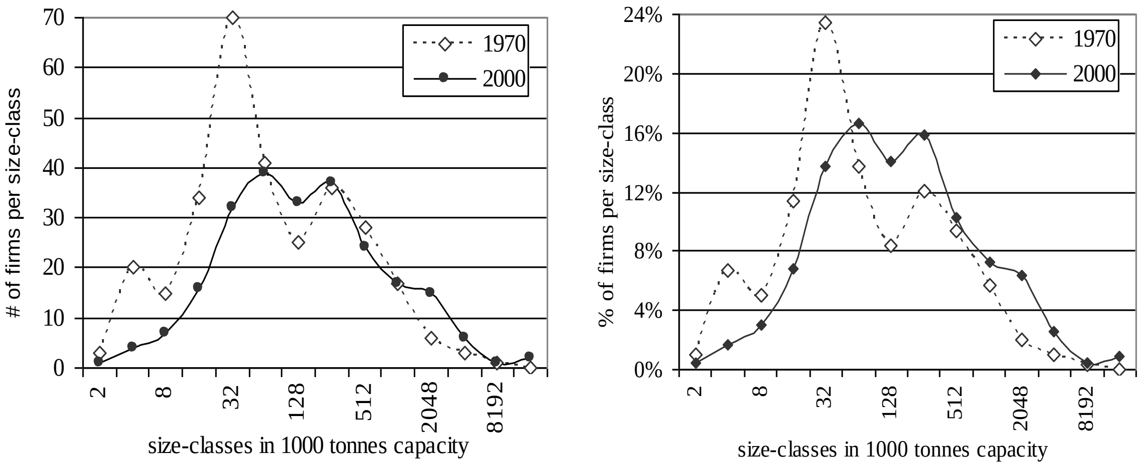
The availability of production capacity data for the population of US p&p firms for three decades allows us to study the evolution of seller concentration over a considerable time period as well as the entry, exit and growth of firms. In this subsection we provide a general overview of the dynamism of the US p&p industry. Figure 2.11 shows the evolution of industry concentration during the period 1970-2000 using the Herfindahl concentration index and three concentration ratios - CR5, CR10 and CR20. Similar to the global p&p industry (subsection 2.2.2), there is a consistent pattern of increasing industry concentration especially from the mid 1980s. The result

Figure 2.11 Concentration performance of the US p&p industry 1970-2000



Source: own elaboration, data taken from FPL-UW database of this dynamic process is depicted in Figure 2.12 which compares the number and percentage of firms per different size-classes between 1970 and 2000.

Figure 2.12 Size distribution comparison of US p&p firms, years 1970 & 2000



Source: own elaboration, data taken from FPL-UW database

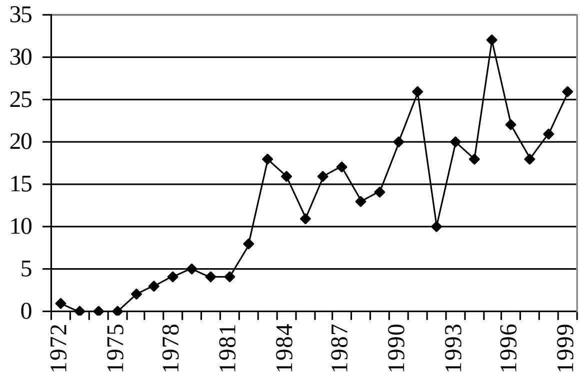
The above antecedents illustrate an industry that became more concentrated in the period 1970 to 2000. The number of p&p firms and mills reduced from 300 to 234 and from 1,122 to 675 respectively. Average firm size capacity increased from 0.19 to 0.43 million tonnes. During this period the number of small firms (smaller than 0.1 million tonnes) decreased significantly and the number of large firms (larger than 1 million tonnes) increased. The capacity of the p&p industry almost doubled and continuous technological changes in paper machines allowed enormous increases in firm scale and productivity. The size distribution curve moved towards the larger size classes.

This industry context raises interesting questions and hypotheses related to the dynamics of industrial structure that will be examined in more depth in Chapter 3. What are the forces behind this industry concentration dynamic process? Has the growth of p&p firms been random as the LPE hypothesizes? If not, what is the nature of the departure from a stochastic growth process and what are the forces that explain this departure? What are the patterns and determinants of firms that exit the industry (exit hazard rate analysis)? Considering that growth of p&p firms is directly related to the acquisition of new capital equipment, are there distinctive patterns of technology adoption behaviours along the size distribution? Have technology adoption patterns varied significantly over time? What are the causes that may explain this heterogeneous adoption behaviour over time?

M&A in the US p&p industry

Similar to the pattern in the global p&p industry, since the early 1980s M&A activity increased in the US p&p sector as depicted in Figure 2.13. M&A have constituted an important way for firms to augment their production capacity and thus to grow (Li, McCarthy et al. 2004). Firms involved in acquisitions tend to be among the largest in the industry. According to Pesendorfer (1998) more than half of the mergers occurred during the period 1978-1992, the acquiring firms were among the largest 15% in the size distribution, and the acquired firms were among the largest 25%. This M&A activity accelerated the industry trend towards higher levels of concentration.

Figure 2.13 Number of mergers per year in the US p&p industry, 1972-2000



Source: NAFB various years

Main technological classes (commodity grade categories) within the p&p industry

Among the huge variety of products that comprise the p&p industry, we can identify 13 commodities as being very important (Ince, Li et al. 2001). Table 2.9 summarizes aggregate US capacity for market pulp, paper and paperboard by commodity category in 1970 and 2000, and number of firms, and industry concentration. These 13 technological classes represent the different sub-markets in which each firm might operate and they are also differentiated by process type. Although in most p&p commodity categories production capacity increased, with an industry total growth of 85% over the three decades, each shows distinctly different growth and concentration

Table 2.9 US p&p industry capacity and concentration at 13 main technology classes, comparison years 1970 & 2000

Technology class	year 1970							year 2000							% total capacity growth	% of Herf. change
	# of firms	Capacity (th. tonnes)			Concentration			# of firms	Capacity (th. tonnes)			Concentration				
		total	mean	max	CR4	CR10	Herf.		total	mean	max	CR4	CR10	Herf.		
market pulp	45	5,720	127	721	0.43	0.68	0.062	42	10,983	262	1,932	0.47	0.70	0.076	92%	23%
newsprint	17	3,444	203	436	0.46	0.84	0.084	19	6,606	348	930	0.44	0.79	0.077	92%	-8%
uncoated free sheet	68	6,135	90	747	0.30	0.51	0.040	49	14,717	300	2,971	0.52	0.78	0.091	140%	128%
coated free sheet	21	2,050	98	328	0.45	0.76	0.077	18	5,304	295	812	0.54	0.90	0.101	159%	31%
uncoated groundwood	17	1,037	61	217	0.58	0.88	0.111	14	1,680	120	218	0.45	0.88	0.089	60%	-20%
coated groundwood	14	1,820	130	343	0.64	0.92	0.121	10	4,088	409	898	0.62	1.00	0.134	125%	11%
tissue and sanitary	67	4,270	64	984	0.54	0.74	0.098	46	6,823	148	2,037	0.72	0.84	0.158	60%	61%
specialty papers	45	1,791	40	221	0.36	0.64	0.053	45	3,428	76	603	0.44	0.71	0.078	91%	47%
kraft paper	25	3,326	133	500	0.49	0.82	0.085	17	2,525	149	526	0.63	0.93	0.125	-24%	47%
linerboard	46	11,652	253	1,045	0.29	0.57	0.043	38	25,711	676	3,879	0.37	0.68	0.063	121%	47%
corrugating medium	39	4,327	111	357	0.27	0.52	0.042	40	9,353	234	1,163	0.37	0.68	0.057	116%	36%
solid bleached board	17	3,858	227	1,223	0.52	0.83	0.136	11	6,147	559	2,318	0.71	0.97	0.195	59%	43%
recycled board	99	6,683	68	466	0.23	0.45	0.028	45	6,320	151	999	0.48	0.74	0.078	-5%	179%
Total	520	56,114	123	584				394	103,785	263	1,484				85%	

Source: own elaboration, data taken from FPL-UW database patterns. Growth in the period varies from a minimum of -24% in the case of kraft paper to a maximum of 159% in the case of coated free sheet. Except for two commodity products, newsprint and uncoated groundwood, the other 11 technological classes increased their concentration levels significantly measured by the Herfindahl index, from 1970 to 2000. The largest concentration expansions were recycled board with 179% and uncoated free sheet with 128%.[12] Based on these 13 technological classes, Chapter 6 will investigate the hypothesis that distinctive firm's technological configurations give rice to strategic groups that have significant and persistent heterogeneous growth performance.

Production diversification of US p&p firms

The 13 main p&p technology classes presented in Table 2.9 are used to analyse the production diversification of US p&p firms. Table 2.10 shows the degree of production diversification and Figure 2.14 depicts the relationship between diversification and firm size in 1970 and 2000. Firms vary in their degree of diversification from 1 technology class to 11 technology classes. More than 65% of firms are single grade producers. Few firms were diversified in more than 5 technology classes in 1970 and few firms were diversified in more than 4 technology classes in 2000.

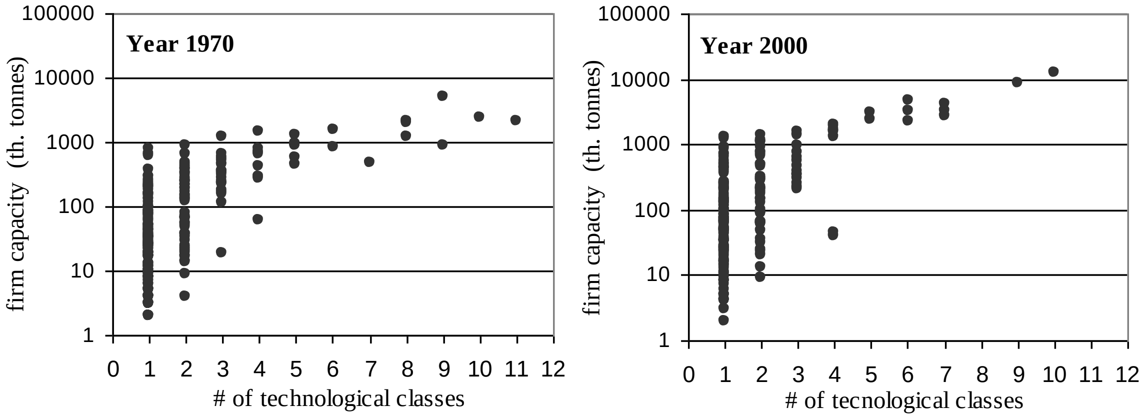
Table 2.10 Production diversification of US p&p firms, 1970 and 2000

# of main	year 1970		year 2000	
technology classes	# firms	% firms	# firms	% firms
1	199	66.3%	154	65.5%
2	54	18.0%	49	20.9%
3	23	7.7%	14	6.0%
4	8	2.7%	8	3.4%
5	6	2.0%	2	0.9%
6	2	0.7%	3	1.3%
7	1	0.3%	3	1.3%
8	3	1.0%	0	0.0%
9	2	0.7%	1	0.4%
10	1	0.3%	1	0.4%
11	1	0.3%	0	0.0%
12	0	0.0%	0	0.0%
13	0	0.0%	0	0.0%
Total	300	100%	235	100%

Source: FPL-UW database

[12] It is interesting to note that the number of firms that produced the recycled board technology class decreased from 99 to 45 from 1970 to 2000, and the number of firms that produced recycled board decreased from 68 to 49 during the same period.

Figure 2.14 Production diversification versus size of US p&p firms, 2000 and 1970



Source: FPL-UW database

In both years 1970 and 2000 there is a clear positive correlation between diversification and firm size. Larger firms tend to be more diversified than smaller ones; however, in 2000 the industry as a whole was less diversified than in 1970.

To achieve a more accurate understanding of the evolution of production diversification over time, we use the entropy index as a proxy for firm diversification as proposed by Jacquemin and Berry (1979) in their study of the relationship between firm diversification and growth. The entropy concept is based on the Herfindahl concentration index and for an individual firm takes the form:

$$E_{i,t} = \sum_{j}^{np} P_j * \ln(1/P_j)$$ entropy index of firm *i* at time *t*

where:

P_j is the share of the *j* th product category within the firm

np is the total number of product category within a firm

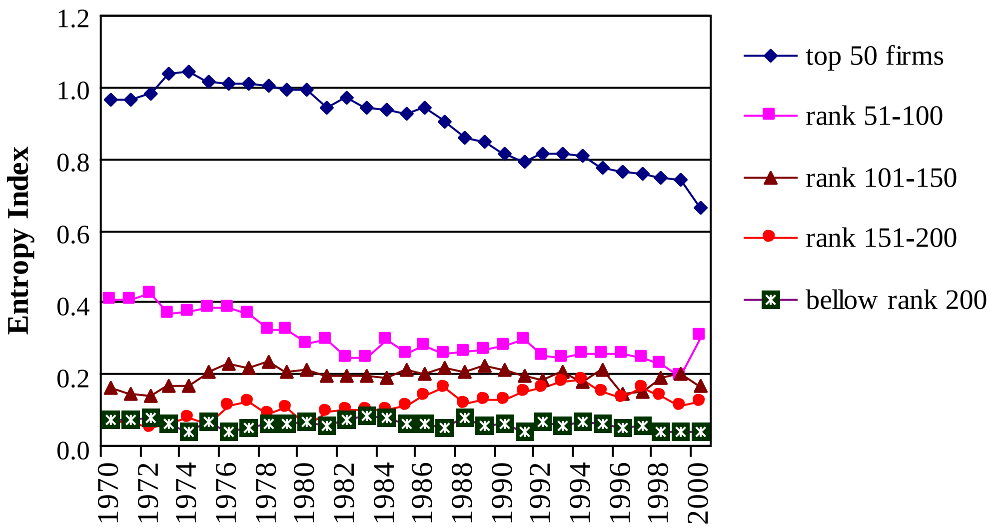
We use the annual average entropy index for the population of US p&p firms as a proxy for industry production diversification which takes the form:

$$E_t = \sum_{i}^{m} \sum_{j}^{np} P_j * \ln(1/P_j)/m$$ annual average entropy index at time *t*

where m is the total number of firms in the industry each year

Figure 2.15 shows the evolution of production diversification of US p&p firms for 5 size-classes in the period 1970-2000, using the entropy index as proxy for diversification. There are two main conclusions. First, the top 50 size-class is significantly more diversified than the other four size-classes across all three decades. While the top size class has an entropy index above 0.80, the other four have entropy indexes below 0.40. Secondly, the entropy index of the top 50 size-class is relatively stable at around 1.0 until the early 1980s, then begins to fall, reaching a minimum of 0.65 in 2000. The group of firms ranked 51-100 also show a pattern of diminishing diversification, but less pronounced. The next three size-classes of smaller firms show lower degrees of diversification in comparison with the first two groups, and their entropy indexes are relatively stable over time.

Figure 2.15 Production diversification evolution of US p&p firms for different size-classes, 1970-2000



Source: FPL-UW database

The important differences in industry concentration across the 13 technological classes and over time, described above (see Table 2.9), raise interesting research questions and hypotheses in relation to the 'heterogeneity within industry' literature. Are there significant and persistent differences in firm growth performance within the p&p industry? If there is systematic heterogeneity, what might be the causes? For example, are there distinctive technological configurations of firms (strategic groups) that may explain this significant intra-industry performance differences over time?

2.4 Summary and conclusions

This chapter has provided a brief overview of the p&p industry (global and US), covering the main process technologies, industry characteristics, structure and dynamics. We analysed five key technological and economic features that have shaped the international market structure: capital and scale intensity; energy intensity; cyclical market behaviour; continuous technological innovation; and environmental impact.

The p&p industry is often considered a mature, rather homogeneous and static sector and perhaps a less interesting arena in which to investigate issues related to the dynamics of industrial structure and the influence of technology. This chapter shows that in reality the p&p industry has displayed considerable dynamism and technological change during the observed period 1970-2000 and thus is an interesting sector to empirically investigate questions and hypotheses proposed in the literature. There are three families of questions that emerge from this industry context chapter that Chapter 3 will expand on. The first is related to patterns of growth among p&p firms and testing Gibrat's law hypotheses of stochastic growth. The second is related to the 'heterogeneity within industry' literature. We are interested in investigating the patterns and forces that may explain systematic inter-firm differences observed in this industry and the hypothesis that the existence of different technological configurations of firms may explain this heterogeneity. The third is related to the effects on the industry structure dynamics of the important technological changes taken place in this sector since the mid 1980s. We are interested in investigating the patterns and determinants of non-survivor firms (exit hazard analysis). Considering that the p&p sector is one of the most capital intensive and its growth is directly related with the adoption of new capital equipment, we are also interested in investigating the patterns of technology adoption behaviour in relation to the size distribution of firms and over time.

The following Research Questions and Literature Review chapter (Chapter 3) will examine the existing p&p industry research related to the facts and questions highlighted in this chapter. It discusses their importance in terms of being the subject of academic research and it presents the three research questions investigated in this thesis. It provides a review of the dynamics of the industrial structure and inter-firm heterogeneity literatures in which these research questions are positioned.

CHAPTER 3

RESEARCH QUESTIONS AND LITERATURE REVIEW

Chapter 3 reviews the research on the p&p industry related to its dynamics and technological structure. It shows that the existing literature provides incomplete answers to the questions that emerge from the industry review in Chapter 2. It proposes three research questions that will contribute to fill the gaps identified which are investigated in depth in Chapters 5, 6 and 7. Finally, it provides a review of the two principal literatures in which the research questions are situated: a) the dynamics of industry structure, specifically the dynamics of firm growth in relation to size; and b) heterogeneity within industries (strategic groups).

3.1 Previous research in the p&p industry related within the dynamics of industry structure and inter-firm differences fields

In this subsection we review the research on the p&p industry related to its dynamic structure and inter-firm heterogeneity. We discuss the facts arising from the descriptive analysis in Chapter 2 that existing studies do not explain or provide only partial explanations. We group the existing research into four areas according to their specific focus:[13]

a) the relationship between firm performance and different contextual, industry structure and firm conduct explanatory variables;

b) the relationship between vertical integration of p&p firms and market concentration;

[13] In making this classification we do not intent to construct a typology of research on the p&p industry related to its dynamic structure and inter-firm differences. The purpose is simply to present a clearer link among the existing research, to identify some of the gaps in the literature, and to provide a straightforward introduction to the three research questions that this thesis investigates in order to fill some of these gaps.

c) technology adoption, technology upgrading and innovation activities at firm level;
d) case studies that investigate specific features of the p&p industry at the country, sector and firm levels.[14]

We review the relevant research in these four areas and discuss the gaps in the literature, on the basis of which we formulate the research questions in Subsection 3.2.

a) Relationship between firm performance and contextual, firm structure and firm conduct explanatory variables

Few works investigate the relationship between p&p firms' performance (e.g. profitability, market share and capacity growth) and different explanatory variables (either exogenous to the firm e.g. p&p price or energy price, or endogenous e.g. firm size or age). One of the earliest investigations of growth in p&p firms is by Sutton (1973), which studied the US industry and concludes that larger pulp and paper mills tend to grow faster than their smaller counterparts because they are persistently more profitable. Buongiorno, Stier et al. (1981) produced a different finding, and showed that medium size p&p firms with less than 500 employees were the most productive. More recently Pohjakallio's (2000) doctoral thesis studied the implication of industry concentration on industry conduct and performance based on the North American p&p industry from 1977 to 1998. Firm size is found to be negatively associated with changes in production capacity which implies that small firms are more likely than large companies to increase capacity, and thus more likely to grow faster.[15]

Li, Buongiorno et al. (2004) studied the determinants of p&p mill growth in the US, in the period 1970 to 2000 and found no growth-size relationship; thus mills grew

[14] A number of p&p industry studies and reports at the global and US levels provide valuable contextual information on the sector however they are not directly related to the specific focus of our research the dynamic structure of the p&p industry. Some examples are: Arpan, Bauerschmidt et al. (1986); Higham; Higham (1995); Higham (1996); Carrere and Lohmann (1996); Smith (1997); Christensen and Caves (1997); Diesen (1998); Pesendorfer (1998); Ince (1999); Ince, Li et al. (2001); Ganzleben (2001); Berends (2001); Smith, Rice et al. (2003); Li, McCarthy et al. (2004); Toivanen (2005).

[15] Pohjakallio compares just two groups of firms, small and large, using three cut-off levels for capacity share (5%, 7% and 10%) to classify them.

according to Gibrat's law. Li, Buongiorno et al. found also that firm size and age were the two most important variables influencing growth.[16]

These inconsistent results are not uncommon in investigations of firm growth-size relationships in several industries including p&p, due to the econometric and data sampling problems such as heteroskedasticity, sample selection bias, presence of serial correlation, linearity assumptions along the size-distribution, etc. which are discussed in depth in Section 3.3.1 and Ch. 5, Section 5.1.1. These studies suffer from several of these problems which could explain their ambiguous results.

A focussed and robust investigation of the growth-size relationship in this industry, avoiding the most important econometrical and data problems, with a large enough number of size-classes to capture heterogeneous growth patterns in relation to the size distribution is needed. The causes of the heterogeneous growth performance of firms also need to be researched and understood.

Suleman's (2003) studied the influence of firm structure on profitability in the US p&p industry. Cross sectional data for 60-70 US firms covering the study period 1960-1998 were used for the empirical investigation. The research concludes that firm size, market share and equity/sales ratio are the principal factors contributing to the profitability of p&p firms in terms of net income in the US. Large firms take advantage of their scale to achieve higher productivity, but also better access to markets than small firms. However, Suleman's research does not explore in depth the technological structure of the industry as a factor explaining the systematically heterogeneous inter-firm performance that is demonstrated in our research. To do so, not only the 25% largest companies (60 to 70 firms) needs to be studied, but the complete size distribution which involves 230 to 300 companies that existed during the study period.

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[16] In Li, Buongiorno et al.'s (2004) study, the conclusion that the US p&p industry follows Gibrat's law during the observed period 1970-2000, did not consider the presence of heteroskedasticity nor the existence of serial correlation, both of which are severe, as will be demonstrated in Ch. 5. They also assume linearity along the size-distribution which is not warranted, and they study just the survivor plants during the full period 1970-2000. Survivor year 2000 firms represent less than half of the number of plants that existed during that period and this group is biased towards the larger size classes. After considering these econometric and sampling issues, Ch. 5 shows that Gibrat's law does not apply because smaller firms tend to grow faster than larger companies and this relationship is not linear. Additionally p&p growth variance diminishes with size and there is strong serial correlation in growth during the 1980s, which confirms the departure from a random growth process.

Siitonen (2003) investigates the drivers and main objectives of large p&p companies who entered the international market during the 1990s and the impact of different globalization and regionalization strategies on their performance. Data for the 100 largest p&p companies in the world are used to analyse this study's central research question: 'what kind of impact have different globalization and regionalization strategies had on the performance of the world's p&p companies during 1990-1998?' (Siitonen 2003, p.5). Siitonen finds a significant positive correlation between company performance and industry globalization during the 1990s. While increased globalization plays a role in the analysis in this investigation, particularly because it drives firms growth, it is not a primary objective to explain the relationship between globalization and firm performance. Siitonen's (2003) study therefore complements the findings in this thesis, further explaining the advantages of larger sized firms in this industry.

There are also several investigations on the relationship between firm growth and size in manufacturing industries including the p&p sector in specific countries. These are general industry comparative studies based usually on aggregated data for medium and large firms (not the complete size distribution) and their results for the growth-size relationship are erratic: we can draw no clear conclusions from these studies. For instance Harris and Trainor (2005) tested the relationship between plant size and growth in 26 (4-digit) UK manufacturing industries including p&p, for the period 1973-1998, and found that in all sectors smaller plants tend to growth faster than large ones. Using a similar approach, but in a developing country context, Shanmugam and Bhaduri (2002) studied eight Indian manufacturing sectors (including 53 pulp and paper companies) during the period 1989 to 1993. The results indicate that for all industries smaller firms grow faster than medium and large companies. On the other hand, Chen and Lu (2003) studied 17 Taiwanese industries between 1988 and 1999 and found that in the p&p industry there is no growth-size relationship.

From the above type of studies we can conclude that this general industries comparison do not provide robust results or clear conclusions about the growth patterns in the p&p industry during our study period 1970-2000. Thus, in this first line of research there is a gap in understanding the relationship between firm size and firm growth performance and the forces that might explain the existence of significant patterns in the p&p industry. This is a matter of great economic importance since it allow us to understand corporate growth and industry evolution which are discussed in depth in the literature review in subsection 3.3.1. We do not know whether the p&p industry follows Gibrat's law, the proposition that firm growth-rate is random, independent of size and independent of past growth, or whether firm growth is biased in favour of any particular size-class. If some size-class is favoured, we do not know the extent of the departure from a random growth process. The p&p industry is an interesting area for such an investigation based on its renewed dynamism since the mid 1980s noted in the Industry Chapter 2 (Subsections 2.2.2 and 2.3.2), where it is shown to be one of the most capital intensive industries in the world, and that the size variability in the population of firms is very wide, and has persisted over time.[17]

b) Relationship between vertical integration of p&p firms and market concentration.[18]

There are several studies related to vertical integration issues in this industry. Wang (2005) investigates the relationship between market concentration and vertical integration during the period 1970-2000 focusing on mills producing free sheet paper, one of the most profitable paper grades in the industry. The results show a significant positive correlation between market concentration and vertical integration. Wang found that the most important determinants of vertical integration are production-cost and transaction-cost reductions. While vertical integration plays a role in the analysis in this thesis, it is not a primary objective to explain the pattern or timing of vertical integration. Similar to Siitonen (2003) discussed above, Wang's (2005) study complements the findings in this thesis, further explaining the advantages of larger size firms in this industry.

Damani (2004) investigates the factors that positively influence US paper firms' decisions to vertically integrate to production of pulp during the period 1970-2000. Among other reasons, she finds that vertical integration increases the ability of the integrated firm to maintain or raise prices as their production costs decrease. Widespread vertical integration leads to barriers to entry, as potential new entrants need

[17] In the US, the average size for a p&p firm in year 2000 was 434,000 tonnes capacity. Firm size varies from very small firms of just 2,000 tonnes to very large firms of more than 12 million tonnes capacity, thus more than 6,000 times bigger, and these size differences have persisted over time.

[18] Vertical integration in the p&p industry means that a firm has both pulp and paper production capacities.

to be able to secure pulp inputs and thus must operate at all stages of production as well as distribution, making entry more difficult. Along with Wang (2005), Damani (2004) adds to our understanding of the advantages enjoyed by larger firms.

Ohanian (1994) in her doctoral dissertation, investigates the patterns of vertical integration in the US p&p industry using mill level data for the period 1900-1940. The results show that most paper mills are backward integrated towards pulp production and vertical integration is found to be positively associated with regional concentration and the size capacity of p&p commodity grades, thus she finds that vertical integration is a determinant of mill growth and mill survival. As in the case of Wang (2005) and Damani (2004), Ohanian’s study adds to our understanding of the advantages enjoyed by larger firms. It also adds to our understanding of the ‘starting positions’ or accumulated market positions of larger firms.

In summary, this second line of research focuses on the determinants and effects of vertical integration of p&p firms, taking account of the fact that the industry includes a variety of families of products (referred to as ‘technological classes’), ranging from standardized commodities such as newsprint, to highly specialized and customized products such as specialty papers (see Figure 2.1). It remains to be investigated the existence, determinants and effects of the technological configurations of firms. This would require a focus not just on vertical integration, but more importantly, on possible combinations of vertical and horizontal integration which could explain a within industry structure and the persistent inter-firm heterogeneity described in Chapter 2.

c) Technology adoption, technology upgrading and innovation activities.

Paper production technology is very much embedded in paper production machinery, thus the adoption of new capital equipment and the modernisation of existing equipment are fundamental to the competitiveness of firms. Understanding these adoption and investment activities involves investigating, on the one hand, p&p firms’ new technology adoption patterns, and on the other, the activities and competencies that firms employ in upgrading their existing technologies.

Lehtoranta (1994) studied the factors that affect the lifetimes of paper machines in the Finnish p&p industry.[19] She found that rapid technical progress has shortened the life-cycles of modern capital equipment and increased the rate and scale of technical obsolescence. In this area of study, it would be interesting to investigate the impact of the rapid increase in paper machine operating speeds, described in Subsection 1.1, on firm's technology adoption patterns and on firm's exit hazard rate across size-classes and over time. The exit hazard rate is an important determinant of the industry dynamics. A positive finding would support the hypothesis related to the significant effects of technological progress on industry structure (Brock 1981; Kamien and Schwartz 1982; Abernathy, Clark et al. 1983; Baldwin and Scott 1987).

Ghosal and Nair-Reichert (2007) studied the role and value of innovation activities in the US and European p&p industries. Their results show that incremental innovation and investment in capital equipment modernization appear to be important for firms to remain competitive. Breakthrough innovations at firm level are a less frequent factor driving the changing competitive position and performance of firms. In fact, they conclude that companies that succeed in implementing continuous technological improvements on a year-to-year basis achieve relatively better competitive position in the medium-to-longer run, than those firms that do not have these technological competences. In a complementary type of investigation, Laestadius (1998b) studied technological competences in p&p manufacturing. He identifies two different systems of knowledge formation. The first is the wide cluster related to the production chain of p&p manufacturing including part of the forestry industry, paper machinery producers, process and control systems manufacturers, consultants, universities, and so on. The second is a narrow system that involved the p&p making process and the manufacturing plant. A key aim of this system is to obtain high and efficient capacity utilization of very expensive capital equipment.

Ghosal and Nair-Reichert (2007) and Laestadius (1998b) add to our understanding of the processes through which the p&p industry and firms develop endogenous technological competencies for the upgrading and efficient use of their capital equipment. However, considering that the p&p industry is one of the most capital

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[19] In 2000 Finland was the world's 6th largest producer of paper and board and the 4th largest producer of pulp (see Tables 2.1a and 2.1b in Ch. 2).

intensive in the world, a remaining gap in the literature is to understand the patterns of adoption of new capital equipment and its impact on the dynamics of the industry. P&p technology is very deeply embedded in expensive machines thus we could hypothesize that distinctive patterns of technology adoption could be a source of heterogeneous inter-firm performance.

d) Case studies that investigate specific features of the p&p industry at the country and sector levels.

A fourth line of research within the p&p industry is qualitative case studies focused on the industry and country levels. An example of such research is Van Dijk's (2005) doctoral thesis which studies the Indonesian p&p industry in a bid to increase understanding of the catch-up process. He finds that in spite of Indonesia being a country with one of the fastest forestry growth rates, which represents a very important cost advantage; its indigenous production capabilities are limited. The accelerated development of the Indonesian p&p industry has been driven mainly by rapid state-of-the-art capital equipment accumulation by few large firms, facilitated by the involvement of foreign engineers and managers. He finds little evidence of indigenous technological assimilation and innovation. In similar types of investigation Melander (1997) studied 'strategic change' in the Swedish p&p industry during the period 1945-1990 and Tremblay (1994) conducted a comparative analysis of technological capability and productivity growth focused on the p&p industries of Canada and India from 1900 to 1991. This type of studies do not contribute much to answering the questions related to p&p industrial dynamic structure from the 1970s onwards when the global p&p industry was impacted by important technological changes and the increased internationalization of firms.

The main conclusions from this review of the research on the p&p industry, and specifically those studies concerned with the dynamics of industrial structure, are that there are several major problems that the existing studies do not address and that there are important facts not yet explained in the literature. In addressing some of these gaps in the existing research, there are opportunities to formulate and test several hypotheses concerning the dynamic structure of a very highly capital intensive industry which might increase our understanding of other branches of modern industrial activity where a growing number of industries is becoming highly capital intensive (Clark 1923).

3.2 Research questions

In this section we present the three research questions that will be investigated to fill the four gaps that we have identified from the literature reviewed above.

First research question:

We base the first research question on the fact that in the p&p literature there is no explanation of the patterns that govern the growth dynamics of p&p firms during the period 1970-2000, when the industry underwent an important set of changes which are documented in Chapter 2 Subsection 2.3.2. After the mid 1980s the industry experienced a major transformation (Ghosal and Nair-Reichert 2007), which changed its global structural composition and significantly increased its global concentration (see Figures 2.8 and 2.11). The size distribution curve of individual firms moved towards the larger size classes (see Figure 2.12) although there is significant and persistent heterogeneity in firm size even among the world's 150 largest companies. The size of the largest firm in year 2000 is 192 times larger than the 150th firm in terms of sales, and 164 times larger in terms of total output.

In this industry context we do not know whether p&p firm growth is based on a simple stochastic growth mechanism such as Gibrat's law (also known as 'random-walk' or 'Law of Proportional Effect' (LPE) in the literature) hypothesizes, which means that firm growth is independent of size and independent of previous growth trajectory, or is biased to some size classes or to past growth.

It is important to study Gibrat's law to inform us about the role played by chance in the process of firm growth and the way in which we understand the reasons for success or failure of firms. Central to Gibrat's law is its capacity to explain the appearance of log-normal distributions of firm sizes in most industries, including the p&p (see Figure 2.10) and thus to understand industry evolution. In fact Gibrat's law is considered a *stylized* *fact* (Geroski 1999)[20] in the corporate growth literature, idea that will be extended in the literature review of Section 3.3.

The first - three part - research question investigates whether the growth dynamics of p&p firms follow Gibrat's law in its strongest form[21] at the global and US industry levels in the period 1971-2000:

- Is there a significant relationship between the growth-rate and size of the p&p producers? If such a correlation exists, what is its nature?
- Is there a significant relationship between the growth-rate variance among p&p producers and their size? If such a correlation exists, what is its nature?
- Is there significant serial correlation[22] among the growth-rates of p&p firms? If so, what is its nature?

<u>Second research question:</u>

The second research question is formulated based on the fact that the existing literature does not explain the causes of the significant and persistent inter-firm heterogeneity in the p&p industry, specifically heterogeneity in firm size and growth. This is an important research area in industrial economics because increase our understanding of the degree and type of competition among firms and would provide valuable insights for policy on regulation, job creation, trade barriers, etc.

The second - four part - research question investigates the causes of departure from Gibrat's law in the p&p industry during the period 1985-2000, when the industry had the most interesting dynamics, as described in Industry Chapter 2. It investigates the hypothesis that a random-walk process is not in operation because of some firms' technological configurations which give rise to clusters or strategic groups that define the structure of the industry more accurately than the simple size distribution of firms or studies of vertical integration alone are able to do. More specifically we investigate:

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[20] For a discussion and review see Ijiri and Simon (1974), Lucas (1978), Sutton (1997), (Klomp, Santarelli et al. (2006).

[21] The literature refers to a 'strong form' of Gibrat's law when its three hypotheses hold, which means that there is no presence of growth-size relationship, no growth variance-size relationship and no serial correlation. When only the first two hypotheses hold this is called a 'weak form' of Gibrat's law.

[22] The non-existence of serial correlation means that the rate of growth of the firm in one period has no influence on its growth in the following periods.

- Within the p&p industry are there distinctive configurations of technological specialization (strategic groups) of p&p firms at one point in time (year 2000)? (The number of configurations will be deduced from a cluster analysis).

On the basis that it is possible to identify strategic groupings:

- Does firm performance, measured as annual growth rate, differ systematically across strategic groups?

On the basis that it is possible to identify systematic differences in growth performance across strategic groups:

- Is there distinctive firm behaviour associated with each cluster that may explain systematic performance differences across groups?
- What portion of inter-firm difference cannot be explained by these behaviours (and thus may be due to firm-specific fixed effects)?

<u>Third research question</u>

As explained in Industry Chapter 2, the most important technological feature of p&p machines is their operating speed, which increased significantly after the mid 1980s with the introduction of 'automatic process control' technologies (see Figure 1.2). This technological innovation can be seen as introducing an inflection point, which, from an evolutionary perspective, could be interpreted as a technological regime change (Breschi, Malerba et al. 2000, p.388).[23] As noted previously, the p&p industry is one of the most capital intensive sectors in the world and a significant proportion of industry capacity expansion is explained by the adoption of new capital equipment, thus it is a possible source of persistent heterogeneity among firms. In the US, the largest p&p producer and consumer country in the world, the number of firms decreased from 300 in 1970 to 234 in 2000 while average capacity increased from 187,000 to 434,000 tonnes and total industry output doubled during the observed period (see Figure 1.1).

[23] The literature refer to 'technological regime change' as 'the particular combination of technological opportunities, appropriablility of innovations, cumulativeness of technical advances and properties of the knowledge base'(Breschi, Malerba et al. 2000, p.388).

We base the formulation of the third research question on three gaps in the literature on the p&p industry related to the above evidence. First, the literature has not deepened on the patterns of p&p technology adoption behaviour across firm's size-classes and over time. Second, it has not investigated the effect of the rapid increase in paper machine operating speeds (Figure 1.2) on firm growth performance. Third, the literature does not explain the pattern and determinants of p&p firms that exited the industry in the period 1970-2000. Thus, in our third research question, which is constituted of four parts, we are interested in investigating how effectively a technologically based analysis might explain the changing structure of the industry over time. [24]

- Within the US p&p industry, are there distinctive patterns of non-survivor firms during the period 1970-2000?
- If so, what are their sources?
- Within the US p&p industry, are there distinctive patterns of firm technology adoption behaviour over time and across strategic groups (the second research question studied the existence and performance of strategic groups)?
- What proportions of US p&p industry capacity expansion can be explained by state-of-the-art technology adoptions and by incremental technology improvements and upgrading?

These three research questions are positioned within two related bodies of the literature which are reviewed next: a) dynamics of industrial structure, specifically the dynamics of firm growth in relation to size; b) heterogeneity within industries (strategic groups).[25] These research questions will contribute to the literature by providing new empirical evidence of the persistence over time of an intra-industry technological structure that systematically influences the heterogeneous performance of firms with different technological configurations and whose origins are linked to firms' growth processes (industrial dynamics and technological choices) in the p&p industry.

[24] Other sources than technology – e.g. globalization or environmental regulation, might be responsible for explaining part of the changing structure of the industry over time, however our purpose is not to examine these alternatives interpretations, but to focus on the technological change dimension.

[25] More specific bodies of literature such as firm's technological configurations, exit hazard rates and technology adoption behaviour, are reviewed in Chapters 5, 6 and 7, which address each of the three research questions in this thesis.

3.3 Literature review

This section reviews the two bodies of literature within which this thesis is positioned. These are the dynamics of industrial structure (firm size distribution, Gibrat's law) and heterogeneity within industries (strategic groups).

3.3.1 Dynamics of industrial structure (firm size distribution, Gibrat's law)

An industry can be defined as a group of firms that produce similar goods/services or close substitutes, and which compete with one another such that the behaviour of one firm directly or indirectly affects the behaviour of another. It may also be defined as a group of firms that employ a similar set of techniques or utilise similar resources even if the resulting products or services are not such close substitutes – e.g. the scientific instruments or petro-chemicals industries. McGee and Thomas (1986, pp.141-142) state that markets and technology criteria could define the boundaries of an industry:

> Market criterion is used to include within a specific industry those products which are sufficiently similar as to be close substitutes in the eye of the buyer, the similarity being the familiar cross-elasticity of demand. The technological criterion focuses upon the classification of industries according to their similarity of processes (supply side).

Industry structure is understood as the number and size distribution of the firms that constitute an industry and influence the type of competition; thus it comprises variables such as number of sellers and buyers, size distribution of sellers and buyers, barriers to entry and exit, mobility barriers, diversification, vertical integration, etc. (Porter 1979; Carlton and Perloff 2004). The highly skewed firm-size distribution with high presence of small firms, medium presence of medium size firms, and small proportion of large companies, has received considerable attention since the seminal study by Simon and Bonini (1958) because it is observed in almost all industries and the asymmetry persists over time.

The *structure-conduct-performance* tradition (Mason 1939; Bain 1956) concentrated its attention on static cross sectional analyses of industries structure stressing issues such as economies of scale and other cost advantages as a source of firms heterogeneity. A principal question of investigation was concerned with the links between structural features and the performance of industries (Dosi, Malerba et al. 1997). However, after several decades of predominance of this static *structuralist* tradition, interest in understanding the dynamic aspects of how industries and firms change over time have started to emerge. The dynamics of industrial structure has become a major research field in industrial economics and strategic management because of the high degree of turbulence and change that characterize modern economies. The growing availability of large longitudinal databases at firm level allow observation of dynamic variables such as entry, exit and growth of firms, however little is known about the patterns that govern the dynamics of industries and firms over time (Dosi and Malerba 2002). As Audretsch (1997, p.51) points out:

> It is an economy in motion, with a massive number of new firms entering each year but only a subset surviving for any length of time, and an even smaller subset that can ultimately challenge and displace the incumbent large enterprises. Despite the high degree of fluidity and turbulence in modern economies, very little is actually known about the dynamic process through which industries and firms evolve over time.

Having defined the industry structure concept and explained the importance of the dynamics of industrial structure, the review of this literature is organized in four sub areas: the static structure-conduct-performance paradigm; the dynamics of industrial structure and firm’s growth size relationship; Gibrat’s law or the LPE; and the most important empirical studies of Gibrat’s law.

<u>Structure-conduct-performance paradigm</u>

The relationship between industry structure and economic performance is the important focus on the industrial organisation field (Mason 1939; Bain 1956; Markham 1965; Dalton and Penn 1976; Kwoka 1979; Geroski 1982; Schmalensee 1989; Scherer and Ross 1990). One of the first influential contributions is the *structure-conduct-performance* (SCP) paradigm developed by Mason (1939) and revised by Bain (1956). The central argument of this model is that the *basic conditions* of an industry determine its *structure*,[26] which is relatively constant over time and becomes a determinant of business *conduct* which, in turn, determines industry *performance* (Scherer and Ross 1990, p.5).[27] The main objective of the industry SCP paradigm is to allow ultimate industry performance to be predicted. As Caves (1972, p.36) notes:

> The importance of market structure lies in the way it induces firms to behave. Their behaviour in changing process, outputs, products characteristics, selling expenditures we shall call their market conduct. Conduct links an industry's structure to the quality of its performance. In fact, market performance is our evaluation of the results of firm's behaviour.

The barriers to entry of new firms is a central concept in the SCP paradigm since they have a direct impact in performance. The higher the cost of entry, the easier it is for existing firms to maintain monopoly profits. Bain (1956, p.3) defines entry barriers as:

> the advantage of established sellers in an industry over potential entrant sellers, these advantages being reflected in the extent to which established sellers can persistently raise their prices above a competitive level without attracting new firms to enter the industry.

In spite of the important influence that the SCP paradigm produced on the Industrial Organization and Strategic Management fields, empirical investigations of its implications do not provide clear evidence that concentration is associated with

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[26] One of the most important features of industry structure is industry concentration.

[27] *Basic conditions* include supply and demand conditions. Supply factors include location and ownership of the relevant raw materials; the notion of the technology, the durability of the product, and so on. The demand side includes demand price elasticity; availability of substitute products; variability of demand over time; marketing characteristics of products sold, and so on.

Industry structure refers to the ways industries are organized. Its elements are the number and size distribution of firms (industry concentration), entry and exit of firms, barriers to entry of new firms, degree of vertical integration and product diversification.

Conduct of sellers and buyers refers to aspects such as pricing behaviour, product line and advertising strategy, research and development (R&D) commitment, investments in production facilities, and so forth. McGree and Thomas (1986) provides a good review of the concept of 'conduct'.

Performance in an IO context is concerned with issues such as firm growth, firm profitability and market power, production efficiency, technological progress, full employment of resources, equity of income distribution.

performance or high concentration and barriers to entry (Demsetz 1973; McGee 1988; Hill and Deeds 1996), findings that would have important policy implications for antitrust regulation.

Based on empirical evidence, scholars have identified some drawbacks to this model that limit its application. The first is the use of industry as the unit of analysis and the consequent assumption that firms within an industry are homogeneous (Rumelt 1991). In contrast, numerous investigations have found significant and persistent inter-firm differences in many industries as discussed in Subsection 3.3.2. A second shortcoming is the use of static rather than dynamic analysis as in this research. The SCP relationships are derived from a microeconomic model of perfectly competitive markets (McGee 1988) where competition is viewed in terms of equilibrium conditions. This implies long run optimal allocation of resources that can be sustained over time and that maximize social welfare. However, more recent empirical evidence shows that, contrary to the assumption of relatively constant industry structure, most sectors experience rapid changes (McWilliams and Smart 1993), therefore industry concentration is best understood as a flow in the number and size distribution of firms rather than as a static state (Cabral and Mata 2003).

Based on these limitations of the SCP paradigm, alternative approaches to explain this relationship have been suggested (Singleton 1986). One of this conceptualizations is the so-called e*fficiency paradigm* which is rooted in Schumpeter (1942). The efficiency paradigm views competition as a dynamic process rather than a static state, and one that generates superior efficiency in production by particular firms. These efficient firms gain market share, which in turn tends to produce increases in market concentration (McWilliams and Smart 1993). Above average performance by particular firms can be seen as rewards to the efficient competitor rather than an indication of monopoly. This paradigm also argues that as long as demand is changing or innovations take place, the industry will not achieve a static equilibrium, as the SCP suggests, and thus heterogeneous firm performance can be expected (Demsetz 1973) as will be discussed in subsection 3.3.2.

Dynamics of industrial structure and firm growth-size relationship

The theoretical and empirical literature in industrial dynamics is broad and has different influences such as the seminal work of Hannan and Freeman (1977) on Organizational Ecology. These authors argue that natural selection occurs in organizations and based on insights from biology, economics and sociology try to understand the conditions under which organizations emerge, grow and die. For reviews of the different perspectives of this vast literature see the work of Baldwin and Scott (1987), Hannan and Carroll (1992) and the more recent wotk of Dosi, Malerba et al. (1997) which suggests the following three levels of analysis:

- *Specific dimensions of industry dynamics* which refers to the dynamics of specific features of industrial structure such as firm size distribution, firm growth, persistence, asymmetric performance and industrial demography.
- *Structural dynamics of specific industries* which refers to the dynamics over time of structural variables such as entry and exit of firms, firm size, industry concentration, product and process innovation.
- *Structural evolution* which refers to a broader view of industrial structure and its evolution over long periods of time. It studies dimensions such as the emergence of new industries, the creation and transformation of technologies within industries, the development of networks, and the role played by institutions (e.g. government, scientific institutions, financial institutions).

In this research we focus on some aspects related to the first two levels, such as firm size distribution, firm growth, persistence of heterogeneity, and firm exit. In general, the dynamics of industry structure depend on the interplay between overall market growth and development, and industry technological innovation frequency and magnitude (Abernathy, Clark et al. 1983). Technical progress may affect market structure in several ways. For instance, it could influence the optimal scale of production, which is especially relevant in capital-intensive industries such as p&p. It could influence the entry of new firms trying to reap the advantages of new technological opportunities, or the exit of firms. It could also have an effect through the erection of entry barriers derived from patents (Kamien and Schwartz 1982, p.70).

The dynamics of industrial structure are traced by firm size distributions which are inherently dependent on the process and characteristics of individual firm growth (Reichstein and Jensen 2005). Firms differ significantly in size, and size distribution is the subject of a large body of theoretical and empirical research starting with Gibrat (1931), Simon and Bonini (1958), Ijiri and Simon (1971; Ijiri and Simon 1974), Lucas (1978); and more recently, Sutton (1997), Lotti, Santarelli et al. (2003), Geroski, Lazarova et al. (2003), Bottazzi, Coad et al. (2005).

Early studies of firm size distribution focus on the appropriate functional specification to describe it, including Pareto and Log-normal (Simon and Bonini 1958; Ijiri and Simon 1964). These functional forms, all of which are asymmetric about the mean with a longer tail in the direction of larger size (positively skewed), are a first approximation of the empirical firm size distribution observed in most sectors. These models also have an important property that can be derived from a stochastic growth assumption, that growth and growth variance are independent of size and independent of past growth. This stochastic explanation of the size distribution is of considerable interest for economic theory and policy since it can be use to study the dynamics of firm growth instead of static cost curves (Ijiri and Simon 1964) as will be explained next.

Gibrat's law (or LPE or random walk)

One of the first formal models of the dynamics of firm size and industry structure was proposed by Robert Gibrat (1931) in his *Inégalités Économiques*. Gibrat's central argument was that, within industries, firm growth rates are a random variable independent of firm size. This means that the chances of a given proportional change in size during a specific period is the same for all firms in an industry, regardless of their size at the beginning of the period and regardless of their previous growth history. In the literature this phenomenon is also known as the LPE or 'random walk' because growth is regarded as a pure stochastic phenomenon resulting from the cumulative effects of a large number of factors acting independently of each other. This implies that the chances of growth or shrinkage of individual firms depends on many factors including the quality of firm management, the economic environment of the firm, product diversification, level of profitability, technological opportunities, etc. Gibrat's law does not exclude the possibility that ex post, strong growth performance can be attributed to ‘systematic’ factors such as managerial talent, successful innovation, efficient organizational structure or favourable shifts in consumer demand. Rather, it implies that growth originating from these factors cannot be predicted ex ante. Such factors may determine growth, but they are distributed randomly across firms (Goddard, McMillan et al. 2006).

LPE has received significant attention in the empirical and theoretical literature, first because of its capacity to provide an explanation of the evidence of significant and persistent heterogeneity in firm size within industries (Hymer and Pashigian 1962; Sutton 1997; Goddard, Wilson et al. 2002). Second, because it provides a reasonable explanation of the typical positively skewed firm size distribution curve observed in many industries (Hart and Prais 1956). The empirical occurrence of this type of distribution suggests a general law of the growth of firms (Gibrat’s law or LPE) which is able to generate this recurrent distribution pattern (Hart 1962). A normal curve is generated when a large number of independent random forces act on variety in an additive manner. This means that the determinants of firm growth tend to change the size of firms by randomly distributed proportions, thus there is no tendency to favour or disfavour firms of any particular size which is what LPE argues. Thus, the LPE became a reference model for discussing the corporate growth process (Bottazzi, Cefis et al. 2002).

The LPE proposes three hypotheses regarding firm growth dynamics. The first, as already explained, states that firms in different sizes-classes show the same average proportional growth. The second states that the dispersion of growth rates around the common average is the same for all size-classes. The third states that there is no serial correlation in growth rates. This means that the growth rate of an individual firm in a specific period is independent of the growth rate of that firm in previous periods and that growth in a future period is independent of growth in the current period.

If growth is in accordance with Gibrat’s Law, logarithmic firm sizes will follow random walk. A direct consequence of this is that there will be no convergence process within industries and thus no predictable differences in growth will exist. It implies also that there is no minimum efficient scale or optimum firm size. However, Simon and Bonini (1958, p.610) argue that, assuming there is a minimum firm size within an industry, Gibrat's law will hold for firms that are 'well above' that minimum efficient scale, but not for the whole distribution. Another implication of the LPE is no presence of serial correlation in the growth process, which means that growth rates can be treated as a first-order Markov stochastic process. When a growth distribution exhibits positive first order serial correlation, firms that achieve rapid growth in one period will also tend to grow rapidly in the following period. All the above implication of the LPE produce direct influences on the industry structure dynamics.

Review of the Empirical Literature on Test of Gibrat's Law

A large number of studies test Gibrat's law in different sectors and using a variety of methods and time periods. Singh and Whittington (1975) provide an interesting review of several theoretical frameworks used to study the relationship between firm size and growth. During the 1990s, three comprehensive and influential surveys related to firm growth rates are Geroski's (1995) stylized results, Sutton's (1997) statistical regularities, and Caves (1998). During the 2000s Audretsch et al. (2002) provide an exhaustive survey of 58 studies related to Gibrat's Law while Lotti et al. (2003) investigate an additional 17 selected studies and Klomp, Santarelli et al. (2006) review more than 60 empirical studies.

From this large body of empirical evidence, we can distinguish two broad phases (Sutton 1997). The first phase began when Gibrat formulated his law in 1931 and concludes in the late 1970s when many studies had confirmed the empirical validity of the law for many sectors and different time periods (Goddard, McMillan et al. 2006).[28] For example, two important studies in this phase are Simon and Bonini (1958) which investigated the 500 largest UK manufacturing firms in terms of sales, and Hymer and Pashigan (1962) which analysis 1,000 of the largest US manufacturing firms measured by assets, in the 1940s. In both cases Gibrat's law is confirmed.

In the second phase that started roughly in the early 1980s, numerous studies using larger databases challenged the validity of previous results. Most of them concluded that

[28] However a few studies do not confirm the LPE hypothesis during this first phase, e.g. Mansfield (1962) which investigates the US steel, petroleum and tyre industries in different time intervals within the period 1916-1957 and finds that Gibrat's law does not hold because smaller firms tend to have higher and more dispersed growth rates than larger firms.

Gibrat's law fails to hold because firm growth rates and variance tend to fall with size (Mansfield 1962; Kumar 1985; Hall 1987; Evans 1987b; Dunne, Roberts et al. 1989; Mata 1994; Hart and Oulton 1996; Sutton 1997; Caves 1998; Almus and Nerlinger 2000). There are three explanations for the results being different between the two phases. The first is the use during the second phase of larger databases that include both cross sectional and longitudinal data. The second is the use of more sophisticated statistical techniques that correct for different econometric problems in testing for LPE in its strongest form. These problems include heteroskedasticity, the presence of serial correlation and the presence of non-linearity along the size distribution.[29] For instance, Hall (1987) in her study of the US manufacturing sector using a sample of 1,778 firms in 1976, concludes that there is a slightly negative relationship between size and growth for smaller firms, which is robust to corrections for selection bias and heteroskedasticity. However, substantial differences in the variance of growth rates across size classes is observed, with smaller firms showing variances that are at least twice as large the growth variance of big firms.

The third explanation for the difference between the two phases is that the samples of firms used to test Gibrat's law impede clear comparison of the results. According to Mansfield (1962), Gibrat's law can be formulated in at least three ways, depending on how the death of firms in the sample and the comprehensiveness claimed for the law are treated. Firstly, we can study whether the law holds for all firms, including those that leave the industry during the period of study. The size of these companies after they leave the industry is considered to be zero. Secondly, we can examine whether it holds for all firms that survive over the time period, which means that those firms that leave the industry are omitted from the sample. Hart and Prais (1956) adopted this procedure. The third possibility is to study the law in the case of firms exceeding the minimum efficient size in the industry, below which unit costs rise sharply and above which they vary slightly. This is the approach taken in Simon and Bonini (1958).

Alongside the wide disparity of results across studies, most scholars agree that LPE cannot be considered a general law, since it is better suited to describing the growth process of relatively big and mature firms that have reached a minimum efficient scale,

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[29] In Chapter 5 each of these econometric problems is analysed in depth.

and not for the whole size distribution where smaller firms operate just above this threshold (Geroski and Machin 1992; Sutton 1997; Cefis, Ciccarelli et al. 2004).

There is also a possible third phase in the LPE studies which is the work done during the 2000s. These more recent investigations move from employing data and econometric corrections for explaining the erratic results, to a new strand of analysis where the basic Gibrat model is modified in order to capture departures from the LPE found in the latest empirical studies. One example is Lotti, Santarelli et al. (2007) who try to reconcile the different results described above by taking account of the role of market selection and learning (Jovanovic 1982) in reshaping a given population of firms through time. Using data from the Italian radio, TV and telecommunications equipment industries in 1987-1994 they find a convergence towards Gibrat behaviour. They test two hypotheses. An *ex-ante hypothesis* where Gibrat's law is valid for the entire period and an *ex-post hypothesis* where there is a convergence toward a Gibrat pattern of growth over time. Consistent with previous studies, they reject Gibrat's law *ex ante* for the complete size distribution since smaller firms tend to grow faster than larger companies. However, a significant convergence towards Gibrat behaviour is detected *ex post*. As Lotti, Santarelli et al. (2007, p.14) note:

> This finding is an indication that market selection 'cleans' the original population of firms, so that the resulting industrial 'core' does not depart from a Gibrat-like pattern of growth. From a theoretical point of view, this result is consistent with those models based on passive and active learning, and can be seen as a defense of the validity of the Law in the long-run.

Another strand of analysis proposes a more complex characterization of firm growth dynamics where growth depends on both current and past firm size. The results show a growth rate distribution that does not look like a Gaussian curve as Gibrat's law suggests, but is tent-shaped (Bottazzi and Secchi 2005, p.18) with 'fatter tails than the Gaussian' shape (Reichstein and Jensen 2005, p.1146). Some empirical studies confirm this hypothesis e.g. Stanley, Amaral et al. (1996) for all publicly traded US manufacturing firms between 1975 and 1991. A similar tent-shaped growth distribution was found by Bottazzi, Dosi et al. (2001) for the world pharmaceutical industry.

Intended contribution to the above literature

This thesis contributes to the above literature in four ways. First, Gibrat's law is tested in its strongest form which involves growth-size relationship, growth variance-size relationship and growth autocorrelation over time. This is done taking account of the four econometric problems that are commonly present in dynamic analysis: heteroskedasticity, sample selection bias, serial correlation, and non-linearity. We demonstrate that neither global nor US p&p industries follow Gibrat's law, thus the growth process of p&p firms is not stochastic in nature. We demonstrate that smaller firms tend to grow faster on average than large firms during the long study period, a result that is consistent with many of the recent empirical investigations discussed in the above literature review.

The second, more interesting, contribution to the literature is the possibility of nonlinearity, in contrast to the linear assumption in many previous studies. In the p&p industry medium-size and technology-specialized firms exhibit growth rates that are consistently among the highest in the size distribution, even higher than the growth of small firms. The explanation for this non-linearity is the existence of distinctive technological configurations or strategic groups of firms which show persistent heterogeneous growth performance.

The third intended contribution of this thesis is related to testing the third of Gibrat's hypotheses. We show that p&p firm's growth persistence varies along the size distribution and over time, thus demonstrating that the assumption of constant serial correlation, which most of the previous investigations adopt, is not appropriate. The existence of growth persistence provides support for the 'evolutionary' and 'resource based view' of the firm (Nelson and Winter, 1982; Teece and Pisano, 1994), which suggests that the growth of successful firms tends to persist over time.

Fourth, despite finding that the p&p industry does not follow Gibrat's law, we demonstrate that Gibrat's law *does* operate within subgroups of p&p firms that exhibit similar intra-group features and different inter-group features. We argue that Gibrat's law is not an industry level feature, but that it operates within subgroups of firms that exhibit similar strategic choices and resource commitments.

The causes of non stochastic growth and inter-firm performance differences are related to the heterogeneity within industries and the strategic group literatures reviewed in the next section.

3.3.2 Heterogeneity within industries and strategic groups

This subsection reviews the second body of literature in which this research is positioned, heterogeneity within industries, which is a major research field in industrial economics and strategic management. It is a major area because of its greater capacity to explain the sources and significance of systematic inter-firm differences in behaviour and performance which help our understanding of industry dynamics – how industries evolve over time (Nelson 1991; Cabral and Mata 2003). Specifically, research in this area might improve our comprehension of the type and degree of competition among firms and provide insights for areas of industrial policy such as regulation, subsidies, and incentives to influence job creation, trade barriers, and so forth.

The review is organized in four sub areas: Industrial Organisation view of heterogeneity within industries; Evolutionary and Resource Based View of the firm perspectives of heterogeneity within industries; strategic groups as an explanation for systematic inter-firm differences; and previous research on strategic groups and some main criticisms of this literature.

<u>Industrial Organisation (IO) view of inter-firm differences</u>

One of the first studies of firm size, growth and performance heterogeneity is Viner (1931), an influential paper which predicts a unique size distribution as the outcome of cost-minimizing firms engaged in product market competition. Viner assumed that individual firms have U-shaped long-run average cost function. As noted by Lucas (1978, pp.508-509):

> In equilibrium, each firm produces at the minimum point of the curve, with firm entry or exit adapting so as to adjust aggregated industry production to aggregated demand at the zero-profit price. The size distribution that emerges from Viner's scenario is the result of the

> economic problem of allocating production over firms so as to minimize total costs.

Traditional economic thinking argues that the long run differences in firm conduct and performance are the consequence of differences in the contexts in which they operate rather than differences in firm choices and strategies. Prior to the more recent literature on information economics, where assumptions of perfect information are relaxed, neoclassical economists struggled with the question of the heterogeneity resulting from ‘firm choices and strategy’ (discretion). Knight (1921), who anticipated important later developments in information economics, identified uncertainty as a source of heterogeneity. For Knight, conduct and performance differences among firms that operate in the same industry and in the same context, can be attributed to the realization of what he calls an ‘uninsurable chance event’, which means, for instance, the introduction by an entrepreneur of a new technology or a manager’s successful bet on a change in consumer preferences. The heterogeneous performance of firms operating in similar contexts can then be seen as a temporary phenomenon; the general prediction is that in the long run the dispersion of firms’ conduct and performance should be reduced since there is a convergence that takes place, as better practices and technologies become diffused and are imitated (Lööf and Heshmati 2002). This neoclassical theory also suggests that small firms tend to grow rapidly in order to reach the so called ‘minimum efficient scale’ (Hart 2000).

However, the proposition of non-persistent conduct and performance heterogeneity in similar competitive contexts has been challenged from a theoretical as well as an empirical point of view. A large body of empirical literature gathered from different sectors shows that the conduct and performance of firms in a given industry could continue to be different for long periods of time. This heterogeneity can be found among firms in narrowly defined industries and much of it is quite persistent over time (Röller and Sinclair-Desgagné 1996; Klette and Griliches 1998). Bartelsman and Doms (2000) in their review documented significant and persistent productivity heterogeneity across firms in several industries. This has suggested to some economists the need for more fundamental reform of theory to reconcile theory and empirical observation.

Evolutionary and Resourced Based View (RBV) perspectives of inter-firm differences

The evolutionary literature recognizes the large and persistent heterogeneity across firms in terms of productivity and seeks to explore the factors behind this heterogeneity within the framework of firm behaviour. From an evolutionary perspective firm heterogeneity is an essential aspect of the processes that create economic progress. As Nelson (1991, p.71) notes:

> If one takes an evolutionary rather than a neoclassical view of what economic activity is about, then firm differences matter importantly regarding issues that traditionally have been the central concern of economists. Competition can be seen as not merely about incentives and pressures to keep prices in line with minimal feasible costs, but, much more important, about exploring new potentially better ways of doing things. Long ago Schumpeter remarked that the former function was trivial compared with the latter, if the measure was contribution to the economic well-being of humankind.

Nelson and Winter (1982) propose an evolutionary model of the growth of firms which departs from the neoclassical view. Instead of optimising, agents react to changes in the market environment using routines that are often specific to the firm. These routines develop from the skills and experience of managers and workers which have an important tacit component. Differences in these skills and experiences and the routines that they produce help to explain differences in firms' growth and adaptation to changes in their environments. Nelson and Winter also argue that successful firms tend to persist over time which means that there is positive serial correlation of growth between consecutive periods. This growth persistence is an important component of their evolutionary model.

A similar perspective, the RBV literature, originated in the work of Penrose (1959), who argued that systematic heterogeneous conduct and performance of close competitors derive from the different choices made by firms as the consequences of different strategies and the unique bundles of firms' resources and capabilities (Wernerfelt 1984; Barney 1986; Barney 1991; Peteraf 1993). Whereas traditional theory suggests that firms' behaviour and performance converge, RBV theory claims that firms are idiosyncratic in terms of what they have and what they do (Grant 2002).

The RBV conceives firms as historical and social entities such that resource accumulation is considered to be a historically-dependent or path dependent process.[30] Thus, the particular set of firm resources, in part, is specific to the firm given its particular trajectory in space and time (Barney 1991). In summary, a central difference between neoclassical approaches to industrial structure and the RBV literatures is the 'elasticity in supply resources and capabilities' concept, which in neoclassical language are the factors of production. As Barney (Barney 2001a, p.644) states:

> The resource-based view acknowledges that many factors of production may, in fact, be elastic in supply. However, this view also argues that because some resources and capabilities can only be developed over long periods of time (i.e., path dependence), because it may not always be clear how to develop these capabilities in the short to medium term (i.e., causal ambiguity), and because some resources and capabilities cannot be bought and sold (i.e., social complexity), at least some factors of production may be inelastic in supply (Dierickx and Cool 1989). Supply inelasticity implies that firms that possess these kinds of resources and capabilities may be able to generate above normal profits, and these profits not lead to increased supply of these resources and capabilities in the short term, and perhaps not even in the long run. Supply inelasticity thus can become a source of sustained competitive advantage (Peteraf 1993).

To be a source of sustained competitive advantage, these types of resources and capabilities are assumed to be heterogeneous across firms, thus not distributed evenly across companies within an industry. This diversity may be long lasting and therefore may explain why some firms consistently outperform others. Resources and capabilities can differentiate a firm strategically if they, partly or completely, fulfil four conditions.

[30] Path-dependence is used in the literature in a loose and also a precise sense. The latter forecloses the possibility of convergence, even in the long term, while the former suggests convergence is difficult but does not formally rule out this possibility.

First, the resource should be valuable to the firm and the market; second, it should be rare; third, it should be inimitable or costly to imitate by competitors; and fourth it should not be easily substitutable (Barney 1991, p.117). From the RBV perspective, if these conditions hold, the firm's bundle of resources can differentiate the firm strategically and assist it in sustaining above average returns.

Several authors examine the relationship between the RBV and structure-conduct-performance views (Conner 1991; Peteraf 1993). One empirical line of research focuses on the relative importance of economic and organizational factors as determinants of firm performance. Rumelt (1991), McGahan and Porter (1997), and others estimate the comparative impact of industry versus firm level characteristics on firm performance, but do not arrive at a definitive conclusion, especially since there is large variance across industries. However, the accumulated empirical research shows that firm effects seem to be significant. Some authors (Hatten and Schendel 1977; Hansen and Wernerfelt 1989) find that firm effects are larger than industry effects which is consistent with the initial theoretical formulation in RBV (Barney 1991).[31]

<u>Strategic groups as an explanation of systematic inter-firm differences</u>

Strategic group theory explains the systematic heterogeneity in firm conduct and performance observed within industries (Mehra and Floyd 1998) and has become an important, intermediate unit of analysis between firm and industry in the field of strategic management. The commonly accepted definition of a strategic group, according to Porter (Porter 1980, p.129) states that 'a strategic group is a group of firms in an industry following the same or a similar strategy along the strategic dimensions'. RBV defines strategic group as a set of firms within an industry with a related strategic configuration of resources (González-Fidalgo and Ventura-Victoria 2002).

The strategic group concept lies between two extremes: one is the traditional IO view in which all the firms in an industry are expected to be homogeneous except in size

[31] A number of studies extend the initial RBV concepts, linking them to innovation and dynamic capabilities or firm's knowledge base (e.g., Amit and Schoemaker, 1993; Dierickx and Cool, 1989; Mahoney and Pandian, 1992; Peteraf, 1993; Teece, Pisano, and Shuen, 1997). These extensions broaden the range of the RBV and strengthen its position as the dominant explanation of interfirm performance differences.

(Mason 1939; Bain 1956); the other is the strategic management and RBV in which each firm is idiosyncratic in its behaviour so that firms are heterogeneous in a strategically unique manner (Wernerfelt 1984; Barney 1991). Thus, a fundamental problem in the strategic field is how to represent a meaningful demarcation between heterogeneous sets of firms within which firms are homogeneous in terms of their conduct and performance (Porter 1985; Hatten and Hatten 1987). As Barney and Hoskisson (1990, p.188) point out:

> Strategic group theory represents a theoretical compromise between traditional IO and traditional strategy theory. Strategic group theory does not totally reject the assumption of firm homogeneity, but rather, it hypothesizes that firms are homogeneous within strategic groups and heterogeneous between groups.

Although there is substantial variation in the definition of strategic groups, there is a general agreement that the following elements are the basic building blocks (Cool and Schendel 1987; 1988):

- a strategic group consists of firms that compete against each other on the basis of similar combinations of strategic (resource and scope) commitments;
- different groups are distinguished by mobility barriers;
- intra-industry differences in performance level can be basically explained by the group membership and the size of the barriers to mobility across groups.

By selecting the most important strategic dimensions and location of each firm, it is usually possible to identify groups of companies that have adopted more or less similar competitive strategies within the industry (Grant 2002). Relevant strategic dimensions could include product market scope, degree of vertical integration, choice of technology, level of product quality. In this regard, an industry is no longer viewed as a homogeneous unit to the extent that the concept of strategic groups exposes long run heterogeneity among firms within the same industry (Porter 1979).

A key concept related to strategic groups is *mobility barriers* (Caves and Porter 1977) which is an extended theory of Bain’s (1956) *entry barriers* that exist at industry level, but is applied here to strategic groups of firms within an industry. Bain (1956) provide a first discussion in economics of barriers to entry. Starting from the observation that in competitive conditions new firm entry will occur until the price is equal to the average cost of production, Bain concludes that the persistence of price above this level indicates the existence of an entry barrier that limits the level of competition among the firms within an industry.

Mobility barriers are factors that obstruct the ability of firms to enter or exit a strategic group, or to move from one segment of an industry to another. Harrigan (1985, p.57) defines them as:

> structural factors that protect successful firms from invasion by adjacent competitors (Caves and Porter, 1977). They are internal (to the industry) entry barriers which delineate boundaries between different strategic groups, and they may be contrasted with the external entry barriers discussed in traditional economic theory which deter outside firms from entering any part of the industry.

Thus, mobility barrier is a general term at strategic group level which includes barriers to entry, barriers to exit, and also barriers to intra-industry changes in the firm's product-market position.[32] A firm can change its product-market position by three means. First, by changing its product portfolio significantly, but keeping its customer base the same. Second, keeping its product portfolio the same but changing its customer base significantly. Third, a firm can change both product portfolio and customer base. Mobility barriers are forces that reduce the possibilities for new entrants to occupy similar product-market positions to existing firms in a specific strategic group, and reduce the possibilities for existing firms from moving across strategic groups through different product-market positions.

Strategic group characteristics define the existence and importance of mobility barriers and also firm level factors. Firm investment plays an important role in defining groups

[32] Firms' 'product-market position' is often referred to in the IO and strategy literatures. To understand it, it is convenient to separate it into product position and market position. Product position refers to the portfolio of products that a firm produces compared to those of the industry or its strategic group. Market position refers to the markets or segments of customers and geographic locations where these products are launched compared to the industry or its strategic group.

and their barriers (Caves and Porter 1977). If one firm invests then it may alter the behaviour of the group and change the initial conditions for other firms that may want to enter. However, if there is mutual dependence among firms in the same group, then the group structure will be maintained.

Previous research in strategic group and main criticism

The study of strategic groups is one of the most active areas in strategic management research (Peteraf and Shanley 1997). A large number of theoretical and empirical studies of strategic groups has been carried out since Hunt's (1972) first investigation of the home appliance industry to explain significant group stratification within an industry. Hunt observed empirically three sources of asymmetry among firms: vertical integration; degree of product diversification; and differences in product differentiation. Based on these three sources of heterogeneity he defines four types of strategic groups that minimize economic asymmetry and have different barriers to entry. Since then a growing literature, both theoretical and empirical, has adopted the concept of strategic groups (for reviews see: Cool 1985; McGee and Thomas 1986) as an important unit of analysis for understanding competitive strategy.

Hatten and Schendel (1977) studied the US brewing industry in the period 1952-1971 and demonstrated the existence of strategic groups that showed significant differences in terms of profitability (measured as return on equity). Newman (1978) studied 34 producer-goods firms in the chemical industry and verified the existence of strategic groups based on different degrees of vertical integration. He found that these strategic groups had persistent performance differences and concludes that group membership is a better predictor of firm profitability than industry membership, and that intra-industry heterogeneity reduces the explanatory power of the structure-conduct-performance model.

Fiegenbaum and Thomas (1990) studied the US insurance industry for the period 1970 to 1984 and find evidence of the existence of three basic strategic groups (diversified, life insurance, and personal) based on eight key strategic variables reflecting similar firm scope and resource deployment. They demonstrate that systematic performance differences exist across these strategic groups, using nine industry specific performance variables along the three strategic dimensions of economic, risk, and risk-adjusted.

Some of the latest research on strategic groups is oriented to investigate its dynamic aspects. Nair and Filer (2003) investigate the existence of strategic groups within the Japanese steel industry and the long-run behaviour of firms within two strategic groups: integrated mills and mini-mills. They find support for Dranove, Peteraf et al.'s (1998) argument that the behaviour of strategic group members is oriented towards that of other firms in the group. Boyd (2004) studied the world airline industry to find whether companies can move among clusters, whether clusters show similar performance levels and whether firms can improve their strategies relative to their group. Using a sample of world airlines with annual sales of more than US$1 billion, the author shows that intra-industry modelling (strategic groups) is a significant predictor of performance differences among firms.

Despite the many studies on strategic groups, this stream of research has attracted some criticism (McGee and Thomas 1986; Barney and Hoskisson 1990; Ketchen and Shook 1996). First, there is an absence of theory to predict the presence or existence of groups. Cluster analysis as a methodological approach has been criticized because sometimes it requires the researcher to define the expected number of strategic groups before applying the method, and the cluster algorithm confirms only whether or not those groups are strategic after performance is observable, hence imposing structure on results data ex post. A second criticism is that the method does not suggest an explicit mix of variables used to analyse strategic groups. Each study uses a set of variables related to the industry nature (Mehra and Floyd 1998), and the results related to strategic groupings might change if different variables are used for the cluster analysis.

Thus, the finding of strategic groups in an industry could rest on the researcher's presumption that strategic groups do actually exist and resulting groupings may be statistical artifacts of the cluster analysis procedures used to create the groups. In an attempt to overcome these problems, several authors recommend the use of more robust methods controlling for the different econometric problems that are present in dynamic analysis (Barney and Hoskisson 1990; Dranove, Peteraf et al. 1998) to determine the existence of strategic groups.

<u>Intended contribution to the above literature</u>

This thesis intends to make four contributions to the literature. First we explain the causes of the significant and persistent inter-firm differences identified in the p&p industry in Chapter 2, despite it being one of the most mature and high capital intensive industries in the world. We argue that the existence of an intra industry structure characterized by distinctive technological configuration of p&p firms explains their persistent heterogeneous performance and, in turn, departure from Gibrat's law. In order to avoid the methodological problems associated with the cluster analysis explained above, different clustering methods will be used and reliability and validation techniques will be applied to validate the robustness of our findings avoiding dealing with statistical artefacts (Punj and Stewart 1983).

The second expected contribution is the demonstration that the significant and persistent inter-firm differences in growth performance between p&p strategic groups are not random, but the consequence of at least two factors. On the one hand, different strategic choices and resource commitment between strategic groups, on the other, different patterns of new entrant firms between strategic groups.

The third contribution to the literature is related to the industrial dynamics of the p&p industry, specifically with the exit of firms. Using a semi-parametric Cox Proportional hazard model and a Weibull parametric distribution we investigate the patterns and determinants of p&p firm survival and demonstrate that exit hazard rate, among other variables, is strongly correlated to the principal technological advances during the study period 1970-2000, i.e. the very rapid increase in paper machine operating speeds. This finding confirms the important effect of technological progress on industry structure (Abernathy, Clark et al. 1983; Baldwin and Scott 1987) as argued by several scholars.

The fourth intended contribution is that p&p firms exit hazard rate on the one hand, and technology adoptions on the other have increased significantly over time because of a technology regime change that may have taken place in the industry during the mid 1980s with the introduction of automatic process control technologies which allowed an enormous increase in firms' production capacity and productivity.

3.4 Summary and conclusions

The first section of this chapter reviewed the most recent research at the time of writing, on the p&p industry, its dynamics and technological structure. The main conclusion of the review is that in spite of the fact that the industry presents evidence of important structural dynamism since the mid 1980s, as documented in Chapter 2, there are questions and research problems that remain relatively unexplored by academic study. In this context the second section formulates three research questions that this thesis investigates in depth in Chapters 5, 6 and 7.

The first research question investigates whether p&p firms' growth dynamics follows the LPE in its strongest form, which means that there is no growth size relationship, no growth variance size relationship, and no serial correlation. The second research question investigates the reasons why this industry does not follow the LPE. It hypothesizes that random-walk is not in operation due to the existence of a technological configurations of firms which give rise to strategic groups that indicate a structure within the industry. It investigates firm performance differences across strategic groups and distinctive firm behaviours associated with each of them, which in turn explain their persistent heterogeneous performance. It also investigates inter-firm difference that cannot be explained by group behaviour and thus may be due to firm-specific fixed effects.

The third research question investigates how the technology advances in p&p capital equipment have affected the dynamics of the industry. Specifically it studies the patterns and determinants of firms that exit the industry and the patterns of technology adoption behaviour over time and across strategic groups. It investigates the proportion of US p&p industry capacity expansion that can be explained by state-of-the-art technology adoption behaviour versus technology improvements and upgrading efforts that could be associated with learning by doing efforts.

Section 3 of this chapter reviewed the two central literatures in which this thesis is situated, the dynamics of industrial structure (firm size distribution, Gibrat's law) and heterogeneity within industries (strategic groups).[33] Both literatures are major research fields in industrial economics and strategic management, where important questions remain to be investigated such as the patterns that govern corporate growth within industries, and the sources of significant and persistent inter-firm differences observed empirically in almost all sectors. They are important research fields because a better capacity to explain the patterns of firms growth and the causes of systematic inter-firm differences in behaviour and performance would allow us to improve our comprehension of industry dynamics and how they evolve over time (Nelson 1991; Cabral and Mata 2003).

The main conclusion that emerges from our review of these literatures, dynamics of industrial structure and heterogeneity within industries, is that both are major research fields with important questions and problems still to be investigated. The thesis investigates not just the existence of a stochastic growth process in the p&p industry, but deepens understanding of the patterns that emerge in relation to growth and the causes of those patterns, which, in turn, may explain systematic and persistent inter-firm heterogeneity.

[33] We discuss more specific bodies of literature, such as firms' exit hazard rates and technology adoption decisions, when investigating the research questions addressed in Chapters 5, 6 and 7.

CHAPTER 4

THE DATA

This chapter provides a description of the data employed in this research, their sources, their preparation and the variables used in the analysis. The empirical investigation in this thesis is based on a panel of firm and industry level data. The thesis studies the p&p industry from two perspectives. The global industry based on data for the 150 largest p&p firms in the world for the period 1978-2000. The US p&p industry analysed using data from the complete population of US p&p companies for the period 1970-2000. We also collected industry and company reports, and gathered qualitative information from industry expert interviews. This information allowed us to check the validity of the longitudinal and cross sectional data gathered, and to explore in depth the main features of this high capital intensive industry and its evolution over three decades.

The chapter is organized in three sections. The first describes global p&p industry data, their sources, the variables used and data validity. The second presents the data for the US p&p industry, their sources, the variables used and data validity. The third section is a conclusion to the chapter. Appendix A4.1 contains the data and reports on the p&p industry since early 1970s, at different levels of aggregation - firms, industry, countries, regions (North America, Europe, Asia & Australia, Latin America, Africa) and the world. Appendix A4.2 lists the 38 industry experts interviewed during 2002-2004. Appendix A4.3 describes the firm and industry level variables constructed from the global and US p&p databases. These data enable us to conduct a deep and robust analysis of the dynamics of the p&p industry over the last three decades, to identify significant patterns in the dynamics and, more important, to identify what drives these patterns.

4.1 Sources and description of the Global p&p industry data and variables

4.1.1 Sources of the Global p&p industry data

The panel database of the 150 largest p&p firms was gathered from two secondary sources. Firstly the *Pulp & Paper International Magazine*[34] (PPI), which is the most important publication of p&p industry. The firm level data were extracted from 'TOP 150', an annual feature in the PPI included in its September issue.[35] Secondly the *Scandinavian Pulp & Paper Report (SPPR),*[36] which is a Norwegian publisher that produces reports on the world's 300 largest p&p firms. These reports are between five and ten pages in length and describe key aspects of the companies they review for previous periods of up to 10 years.

The industry and country level data were collected from three different sources. The 'PPI Annual Review' which is published annually by PPI magazine in July. This issue contains detailed information on production, consumption and capacity for different technology classes at country level. The *Global Pulp & Paper Fact & Price Book*[37] is published annually by RISI and contains detailed industry and country level information on trade, capacity and production for the main grade categories. FAOSTAT[38] is an on-line database that contains historical p&p country and world level data. Qualitative information regarding key aspects of the global p&p industry and firms were gathered via several interviews with industry experts (see Appendix A4.2).

4.1.2 Description of global p&p industry data and variables

The global p&p database contains annual information on the world's 150 largest p&p firms for the period 1978 to 2000. Data were collected on 320 individual firms over the 23 year period, giving a total of 3,450 company-year observations. The firm level data includes the variables: consolidated sales (US$),[39] paper-related sales (US$),

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[34] Monthly p&p industry magazine published by RISI the world largest information company for the industry. See RISI web page at: http://www.risiinfo.com/

[35] Pre-1989 'Top 150' was published as two separate lists: the September issue included 'Top 100' firms and the October issue listed the 'Top 50 Runners Up' that included data on the next ranked 50 firms, this is from Top 101 to Top 150.

[36] http://www.sppr.no/

[37] http://www.risiinfo.com/risi-store/do/product/detail?id=10563&pcId=31&parentId=&rootId=13

[38] United Nations FAO database: http://faostat.fao.org

[39] US$ is the currency used in this research.

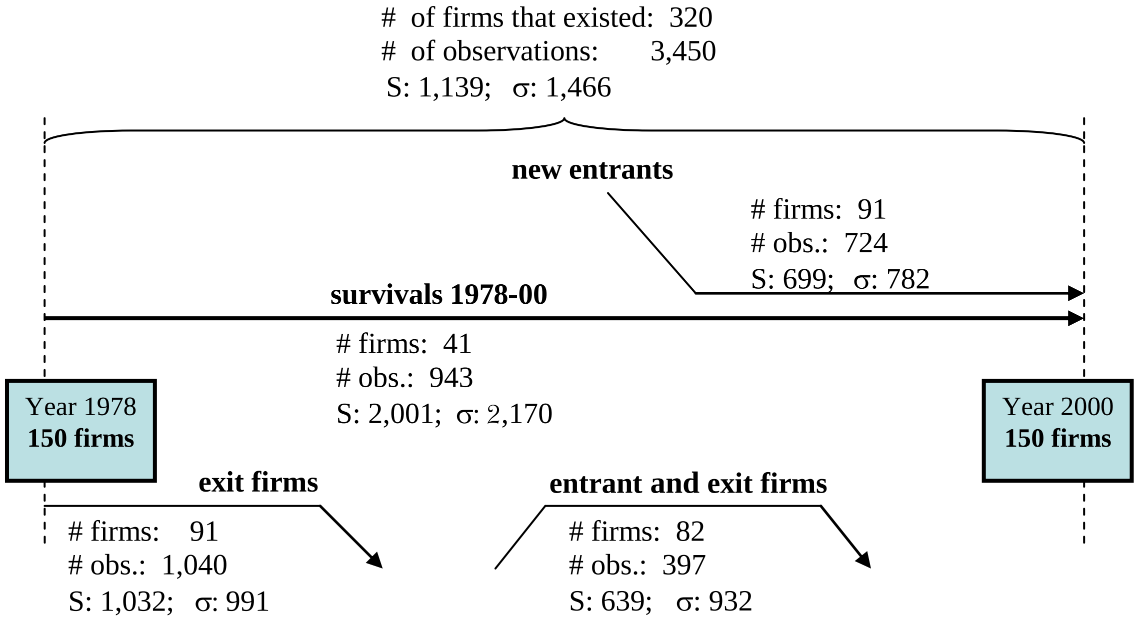
consolidated net earnings[40] (US$), consolidated assets (US$), market pulp production (tonnes), paper production (tonnes), converted products production (tonnes), workforce (number of employees), and nationality of the firm.

Figure 4.1 depicts the database according to four types of firms: survivors, new entrants, exiting firms, and entrants & exiting firms.

Period 1978-2000

- 41 firms existed over the 23 years from 1978 to 2000 (943 observations). This group of companies has the highest average annual output of 2,001 th. tonnes.
- 91 firms entered the industry after year 1978 and survived until 2000 (724 observations). This group of companies has an average annual output of 699 th. tonnes.
- 91 firms that existed in year 1978 did not survive to year 2000 (1,040 observations). This group of companies has an average annual output of 1,032 th. tonnes.
- 82 firms entered and exited the industry in 1978-2000 (397 observations). This group of companies has the smallest average annual output of 639 th. tonnes.

Figure 4.2Synthesis of the global p&p industry, data at the firm level, 1978-2000



Notes: "S" is firm's average size measured in 000s tonnes of production capacity
"σ" is firm's size standard deviation measured in 000s tonnes of production capacity

[40] Earnings are calculated after tax.

Below we list the ten variables constructed from data gathered from p&p firms and industry reports: [41]

mp:	market pulp production in th. tonnes
pb:	paper & board production in th. tonnes
mppb_s:	market pulp, paper & board sales in million US$
tot_s:	consolidated sales, including non-paper related sales in million US$
tot_asset:	consolidated assets in million US$
n_empl:	number of employees
country:	firm's country
n_ctry:	number of countries where the firm has production facilities
w_mp:	world annual pulp production in th. tonnes
w_pb:	world annual paper & board production in th. tonnes

To indicate how the world's 150 largest p&p firms were distributed over the five continents during the study period, Table 4.1 provides information on the number of firms, average size and number of observations per geographic region. Europe has 150 firms with an average capacity of 840 th. tonnes; Africa has 3 firms with an annual average output of 1,875 th. tonnes.

Table 4.1 Distribution of the 150 largest p&p firms in the world in 1978-2000

Region	# of firms	# of observations	firm's average output
North America	89	1,056	1,771
Europe	150	1,497	840
Asia	60	674	925
Latin America	18	183	559
Africa	3	40	1,875
World	320	3,450	1,139

4.1.3 Preparation and validity of the global p&p industry database

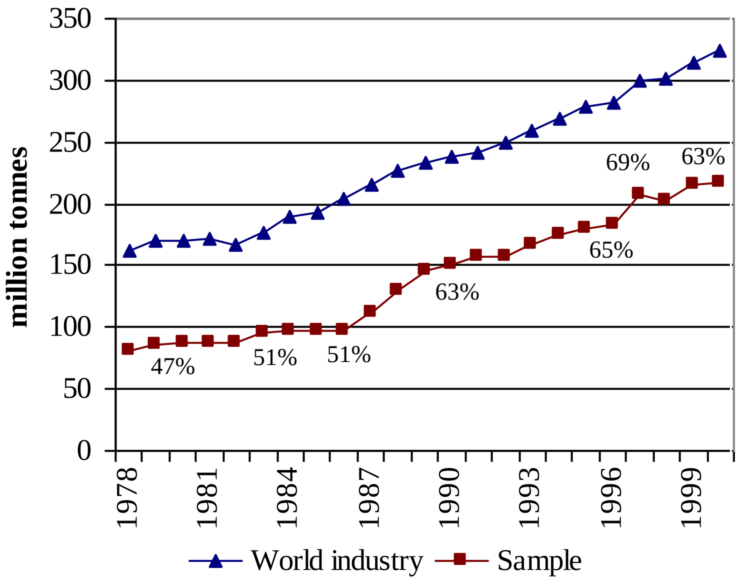
This subsection describes how the data were checked for validity and representativeness, for the 150 largest p&p firms in 1978-2000. For research to make a tangible contribution to the literature it is important to demonstrate the validity of the data sources and data measures which can be achieved by cross checking techniques, comparisons with several sources, expert opinions, etc.

[41] Appendix A4.3 describes the firm and industry level variables constructed from the global p&p dataset to investigate the research question.

The first version of the global p&p firm database constructed from the information published in PPI had only 2.3% missing or unreliable data. In large databases this kind of problem is common; we tried to fill the gaps using other sources such as company reports or estimating it based on other available information. Appendix A4.1 lists the multiple data and reports gathered from several p&p industry sources which allowed us to improve the PPI dataset and to crosscheck it for accuracy and compare with other sources. Some aggregated figures were checked with industry experts.

In order to analyse the ability of the dataset to characterize the global p&p industry, Figure 4.2 shows the aggregated output of the sampled 150 p&p firms versus total industry output along the study period. In the 1980s the sample data correspond approximately to 50% of world output. In the 1990s this increased to over 60% reaching a maximum of 69% in 1997 as a result of the industry concentration that occurred in the 1990s and which is reported in Chapter 2, subsection 2.2.2. Across the whole period, the sample data are an important percentage of world output (between 47% and 69%) thus they are a good representation of the industry and include the 150 largest and most interesting companies for the purpose of studying dynamic behaviours and the performance of a single industry such as the p&p.

Figure 4.2 World and sample p&p industry annual output



Sources: FAO statistics 2006 and PPI 2001

4.2 Sources and description of the US p&p industry data and variables

4.2.1 Sources of the global p&p industry data

The panel data for the US p&p industry at firm level were gathered from two different sources. The most important one was the FPL-UW database that is housed at the USDA[42] (US Department of Agriculture) in Madison Wisconsin, in collaboration with the University of Wisconsin-Madison.[43] This dataset contains estimates of annual production capacity for all mill locations in the US where paper, paperboard, and market pulp were produced in the period 1970-2000 in 13 principal technological classes. A second source was company reports from the 100 largest US p&p firms which are published annually by Scandinavian Pulp & Paper Reports.[44] These five to ten page documents describe key aspects of the firms in previous years.

US p&p industry level data were collected from various sources including the monthly *Pulp & Paper Magazine*[45] whose September issue contains detailed information on US p&p consumption, trade, capacity, production in the main grade categories, etc. We also used the *American Fact & Price Book* published annually by American Paper and Pulp International, which contains detailed information at industry and country level, on trade, capacity and production of the main grade categories. The FAOSTAT[46] database was used to gather information on the US p&p industry from 1970. Qualitative information of key aspects of the US p&p industry was gathered through interviews with industry experts.

4.2.2 Description of the US p&p industry capacity dataset and variables

The FPL-UW database contains estimates of annual production capacity for all mill locations in the US where paper, paperboard, and market pulp were produced between 1970 and 2000. In order to illustrate capacity changes meaningfully, the industry

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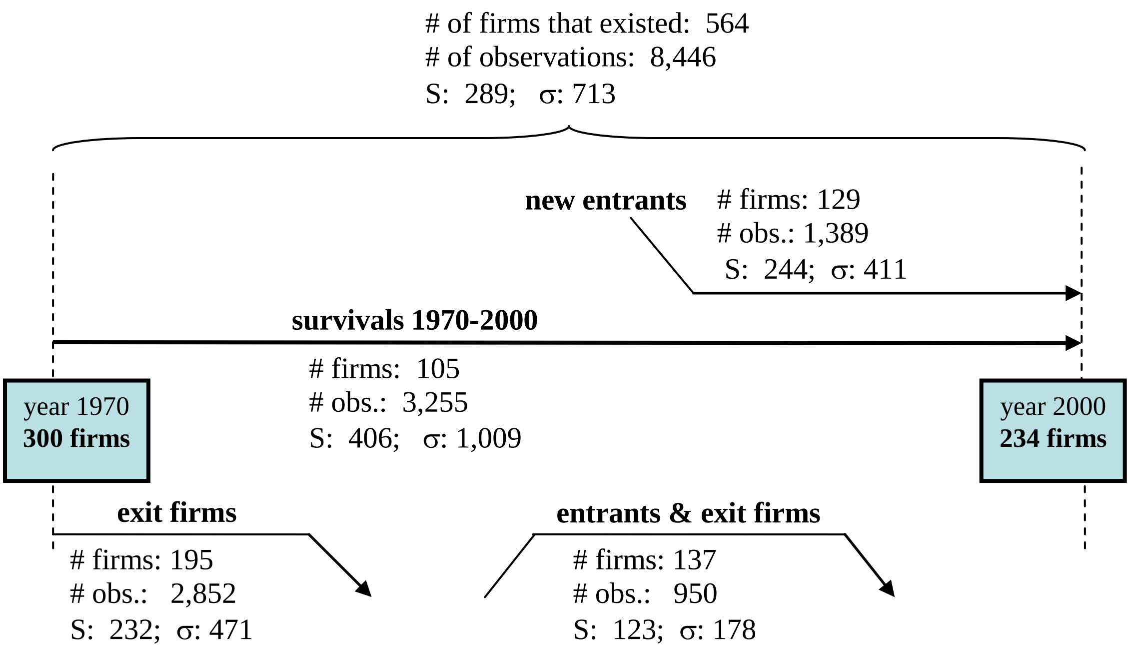
[42] http://www.usda.gov/wps/portal/usdahome
[43] We thank Professor Peter J. Ince, PhD from the University of Wisconsin Madison who generously made this database available for this research.
[44] http://www.sppr.no/
[45] Magazine published by RISI which can be viewed at: http://www.risiinfo.com/pulpandpaper/magazine/archives?archType=PP&Type=PP
[46] UN FAO database: http://faostat.fao.org

product spectrum is divided into 13 principal categories of the paper, paperboard and market pulp commodities. The paper group includes eight conventional categories: newsprint, four categories of printing and writing paper (coated and uncoated growndwood, coated and uncoated free-sheet), tissue paper, unbleached kraft paper, specialty packaging and industrial papers. The paperboard group includes four conventional commodity categories: linerboard, corrugating medium, solid bleached board, and recycled paperboard. The market pulp category is not subdivided and contains all the pulp that is commercialized.

The US p&p dataset contains information on the 564 US p&p firms that existed between 1970 and 2000. The number of firms decreases from 300 in 1970 to 234 in year 2000, thus the number of observations per year varies along time. The total number of firm-year observation is 8,446. Figure 4.3 provides a general description of the database according to four types of firms: survivors, new entrants, exits, and entrants & exiting firms.

Figure 4.3 Synthesis of the US p&p industry, data at the firm level, 1970-2000



Notes: "S" is firm's average size measured in 000 tons of production capacity.
"σ" is firm's standard deviation measured in 000 tons of production capacity
Source: FPL-UW database

<u>Full period 1970-2000</u>

- The total number of firms between 1970 and 2000 is 564 (8,446 observations). Average firm capacity is 289 th. tonnes, and the average standard deviation is 713 th. tonnes
- Of the total firms, 105 companies (18.5%) survived across the 31 year period from 1970 to 2000 (3,255 observations). This group of companies has the highest average annual capacity of 406 th. tonnes, and the highest standard deviation of 1,009 th. tonnes.
- 129 firms entered the industry after 1970 and survived to year 2000 (1,389 observations). This group of companies has an average annual capacity of 244 th. tonnes, and a standard deviation of 411 th. tonnes.
- 195 firms existed in 1970 and did not survive to year 2000 (2,852 observations). This group of companies has an average annual output of 232 th. tonnes, and a standard deviation of 471 th. tonnes.
- 137 firms entered and exited the industry within the period 1970-2000 (950 observations). This group of companies has the smallest average annual output of 123 th. tonnes, and the smallest standard deviation of 178 th. tonnes.

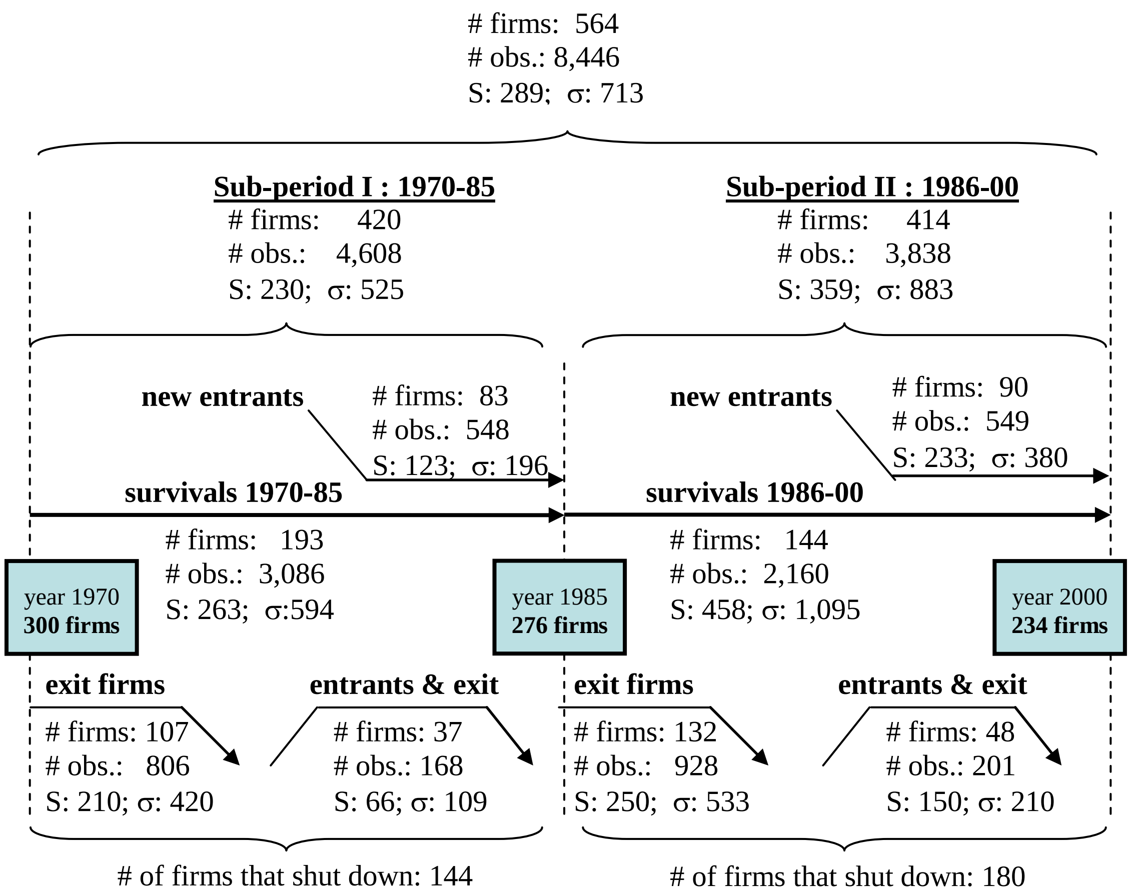
Figure 4.4 describes the data used to compare the two periods 1970-1985 and 1986-2000 according to the four types of firms: survivors, new entrants, exits, and entrants and exiting firms. In Chapter 7 we compare the some feature of industry dynamics for these two periods.

<u>Sub-period 1970-1985</u>

- The total number of firms that existed across the years 1970 and 1985 is 420 (4,608 observations). Average firm capacity is 230 th. tonnes, and the average standard deviation is 525 th. tonnes.
- Of the total firms that existed in this sub-period, 193 (46.03%) survived the 16 years from 1970 to 1985 (3,086 observations). Average annual capacity is 263 th. tonnes, and the standard deviation is 594 th. tonnes.
- 83 firms entered the industry after year 1970 and survived to 1985 (548 observations). This group of companies has an average annual capacity of 123 th. tonnes, and a standard deviation of 196 th. tonnes.

- 107 firms that existed in year 1970 did not reach year 1985 (806 observations). This group of companies has an average annual output of 210 th. tonnes, and a standard deviation of 420 th. tonnes.
- 37 firms entered the industry after 1970 and exited before 1985 (168 observations). This group of companies has by far the smallest average annual output of 66 th. tonnes, and the smallest standard deviation of 109 th. tonnes.

Figure 4.4 Synthesis of two sub-periods of the US p&p industry
Data at the firm level, 1970-2000



Notes: "S" is firm's average size measured in 000 tons of production capacity.
"σ" is firm's standard deviation measured in 000 tons of production capacity
Source: FPL-UW database

<u>Sub-period 1986-2000</u>

- The total number of firms that existed any time in the period 1986 and 2000 is 414 (3,838 observations). Average firm capacity is 359 th. tonnes, and the average standard deviation is 883 th. tons

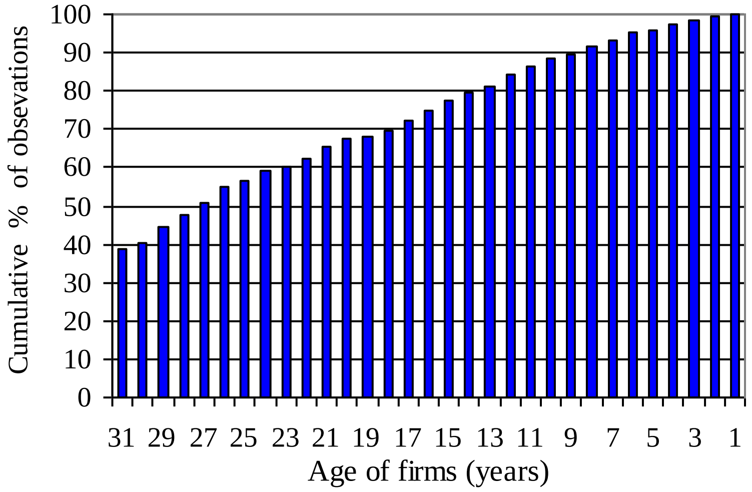
- Of the total number of firms that existed in this sub-period, 144 companies (34.5%) survived the 15 year sub-period from 1986 to 2000 (2,160 observations). This group of companies has the highest average annual capacity of 458 th. tonnes, and the highest standard deviation of 1,095 th. tonnes.
- 90 firms entered the industry after year 1986 and survived to year 2000 (549 observations). This group of companies has an average annual capacity of 233 th. tonnes, and a standard deviation of 380 th. tonnes.
- 132 firms that existed in year 1986 did not survive to year 2000 (928 observations). This group of companies has an average annual output of 250 th. tonnes, and a standard deviation of 533 th. tonnes.
- 48 firms entered the industry after 1986 and exited before 2000 (201 observations). This group of companies has by far the smallest average annual output of 150 th. tonnes, and the smallest standard deviation of 210 th. tonnes.

From the analysis of these three scenarios we can draw the following conclusions:

- Incumbents firms across the whole period and within each sub-period have the highest average size and average size variance.
- Entrants & exit firms across the full period and within each sub-period have the smallest average size and average size variance.
- The second sub-period 1986-2000 is more dynamic than the first 1970-1985 based on the fact that the number of incumbents diminishes significantly over time (from 193 to 144); the number of entrants, exit, and entrants & exit firms increased in all three scenarios; and the number of shut downs increased from 144 to 180.

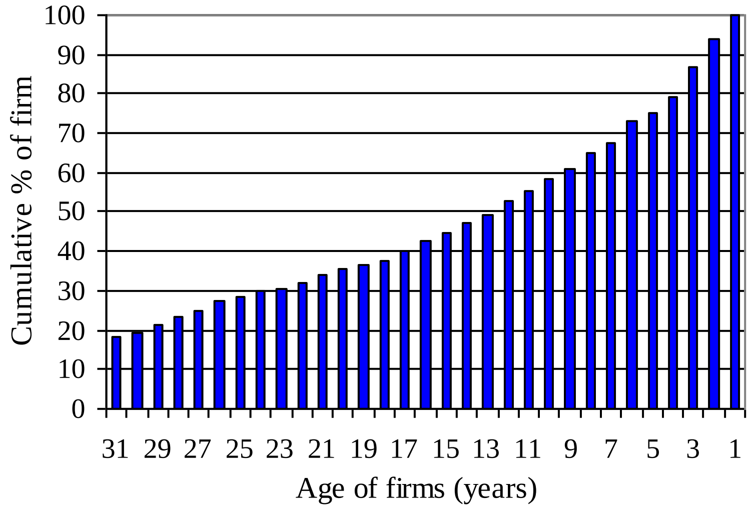
Figure 4.5 shows the cumulative percentage of firm-year observations versus firms' ages for the period 1970-2000. Almost 40% of observations are from firms that existed for the full 31 year period. Almost 90% of the observations are from firms that existed at least 10 years. Figure 4.6 shows the cumulative percentage of firms versus firms' ages for the period 1970-2000. Almost 20% of the firms existed the full 31 years period, and almost 60% existed for 10 years or more. These features allows us to investigate the dynamics of the industry such as growth persistence (see Chapter 5), because we can construct panel data with long series which allow comparisons of firm performance over different periods or decades based on a sufficient number of firms and observations.

Figure 4.5 Cumulative % of observations v/s US p&p firm's age, 1970-2000
(total number of observations: 8,446)



source: FPL-UW database

Figure 4.6 Cumulative % of firms v/s US p&p firm's age, 1970-2000
(total number of firms: 564)

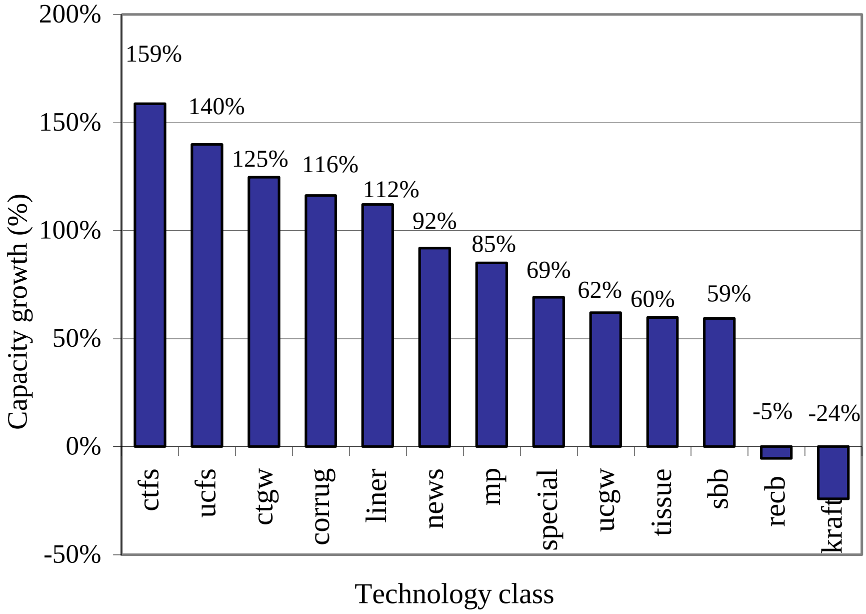


source: FPL-UW database

<u>Thirteen technology classes data</u>

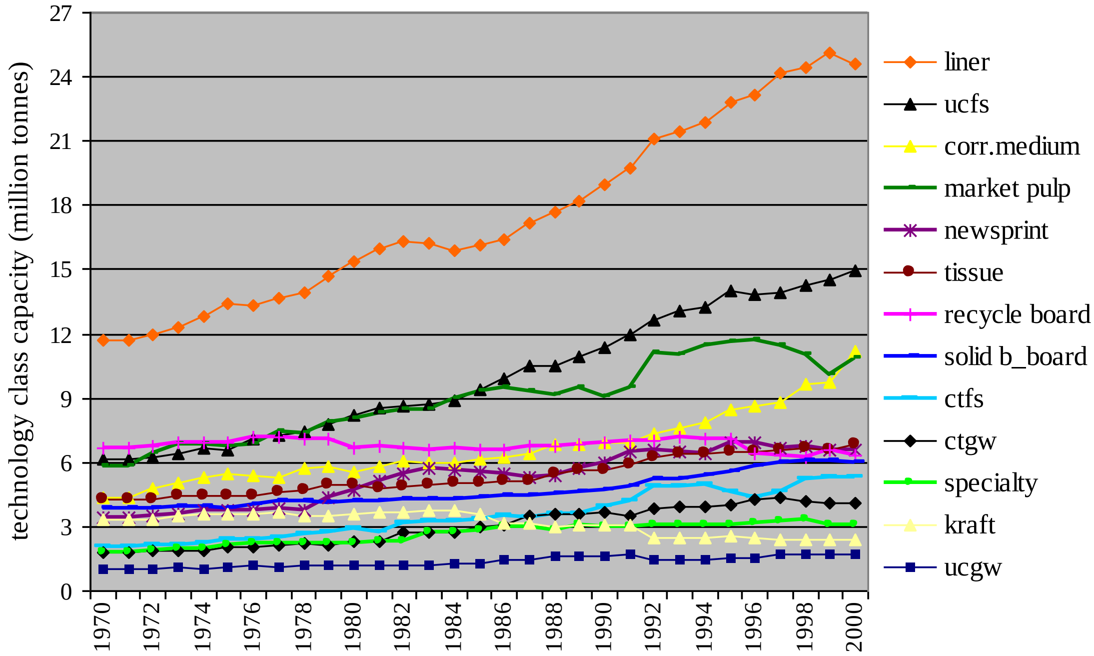
The US p&p dataset contains capacity information disaggregated at 13 principal p&p technology classes. Although at country level capacity increased by 82% during the study period 1970-2000, from 56 to 102 million tonnes (see Figure 2.9), at the technological class level the 13 principal commodities show quite different patterns of growth (see Figures 4.7 and 4.8). While the capacity of some technological classes, such as coated free sheet paper (ctfs) increased more than 150% over the period, others decreased by more than 20%, e.g. kraft paper. These technological classes represent the different sub-markets in which each firm operates. These data allow us to study the existence of an intra-industry technological structure and its dynamic behaviour in terms of market growth and development during the period 1970-2000 (see Chapter 6).

Figure 4.7 US p&p capacity growth-rates per technology class period 1970-2000



Source: FPL-UW database

Figure 4.8 US p&p capacity at thirteen technology classes' level, 1970-2000



Source: FPL-UW database

<u>US p&p main variables</u>

The US p&p database has the following variables related to firms per year (all technology class capacities are expressed in tonnes/year):[47]

f_code:	code and name of each firm
year:	year of the data collected
nm:	number of mills of the firm
mp:	market pulp capacity
news:	newsprint capacity
ctfs:	coated freesheet capacity
ucfs:	uncoated freesheet capacity
ctgw:	coated grownwood capacity
ucgw:	uncoated grownwood capacity
tissue:	tissue capacity
special:	specialty papers capacity
kraft:	kraft paper capacity
liner:	liner board capacity
corr:	corrugated medium capacity
sbb:	solid bleach board capacity
recb:	recycled board capacity

4.2.3 Validity of the US p&p industry database

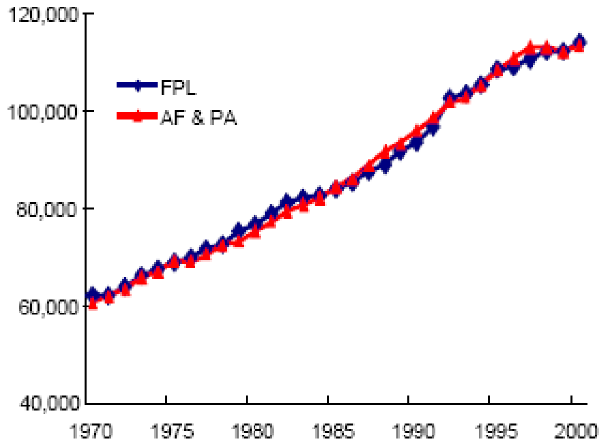
The validity of the FPL–UW database used in this research was checked by Professor Ince et al. (2001). To test the accuracy of this p&p mill-level capacity dataset, Ince and colleagues compared the country level aggregated figures with national p&p industry capacity data published by the American Forest & Paper Association (AF&PA).[48] Figure 4.9 shows that the curves are close together during the study period 1970-2000. Annual differences between datasets for most years are less than 1%, with a maximum of 2.9% in 1988 which is still low in the context of the present investigation.

The multiple data and reports gathered from the US p&p industry sources listed in Appendix A4.1 allow us to conduct our own quality and validity checks on the FPL–UW database and improve it through cross checking and comparison. For example, firm level capacity data contained in company reports, such as SPPR, were compared with the capacity data for the same company and period in the FPL–UW database. Some of

[47] Appendix A4.3 describes the firm and industry level variables that were constructed from the US p&p dataset in order to investigate the research questions.
[48] US leading p&p industry trade association, see it's web page at: http://www.afandpa.org/

the aggregated figures in the database were checked with industry experts. In all cases the differences were small, thus the quality and validity of the FPL–UW dataset to represent the dynamics of the US p&p industry are sufficient.

Figure 4.9 Comparison of total US p&p capacity according to FPL–UW database and AF&PA annual capacity report.



Source: US Paper, Paperboard, and Market Pulp Capacity Trends by Process and Location, 1970–2000 (Ince, Li et al. 2001)

4.3 Summary of the results and Conclusions

The main conclusion from this chapter is that there is consistency between the research questions formulated in Chapter 3 regarding the dynamics of a very capital intensive industry such as the p&p over the period 1970-2000 and the amount, type, quality and validity of the data that it was possible to gather in order to investigate those research questions. Most of the empirical investigation in this thesis is based on longitudinal firm and industry level global and US data.

The global p&p industry will be studied using data from the 150 largest p&p firms in the world for the period 1978-2000 which account for an important percentage of world output (between 47% and 69%). These companies are a good representation of the industry and allow us to study its dynamic behaviour and performance characteristics. The percentage of world output not captured by our global database, which is between 53% and 31%, corresponds to the output of almost 900 companies most of them quite small, which fill local demand, as explained in the Industry Chapter 2. They do not compete internationally and are generally far behind the industry technology frontier.

This big group of firms is of less interest for this research and it would be extremely difficult and costly to gather data for the whole world population of p&p firms. However, it is fairly straightforward to gather US p&p industry data which is by far the largest p&p producer and consumer country in the world and it has a very diverse weather condition which makes it comparable with the world climate situation. We can conclude, then, that we can study the dynamics of this industry using data for US p&p firms to complement the investigation of the global p&p industry based on a sample of 150 of the world’s largest firms.

We also sourced information from industry and company reports and gathered qualitative information from interviews with industry experts to provide a deeper and more comprehensive understanding of this high capital intensive industry’s main features and its evolution over the period 1970-2000.

Appendix A4.1 Data and reports gathered from different p&p industry sources, and industry experts interviews

TYPE OF INFORMATION	PERIOD	INFORMATION LEVEL	GRADES / INFORMATION	SOURCE
CAPACITY				
Capacity of P, P&B	1992-2004	Firm, country, region, top 20	Nine major grades	Paperloop[49] reports
Capacity of P, P&B grades	2002	Firms, countries & regions	Eleven major grades	NLK[50] database
Capacity changes of P, P&B grades	1999-2002	Firms, countries & regions	Eleven major grades	NLK database
Capacity of P, P&B	1970-2000	All North American firms	Eleven major grades	USDA[51] & CPBIS[52]
Capacity and capacity changes of P&B grades	1978-1998	North American large and medium size firms	Seven major P&B grades (not pulp & not tissue grades)	Mr. Timo (Finnish DPhil student)
COMPANY PROFILES				
Company profiles, Europe	1995-97 to 2001	50 largest European firms	Very detailed information	Paperloop report
Company profiles, North America	1992-95 to 2002	50 largest North Am. firms	Very detailed information	Paperloop report
Company profiles, World	1997-2002	300 largest companies	Very detailed information	SPPR[53] report
Financial and production data of firms	1991-95 to 2002	120 firms: 50 North Am., 40 Europe, 30 of rest world	20 to 30 indicators	SPPR database
COMPANY RANKINGS				
Ranking of North America + European firms	1997-2001	100 largest North Am. & European firms	20 to 30 indicators	SPPR database
Rankings of North American firms	1990, 1995, 200	60 largest North Am. firms	20 to 30 indicators	Paperloop report
Ranking of world largest 150 firms: consolidated sales, earnings, total assets; paper related sales; # of employees; # of countries; production of P, P&B.	1975 - 2001	World largest 150 firms	Production data is aggregated in market pulp and paper&board. There are not further desegregation.	PPI magazine[54]

[49] Paperloop – US paper and pulp consulting company.
[50] NLK – NLK Associates, Reports & Databases
[51] USDA – US Department of Agriculture.
[52] CPBIS – Centre for Paper Business and Industry Studies which is linked to the Georgia Institute of Technology in the US.
[53] SPPS – Scandinavian Paper and Pulp Report. Norwegian paper and pulp consulting company specialized in firm level information.
[54] PPI Magazine – Paper & Pulp International Magazine published monthly by Paperloop.

Appendix A4.1 Data and reports gathered from different p&p industry sources, and industry experts interviews (continuation)

TYPE OF INFORMATION	PERIOD	INFORMATION LEVEL	GRADES / INFORMATION	SOURCE
PRODUCTION & TRADE				
Production and trade (annual production, imports, exports, consumption, capacity)	1975 to 2001	Country, region and world	Ten major grades	PPI Fact and Price book[55]
Prices of different specific grades	1970-80 to 2003	Annual, quarterly or monthly prices	USA, Germany, UK, France, Japan prices	Paperloop. Internet research.
PAPER MACHINES & TECHNOLOGY				
Speed and width of paper machines	1920-2000	Speed and width of the state of the art paper machine per year	Three main grade categories: printing & writing paper, newsprint and tissue.	M. van Dijk DPhil Student
DIRECTORY & REFERENCES				
Directory of P&P firms	2003	All firms in the world	Firm's general information	Birkner[56] CD Rom
Bibliographic database	1970-2003	Academic and non-academic publications		PIRA[57]– Internet membership

W: World **EU:** Europe **N.Am.**.: North America
P, P&B: pulp, paper & board **P&P**: paper and pulp **P&B**: paper & board

[55] PPI Fact & Price book – Annual report of the global paper and pulp industry published by Paperloop.
[56] Birken – German paper and pulp consulting company.
[57] PIRA – UK paper and Pulp consulting company.

Appendix A4.2 Paper and pulp industry experts interviews

	FAMILY NAME	FIRST NAME	ORGANIZATION	COUNTRY	WORK RESPONSIBILITY
1	AINAMO	ANTTI	JAAKKO POYRY	FINLAND	ASSOCIATE PRINCIPAL
2	ANNALA	TALVIKKI	KCL SCIENCE AND CONSULTING	FINLAND	VICE PRESIDENT
3	BOOTH	GRAHAM	THE UK PAPER FEDERATION	UK	SENIOR SERVICES EXECUTIVE
4	DIESEN	MAGNUS	STORAENSO	UK	EXECUTIVE VICE PRESIDENT
5	EBELING	KARI	SENIOR SCIENTIFIC ADVISOR	FINLAND	SENIOR SCIENTIFIC ADVISOR
6	EEROLA	ANNELE	VTT GROUP FOR TECHNOLOGY STUDIES	FINLAND	SENIOR RESEARCH
7	FOGELHOLM	JOHN	HELSINKI UNIVERSITY OF TECHNOLOGY	FINLAND	ENGINNERING & MANAGEMENT
8	HAGGBLOM	RAINER	JAAKKO POYRY	FINLAND	CHAIMAN AND CEO
9	HAINARI-MAULA	JAN	AHLSTROM	FINLAND	PRODUCT LINE MANAGER
10	HASSINEN	MIKA	STORAENSO	FINLAND	VICE PRESIDENT CORPORATE STRATEGY
11	HEINOLA	MARTTI	TAMFELT	FINLAND	VICE PRESIDENT
12	HIGHAM	ROBERT	EURO-DATA ANALYSTS	UK	MANAGING DIRECTOR
13	HOLMSTROM	RIITTA	STORAENSO	FINLAND	TECHNICAL MARKETING MANAGER
14	JAMES	RHIAMON	PPI MAGAZINE	BELGIUM	EXECUTIVE EDITOR
15	KATKO	TAPIO	TAMPERE UNIVERSITY OF TECHNOLOGY	FINLAND	SENIOR RESEARCH FELLOW
16	LEENA LOHI	MARJA	PAPER AND WOOD	FINLAND	COMMUNICATIONS ASSISTANT
17	LILJA	KARI	HELSINKY SCHOOL OF ECONOMICS	FINLAND	PROFESOR
18	LINNA	HANNU	VTT RESEARCH CENTRE OF FINLAND	FINLAND	GROUP MANAGER
19	LLANOS	LUIS	CMPC CELULOSA S.A.	CHILE	STUDY AND RESEARCH MANAGER
20	LOIKKANEN	TORSTI	VTT GROUP FOR TECHNOLOGY STUDIES	FINLAND	RESEARCH MANAGER
21	MELANDER	ANDERS	JONKOPING BUSINESS SCHOOL	SWEDEN	ASSISTANT PROFESSOR
22	METSARINTA	URSULA	BOTNIA	FINLAND	PRODUCT MANAGER
23	MITROU	TRIFONAS	PIRA INTERNATIONAL	UK	BUSINESS ANALYST

Appendix A4.2 Paper and pulp industry experts interviews (continuation)

	FAMILY NAME	FIRST NAME	ORGANIZATION	COUNTRY	WORK RESPONSIBILITY
24	MOLKENTIN	PIRKKO	FINNISH PAPER ENGINEERS ASSOCIATION	FINLAND	PRESIDENT
25	NIEMINEN	SUSANNA	KCL SCIENCE AND CONSULTING	FINLAND	DIRECTOR OF RESEARCH
26	OSSES	MIGUEL	ARAUCO	CHILE	R&D DIRECTOR
27	PALMBERG	CHRISTOPHER	VTT GROUP FOR TECHNOLOGY STUDIES	FINLAND	SENIOR RESEARCH
28	PIKKARAINEN	HEIKKI	UPM KYMMENE GROUP	FINLAND	STRATEGIC DEVELOPMENT DIRECTOR
29	RODDEN	GRAEME	PAAPERLOOP	BELGIUM	EUROPEAN EDITORIAL DIRECTOR
30	RODRÍGUEZ	EDUARDO	BIOFOREST S.A.	CHILE	GENERAL MANAGER
31	RUIZ	MARIO	CMPC CELULOSA S.A.	CHILE	STUDY MANAGER
32	STIEDE	PATRICIA	TAPPI	USA	PRESS PRODUCTION SPECIALIST
33	SUPPANEN	URSULA	FINNISH PAPER ENGINEERS ASSOCIATION	FINLAND	PROJECT MANAGER
34	TAHVANAINEN	MIKKO	FINNISH FOREST INDUSTRIES FEDERATION	FINLAND	MARKET RESEARCH MANAGER
35	VAN DIJK	MICHIEL	ECIS, TECHNISCHE UNIVERSITY EINDHOVEN	NETHERLANDS	Ph.D STUDENT
36	WALUSZEWSKI	ALEXANDRA	UPPSALA UNIVERSITET	SWEDEN	ASSOCIATE PROFESSOR
38	YLA-ANTTILA	PEKKA	RESEARCH INSTITUTE OF FINNISH ECONOMY	FINLAND	RESEARCH DIRECTOR

Appendix A4.3 Variables created from the global and US p&p databases

global p&p database

The followings are the firm and industry levels variables that were created out of the global p&p dataset in order to investigate the research questions (capacity data are expressed in 1,000 tonnes/year):

mppb:	market pulp + paper & board production
pb:	paper & board production
pb_mkt_sh:	paper & board market share (pb/w_pb)
mppb_ch1y:	firm mppb growth one year lag
mppb_ch1y:	firm mppb growth three years lag
mppb_ch5y:	firm mppb growth five years lag
gth_1y:	firm mppb growth-rate one years lag
gth_3y:	firm mppb growth-rate three years lag
gth_5y :	firm mppb growth-rate five years lag
g_code:	firm's geographic code (North America=1, Europe=2, Asia=3, Latin America=4, Africa=5)
w_mppb_pr:	world market pulp + paper & board production
w_mp_pr:	world market pulp production
w_pb_pr:	world paper & board production
cr_w_mppb:	concentration ratio of world mppb production
herfin150:	world largest 150 p&p firms herfindahl index

US p&p database

The followings are the firm and industry levels variables created out of the US p&p dataset in order to investigate the research questions (capacity data are expressed in 1,000 tonnes/year):

mppb:	sum of market pulp, paper and board grades capacity per firm
mppb_msh:	mppb market share per firm
pb:	sum of paper and board grades capacity per firm
n_grds:	number of grade categories of each firm (0 to 13)
n_year:	number of years with production capacity > 0
r_year:	number of years from firm's first year to last year appearance
mppb_ch1y:	firm mppb growth one year lag
mppb_ch3y:	firm mppb growth three years lag
mppb_ch15:	firm mppb growth five years lag
gth_1y:	firm mppb growth rate one year lag
gth_3y:	firm mppb growth rate three years lag
gth_5y:	firm mppb growth rate five years lag
entropy:	firms' capacity entropy index (degree of product diversification)
type_class:	firms' type class
c_ratios:	industry concentration ratios
herfin:	industry herfindahl index
n_firms:	industry number of firms per year with capacity > 0

Appendix A4.3 Variables created from the global and US p&p databases (continuation)

t_mppb:	US market pulp, paper and board grades capacity
t_mp:	US market pulp capacity
t_news:	US newsprint capacity
t_ctfs:	US coated freesheet capacity
t_ucfs:	US uncoated freesheet capacity
t_ctgw:	US coated grownwood capacity
t_ucgw:	US uncoated grownwood capacity
t_tissue:	US tissue capacity
t_special:	US specialty papers capacity
t_kraft:	US kraft paper capacity
t_liner:	US liner board capacity
t_corr:	US corrugated medium capacity
t_sbb:	US solid bleach board capacity
t_recb:	US recycled board capacity

CHAPTER 5

IS FIRM GROWTH STOCHASTIC IN THE PAPER & PULP INDUSTRY?

The central aim of this chapter is to investigate the patterns of firm growth in one of the most capital intensive industries in the world, the p&p industry. Specifically this chapter focuses on responding to the first research question posed in the thesis, formulated in Chapter 3, section 3.2, and which is concerned with testing the three hypotheses formulated by the LPE also known as Gibrat's law (1931). The LPE assumes that firm's growth rate is a random variable independent of the size of the firm. This means that the chances of a given growth rate during a specific period is the same for all firms in a given industry, regardless of their size at the beginning of the period and regardless of their previous size history. In the literature this phenomenon is also known as 'random walk' (Geroski 1999).

As explained in the Research Questions and Literature Review Chapter 3, it is important to investigate the form and causes of the relationship between firm growth and size because several theories that have been proposed in the literature to explain the patterns of corporate growth 'either assume or imply a certain relation' (Evans 1987a, p.658). For discussion and review see Ijiri and Simon (1974), Lucas (1978), Sutton (1997).

The LPE has several economic implications that have interest economists since it was formulated in 1931. One of the most important is that there would be no convergence within industries and thus no predictable differences in growth would exist along the size-distribution. It also implies that there is no minimum efficient scale or optimum firm size, which challenges an important concept in the industrial organization literature. In its strongest form the LPE implies that the rate of growth of the firm has no first-order serial correlation which means that the rate of growth of the firm in one period has no influence on its growth in the following periods and thus it can be treated as a first-order Markov stochastic process.

This chapter investigates the three hypothesis formulated by the LPE across the three decades 1970-2000, for the global and the US p&p industries:

- Is there a significant relationship between the growth rate and size of p&p producers? If such a correlation exists what is its nature?
- Is there a significant relationship between the growth rate variance of the p&p producers and their size? If such a correlation exists what is its nature?
- Is there significant serial correlation among growth rates of p&p firms over time? If so what is its nature?

Specifically in this chapter we want to understand whether p&p growth dynamics follows a random walk process or not. In the case we observe a non-random walk growth process; we will investigate the main characteristics of this departure. In Chapter 6 we investigate the forces that might explain non-stochastic growth patterns. The availability of p&p industry data at both firm and sectoral level from 1970 onwards allows us to empirically test the LPE. The analysis will consider the 150 largest world[58] firms during a 23 year period (1978-2000) and the complete population of US p&p firms during the 30 year period (1971-2000).

The chapter is organized as follows. Section 5.1 discusses the different methods used to test Gibrat's law and the econometric problems that should be considered in order to obtain non-biased results. Section 5.2 presents the results of the empirical analysis conducted at both global and the US p&p industry. Section 5.3 summarizes the results and presents the main conclusions of the chapter.

5.1 Methods for testing Gibrat's law and some related econometric problems

There are several methods in the literature for testing this law, developed since its formulation in 1931, each of them has certain strengths and weaknesses. Some of the

[58] The 150 largest p&p firms account for two thirds of world p&p output.

technical problems that involve dynamic studies of growth, such as heteroskedasticity, serial correlation, sample selection bias, and the difficulty to gather longitudinal data, originate in the exploration of different approaches to analyse firms' growth-size relationships. The three methods most commonly used are presented and discussed below.

a) <u>Grouping firms into size classes across the same cross sectional periods</u>

The first method consists of grouping firms into different size classes (say 'very small', 'small', 'medium', 'large', 'very large') within same cross-sectional periods, and the null hypothesis of no significant differences in the probability distribution of growth rates across size-classes is tested. We do so by testing for differences in the means and variance of growth rates across size-classes. The Welch-Aspin (1949) test can be used to test multiple means when equal variances are not assumed, and Levene's (1960) test or Bartlett's (1937) test can be used to check the equality of the variance when more than two variables are compared. The strength of this method lies in its simplicity, thus it has been used widely to study multiple industries which enables comparison with existing work, see Hart (1962), Hymer and Pashigian (1962), Mansfield (1962), Singh and Whittington (1975), Dunne and Hughes (1994), Hart and Oulton (1996). Its weakness compared with quantile regresion or panel data analysis (discussed next), is that it does not allow the modelling of autocorrelation patterns for firms within size classes.

One of our findings is that p&p firms' growth process is not a random walk. In general smaller firms tend to grow faster on average than larger firms, and the variability in firm growth decreases with size being larger for smaller firms than for big companies. However, the most interesting finding is that the growth-size relationship is not linear along the size distribution since the 'large' size-class exhibits, on average, one of the largest growth rates and growth rate variances. Subsection 5.2.1 extends these findings.

b) <u>Log linear regression model</u>

Another way to test whether the LPE requirements are met is to study the relationship between firm size at the beginning and end of a period. The model that can be used to empirically test Gibrat's law applying ordinary least squares (OLS) is:

$$\log S_{i,t} = \alpha + \beta \ \log S_{i,t-\Delta} + \varepsilon_{i,t} \tag{5.1}$$

where:

$S_{i,t}$ is the size of the *i-th firm in the industry at time t*

$S_{i,t-\Delta}$ is the size of the *i-th firm in the industry at time* $t-\Delta$

β is the parameter to be estimated which corresponds to the linear regression slope

α corresponds to the constant term of the linear regression

$\varepsilon_{i,t}$ is the error term of the model

Gibrat's law holds if the null hypothesis β = 1 is not rejected by the data, and the error term $\varepsilon_{i,t}$ is a homoskedastic random variable,[59] and serial correlation is not significant: thus the three requirements of the LPE are met. This implies that firms' growth rates are independent of their size and the growth process can be considered a random walk. If β >1 this means that systematic factors favour large firms and, as a consequence, they grow faster than smaller firms. The case where β <1 implies the opposite, that systematic factors favour small firms which grow faster than large companies. This methodology has been used by several authors such as Chesher (1979), Tschoegl (1983), Kumar (1985), Dunne and Hughes (1994), Audretsch, Klomp et al. (2002).

One assumption of model (5.1) is that the intercept and slope parameters α and β are the same for all firms within each industry. This means that homogeneity across firms has been considered and thus the parameters α and β are constant and industry dependent. This is a strong assumption that has been challenged by empirical evidence since firms have been found to exhibit high degrees of heterogeneity within industries (Caves 1998; Hart and Oulton 2001).

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[59] A homoskedastic random variable refers to a variable that has variance homogeneity.

Because homogeneity across firms is a strong assumption, a variant of this assumption is used by some authors using quantile regression analysis, which was introduced by Koenker and Bassett (1978). It explicitly recognizes heterogeneity across firms (for a complete review see Coad 2007) by deriving results using specified quantiles of the conditional growth rates distribution. The application of this method has resulted in the emergence of a robust ‘stylized fact’ which states that firms’ annual growth rate distributions are remarkably fat-tailed and can be approximated by a Laplace distribution (Stanley et al., 1996; Bottazzi et al., 2005; Bottazzi et al., 2007). This technique has the benefit that it studies firms’ average growth rates and also focuses on understanding the growth of fast-growth firms especially in high tech sectors (Coad and Rao 2006).

c) Panel data analysis

The third method consist of using a panel data which is a cross section of observations over time, thus it has a spatial and a temporal dimension. The spatial dimension corresponds to a set of cross-sectional observations usually indicated by the subscript ‘*i*’. This might be the different characteristics of the p&p firms being studied in this research, such as production capacity or output variables. The temporal dimension corresponds to time-series observations of the variables characterizing the cross-sectional observations over a particular time period. It is indicated by the subscript ‘*t*’. The following model can be used to empirically test Gibrat’s law applying panel data. It does not assume that the intercept and slope parameters are the same for all firms in a given industry, which means that α_i and β_i are not constant.

$$\log S_{i,t} = \alpha_i + \beta_i \log S_{i,t-\Delta} + \varepsilon_{i,t} \tag{5.2}$$

Several authors use panel data in order to study the growth dynamics of firms such as: Hall (1987); Bottazzi, Dosi et al. (2001); Goddard, Wilson et al. (2002); Bottazzi, Cefis et al. (2002); Lotti, Santarelli et al. (2003); Geroski, Lazarova et al. (2003). Panel data sets have several advantages over conventional cross-sectional or time-series databases. They allow greater capacity for modelling more complex processes such as dynamics behaviours of companies since they use multiple observations of multiple firms over time. Panel data usually contain more sample variability and more degrees of freedom than cross-sectional or time series data, which improves the efficiency[60] of the econometric parameters estimated, and the statistical tests have higher degrees of power[61] (Greene 1999).

Subsection 5.1.1 discusses several econometrical problems that need to be taken into account in a growth dynamic analysis in order to avoid biased results.

5.1.1 Econometric problems that should be considered

One of the difficulties of studying firms' growth dynamics is the presence of several econometric problems that can bias the results obtained from any of the methods explained in the previous subsection. Four econometric problems should be considered in order to conduct a robust dynamic analysis of the firm growth-size relationship. The first problem is the heteroskedasticity[62] that arises from inequality in growth rate variances across firms of different sizes. The second problem is related to the effects of sample selection bias[63] on the growth-size relationship. This is especially important since firms' entry and exit are key features in a study of the dynamics and evolution of industries. The third problem refers to the presence of serial correlation[64] when testing Gibrat's law, which may render[65] least-squares estimators inconsistent. The fourth problem is related to the linearity assumption (constant β along the size distribution) discussed in many studies using longitudinal models.

The corporate growth literature developed in the 1990s and 2000s (Dunne and Hughes 1994; Hart and Oulton 1996; Geroski 1999; Audretsch, Klomp et al. 2002; Goddard, Wilson et al. 2002; Geroski, Lazarova et al. 2003) emphasizes the need to correct for these econometric problems which especially affect dynamic analyses of this type

[60] An efficient parameter estimate is one that has a very small standard error among all unbiased estimators. An estimate is unbiased in a given parameter when the expected value of that estimator is equal to the true value of the parameter being estimated.
[61] The degree of power of a test is its ability to detect whether an effect exists, thus it assesses the accuracy of the test. It is defined as the probability of correctly rejecting a false null hypothesis and is inversely related to the probability of not rejecting the null hypothesis when it is false.
[62] In the literature heteroskedasticity is also called size-dependent growth variance.
[63] In the literature sample selection bias is also called sample attrition or birth and death problems.
[64] The literature uses different names to refer to serial correlation such as 'growth persistence', 'lagged correlation', 'autocorrelation' and correlation between $S_{i,t-1}$ and $\varepsilon_{i,t}$
[65] An inconsistent estimator is one that does not converge in probability to the true value of the parameter being estimated.

because they can severely bias results. Much of the research in this field does not consider these four problems simultaneously which might be one of the reasons why the results obtained are inconsistent, see reviews by Sutton (1997) and Hall (1987).

a) The first econometric problem is the phenomenon of heteroskedasticity which arises from inequality in growth rate variances across firms of different sizes. Several studies (Hymer and Pashigian 1962; Hall 1987) show that variance in growth rates decreases with increasing firm size, thus they are size-dependent. This suggests that the error term of the residuals is not constant across firms which imply that the estimated standard errors are biased and therefore should be adjusted for heteroskedasticity.

b) The second econometric problem which is related to the effect of sample selection bias on growth-size relationship, has been discussed by several authors such as Mansfield (1962), Hall (1987), Evans (1987a; 1987b), Dunne and Hughes (1994). Depending on the sample selection criteria, the law can be tested in two ways. The first method is to use a sample of firms that existed during all the period studied, thus ignoring entry and exit of firms within the period (in the case of panel data analysis this implies using a ‘balanced’ panel). The second method is using a population of firms with sample attrition taken into account because some firms that exist at the beginning of the study period do not survive until the end of it (exit firms), and some firms that exist at the end of the period did not exist at the beginning of it (entry of new firms). In the case of panel data analysis this implies using an ‘unbalanced’ panel.

The former case means that only incumbent surviving firms are going to be considered in the sample obscuring relevant industrial dynamics information, such as entries and exits of firms. As Mansfield (1962) points out, if small slow-growing firms are more likely to fail than large slow-growing-firms, then the analysis of growth rate by size of firm based on survivors alone is biased towards finding an inverse size growth relationship. Thus Gibrat’s law should be tested over the entire population of firms. This is the latter case where new entry and exit firms within the study period are included.

c) The third econometric problem that arises when testing dynamic models is the presence of serial correlation. Chesher (1979) demonstrated that serial correlation in the disturbances of model 5.1 induces dependency between $S_{i,t-\Delta}$ and $\varepsilon_{i,t}$ which may render OLS estimators of β inconsistent. Therefore, even if β is estimated to be equal to unity, Gibrat's law will not be in operation if $\varepsilon_{i,t}$ are not independently distributed over time. He argues that the law is in operation only if β is equal to 1 and the residuals $\varepsilon_{i,t}$ are independently distributed over time. Thus serial correlations needs to be tested and if it is significant needs to be corrected.

d) The fourth econometric problem that should be considered is the assumption of a linear relationship which means that β is constant along the size distribution. In this research we do not make this assumption, thus different samples of firms along the size distribution will be studied allowing the growth rate relationship to vary alongside it.

5.1.2 Firm size and growth rate calculations

How to measure firm growth rate over time, and calculate firm size, and the method used to test the growth-size relationship need to be studied in some depth in order to define the mechanisms that assure robust results and avoid bias. To this end, we analyse the following seven methodological issues: a) firm growth and growth rate calculation; b) firm size measurement (different possible variables); c) time period used to study firm growth; d) firm size-class and type-class definitions; e) calculation of firm growth means and variances; f) test of growth means homogeneity across size-classes; g) test of growth variance homogeneity across size-classes.

a) <u>Firm growth and growth rate calculation</u>

Firm growth can be calculated using the following formula:

$$\Delta S_{i,t-\Delta} = (S_{i,t} - S_{i,t-\Delta}) \tag{5.3}$$

where:

$\Delta S_{i,t-\Delta}$ is the growth of the *i-th* firm in the industry between time *t* and time *t*-△

$S_{i,t}$ is the size of the *i-th* firm in the industry at time *t*

$S_{i,t-\Delta}$ is the size of the *i-th* firm in the industry at time *t-△*

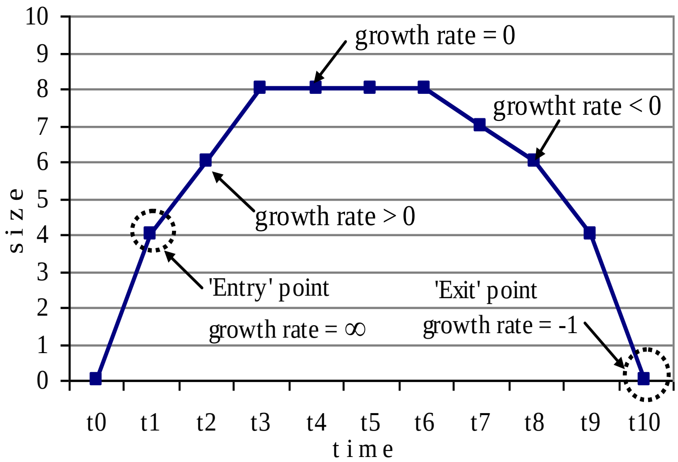
Firm growth rate can be calculated using the following formula:

$$Gr_{i,t} = (S_{i,t} - S_{i,t-\Delta}) / S_{i,t-\Delta} \tag{5.4}$$

where $Gr_{i,t}$ is the growth of the *i-th* firm in the industry between time *t* and time *t-△*

When calculating firm growth rates, entry of new firms and exit of existing firms need to be treated carefully since they strongly influence the results of Gibrat's law analysis. Figure 5.1 shows how a firm's size can change over time from its entry to its exit from the industry. The growth rate of the entry year is infinite. As the firm grows, the resulting annual growth rate is positive. If the firm size stays the same from one year to the next, the growth rate is zero. If the firm size decreases the annual growth rate is negative and when it exits the industry the growth rate is equal to -1.

Figure 5.1 Example of different firm's growth rate over time



The firm size data that we consider for each firm starts for the first year it reported output (in the global database) or capacity (in the US dataset), and finishes the last year it reported output/capacity. Thus the first growth rate is calculated as the output/capacity difference between the end of the second year and the end of the first year. The last growth rate of a firm before it exits the industry is calculated as the output/capacity difference between the end of the last year the firm reported output/capacity and the previous year.[66]

The entry points (firms that enter the industry) cannot be included in the Gibrat's law analysis because their annual growth rates are infinite. The exit points (firms that shut downs) with an annual growth rate of -1 cannot be included because this asymmetry would bias results toward negative mean growth. The exit cases which are the most important during the study period since the number of firms decreases significantly, are analysed in Chapter 7 which investigates hazard exit and technology adoption patterns.

b) Firm size measures

Different variables are used in the literature to calculate firm growth such us: total output, total capacity, total sales, total assets, number of employee, etc. The different proxies for firm size have strengths and weaknesses. Hart and Oulton (1996) discuss the limitations of variables such as turnover, total assets and employment.

From the global p&p industry dataset, there are four types of data that can be used as proxies for firm size:

- 'market pulp, paper & board' sales (mppb_s) in millions US$
- 'market pulp, paper & board' (mppb) output in metric tons
- 'total assets' in millions US$ (assets)
- 'number of employees' (n_empl).

Table 5.1 shows the high correlation among these four firm size variables. In all cases it is significant at the 1% level, thus we can choose any one of them as a proxy for firm size. The one that best represents firm size over time in the context of the p&p industry is 'market pulp, paper & board' output (mppb). The 'Sales' variable is very much influenced by the highly cyclical prices of p&p products (see Figure 2.4) and this distorts the longitudinal analysis. 'Number of employees' is heavily influenced by the type of technology used in the production processes. Companies with similar capacity could have very different numbers of employees depending on how old (or how modern) are their p&p machines, thus this distorts firm size comparisons. Finally, 'total assets' is

[66] Obviously the zero growth rates have to be included on the calculation of growth rate mean and variance since its exclusion would make the sample meaningless.

problematic in that it includes the assets of non p&p operations in diversified firms, thus it distorts both cross sectional and longitudinal analyses. The ‘output’ variable that we use to analyse Gibrat’s law has the drawback that it is influenced by aggregate demand variations over time. However, since the industry has grown quite steadily during the three decades, at an average of 4% per year (see Figure 2.3), there are no important changes in aggregate annual growth rate demand along this period and thus this error component is much smaller than for the other three.

In the US dataset, the only variable to proxy firm size is ‘total capacity’ measured in metric tons. This variable is not affected by the four factors explained above, thus it constitutes a good proxy for firm size. Considering that this industry tries to operate at very high capacity,[67] this variable is similar to the total output used with the global dataset, allowing a reasonable comparison between the two datasets.

Table 5.1 Correlation matrix of firm size variables, Top 150 p&p firms
(correlation coefficient and number of observations)

variable	mppb	mppb_s	assets	n_empl
mppb	1.000			
# of obs.	3,445			
mppb_s	0.89**	1.000		
# of obs.	3,445	3,450		
assets	0.86**	0.88**	1.000	
# of obs.	3,259	3,264	3264	
n_empl	0.76**	0.74**	0.75**	1.000
# of obs.	3,403	3,408	3,237	3,408

*** Significant at 1% level*

c) Time period used to study firm growth

When studying firms’ growth processes it is necessary to decide the number of years over which an individual firm’s growth will be calculated. There is a trade-off that has to be considered when deciding the growth time period $(t-\Delta)$. On the one hand the maximum number of observations is obtained when calculating growth over the shortest period of time which in this case is one year. On the other hand annual growth rates tend to be noisy (Goddard, Wilson et al. 2002, p.421) thus measurement over longer periods

[67] A well managed p&p plant operates at least at 95% capacity.

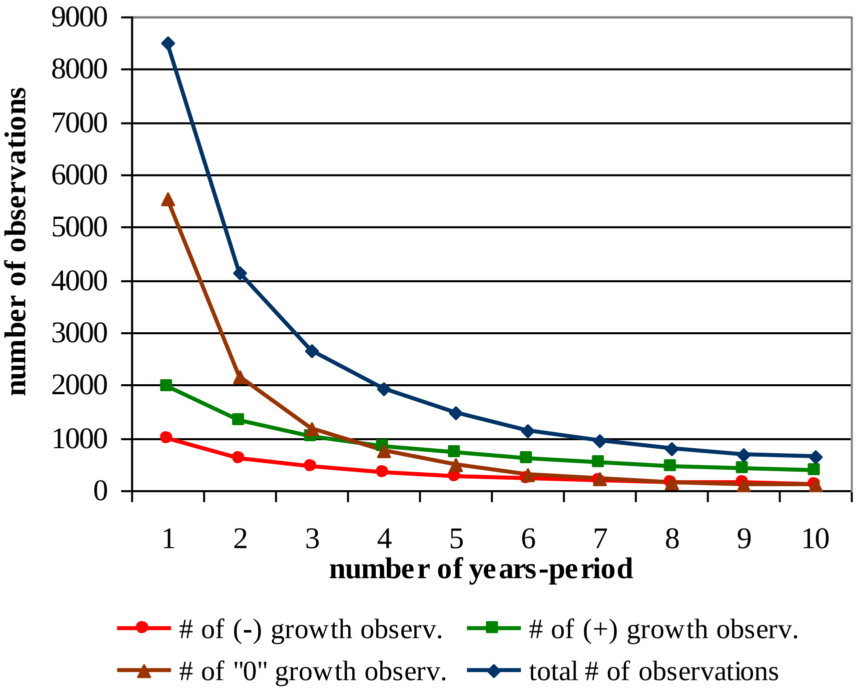
of time yield more meaningful growth data, however increasing the number of years reduces the number of observations considerably.

The p&p industry is one of the world's most capital intensive industries, and paper machines are one of the largest single machines in the world. One of the consequences of this latter technological feature is that the addition of new capacity is normally done on a large scale and, therefore, it is not common for firms' capacities to change annually, but over the longer term. Table 5.2 and Figure 5.2 show the number of firm-year observations in the US dataset that have positive, negative and zero growth, and the

Table 5.2 Number of growth observations for different number of years-period US p&p database

# of years-period	1	2	3	4	5	6	7	8	9	10
total # of obs.	**8,514**	**4,122**	**2,644**	**1,930**	**1,479**	**1,155**	**940**	**800**	**700**	**627**
# of (0) growth	5,547	2,176	1,168	760	497	320	215	155	130	118
% over total obs.	65%	53%	44%	39%	34%	28%	23%	19%	19%	19%
# of (+) growth	1,962	1,338	1,038	852	715	607	520	460	415	385
% over total obs.	23%	32%	39%	44%	48%	53%	55%	58%	59%	61%
# of (-) growth	1,005	608	438	333	267	228	195	167	144	124
% over total obs.	12%	15%	17%	17%	18%	20%	21%	21%	21%	20%

Figure 5.2 Number of growth observations for different number of years-period US p&p database



total number of observations for different numbers of years used to calculate growth. When the time period is just one year the number of observations with no growth is 65% (5,547 observations) of the total. This percentage falls to 44% (1,168 observations) over a three year period and to 34% (497 observations) for a five year period. Taking into account the above arguments, the dynamics of p&p firms' growth will be analysed using three different periods: one, three and five years. This will allow us to study the stability of the results.

d) Method for testing Gibrat's law and firm size-class and type-class definitions

The method used to study Gibrat's law involves grouping firms into different size-classes within size distribution and testing for differences in the mean and variance of growth rates across them. This method is chosen for its simplicity and its suitability for investigation of the first and second form of Gibrat's Law test (firm growth-rate and size relationship, and firm growth-rate variance and size relationship). It also allows the relationship between firm growth and size to be studied along the size distribution curve not assuming linearity. Finally, because this method has been used widely to the study of multiple industries, thus comparison with numerous investigations is possible (see discussion on p. 111). Its main weakness is that it is does not allow us to model firms´ autocorrelation patterns (third Gibrat's law form) within size classes. However in this thesis this relationship is studied using the Chesher (1979) model (see Section 5.2.2).

To do this we define for both datasets five size-classes: 'very small', 'small', 'medium', 'large' and 'very large'. Table 5.3 shows for the global 150 dataset the borders of the five size-classes and the number of firms within each group in four selected years. Considering that firm size varies from a minimum of 53,000 tonnes to a maximum of 16,767,000 tonnes, thus 316 times larger (see subsection 4.2.2), the borders of the size-classes were chosen in order to get the upper limit be approximately twice the lower limit in each case. Table 5.4 shows for the US p&p dataset the borders of the five size-classes and the number of firms within each group in selected years. Taking into account that firm size varies from a minimum of 2 th.tonnes to a maximum of 12,235 th.tonnes, thus 6,117 times larger (see subsection 4.2.2), the borders were chosen in order to get the upper limit to be approximately four times the lower limit in each case.

Table 5.3 Size-classes definition and # of firms in selected years, global p&p industry

Size-class	Size-class (000 tonnes)	Number of firms 1978	1980	1990	2000
very small	mppb <= 256	33	28	25	14
small	256 < mppb <= 512	55	52	35	32
medium	512 < mppb <= 1,024	32	39	38	39
large	1,024 < mppb <= 2,048	20	18	24	35
very large	2,048 < mppb	10	13	28	30
	Total # of firms	150	150	150	150

Table 5.4 Size-classes definition and # of firms in selected years, US p&p industry

Size class	Size-class (000 tonnes)	Number of firms 1970	1980	1990	2000
very small	mppb <= 16	72	51	35	28
small	16 < mppb <= 64	112	117	100	71
medium	64 < mppb <= 256	61	56	70	70
large	256 < mppb <= 1,024	45	50	37	41
very large	1,024 < mppb	10	14	23	25
	Total # of firms	300	288	265	235

Considering the particular features of the p&p industry explained in Chapter 2 (sections 2.2 and 2.3), five size-classes were considered to be an appropriate number of groups of firms in order to capture specific variations along the size distribution. The reasons for our choice of these five size-classes are that on the one hand, the 'very small' and 'small' firms are mostly single p&p plants thus it is suitable to group them separately from the larger firms which are mostly multiple plants. Within this part of the size distribution, it is convenient to break these single plants into two size-classes, ('very small' and 'small' firms) in order to achieve greater sensitivity to some of their specific dynamism.[68] On the other side of the size distribution the 'large' and 'very large' firms are multiple plants and it is worth comparing companies with different capacities among them in order to have greater sensitivity to capture some of their specific dynamism. Thus we decided to split this multiple plant group into two size-classes: 'large' and 'very large'. Finally, the 'medium' size-class differs from the other four because there is not a predominant group of single or multiple plant firms, thus it is convenient to treat it separately from the other four groups.

[68] E.g. Chapter 2 (Table 2.4) shows that a relatively large percentage of the 'very small' firms exited the industry during the study period and this pattern tends to diminish for the upper size-classes.

To conclude this part of the analysis, five size-classes seem to cover the variety of the size distribution within the p&p industry. With a smaller number of groups we would not be able properly to isolate some of the industry dynamic features that we are interested in studying since they would be indistinguishable among the few big size-classes. A larger number of groups, would result in specific dynamics being diluted among the many size-classes with a small number of firms.

The above size-class definitions allow us to compare average growth rates across them; however they have two limitations. Firstly, the borders of each size-class are fixed over time in spite of the fact that average firm sizes grow significantly during the study period. This secular industry increase[69] produces movements along the size distribution with the consequence that the number of firms in both of the extreme size-classes changes considerably over time. For example the number of 'very small' firms goes from 72 in year 1970 to 28 in year 2000. The number of 'very large' firms goes from 10 in year 1970 to 25 in year 2000 (see Table 5.4). The second undesirable effect of the above size-classes definitions is that the number of firms varies considerably across size-classes for the cross sectional data. For instance in 1970 there are 112 'small' firms and only 10 'very large' firms. To correct for these drawbacks we also test Gibrat's law using normalized size data that correct for the industry secular increase effect. This allows us to apply a second criterion for size-class definition and thus to study the robustness of the results.

To normalize the data for each year around zero on a log scale, we subtract the average log size of all the firms within each year from the log size of each individual firm for each year as shown in the following equation:

$$S_{t,i} = \log(S_{t,i}) - 1/n_t * \sum_{i=1}^{n_t} \log(S_{t,i}) \tag{5.5}$$

where n_t is the total number of firms in year *t*.

Figures 5.3 and 5.4 shows the log size-distribution curves for pooled not normalized and pooled normalized data for both databases. The new data are centred on zero and the

[69] By 'secular increase' we mean a uniform pattern of increase throughout an industry.

average size difference among years is removed. Under this new variable, firm size varies from -3.0 to 3.0 for the global dataset, and from -4.0 to 5.0 in the US dataset.

Figure 5.3 Global p&p industry log size distribution
(not normalized and normalized pooled data, period 1978-2000)

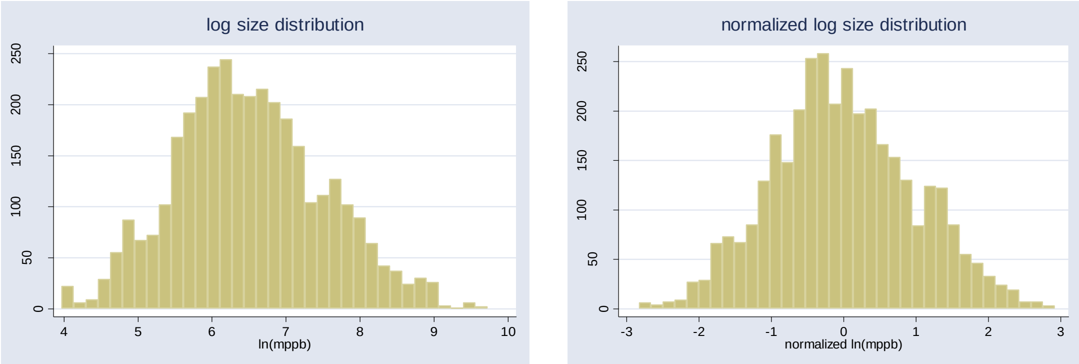
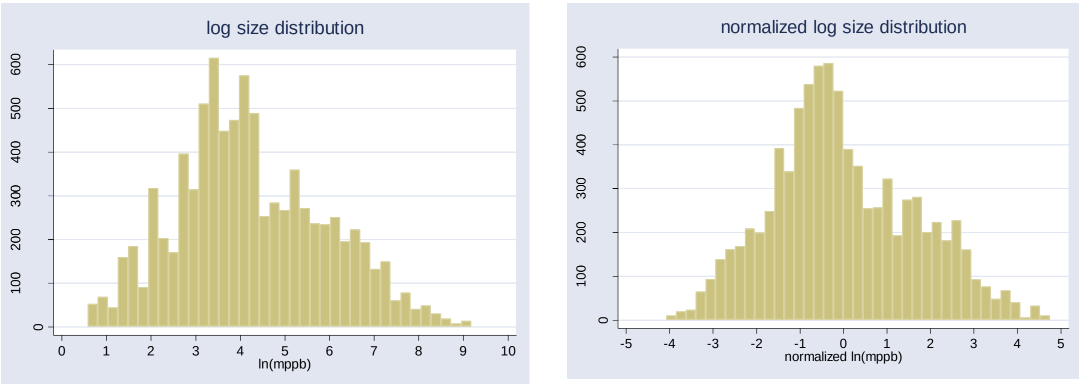


Figure 5.4 US p&p industry log size distribution
(not normalized and normalized pooled data, period 1971-2000)



Tables 5.5 and 5.6 shows the new borders of the five size-classes using normalized data, and the number of firms in selected years for each dataset where it is possible to confirm that the industry 'secular increase' effect has been corrected for.

Table 5.5 Size-classes definition, global p&p industry

Size-class	Size-class limits (normalized log size)	Number of firms			
		1978	1980	1990	2000
very small	size <= -0.75	27	26	37	39
small	-0.75 < size <= -0.25	39	35	26	29
medium	-0.25 < size <= 0.25	32	34	28	23
large	0.25 < size <= 1	31	37	29	33
very large	1 < size	21	18	29	25
	Total # of firms	150	150	149	149

Table 5.6 Size-classes definition, US p&p firms

Size-class	Size-class limits (normalized log size)	Number of firms			
		1970	1980	1990	2000
very small	size <= -1	80	77	75	65
small	-1 < size <= 0	86	86	74	60
medium	0 < size <= 1	44	48	47	47
large	1 < size <= 2.5	67	54	45	43
very large	2.5 < size	23	23	24	20
	Total # of firms	300	288	265	235

e) Calculation of firm growth mean and variance

Having defined size-classes borders, using the following equations it is possible to calculate and compare the pooled mean and variance growth rates within size-classes.

$$\overline{Gr}_k = 1/n_k * \sum_{j=1}^{n_k} Gr_j \qquad \text{pooled annual } \textit{growth rate mean} \text{ of size-class } k \qquad (5.6)$$

$$\sigma_k^2 = 1/n_k * \sum_{j=1}^{n_k} (Gr_j - \overline{Gr}_k)^2 \quad \text{pooled annual } \textit{growth rate variance} \text{ of size-class } k \quad (5.7)$$

where:

n_k is the number of firms in size-class *k*

Gr_j is the growth rate of the *j-th* firm in size-class *k*.

f) Test of homogeneity in growth means across size classes

In order to investigate the first Gibrat’s law proposition regarding the homogeneity of growth means across the five p&p size-classes defined, we need to run a simultaneous test of means. This is not a conventional ANOVA test since we cannot, as this method does, assume equal variances across the size-classes.

If μ_i is the mean growth rate for those firms that belong to size-class *i*, then the hypothesis to be tested can be stated as:

$H_o : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ versus

$H_1 : \mu_i \neq \mu_j$ for $i \neq j$

The test can be expressed as a joint difference of means using the following matrix:

$$H_o : \begin{bmatrix} \mu_1 - \mu_2 \\ \mu_2 - \mu_3 \\ \mu_3 - \mu_4 \\ \mu_4 - \mu_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Rencher (2002) shows that the simultaneous test of means across groups is given by:

$$T > \chi^2_{k-1,\alpha}$$

where $\chi^2_{k-1,\alpha}$ is the upper critical value of the chi-squared distribution with *k-1* degrees of freedom at a significance level of α, and the test statistics is defined as:

$$T = n(R\overline{\mu})'(RSR')^{-1}(R\overline{\mu}) \tag{5.8}$$

where:

n is the total number of observations

k is the number of size-classes (or type-classes)

$\overline{\mu}$ is the vector of sample means estimates (5 * 1)

S is the matrix of sample variance estimates (5 * 5)

R is the matrix that defines Ho (4 * 5) which has the following form:

$$R = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}$$

Subsection 5.2 presents and analysed in depth the results of these tests for the global and the US p&p industries, where the first Gibrat's law proposition of random growth of p&p firms is rejected (Tables 5.7 and 5.8).

g) <u>Test of growth variances homogeneity across size-classes</u>

In order to investigate the second proposition in Gibrat's law regarding the homogeneity of growth variance across different firms' size-classes, we need to run a simultaneous test of variances across the five size-classes defined. This is not a conventional variance pair comparison but is a simultaneous multi variance comparison. Two tests suggested by the literature to study the null hypothesis for equality of variances across different size-classes against the alternative hypothesis that variances are unequal for at least two groups are the Bartlett (1937) and the Levene (1960) test statistics. The former is more commonly used; however, one assumption is that data come from normal or nearly normal distribution which occurs in our case.

If σ_i is the standard deviation of the growth rate for those firms that belong to the size-class *i*, then the hypothesis to test can be stated as:

$H_o : \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2 = \sigma_5^2$ versus

$H_1 : \sigma_i^2 \neq \sigma_j^2$ for at least one pair $i \neq j$

Bartlett rejects the null hypothesis that the variances are homogeneous if:

$$T > \chi^2_{k-1,\alpha}$$

where $\chi^2_{k-1,\alpha}$ is the upper critical value of the chi-squared distribution with *k-1* degrees of freedom at a significance level of α, and Bartlett test statistics is defined as:

$$T = \frac{(N-k)\ln S_p^2 - \sum_{i=1}^{k}(N_i - 1)\ln S_i^2}{1 + (1/(3(k-1)))((\sum_{i=1}^{k} 1/(N_i - 1)) - 1/(N-k))} \tag{5.9}$$

and:

$$S_p^2 = \sum_{i=1}^{k}(N_i - 1)S_i^2 / (N-k)$$

Subsection 5.2 presents and analysed the results of these tests for the global and the US p&p industries, where the second Gibrat's law proposition of no significant relationship between growth variance and size is rejected (Tables 5.7 and 5.8).

Having explained with some detail the above seven methodological, data and calculation issues we next present the empirical results.

5.2 Empirical results and test of significance

This section presents and analyses the empirical results of the Gibrat's law tests conducted on the global and US p&p databases. The section proceeds in the order of the research question. The results are presented in tables and graphs, each considering one full period that comprises the years 1978 to 2000 for the global dataset and 1971 to 2000 for the US dataset. Firm growth and growth variances are calculated using three different time lags (1, 3 and 5 years). Two criteria are used for the definition of firm size-classes: raw and normalized firm size data. These different approaches to test Gibrat's law allow us to check the robustness and stability of the results.

5.2.1 Are p&p firm growth and firm growth variance correlated with firm size?

In order to have a first idea of the type of relationship between firm growth and size, Figures 5.5 and 5.6 shows scatter diagrams with the plots of growth rate versus size for the 150 global p&p firms and the complete US size distribution respectively, using 5 lagged years. Both graphs suggest that growth variance is not constant since it reduces with firm size as shown by the broken lines.[70]

Next we calculate for the global and US p&p industries the growth means and growth variances for the five size-classes defined in Table 5.5 using the raw size data and the normalized logarithm size data, and 1, 3 and 5 years lag. Using the statistics defined in equations 5.8 and 5.9 we test the homogeneity of growth and growth variance. Tables 5.7 and 5.8 present the data (growth mean, growth st. dev. and number of observations)

[70] The graphical analysis was done also for several different periods and using different growth time lags presented in Appendix 5.1.

and the results (Test Chi2) for the six different scenarios studied in order to check for consistency of the findings.

Figure 5.5 Firm's annual growth rate versus size for 5 years-lag Global p&p dataset with normalized pooled data

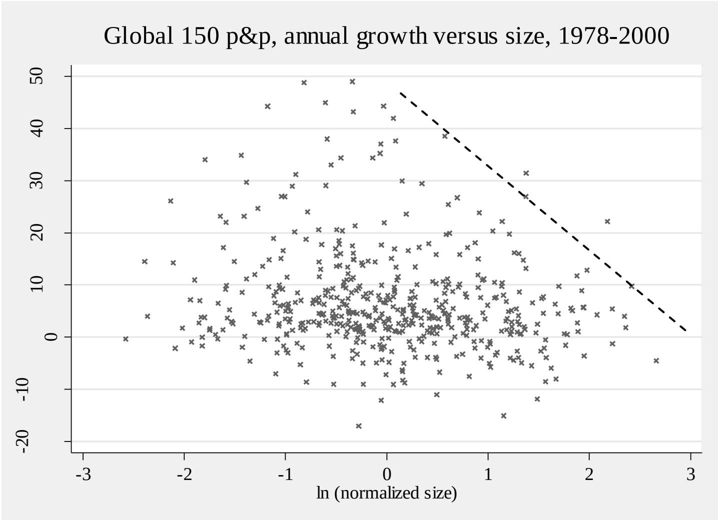
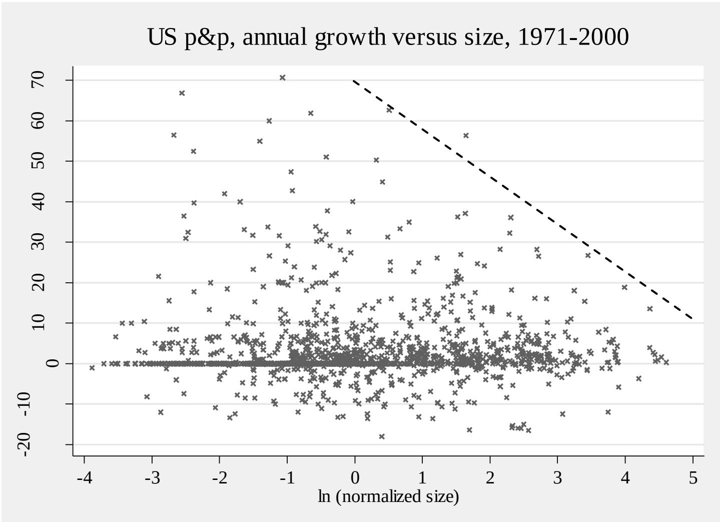


Figure 5.6 Firm's annual growth rate versus size for 5 years-lag US p&p dataset with normalized pooled data



The results of the global p&p industry of Table 5.7 show a clear pattern for diminishing growth and growth variance with firm size. The results of the six scenarios analysed are consistent in confirming that within the world 150 largest p&p firms, the smaller companies tend to growth faster and with a higher variability than the larger firms. This implies that the first two hypothesis of Gibrat's law are rejected.

Table 5.7 Global 150 p&p industry, full period 1978-2000
Firm's annual growth mean (%) and st. dev. (%) for different years-lag and size-classes

lag	size-classes					Test	normalized log. size-classes					Test
	VS	S	M	L	VL	Chi2	VS	S	M	L	VL	Chi2
1 year												
mean	9.1	7.5	5.3	5.9	4.9	35.2**	8.5	8.0	5.0	6.4	4.0	39.7**
st.dev.	23.0	23.9	20.9	20.6	18.6	43.1**	23.8	23.5	21.4	20.4	18.3	51.8**
# obs.	444	787	815	532	473		625	611	599	686	530	
3 years												
mean	8.1	6.8	7.1	6.2	4.9	26.9**	7.3	7.4	6.9	6.7	4.8	19.4**
st.dev.	13.0	12.7	12.4	11.4	10.3	9.8*	13.7	12.7	13.9	12.7	10.1	18.9**
# obs.	139	249	236	151	132		185	192	163	207	160	
5 years												
mean	8.8	8.0	5.7	5.3	4.6	15.5**	8.3	7.8	6.1	5.7	3.9	15.0**
st.dev.	9.9	10.4	10.6	8.4	8.2	9.6*	10.7	10.4	10.8	7.9	8.1	17.7**
# obs.	94	132	126	91	66		107	106	101	108	87	

** significant level at 5%   ** significant level at 1%*

Table 5.8 US p&p industry, full period 1971-2000
Firm's annual growth mean (%) and st. dev. (%) for different years lag and size-classes

lag	size-classes					Test	normalized log. size-classes					Test
	VS	S	M	L	VL	Chi2	VS	S	M	L	VL	Chi2
1 year												
mean	4.0	2.8	2.7	3.5	2.0	156**	3.8	2.5	2.6	3.6	2.2	233**
st.dev.	25.3	19.0	19.7	20.1	15.5	239**	24.0	19.4	21.3	20.4	13.6	316**
# obs.	1,300	2,933	1,835	1,268	534		2,138	2,272	1,286	1,462	712	
2 years												
mean	3.9	2.9	2.9	4.1	2.5	76**	3.6	2.8	2.7	4.1	2.8	97**
st.dev.	14.8	10.9	11.1	12.7	8.6	94**	14.0	10.2	11.7	12.5	8.3	117**
# obs.	413	922	561	397	162		656	710	405	455	229	
3 years												
mean	3.6	3.1	2.9	3.4	2.9	14**	3.5	3.1	2.4	3.6	3.0	19**
st.dev.	10.4	9.2	8.7	8.7	6.9	22**	10.5	8.8	8.8	8.9	6.3	44**
# obs.	242	526	332	223	87		372	400	243	271	124	

* significant level at 5%   ** significant level at 1%

Similar to the above findings, the US p&p industry's results of Table 5.8 also exhibit a clear tendency for diminishing growth and growth variance with firm size. However it is interesting to observe that it is not a linear relationship since the 'large' size-class shows one of the biggest average growth along the size distribution. In fact it has the largest growth rate in three of the six measurements showed in Table 5.8 (4.1%, 4.1% and 3.6%) and the second largest on the other three cases (3.5%, 3.4%, 3.6%). This could be interpreted as 'large' firms trying, with systematic higher growth rates, to achieve the leadership of the 'very large' firms (Chapter 6 will investigate the causes of this non linearity growth pattern). On the left end of the size distribution, the 'very small' firms show the highest growth rates compared with the other three size-classes (small, medium and very large). This can be interpreted as ‘very small’ firms pushing to grow faster in order to reach the so called ‘minimum efficient scale’ and thus survive.

Similarly to the growth pattern, the growth variances of the US p&p firms also tend to decrease with firm size and this relationship is not linear. In fact it is possible to observe three levels of growth variance. The ‘very small’ size-class show systematically the highest figures; the ‘very large’ firms have the lowest growth variance, and the in-between size-classes’ shows intermediate values. This pattern applies to the six measurements of growth variance that were carried out.

There are two important conclusions from the above results. Firstly, there is consistent and robust evidence (two size-classes definition and three different time-lags for growth calculation) that the first two propositions of Gibrat’s law are not fulfilled for either the 150 largest global firms or the complete size distribution of the US p&p industry. There is a tendency for smaller firms to grow faster and with higher growth variance than larger firms. Secondly, in the US p&p industry the growth-size relationship is not linear since the ‘large’ size-class has one of the largest growth rates in the size distribution. This is an interesting result whose causalities will be investigated in depth in Chapter 6 where we hypothesise that this is due to the specific technological configuration of firms. This non-linearity also appears in the 150 global firms but is less pronounced.

The third proposition of Gibrat’s law regarding the growth persistence will be investigated in the following subsection.

5.2.2 Is serial correlation significant in the global and the US p&p industry?

This subsection investigates the third proposition of Gibrat’s law which states that there is no ‘serial correlation’ which means that there in no firm growth ‘persistence’. This proposition implies that the growth rate of firms in one period of time is independent of their growth rate in the subsequent period. The existence of growth persistence implies that firms that had high (or low) growth rates over one period also tend to have high (or low) growth in the following period, thus there is an autocorrelation between firms’ past growth and recent growth or between recent and near future growth. Another way to understand this phenomenon is that when two firms in the same industry and of equal size are compared at one moment in time and significant positive growth persistence exists, the company that grew more recently will have the higher probability of growth in the near future than the firm that has not grown recently or grew only in the distant past.

As Singh and Whittington (1975) point out, serial correlation is of considerable economic interest since it has direct implications for the dynamics of industry concentration and determining the dynamics of corporate growth. Growth serial correlation may have also some policy implications if, for example, it is desirable to prevent large firms from experiencing cumulative growth and thus acquiring surplus market power, or if we want to investigate the ability of small firms to generate more durable employment that could persist over time and not disappear in the short run.

Another motivation for studying serial correlation is that it allows us to judge between different growth theories at firm level, by comparing the hypothetical predictions with our empirically-observed patterns. For instance, if observed to be significant, the existence of serial correlation would lead us to reject Gibrat's law of proportionate effects and the associated stochastic models of industry evolution. This strand of the literature treats firm growth as a purely stochastic phenomenon in which a firm's size at any time is simply the product of independent growth shocks. This implies that future growth performance is difficult to predict from current or past performance, or from average industry growth (Goddard, McMillan et al. 2006).

The existence of growth persistence at firm level, on the other hand, would give support to the 'evolutionary' or 'competence-based' theory of the firm (Nelson and Winter, 1982; Teece and Pisano, 1994), which suggests that the growth of successful firms tends to persist over time, 'success breeds success', thus we would expect to observe positive serial correlation for growth between consecutive periods. From an evolutionary perspective, positive growth persistence implies that the advantages accrued by fast growing firms in one period, carry over to the next one. Consistent negative serially correlated growth could imply the existence of factors that systematically reverse growth success. Finally, the presence of positive growth persistence implies that there is a tendency for industry concentration to increase (Dunne and Hughes 1994) while negative growth persistence implies the tendency for industry concentration to decrease.

The empirical investigations of firms' growth persistence provide mixed conclusions and thus there is no emerging consensus on this matter. Several authors find no significant serial correlation for growth, e.g. Tschoegl's (1983) study of the world's 100 largest international banks in the period 1967-1977; Dunne and Hughes's (1994) study of a large sample of UK stock market quoted and non listed companies for the period 1975-1985; Almus and Nerlinger's (2000) analysis of German start-up manufacturing companies in 1989 to 1994; Bottazzi, Cefis et al. (2002) study of selected Italian manufacturing firms for the period 1989-96; and Geroski and Mazzucato's (2002) study of the US automobile industry in 1910-1941 and 1949-1998.

Other researchers have observed significant positive growth persistence, e.g. Ijiri and Simon (1974) for large US firms; Singh and Whittington (1975) for large UK firms; Chesher (1979, p.408) for 183 UK stockmarket quoted companies in the 1960s; Kumar (1985, p.330) for a sample of 1,747 UK manufacturing and services listed companies; and Wagner (1992) for German manufacturing firms in the 1980s. A smaller number of authors have found evidence of negative growth persistence, including three studies by Hall (1987) for US manufacturing publicly traded firms during the period 1976-1983; Boeri and Cramer (1992) for German firms using data that cover total German private employment during the period 1977-1990; and Goddard, Wilson et al. (2002) for 443 Japanese manufacturing stockmarket listed firms during the period 1980-1996.

These mixed results may be due to different industries, and the different time periods observed. Since there is no empirical study of the existence of persistent growth in the p&p industry we next model and test the third hypothesis in Gibrat's law.

Modelling and testing firm's growth persistence (third Gibrat's law hypothesis)

In order to account for first order serial correlation in the growth process of firms Chesher (1979)[71] proposes the incorporation of a past growth term of the form $\log S_{i,t-2}$ in equation (5.1) and the application of OLS to estimate the following model:

---

[71] Andrew Chesher (1979) studied serial correlation of firms growth dynamics in the disturbances of the equation (5.1) and in his seminal paper proposes estimation of the serial correlation coefficient using the (5.12) model.

$$\log S_{i,t} = \alpha + \gamma_1 \log S_{i,t-1} + \gamma_2 \log S_{i,t-2} + \varepsilon_{i,t} \tag{5.10}$$

where:

$\gamma_1 = \beta + \rho$ and $\gamma_2 = -\beta * \rho$

‘ β ‘ is the slope coefficient in the standard regression test

‘ ρ ‘ is the first-order serial correlation or growth persistence coefficient

The estimates of β and ρ are obtained from the following equation:

$$(\beta, \rho) = 0.5\left\{\gamma_1 \pm (\gamma_1^2 + 4\gamma_2)^{1/2}\right\} \tag{5.11}$$

Replacing (5.11) in (5.10) we derive a model that can be used to test serial correlation, in the form:

$$\log S_{i,t} = \alpha + (\beta + \rho)\log S_{i,t-1} + (-\beta\rho)\log S_{i,t-2} + \varepsilon_{i,t} \tag{5.12}$$

In order for the first two propositions of Gibrat’s law (no correlation between growth rate and size, and no correlation between growth rate variance and size) to hold, this model requires the joint hypothesis β =1 (the growth distribution to be independent of size) and ρ =0 (no serial correlation) to be accepted, in addition to the homoskedasticity conditions.[72] The third proposition of Gibrat’s law (no serial correlation) is valid if ρ = 0 is accepted. This method has been used by several authors. Singht and Whittington (1975) studied nearly 2,000 UK firms over the period 1948-1960 and concluded that a large proportion of the positive relationship found between size and growth is due to the positive serial correlation of growth rates. Kumar (1978) studying 2,000 UK companies over a period 1960-1976 reached similar conclusions.

There are two specific aspects to this test which are worthy of some further comment. Firstly, it is not possible to include in the growth persistence analysis firms that exit the industry during the observed periods (Audretsch, Klomp et al. 2002). Thus the analysis

[72] β =1 is a necessary but not a sufficient condition to fulfil Gibrat’s law since ρ = 0 is also required.

relates only to firms that survived throughout the complete study periods.[73] Secondly, the shorter the time horizon over which growth is examined, the higher the probability of detecting significant growth persistence while the longer the time horizon, the smaller is the probability of detecting significant growth persistence. Considering the above, we study growth persistence for the survivor firms for each dataset and considering the following three time periods:

<u>For the global dataset the following three periods are studied:</u>

- 1994 - 00: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 2000, 1997 and 1994 respectively
- 1986 - 93: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 1993, 1990 and 1986 respectively
- 1978 - 85: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 1985, 1982 and 1978 respectively

Table 5.9 presents the γ_1 and γ_2 coefficients that results from the regressions for these three periods using model 5.10, and the β and ρ coefficients calculated using equation 5.11. None of the serial correlation coefficients ρ are significant; thus we conclude that growth persistence is not present in the three periods analysed for the 150 global p&p firms.

Table 5.9 Serial correlation parameters for global 150 p&p database
(within periods incumbent firms)

Period	γ_1	γ_2	β[74]	ρ	N
1994-2000	(t-1)=1997	(t-2)=1994	(t-1)=1997	(t-2)=1994	94
coeficient	0.934	0.077	1.010	**-0.076**	
SE	0.134	0.139			
1986-1993	(t-1)=1990	(t-2)=1986	(t-1)=1990	(t-2)=1986	102
coeficient	0.945	0.037	0.983	**-0.038**	
SE	0.059	0.061			
1978-1985	(t-1)=1982	(t-2)=1978	(t-1)=1982	(t-2)=1978	115
coeficient	0.961	0.043	1.004	**-0.043**	
SE	0.077	0.076			

** significant level at 5%* *** significant level at 1%*

[73] In the following tables we will call 'within period incumbent firms' to the companies that existed during the complete study periods.

[74] Coefficient β which represents the relationship between firm growth and size is not analysed here since it is biased due to the non-constant growth variance along the different size distributions (homoskedasticity conditions are not met). This relationship is analysed in section 5.2.1.

For the US dataset we study the following three periods:

- 1991 - 00: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 2000, 1996 and 1991 respectively
- 1981 - 90: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 1990, 1986 and 1981 respectively
- 1971 - 80: $S_{i,t}$, $S_{i,t-1}$ and $S_{i,t-2}$ denote size in years 1980, 1976 and 1971 respectively

Table 5.10 presents the γ_1 and γ_2 coefficients from the regressions carry out on these three periods for the US dataset using equation 5.10, and the β and ρ coefficients calculated using equation 5.11. The only significant serial correlation occurred in the period 1981-1990. Its positive value means that firms that grew faster during the first half of the 1980s also grew faster during the second half of that decade, independent of their size. There is no evidence of serial correlation before and after the 1980s.

The autocorrelation coefficients calculated in Tables 5.9 and 5.10 correspond to the average growth persistence of the size distributions within each period, thus the underlying assumption is that it is constant across size-classes for each dataset. Although this is a rather sweeping assumption, it is adopted in most of the previous research in this field. We want to progress the analysis and calculate growth persistence not only over time but also across three different size-classes: small, medium and large firms.[75] We run this analysis only for the US p&p industry since we have firm size data

Table 5.10 Serial correlation parameters for US p&p database
(within periods incumbent firms)

Period	γ_1	γ_2	β	ρ	N
1991-2000	(t-1)=1995	(t-2)=1991	(t-1)=1995	(t-2)=1991	169
coeficient	0.981	-0.013	0.968	**0.013**	
SE	0.137	0.138			
1981-1990	(t-1)=1985	(t-2)=1981	(t-1)=1985	(t-2)=1981	203
coeficient	1.274	-0.284	0.986	**0.288****	
SE	0.087	0.090			
1971-1980	(t-1)=1975	(t-2)=1971	(t-1)=1975	(t-2)=1971	225
coeficient	1.002	-0.001	1.001	**0.001**	
SE	0.077	0.078			

** significant level at 5%* *** significant level at 1%*

[75] Three size classes allow sufficient data for the nine cases analysed on a per decade basis.

for the complete population of p&p firms. This enables us to analyse nine different cases that result from three size-classes over three decades from 1970 to 2000. Our data do not allow us to conduct this test for the global dataset.

Table 5.11 shows a synthesis of the resulting serial correlation coefficients ρ using raw capacity data and normalized logarithm capacity data for US p&p firms for the 1970s, 1980s and 1990s, and for three size-classes: small (capacity <= 64 th. tonnes), medium (64 <= capacity <= 512 th. tonnes) and large firms (capacity > 512 th. tonnes). These coefficients are the result of longitudinal analysis of the survivor firms during each study period; thus, the number of observations in each case is much smaller compared with the number of observations when studying firms' growth-size relationships in subsection 5.2.1. This is the reason why not five but three size-classes are defined.[76]

We can see from Table 5.11 that, interestingly, growth persistence varies significantly across both size distributions and time. This means that it is not appropriate to analyse serial correlation by calculating the average autocorrelation coefficient of the size distribution, as most of the studies in this field do.[77] One of the exceptions here, is Bottazzi, Dosi et al. (2001), who study the 100 largest pharmaceutical companies from 1987 to 1997. The problem with the industry average figure is that it could be obscuring some important dynamism in the sector.

Table 5.11 Serial correlation coefficients ρ per decade and size-classes, US p&p database
(within periods incumbent firms)

Period	Firms size-classes			normalized log firms size-classes		
	small	medium	large	small	medium	large
1991-2000	-0.19**	-0.28**	0.62**	-0.08**	-0.32**	0.75**
1981-1990	0.22**	0.03	0.14**	0.22**	0.11**	0.08*
1971-1980	0.03	0.1*	0.25**	-0.04	0.03	0.26**

** significant level at 5%* *** significant level at 1%*

[76] Appendix A5.2 shows γ_1, γ_2, β and ρ coefficients that resulted from the per decade regressions and the size classes in the US p&p dataset using equations 5.10 and 5.11.

[77] The majority of the empirical research in this field consists of testing the LPE for multiple industries and comparing them based on proximity to a stochastic growth process. In this scenario it is difficult to conduct an analysis that is robust in terms of the variables for both size and time; however our single in depth industry study enables this.

Table 5.11 enables some additional interesting conclusions. First, the serial correlation coefficients that result from the two variables used to calculate them (raw capacity data and normalized logarithm) and the two different size-classes borders, show a consistent pattern, thus it is reasonable to assume that these results are robust and not statistical artefacts. Secondly, in terms of the ‘size-class’ dimension, we observe that large firms show consistent and significant positive growth persistence along the three decades: this is quite high especially during the 1990s (0.62 and 0.75). Small and medium sized firms show dissimilar autocorrelation over time. They experienced negative growth persistence during the 1990s, positive persistence during the 1980s, and no significance during the 1970s. Thirdly, from the ‘period’ dimension, In the 1990s small and medium size firms show negative growth persistence while large firms show very high growth persistence. During the 1980s growth persistence is significantly positive along all the size distribution. During the 1970s small and medium firms show no evidences of serial correlation; however the large firms have a positive significant value.

An important hypothesis emerges from these data that is related to the different effects that p&p ‘capacity’ changes and p&p ‘technology’ changes produce in the industry dynamics. During the 1980s the entire US p&p industry showed significant positive growth persistent - average of $\rho = 0.288$ (see Table 5.10), and the three size-classes show positive serial correlation, including small firms (see Table 5.11). This is coincidental with the fact that the aggregate capacity of the 1980s incumbent firms experienced the highest increase of 53.4%, compared with the 23.0% increase in the 1990s and 30.6% increase in the 1970s (see Table 5.12).[78] This suggests that all firm

Table 5.12 Annual capacity in selected years and decade growth for US p&p database
(within decades incumbent firms)

year	annual capacity (million tonnes)	decade growth (%)
1970	24.8	-
1980	32.4	30.6% (1970-80)
1990	49.8	53.4% (1980-90)
2000	61.2	23.0% (1990-00)

[78] The aggregated growth capacity of the incumbent firms per decade correspond to 79.4% of the total industry growth capacity during the study period 1970-2000, thus this sample of firms is appropriate for studying serial correlation of the p&p industry.

size-classes reaped advantage from the important aggregate jump in p&p capacity that occurred in the 1980s. It would be interesting to test this hypothesis in a further research with more specific data.

On the other hand, in the 1990s only large firms show strong positive growth persistence while small and medium size firms show significant negative growth persistence. Why there are significant autocorrelation differences among size-classes in the 1990s and not in the two previous decades (see Table 5.11)? A possible explanation is related to the significant technological changes that occurred in this industry starting in mid 1980s with the introduction of 'automatic process control' technologies which accelerated machine speeds (see Chapter 2 subsection 2.2.1 and Figure 1.2). These technological changes allowed an important increment in production scale and productivity but also increased costs and technological complexity. These results provide grounds to think that the strong positive autocorrelation observed in large firms during the 1990s is due to the positive effect of the new p&p technology in that size-class. The negative autocorrelation of small and medium sized firms and the higher number of exits is likely due to the negative effects of the new, more expensive and complex p&p technology on those size-classes in the 1990s. It would be also interesting to test this hypothesis in a further research with more specific data.

5.2.3 Are differences in growth mean and variance significant across type-classes?

In this subsection we investigate whether there is a pattern in firms' mean and variance growth for three firm's type-classes: 'Incumbents', 'New Entrants' and 'Exits', where:

- '**Incumbents**' are firms that existed during all the study period
- '**New-entrants**' are firms that enter the industry after the first year of the study period and survived until the last year.
- '**Exits**' are firms that exit the industry before the last year of the study period

It is central to this analysis that these three firm type-classes are an important component of the industry dynamics. In the previous two subsections we observed that the non-stochastic nature of p&p firms' growth is due to differences in firms' sizes-classes and growth persistence. Now we want to investigate the possible effects on p&p firms' growth dynamics of these three types of firms. The analysis is done for the 150 global p&p firms during the period 1978-2000, and for the US p&p dataset during the period 1971-2000 using the same methodology as in Section 5.2.1. Table 5.15 shows the number of firms and observations available for each type-class and database.

Table 5.15 Number of firms and observations per type-class, global and US databases

Database & period		Firm's type-class: New-entrants	Incumbents	Exits	Total
Global 1978-2000	# firms	91	41	173	305
	# obs.	616	1,197	1,238	3,051
US 1971-2000	# firms	129	105	332	566
	# obs.	1,254	3,150	3,466	7,870

The comparison of growth and growth variance among incumbents, new entrants and exit firms for both global and US p&p industries are presented in Tables 5.16 and 5.17. In both cases there is a clear tendency towards the average growth of 'new entrants' being higher than that of 'incumbents' and 'exit' firms. The growth variance for 'new entrants' is also larger than for the other two groups but is less significant. These results are strong evidence that firm growth and growth variance vary across firm type-classes. It is reasonable to think that this pattern might also explain the non-stochastic nature of p&p growth dynamics discussed in the previous two subsections of this chapter.

Table 5.16 Global p&p industry, full period 1978-2000
Firm's annual growth rate mean and variance across firm's type-classes

Years lagged		Firm's type-class: New-entrants	Incumbents	Exits	Test Chi2
1	mean	8.3	6.7	5.3	124**
	st.dev.	22.7	21.6	20.7	7.3*
	# obs.	616	1,197	1,238	
3	mean	8.5	6.7	5.8	38**
	st.dev.	13.9	13.1	11.6	9.3**
	# obs.	174	368	365	
5	mean	9.4	6.6	5.4	11**
	st.dev.	11.3	9.7	8.9	7.7*
	# obs.	100	214	195	

** significant level at 5%* *** significant level at 1%*

Table 5.17 US p&p industry, full period 1971-2000
Firm's annual growth rate mean and variance across firm's type-classes

Years lagged		Firm's type-class: New-entrants	Incumbents	Exits	Test Chi2
1	mean	5.3	3.0	2.3	254**
	st.dev.	27.6	19.0	18.2	396**
	# obs.	1,254	3,150	3,466	
3	mean	5.2	3.0	2.9	108**
	st.dev.	15.7	12.0	11.1	75**
	# obs.	379	1,050	1,027	
5	mean	5.1	2.8	2.9	46**
	st.dev.	11.6	8.6	8.6	35**
	# obs.	202	628	580	

** significant level at 5% ** significant level at 1%*

5.3 Summary of results and conclusions

This chapter investigated patterns of firm growth in one of the most capital intensive sectors in the world, the p&p industry, over three decades from 1970 to 2000. Specifically it focused on responding to the first research question in this thesis concerned with testing the hypothesis formulated by the LPE or Gibrat's law (Gibrat 1931). The LPE assumes that firm growth rate is a random variable independent of firm size. This means that the chances of a given growth rate during a specific period is the same for all firms in a given industry, regardless of their size at the beginning of the period and regardless of their previous size history.

The LPE holds if three conditions in the industry are fulfilled. Firstly, if firm growth is independent of size. Secondly, if firm growth variance is independent of firm size. Thirdly, if firm growth shows no serial correlation over time. It is important to investigate the form of the relationship between firm growth and firm size in order to better understand the patterns of corporate growth. In addition, there are several economic implications of the LPE that are of interest to economics such as its influence over the dynamics of industry concentration, the existence of growth persistence, and the influence of a minimum efficient scale within the industry. These three LPE conditions were tested at the global p&p industry level using a dataset of the largest 150 p&p firms in the world, during the period 1978-2000, and at US level, the US being the largest p&p producer and consumer country in the world, using a dataset of the complete size distribution of US p&p firms during the period 1971-2000. The method used to study the LPE was to group firms into different size-classes within the size distribution and test for differences in growth rate mean and variance across them. On the basis of the particular features of the p&p industry explained in Chapter 2, five size-classes ('very small', 'small', 'medium', 'large' and 'very large') were considered to be an appropriate number of groups to capture specific variations along its size distribution.

To investigate the first Gibrat's law proposition regarding the homogeneity of growth means across the five size-classes, we ran a simultaneous test of means not assuming equal variances across size-classes as in a traditional ANOVA method. In order to investigate the second Gibrat's law proposition regarding the homogeneity of growth variance across the five size-classes, we ran a Levene test (1960), which is not a conventional variance pair comparison but is a simultaneous multi variance comparison. In order to investigate the third Gibrat's law proposition regarding the existence of first order 'serial correlation' or growth 'persistence' we used model 5.12 proposed by Chesher (1979) in his seminal paper, which incorporates a past growth term in the 5.1 model to estimate the growth persistent coefficient. In order to assure the robustness of the methods and results, the analysis takes account of four econometric problems that are present in dynamic types of investigations such as: heteroskedasticity, sample selection bias, serial-correlation and non-linearity along the size distribution. Also Gibrat's law was run using both raw and normalized firm growth data, and using two size class borders - one that takes account of p&p industry secular increase and one that does not. The different scenarios allowed us to obtain robust results and conclusions.

The main conclusion of our investigation of Gibrat's law is that it does not hold for either the 150 global firms or the complete US p&p size distribution: thus the growth process is not stochastic in nature. At the p&p global level, firm growth shows significant evidence of smaller firms tending to grow faster than larger firms during the study period. Variability in firm growth decreases with size being higher for small firms than for big companies. Also, there is no evidence of growth persistence along time since in the three periods studied 1994-2000, 1986-1993, and 1978-1985, the serial correlation coefficients are not significant.

At the US level the general tendency observed is similar to that for the global dataset; however the availability of the complete size distribution data allowed us to conduct a deeper analysis of the growth patterns and what drives them. We demonstrated that smaller firms tend to grow faster on average than large firms during the study period, a result that is consistent with many of the empirical investigations in the literature (see Chapter 3). However there is an interesting exception. Out of the five size-classes analysed, the ‘large’ size-class firms exhibit growth rates that are consistently among the highest in the size distribution, even higher than the ‘small’ firms’ average growth rate. This demonstrates that the growth-size relationship is not linear and that there are consistent forces that push ‘large’ firms to grow at one of the highest growth rates in the size distribution. Chapter 6 investigates the causalities behind this situation and hypothesizes that it is due to some technological configurations of firms that show persistent growth performance heterogeneity. The variability of firm growth also decreases with size, thus it tends to be larger for small firms than for big companies, meaning that the second Gibrat’s law proposition is also not supported.

The results of the investigation of the third Gibrat’s law proposition on the existence of growth persistence shows that serial correlation is significantly positive during the 1980s with a coefficient of ρ =0.288, however it was not significant during the 1970s and 1990s. The availability of the complete size distribution data allow us to analyse growth persistence along three size classes (small, medium and large firms) and along three decades, a total of nine cases, These more specific lenses of observation reveal an interesting picture mostly overlooked in the literature. Although growth persistence being not significant when calculated as an industry average (or complete sample average) in the different time periods, it is significant when calculated for specific size classes and time periods.

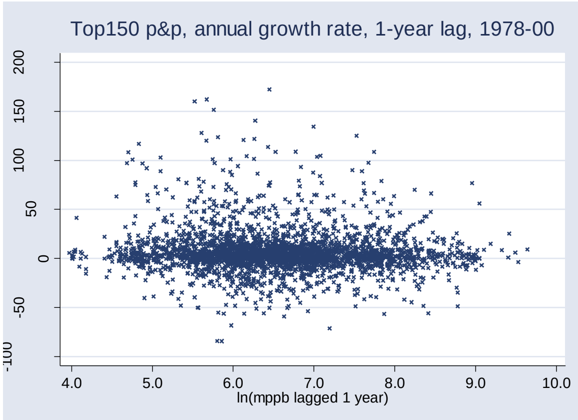
Moreover, at this level of analysis, growth persistence differs considerably between large and small firms and also over time. ‘Large’ firms show positive growth persistence along the three decades while ‘medium’ and ‘small’ firms show dissimilar autocorrelation over time; they show negative growth persistence during the 1990s, positive during the 1980s, and not significant during the 1970s. Within the temporal dimension, we observe that during the 1990s ‘large’ firms show very high growth persistence, while ‘medium’ and ‘small’ size firms show negative growth persistence. During the 1980s there was significant positive growth persistence along all the size-distribution; however it is more important in smaller firms rather than in larger companies. During the 1970s ‘large’ firms show positive growth persistence, but it is not significant for ‘medium’ and ‘small’ firms.

From our analysis of the relationship between firm type-classes (Incumbents, New-entrants and Exits) and growth we can conclude that New-entrants on average have the highest growth rates and also the highest growth rate variance in both the global and the US p&p industry datasets. It is reasonable to think that this pattern might explain the non-stochastic nature of p&p growth dynamics, considering that the size of new entrant firms is not randomly distributed along the size distribution but concentrated in the small and medium size-classes as shown in Chapters 6 and 7.

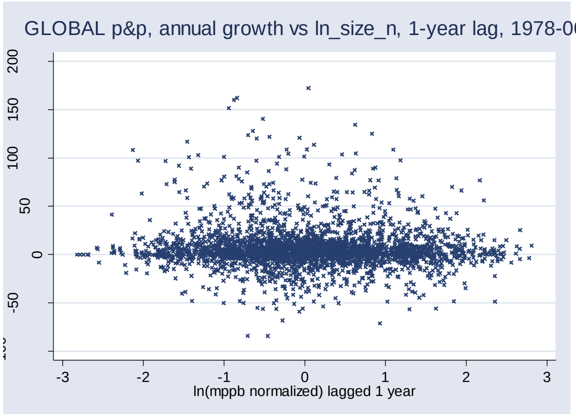
This chapter has added to our understanding of whether Gibrat’s law was in operation in the industry, and more importantly, provides a first understanding of the patterns that govern the growth dynamics process. Gibrat’s law is not just a statistical curiosity to be tested, but provides a valuable benchmark and detection tool for studying the characteristics of firm growth dynamics. Chapters 6 and 7 investigate the second and third research questions which will allow us to move a step forward and deepen our understanding of the forces that might explain this departure from a stochastic growth process. Chapter 6 investigates the hypothesis that Gibrat’s law is not in operation due to the technological configurations of firms that give rise to clusters or strategic groups which suggest a structure within the industry. Chapter 7 examines more deeply the industry dynamics features of the p&p industry, specifically the patterns and determinants of firm exit and the patterns of technology adoption behaviour that explain a significant heterogeneity of firm growth.

Appendix A5.1 Graphical observation of p&p firm's growth rate-size relationship

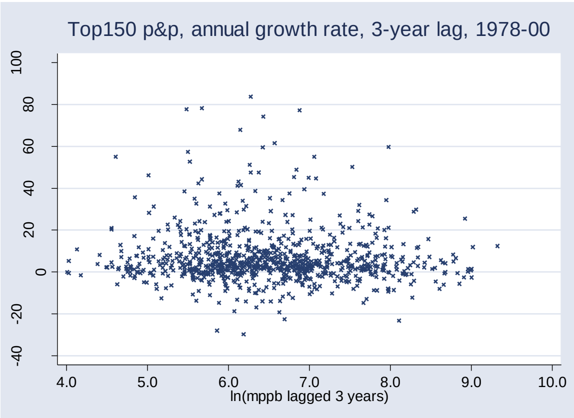
Figure A5.1a Global 150 p&p firms' annual growth versus size for 1, 3 and 5 years lag
(not normalized and normalized pooled data of period 1978-2000)



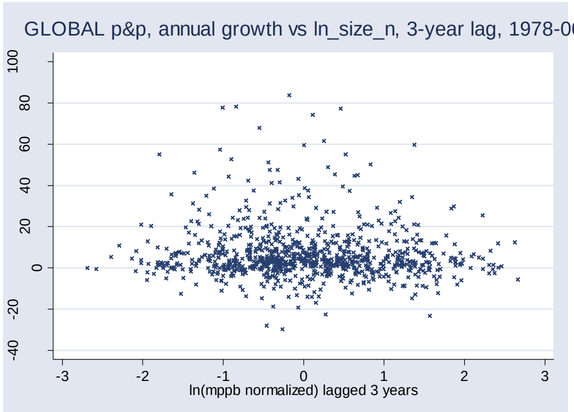
4 outliers removed, gth_1y>175%



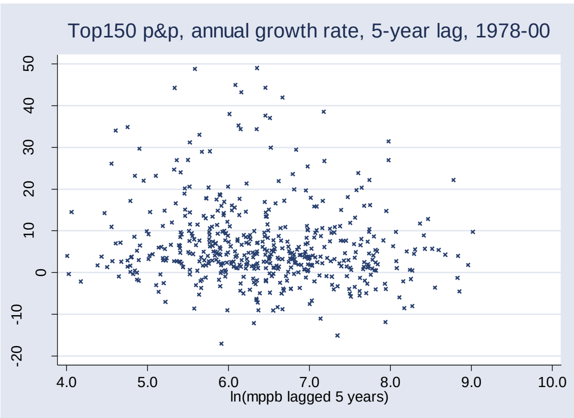
4 outliers removed, gth_1y>175%



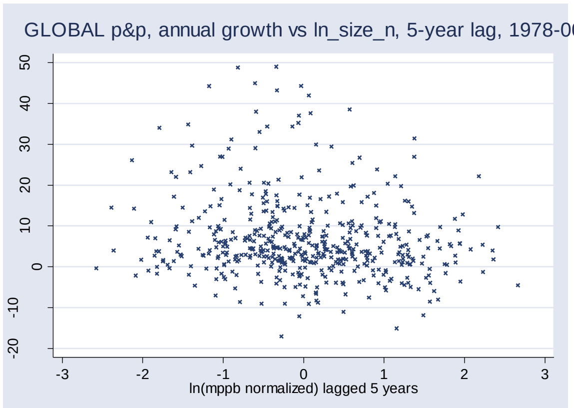
3 outliers removed, gth_3y>85%



3 outliers removed, gth_3y>85%

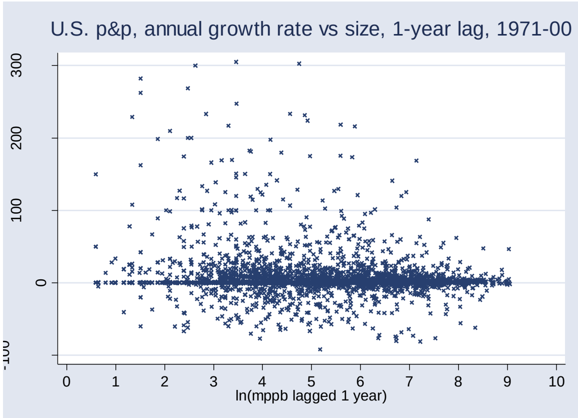


4 outliers removed, gth_5y>50%

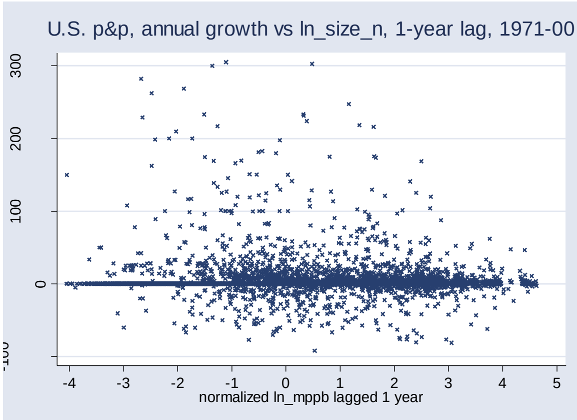


4 outliers removed, gth_5y>50%

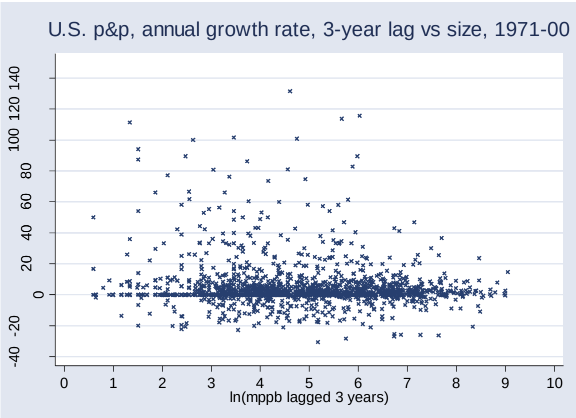
Figure A5.1b US p&p firms' annual growth versus size for 1, 3 and 5 years lag
(not normalized and normalized pooled data of period 1971-2000)



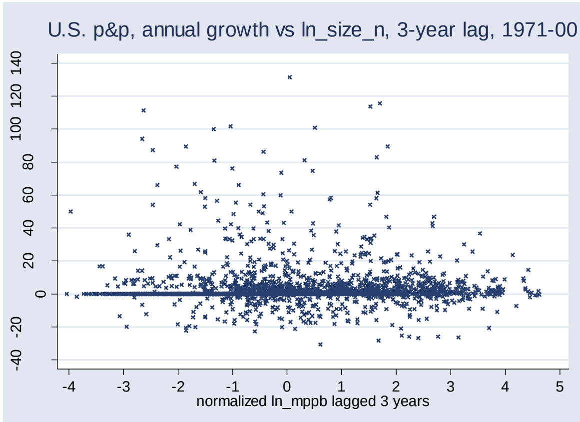
6 outliers removed, gth_1y>380%



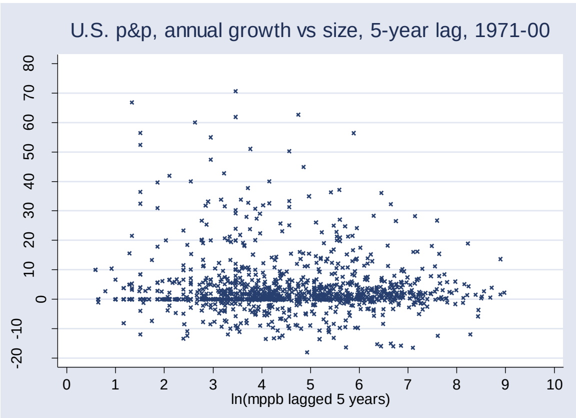
6 outliers removed, gth_1y>380%



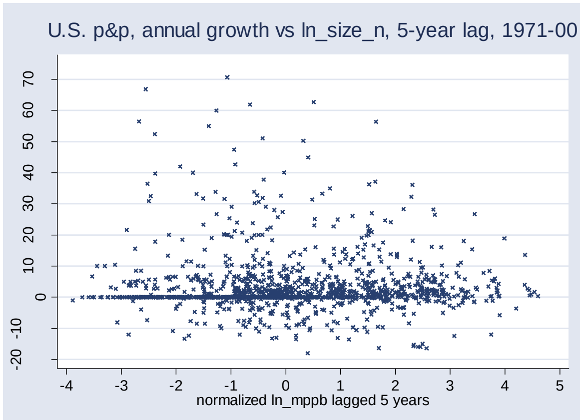
8 outliers removed, gth_3y>140%



8 outliers removed, gth_3y>140%



9 outliers removed, gth_5y>75%



9 outliers removed, gth_5y>75%

Appendix A5.2 Serial correlation analysis for different periods and size-classes, US p&p industry

Table A5.2a Serial correlation parameters per decade and size-classes, US p&p industry

Period	firm's capacity <= 64 (000) tonnes					64< firm's cap. <=512 (000) tonnes					firm's capacity > 512 (000) tonnes					N
	γ_1	γ_2	β	ρ	n	γ_1	γ_2	β	ρ	n	γ_1	γ_2	β	ρ	n	
1991-2000	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	77	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	55	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	31	163
coefficient	0.807	0.191	0.998	**-0.19****		0.827	0.303	1.102	**-0.28****		1.724	-0.803	1.107	**0.62****		
SE	0.116	0.131				0.320	0.340				0.585	0.614				
1981-1990	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	113	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	57	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	27	197
coefficient	1.217	-0.216	1.001	**0.22****		1.031	0.033	1.062	**-0.03**		1.209	-0.145	1.074	**0.14***		
SE	0.138	0.143				0.255	0.260				0.387	0.442				
1971-1980	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	130	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	68	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	23	221
coefficient	1.000	-0.029	0.970	**0.03**		1.018	-0.087	0.923	**0.09***		2.088	-0.935	1.438	**0.65****		
SE	0.093	0.095				0.157	0.184				0.908	0.887				

** significant level at 5% .   ** significant level at 1%*

Table A5.2b Serial correlation parameters per decade and log normalized size-classes, US p&p industry

Period	log normalized firm's size < 0					0 <= log normalized firm's size < 2					log normalized firm's size > 2					N
	γ_1	γ_2	β	ρ	n	γ_1	γ_2	β	ρ	n	γ_1	γ_2	β	ρ	n	
1991-2000	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	85	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	49	(t-1)='95	(t-2)='91	(t-1)='95	(t-2)='91	29	163
coefficient	0.874	0.073	0.950	**-0.08****		0.761	0.338	1.075	**-0.32****		1.907	-0.952	1.160	**0.75****		
SE	0.124	0.135				0.319	0.332				0.640	0.659				
1981-1990	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	113	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	53	(t-1)='85	(t-2)='81	(t-1)='85	(t-2)='81	31	197
coefficient	1.217	-0.216	1.001	**0.22****		1.129	-0.113	1.017	**0.11***		1.059	-0.076	0.982	**0.08***		
SE	0.138	0.143				0.259	0.268				0.373	0.429				
1971-1980	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	119	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	69	(t-1)='75	(t-2)='71	(t-1)='75	(t-2)='71	33	221
coefficient	0.936	0.041	0.978	**-0.04**		1.095	-0.029	1.068	**0.03**		1.447	-0.308	1.188	**0.26****		
SE	0.099	0.103				0.136	0.165				0.451	0.416				

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

CHAPTER 6

TECHNOLOGICAL CONFIGURATION OF THE PAPER & PULP INDUSTRY

Chapter 5 studied the growth dynamics of the p&p industry during three decades between 1970-2000 and it demonstrated that the LPE or Gibrat's law (also called random-walk (Geroski 1999)), was not in operation during this period, thus growth-rate in p&p firms was not a random variable independent of firm size. The aim of this chapter is to investigate the nature of the deviation from Gibrat's law. It investigates the hypothesis that firm growth is not a random-walk process because firm's technological configurations (capacity mix) give rise to strategic groups whose growth performance is consistently biased. We investigate the following specific questions:

- Within the US p&p industry are there clusters of firms with distinctive 'configurations' of technological specialization at one point in time (year 2000)?

On the basis that it is possible to identify clusters or strategic groupings, an additional research question is:

- Does firm performance, measured as annual growth-rate, differ systematically across strategic groups? (such systematic growth heterogeneity could explain the departure from Gibrat's law)

On the basis that it is possible to identify systematic differences in growth performance across strategic groups, we address the following research questions:

- Are there distinctive firm behaviours associated with different clusters that could explain systematic performance differences across strategic groups?
- What portion of inter-firm difference cannot be explained by these behaviours (and thus may be due to firm-specific fixed effects)?

These research questions are positioned within two related bodies of literature - heterogeneity within industries and strategic groups, and provide a deeper understanding of within industry heterogeneity and technological influence in shaping the dynamics and industrial structure of the p&p sector.

The chapter is organized in four sections. The first investigates the existence of technological configurations of US p&p firms using clusters analysis and cross-sectional data for the firms that existed in year 2000. Having determined and validated the existence of a number of clusters at one point in time, Section 6.2 investigates and compares their growth performance using longitudinal data for 1986-2000. Section 6.3 investigates and discusses distinctive firm behaviours associated with each configuration that may explain systematic performance differences across groups of firms, and analyses inter-firm differences that cannot be explained by these behaviours. Section 6.4 concludes the chapter.

6.1 Are there clusters within the US p&p industry? Technological configuration analysis using cross-sectional data

The purpose of this subsection is to explore the existence of technological configurations of US p&p firms (also referred ‘strategic groups’ or ‘clusters’[79]) using cluster analysis techniques and cross-sectional data for all firms that existed in year 2000. The investigation of strategic groups has been a focus of strategy since the 1970s, and has been used to describe intra-industry structure (Cool and Schendel 1987; Peteraf and Shanley 1997). A strategic group is understood as a number of firms that are similar in terms of their competitive strategies and resource commitments, are isolated by common mobility barriers, and differ from firms outside the group in key strategic dimensions (Caves and Porter 1977; Porter 1979). Mobility barriers are factors which impede firms from entering or exiting an industry, or moving from one strategic group to another. They include barriers to entry, barriers to exit, and barriers to intra-industry changes in market position (Gilbert 1989). A strategic group provides the boundary within which competitive interactions among firms occur and shape behaviour, and

[79] In this thesis the term cluster is a synonym for ‘strategic group’ which was explained in detailed in Chapter 3. In the literature cluster is also commonly used to refer to the existence of geographically localised patterns of economic activity; however the location of firms is not examined here.

provides a useful unit of analysis for understanding industry heterogeneity (Pleshko and Nickerson 2006).

From a theoretical perspective, the formation of strategic groups depends on the extent of product-market heterogeneity and the degree of resource inimitability within a particular industry, thus it cannot be assumed to be universal across industry contexts or across time. As the differences among firms along relevant dimensions of competitive strategy decrease, the strategic distance between groups diminishes, and vice versa (Fiegenbaum and Thomas 1995). For example, if all firms employed essentially the same strategy, there would be one strategic group in the industry (Porter 1980, p.129). There must be sufficient strategic ‘space’ between the product market positions of rivals for strategic groups to emerge, and this requires the presence of heterogeneous market positions associated with rare or inimitable resources in order for strategic groups to persist over time (Mehra and Floyd 1998).

As explained in Chapter 2, 2.2.1, the global and US p&p industries are interesting arenas to investigate the research questions posed in this thesis since they have experienced continuous technological changes which have allowed significant increments in production scale, productivity and product diversification. Also, there is a significant variability in the size of p&p firms. In the US production capacity varies from less than 10,000 tonnes per year to more than 10,000,000 thus size varies more than 1,000 times. At global level size differences are even larger.

Since 1990, strategic group research has been criticized for its limitations to explain performance differences within industries (Barney and Hoskisson 1990). Perhaps the most serious criticism of this approach is that it requires the researcher to make several methodological choices, such as selection of clustering variables, clustering algorithm, measurement of cluster distance, cluster identification, etc., which influence the quality of the solution (Thomas and Venkatraman 1988). Moreover, unlike statistical techniques, such as analysis of variance (ANOVA) or econometrics, cluster analysis does not offer a test statistic (such as an F-statistic) that provides a clear answer regarding support (or lack of it) for a set of results for the hypothesis investigated. Instead, the researchers in most cases are the judges in terms of interpretation of the results from cluster analysis. A second criticism is that when cluster analysis is not backed by a theory (Reger and Huff 1993), the clusters identified may not reflect real conditions but instead may be statistical artefacts based on random numerical variation across organizations. Thus, cluster analysis has the potential for inaccurate representation of the groupings in a sample of data, and for suggest the existence of clusters even when there are no meaningful groups contained in the sample (McGee and Thomas 1986; Barney and Hoskisson 1990; Leask 2007)

Being aware of the criticisms of this research approach, we are rigorous in our application of the methodology to conduct a robust cluster analysis taking account of the above challenges. The literature recommends six key steps to conduct this type of investigation (Aldenderfer and Blashfield 1984). These are:

- formulating the problem clearly;
- selecting the proper data sample and variables for conducting the cluster analysis;
- selecting the proper clustering algorithms and distance (or similarity) measure types;
- deducing the correct number of clusters;
- interpreting and profiling the clusters;
- assessing the reliability and validity of the results.

The aim of the research questions is not just to establish the existence of a number of strategic groups, but to identify a relationship between technological configurations of firms within the US p&p industry and their distinctive patterns of growth performance. We use cluster analysis to identify possible groups of firms with similar technological configurations; nevertheless, the questions being investigated are whether such technological configurations are sources of within-industry persistent growth performance heterogeneity, and what are the technological features associated with this heterogeneity.

Having defined the problem and research question (first step in the six proposed above), subsection 6.1.1 addresses the next step related to the data and selection of the variables for the cluster analysis. Subsection 6.1.2 addresses the next four key steps.

6.1.1 Data and variables used to explore firms' technological configurations

<u>The data</u>

The data are from the FPL-UW database (described in Chapter 4, subsection 4.2.2) and consist of annual capacity information disaggregated at 13 principal p&p technology classes (most important commodity products in the industry) for all p&p firms located in the US where market pulp, paper and board are produced for the period 1970-2000.

Exploration of a cluster's existence at one point in time within the industry requires cross-sectional data, and thus the definition of a reference year.[80] Since the dataset covers the period 1970-2000, the most recent year is the most interesting point in time; thus we use cross sectional data for 2000 to study firms' technological configurations.[81] Table 6.1 provides descriptive information for the 234 US p&p firms that existed in year 2000 and the capacity figures at the level of the 13 technology classes.

Table 6.1 Features of the 234 US p&p firms that existed in year 2000

number of firms in year 2000:	**234**
total capacity year 2000 (million tonnes):	**97.8**

feature	**mean**	**sd**	**min**	**max**
capacity	0.42	1.14	2	12.23
# of years	19.9	11.8	1	31
# of tech. classes	1.7	1.3	1	10

	technology classes			**capacity (million tonnes)**		
	family	**name**	**variable**	**total**	**%**	**sum %**
1	pulp	market pulp	mp	10.4	10.6	11
2		newsprint	news	6.2	6.3	
3		coated freesheet	ctfs	5.3	5.4	
4	papers	uncoated freesheet	ucfs	14.7	15.0	38
5		coated grownwood	ctgw	4.1	4.2	
6		uncoated grownwood	ucgw	1.7	1.7	
7		specialty papers	special	3.0	3.1	
8		kraft paper	kraft	2.1	2.2	
9	tissue	tissue	tissue	6.8	7.0	7
10		liner board	liner	23.3	23.9	
11	boards	corrugated board	corr	8.2	8.4	45
12		solid bleached board	sbb	6.0	6.1	
13		recovery board	recb	6.0	6.2	
	total			**97.8**	**100**	**100**

Source: FPL-UW database

[80] Section 6.2 investigates growth differences across the identified clusters, using longitudinal data.

[81] Another reason for choosing the year 2000 is that it is well after the technology regime change that occurred in the mid-1980s. The time lapse of 15 years ensures that a large proportion of the capital equipment in operation in 2000 was acquired after the mid-1980s and thus allows the effect of the technology regime change to be captured.

<u>Selection of variables</u>

Choosing the variables that will be used to group observations is a fundamental step in the application of cluster analysis. Possible variables include annual production capacity of the 13 technological classes described above. However selection in terms of type and number of appropriate variables requires further analysis since there are certain prerequisites for capturing the phenomenon to be investigated.

Firstly, each of the technological classes' selected (e.g. coated freesheet paper) should be such that individual products within that class (e.g. different types of coated freesheet papers) need to be in a competitive relationship. When the class is correctly defined, individual products within it are more likely to be considered substitutes by customers. Secondly, individual products across classes need not to be substitutes (e.g. different specific 'coated freesheet' papers may not be a substitute for particular 'specialty' papers). Thirdly, the conversion process and technical specifications of individual products within classes need to have some technical similarities and, between classes, need to have technological differences since they use different conversion methods.

Thus, there is a trade-off between the number of technological classes selected and the possibility to observe robust patters of firm's configuration. The consideration of a larger number of technological classes would capture more variation in firms' technological behaviour; however, we might not be able to find consistent patterns of technological structure due to the high levels of noise (many possible patterns but not able to be statistically significant). On the other hand when the number of classes is small it is possible to losing important variation in industry technological behaviour thus there is a risk of not being able to detect possible patterns of firm technological configuration.

The industry experts' interviews were a valuable source of information to decide the most appropriate combinations of variables to use for conducting the cluster analysis considering the above conditions (substitutes products and technical similarities within classes, competitive products and technical differences between classes) and the trade-off restriction. Out of the 13 commodity products, the four graphic paper grades (uncoated grown wood, coated grown wood, uncoated freesheet, coated freesheet) could be close substitutes for customers depending on their relative prices, and their production processes are the most similar compared with the other nine product categories. Considering the above, the industry experts recommended that these four paper classes should be aggregated in one graphic paper variable (graphic paper) based on combining their individual grade capacities.

Based on the above, we decided to reduce the number of variables from the original 13 to 10 by aggregating the individual paper grades referred to. The 10 capacity variables that are used to explore the existence of firm technological configurations are presented in the Table 6.2 together with the production capacity of the 234 US p&p companies in 2000, disaggregated at these 10 capacity variables.

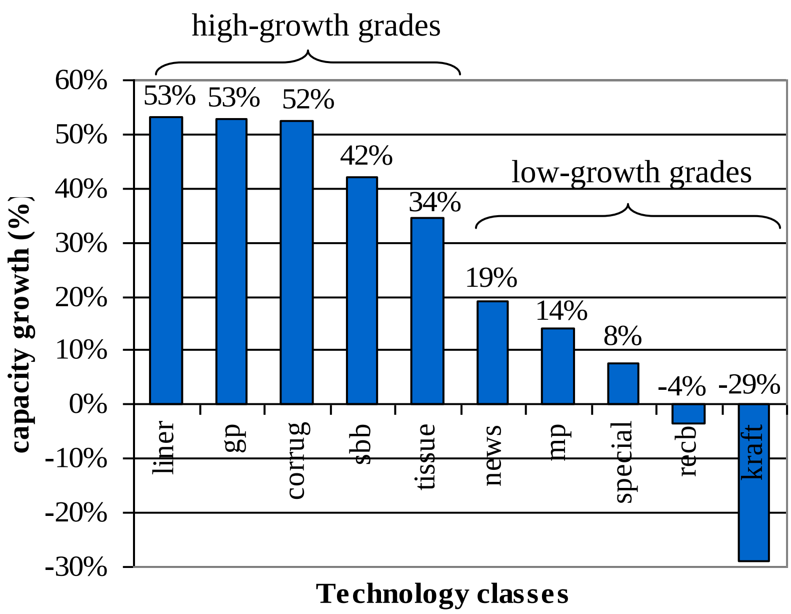
Table 6.2 Capacity of 10 technology classes within the 234 US p&p companies that existed in year 2000

	technology classes			capacity (million tonnes)		
	family	**name**	**variable**	**total**	**%**	**sum %**
1	pulp	market pulp	mp	10.4	10.6	11
2	papers	newsprint	news	6.2	6.3	38
3		graphic papers	gp	25.8	26.4	
4		specialty papers	special	3.0	3.1	
5		kraft paper	kraft	2.1	2.2	
6	tissue	tissue	tissue	6.8	7.0	7
7	boards	liner board	liner	23.3	23.9	45
8		corrugated board	corr	8.2	8.4	
9		solid bleached board	sbb	6.0	6.1	
10		recovery board	recb	6.0	6.2	
	total			**97.8**	**100**	**100**

Source: FPL-UW database

The 10 individual technology classes show very different growth patterns, which could be useful background to our cluster analysis of the p&p industry. Figure 6.1 shows in decreasing order the growth-rates for each of the 10 technology classes during the period 1986-2000. The five grades with the highest growth, varying from 53% to 34%, are referred to as ‘high-growth’ grades (liner board, graphic papers, corrugated boards, solid bleached boards, and tissue paper). The five grades with the lowest growth, varying from 19% to -29%, are referred to as ‘low-growth’ grades (newsprint, pulp, specialty papers, recovery boards, and kraft paper).

Figure 6.1 Ten technology classes capacity growth, period 1986-2000



6.1.2 Do clusters of different firm's technological configurations existed in the US p&p industry?

<u>Cluster algorithm and distance measures selection</u>

The term cluster analysis was first used by Tyron (1939) to encompass a number of different algorithms and statistical methods for grouping 'objects' or 'observations' (in this research firms) of similar kinds into particular categories. Thus it provides a useful way to investigate a question common to many fields, including industrial organization and strategic management, relating to the ways to organize observed data into meaningful structures or categories or taxonomies.

Central to cluster analysis is the notion of degree of similarity (or dissimilarity) among the individual objects being clustered. The degree of association between two objects is maximal if they belong to the same group, and minimal otherwise. Over the years, several types of clustering algorithms have been developed, each with specific features and strengths. There are two main types: non-hierarchical and hierarchical.

The former type starts with a fixed number of clusters to which units are allocated so as to optimize some criterion representing a particular feature of the cluster. It is an iterative procedure and involves reallocating objects among clusters until no further improvement can be achieved. The most common non-hierarchical algorithms are K-means and K-medians. There are two types of hierarchical clustering approaches: divisive and agglomerative. The former is a top-down method in which sequences of clusters are formed from partitions of the initial dataset which is considered a single cluster of N objects, into smaller clusters which may consist of N clusters each containing a single object. Agglomerative clustering is a bottom-up method that begins with each of the N objects being considered as separate clusters and then proceeds to combine them until all observations belong to one cluster. Johnson (1967) proposed the following four steps for running a hierarchical agglomerative clustering method given a set of N items to be clustered, and a distance (or similarity) of NxN matrix:

a) assign each object to its own cluster, resulting in N clusters containing just one object;
b) find the closest (most similar) pairs of objects and merge them into a single cluster, resulting in a total of (N-1) clusters;
c) compute distances (similarities) between the new cluster and each of the old clusters;
d) repeat steps b) and c) until all items are clustered into a single N-sized cluster.

All clustering methods use the distance between objects (also called similarities or dissimilarities) when forming groups. These distances can be based on a single or multiple dimensions, with each dimension representing a rule or condition for grouping the objects. This requires an algorithm and the five most popular hierarchical agglomerative algorithms are: single linkage, complete linkage, average linkage, centroid method, and Ward method. The differences among them lie in the mathematical procedures used to calculate the distance between clusters.[82] The most common way of calculating the distances between objects in a multi-dimensional space

[82] In single linkage, the distance between groups is defined as the distance between the closest pair of objects. In complete linkage, the distance between groups is defined as the distance between the pair of objects that is farthest apart. In average linkage the distance between two clusters defined as the average of the distances between all pairs of objects. In the centroid method, the distance between two clusters is defined as the distance between their centroids (means of all the variables), and every time objects are grouped, a new centroid is computed. The Ward method uses a clustering procedure that minimizes within-cluster variance through applying an ANOVA to evaluate the distances between clusters and to minimize the Sum of Squares of any two of the (hypothetical) clusters that could be formed at each step.

is to compute the geometric or Euclidean distance. It is usual to square this distance in order to resolve the problem that deviations can be either positive or negative and to place progressively greater weights on the objects that are farther apart as shown in equation 6.1. This is the distance measure that we use in our cluster analysis.

$$\textit{Squared Euclidean Distance } (x, y) = \sum_{i=1}^{N} (x_i - y_i)^2 \qquad (6.1)$$

To summarize, hierarchical agglomerative clustering techniques are the most common methods for forming clusters, and among these, Ward's (1963) algorithm is the most commonly used since it is considered very efficient (Everitt, Landau et al. 2001). For these reasons we use this algorithm in our cluster analysis. Nonetheless, the limitations of this method will be considered. Ward's algorithm has a tendency to create clusters of small size, and secondly the clusters solutions that it provides tend to be heavily distorted by outliers (Milligan 1985).

<u>Deducing the number of clusters</u>

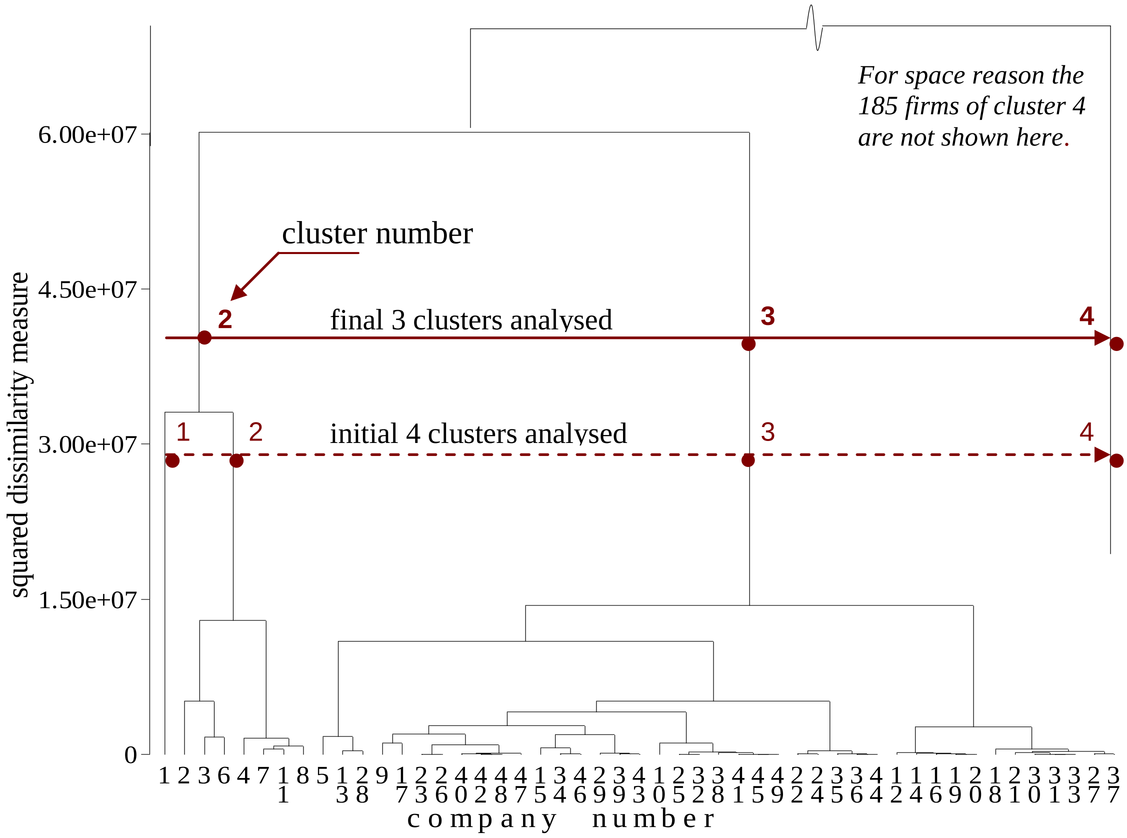
When using hierarchical clustering methods a variety of techniques is available for determining the number of clusters in a data set, two of which are described here. The most basic procedure is to visually inspect a two dimensional diagram known as a dendrogram or family tree graph, which represents the result of the clustering procedure (Figure 6.2). On the horizontal axis the objects (or leaves) are evenly spaced and the vertical axis gives the distance (or dissimilarity measure) linking any two clusters. The natural clusters that can result from the data are suggested by relatively dense branches, however, since this procedure relies on the researcher's interpretation, it is recommended that it be used with caution (Aldenderfer and Blashfield 1984).

Based on numerous iterations using different clustering methods and sets of variables, Figure 6.2 presents the final cluster dendrogram resulting from the application of Ward's algorithm to the 234 US p&p firms that existed in year 2000, and the 10 technology class variables explained in the previous subsection.[83] In an initial stage of the analysis a four cluster solution was considered (broken line in Figure 6.2), that is:

[83] The dendrogram shows 49 firms, for reasons of space the 185 firms in cluster 4 are not graphed.

- cluster 1: formed by 1 Very Large & Diversified firms
- cluster 2: formed by 7 Large & Diversified firms
- cluster 3: formed by 41 Medium & Specialized firms
- cluster 4: formed by 185 Small & Very Specialized firms

Figure 6.2 Dendrogram results from Wards cluster algorithm application to 234 US p&p firms of year 2000

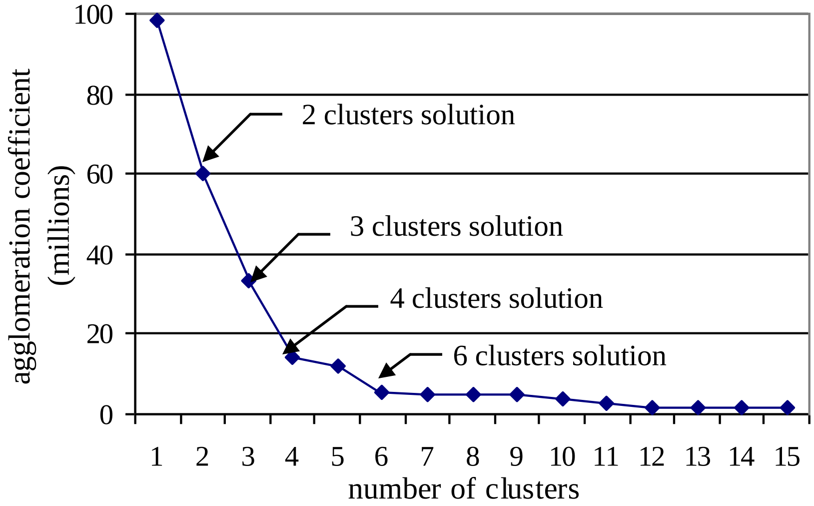


A complementary procedure to determine the number of clusters was proposed by Mojena (1977) which consists of an *x-y* graph using the Agglomeration Coefficient Schedule[84] resulting from the cluster algorithm, where the *x-axis* represents the number of clusters and the *y-axis* is agglomeration coefficients (see Figure 6.3). The flat part of the resulting curve suggests that the clusters being linked are very similar while the sharp change in the curve slope, producing a prominent elbow, is an indication of the cut-off number of clusters. A limitation of this approach is that there may not be large jumps in the coefficients, indicating that there may not be any natural groups in the data;

[84] This is the numerical value at which various cases merge to form a cluster.

however, this is not a problem in our case where the four clusters solution denotes a sharp change in the curve slope as depicted in Figure 6.3.[85]

Figure 6.3 Cluster Agglomeration Coefficient plots



From the application of the techniques described above, we find consistently that the four cluster solution is the most suitable for our dataset. However for the analysis of the data it is problematic to have cluster 1 with a single company (International Paper the world largest p&p firm), thus the second best solution of three clusters numbered 2, 3 and 4 was also considered (solid line in Figure 6.2 and 3 cluster's solution in Figure 6.3). This solution derives from the merging of clusters 1 and 2, thus it implies that International Paper is in the Large & Diversified firms category, with which it has several similarities. For instance, the firms in this cluster are the largest in the industry, all are highly diversified, and all existed throughout the 31 year period analysed. Also the three cluster scenario was favoured by the p&p industry experts, thus it is the one we use in the succeeding sections of this chapter. Appendix A6.1 provides more detailed data on Cluster's 2, 3 and 4 firms including their technology classes' capacities, total capacity and number of grades.

[85] Moreja (1977) proposed an additional technique using the Agglomeration Coefficient to determine the number of clusters, by examining the relative sizes of the incremental changes in this coefficient. A large increase implies that two very different clusters have been merged; thus the number of clusters prior to that merger should be the cut-off number. In order to identify which jumps are significant, stepwise differences in the coefficients are computed and their average and standard deviation calculated. t-values are derived from these data and statistical significance is determined from a t-distribution with (N–3) degrees of freedom, where N refers to the sample size which in our case N=234. Consistent with the previous two methods, the application of this technique to our dataset suggests the same four cluster solution scenario where cluster 1 is formed by just 1 company, International Paper.

<u>Assessing the reliability and validity of the clustering results</u>

A prerequisite for a contribution to the literature is that the research should demonstrate reliability and validity in terms of the results of analyses or tests. The concept of reliability refers to the consistency of the results; this is the extent to which they remain stable over repeated tests of the same subject under identical conditions.[86] The concept of validity involves two dimensions internal and external. The former refers to the extent to which a scale is measuring the concept or feature that is intended to measure. The latter refers to the degree that the result is representative of the general population of interest (Cook and Campbell 1979). In this research we are working with the complete population of US p&p which assure the external validity.

Since cluster algorithms could introduce potential bias due to the way they group observations it is important to asses the reliability and validity of clustering results in order to be assured that the set of clusters is meaningful and useful (Kerlinger 1986).[87] Milligan (1985) suggested that reliability should be evaluated by repeating the cluster analysis with different algorithm. Consistent cluster assignments based on more than one algorithm are evidence of reliability while inconsistent group assignments would suggest a weak cluster solution (Hair, Tatham et al. 2005).

We conducted the two-stage procedure suggested by Ketchen and Shook (1996) to run an appropriate reliability analysis. First we applied Ward's hierarchical algorithm to define the number of clusters and their centroids; these outcomes were used as inputs for the subsequent non-hierarchical clustering application - K-mean. The result obtained from this latter method was very consistent with the result obtained from the Ward's hierarchical method explained above. The number of clusters identified in both cases was three and the firms within each of the clusters were nearly identical. The Large & Diversified cluster contained the same 8 firms and the differences for the other two clusters were less than 8% (see Appendix A6.1). Of the 41 firms in the Medium & Specialized clusters, just three of relative small sizes were different and of the 185 firms that formed the Small & Very Specialized cluster, again just three were different.

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[86] An experiment is described as unreliable if repeated measurements under identical conditions yield different results.
[87] The reasons of this potential bias were explained in Chapter 3, Subsection 3.3.2

Since any cluster technique will impose groups even on almost random data, one way to check validity (Hair, Tatham et al. 2005) is to examine the extent to which a given cluster solution exhibits both within cluster homogeneity (how closely related are the objects within a cluster) and between cluster heterogeneity (how distinct or separated a cluster is from other clusters).[88] The coefficients in the diagonal of Table 6.3 are the results of the within clusters homogeneity analysis and the coefficient below the diagonal are the results of the between cluster heterogeneity analysis. Firms within clusters show an important homogeneity, being firms of Cluster 2 the most closely related and firms of Cluster 4 the less closely related. On the contrary the firms between clusters show high levels of heterogeneity, being Clusters 2 and 4 the most heterogeneous and Clusters 3 and 4 the least heterogeneous.

Table 6.3 Within clusters homogeneity coefficients and between clusters heterogeneity coefficients

Cluster number & name	2. Large & Diversified	3. Medium & Specialized	4. Small & Very Specialized
2. Large & Diversified	0.87	2.82	3.35
3. Medium & Specialized	2.82	0.96	2.67
4. Small & Very Specialized	3.35	2.67	1.07

The two features shown in Table 6.3, these are within clusters homogeneity and between clusters heterogeneity, confirm that the three clusters identified above using Wards and K-mean algorithm are not statistical artefacts (Halkidi, Batistakis et al. 2001) but natural groups that exist in the capacity data of 234 US p&p firms in year 2000.

Another source of evidence of reliability and validity is the judgments of the industry experts on the features of the different categories (Breckenridge 1989; Ketchen and Shook 1996). P&p industry experts (see list of interviewees in Appendix A4.2) provided appropriate interpretations of the clusters identified and acknowledged that their main features were relevant and valid. All the above evidence provides reliability and validation for the cluster analysis presented in this chapter avoiding dealing with

[88] Within cluster homogeneity is the sum of the weight of all links within a cluster and between cluster heterogeneity is the sum of the weights between the nodes inside and outside the cluster.

statistical artefacts (Punj and Stewart 1983) and allow us to proceed with the investigation of their main features and growth performance patterns.

Interpreting and profiling the results of the cluster analysis

Tables 6.4a and 6.4b present the descriptive statistics for the three cluster solution numbered 2, 3 and 4. Some features require some further comment.

- **Main characteristics of cluster 2 Large & Diversified firms**
  This cluster is constituted of 8 large and diversified US p&p firms representing 40% of industry capacity in 2000 (38.9 m. out of 97.8 m. tonnes). These firms have several distinctive features: all are large with an average capacity of 4.8 million tonnes; all are diversified within the industry producing an average of 6.6 technological classes. 82% of their capacity is concentrated in the five high-growth grades and just 18% in the five low-growth grades (4.6 times difference). The most important technological class is graphic paper which accounts for 39% of the cluster capacity (15.2 m. tonnes). Four of the five low-growth grades (newsprint, speciality papers, recovery boards and kraft paper) account for just 6% of the cluster capacity. Finally, none of these firms entered this cluster in the 30 years analysed, thus the 8 firms are incumbents. This suggests the existence of very high mobility barriers (Pleshko and Nickerson 2006) within the cluster, a feature that is discussed in the next section.

- **Main characteristics of Cluster 3 Medium & Specialized firms**
  This cluster is constituted of 41 medium sized and specialized US p&p firms which accounted for 41% of total industry capacity in 2000 (40.5 m. out of 97.8 m. tonnes). These firms include 25 incumbents and 16 new-entrants with an average life of 19.4 years over 31 years analysed. The 41 firms have an average capacity of 0.99 million tonnes; they are specialized in only a few technological classes, producing an average of 2.3 grades. 68% of their capacity is concentrated in the five high-growth grades and 32% in the five low-growth grades (2.2 times difference). The most important technological class is liner board which accounts for 28% of the cluster capacity (11.2 m. tonnes).

Table 6.4a Descriptive statistics of the final three clusters identified in year 2000 (cross sectional data)

CLUSTERS		# of	# years		# grades		capacity (m. tonnes)				high-gth grades		low-gth grades		high/low
#	Name	firms	mean	sd	mean	sd	mean	sd	total	% [1]	capacity	% [2]	capacity	% [2]	capacity
2	Large & Diversified firms	8	31.0	-	6.6	2.1	4.9	3.7	**38.9**	40%	**32.0**	82%	**6.9**	18%	4.6
3	Medium & Specialized firms	41	19.4	11.4	2.3	1.3	1.0	0.6	**40.5**	41%	**27.8**	68%	**12.8**	32%	2.2
4	Small & Very Specialized firms	185	19.5	12.0	1.3	0.6	0.1	0.1	**18.3**	19%	**10.3**	56%	**8.0**	44%	1.3
total # of firms year 2000:		234	19.8	11.9	1.7	1.3	0,4	1.1	**97.8**	100%	**70.1**	72%	**27.7**	28%	2.5

[1] *Corresponds to the % of the total capacity that is distributed across the three clusters (vertical distribution).*
[2] *Corresponds to the % of each cluster's capacity that is distributed in high-growth and low-growth grades (horizontal distribution).*

Table 6.4b Capacity configuration of the final three clusters identified in year 2000

CLUSTERS		total	high-growth grades capacity (m. tonnes)						low-growth grades capacity (m. tonnes)					
#	Name	capacity	subtotal	gp	liner	corr	sbb	tissue	subtotal	news	mp	special	recb	kraft
2	Large & Diversified firms	**38.9**	**32.0**	15.2	9.9	3.2	3.0	0.7	**6.9**	0.4	5.0	0.3	0.2	1.0
3	Medium & Specialized firms	**40.5**	**27.8**	6.4	11.2	3.3	2.5	4.4	**12.8**	4.1	2.9	1.4	3.7	0.7
4	Small & Very Specialized firms	**18.3**	**10.3**	4.2	2.3	1.7	0.4	1.7	**8.0**	1.6	2.5	1.3	2.1	0.5
total and grades capacities (m. tonnes)		**97.8**	**70.1**	25.8	23.3	8.2	6.0	6.8	**27.7**	6.2	10.4	3.0	6.0	2.1
grades capacities / total capacity (%)		**100%**	**72%**	26%	24%	8%	6%	7%	**28%**	6%	11%	3%	6%	2%

- **Main characteristics of Cluster 4 Small & Very Specialized firms**
  This cluster is constituted of 185 small and very specialized US p&p firms which accounted for 19% of total industry capacity in 2000 (18.3 m. out of 97.8 m. tonnes). These firms include 111 incumbents and 74 new-entrants with an average of 19.5 years of existence in the 31 year study period. The 185 firms have an average capacity of 0.10 million tonnes; most are specialized in a single technological class since they produce an average of 1.3 grades. 56% of their capacity is concentrated in the five high-growth grades and 44% in the five low-growth grades (thus 1.3 times difference). The most important technological class is graphic paper which accounts for 23% of the cluster capacity (4.2 m. tonnes).

Some distinctive features from a comparison of the three clusters:

- Cluster 2 consisting of 8 Large & Diversified firms has 20% as many Large & Diversified firms as there are Medium & Specialised companies (41 firms of Cluster 3). Cluster 3 consisting of 41 Medium & Specialised firms has 22% as many Medium & Specialised firms as there are Small & Very Specialised firms (185 firms of Cluster 4).
- The average size of Cluster 2's Large & Diversified firms is approximately 5 times larger than the average size of Cluster 3 Medium & Specialized firms, and Cluster 3's average firm size is approximately 10 times bigger than the average size in Cluster 4 Small & Very Specialized firms.
- Firms in Cluster 2 are significantly more diversified than firms in the other two clusters. On average they produce 6.6 different technological classes compared with 2.3 for Cluster 3 and 1.3 for Cluster 4.
- The total capacities of Clusters 2 and 3 in year 2000 are similar at around 40% of total output, however the capacity of Cluster 4 capacity is only half that total.
- There is a significant difference between capacities in the 5 high-growth grades and the 5 slow-growth grades. The former explains 72% of total capacity in year 2000 (70.1 m. tonnes), the latter explains 28% (27.7 m. tonnes).
- The high-growth grades' capacity of 70.1 million tonnes is distributed significantly differently across clusters, with Cluster 2 accounting for 46%, Cluster 3 40%, and Cluster 4 14%. Within the low-growth grades the 27.7 million tonnes capacity is

distributed across Cluster 2 accounting for 25%, Cluster 3 accounting for 46% and Cluster 4 accounting for 29%.

- The above differences are explained first by the 4.6 times more high-growth grades capacity than low-growth grades capacity in Cluster 2 (32.0 v/s 6.9 m. tonnes) and second by the 2.2 times more high-growth grades capacity than low-growth grades capacity in Cluster 3 (27.8 v/s 12.8 m. tonnes). The capacity of Cluster 4 is quite uniformly distributed with 10.3 million tonnes accounted for high-growth grades v/s 8.0 million tonnes accounted for low-growth grades, that is 1.3 times more.

6.2 Are there significant differences among the growth performance of clusters over time?

Having identified and validated the existence of three distinctive strategic groups determined by three technological configurations of firm capacity at one point in time (year 2000), in this section we examine and compare growth performance over time. Specifically, we investigate whether there are systematic differences in growth across the three strategic groups identified, which would suggest a within industry structure.

This section discusses the longitudinal data (historical annual capacity data for the 234 firms comprising the three clusters), the variables and the methodology approach used. It presents and discusses the empirical results for cluster growth performance, where we observe significant heterogeneity.

6.2.1 Data and variables used for cluster growth performance comparison

To run this analysis we need to select a time period going back from 2000. The maximum period possible based on the data available is 1970-2000, however it is neither necessary nor convenient to use such a long period to capture the phenomenon we want to study. With each additional year the number of firm-year observations decreases (see Figures 4.5 of Chapter 4) and the possible path-dependency[89] effect over year 2000 also diminishes with a longer period. A reasonable time frame would be the

[89] Path-dependence is a broad concept which basically means that history matters. An economic interpretation of this phenomenon is that the outcome of a dynamic process in one moment in time exhibits sensitive dependence on its past conditions (Nelson and Winter 1982; David 2000; Mahoney 2000).

second sub-period 1986-2000 which is more dynamic than the first (1970-1985) (see data description in Chapter 4, subsection 4.2.2) and is long enough to conduct a robust cluster growth performances analysis over time.

Table 6.5 presents descriptive statistics for the US p&p industry panel data for the period 1986-2000 including the number of firms existing in that period (414), survivors to year 2000 (234) and non-survivors to year 2000 (180). The annual cumulative capacity of the population of firms is 1,372 million tonnes. The 234 survivor firms explain 81% of the total cumulative capacity (last raw of Table 6.5) and these data can be used to study cluster growth performance over time. The 180 non-survivor firms explain 19% of total cumulative capacity. These data are not useful for cluster growth performance analysis because they are non-survivors to year 2000 they do not belong to any of the three clusters.

Table 6.5 Descriptive statistics for survivor and non-survivor firms in year 2000 and total firms in existence in 1986-2000

Firm's features			TOTAL FIRMS 1986-2000		SURVIVORS year 2000		NON-SURVIVORS year 2000	
n_firms & n_obs. (n.)			**414**	3,685	**234**	2,612	**180**	1,073
growth_av & sd (%)			**2.9**	21	**3.2**	21	**2.1**	19
size_av & sd (m. tonnes)			0.37	0.88	0.41	0.99	0.23	0.49
n_years_av & sd (n.)			9.3	5.4	11.6	5.1	6.3	4.3
n_grades_av & sd (n.)			1.7	1.5	1.8	1.6	1.5	1.1
Technology classes cumulative capacity (million tonnes)				(a)		(a)		(a)
	high-growth	**gp**	335	24%	293	26%	42	16%
		liner	313	23%	248	23%	65	25%
		corr	116	8%	98	9%	18	7%
		sbb	79	6%	66	6%	13	5%
		tissue	92	7%	51	5%	42	16%
	subtotal		935	68.2%	756	68.1%	179	68.3%
	low-growth	news	93	7%	89	8%	4	2%
		mp	154	11%	123	11%	31	12%
		special	46	3%	32	3%	14	5%
		recb	101	7%	73	7%	28	11%
		kraft	42	3%	36	3%	6	2%
	subtotal		437	31.8%	353	31.9%	83	31.7%
total cumulative capacity			**1,372**		**1,110**		**262**	
% total cumulative capacity			100%		81%		19%	

(a) Percentage of technology classes cumulative capacity over total cumulative capacity

To summarize, Table 6.5 shows that more than 80% of the US p&p industry cumulative capacity during the period 1986-2000 is accounted for by firms that survived to 2000, and these data can be used to study and compare cluster growth performance. The data of non-survivor to year 2000 firms (which are not useful for this purpose but are used for the exit hazard rate analysis in Chapter 7) are less than 20% of total cumulative industry capacity; thus, the data available are good enough to conduct a proper dynamic analysis and compare cluster growth performance.

The variables and methodology applied in the next section to calculate cluster growth performance are similar to those used to calculate the growth-rates in the different size-classes in Chapter 5, section 5.1.3.

6.2.2 Comparison of cluster growth performance

Using the data, variables and methodology described above, Table 6.6 presents the main features of survivor firms during the period 1986-2000 decomposed at the three cluster level: Large & Diversified (8 firms), Medium & Specialized (41 firms), and Small & Very Specialized (185 firms). It presents the following data variables for each cluster: number of firms; growth mean and standard deviation, size, number of years and number of grades; capacities for the 10 technological classes and for the cluster. The results provide interesting information on the p&p industry's evolution and industry heterogeneity in the period 1986-2000.

- There are systematic and significant differences in growth performance among clusters. Cluster 3 Medium & Specialized firms shows annual average growth of 8.1% which is significantly higher than Cluster 2's growth performance at 3.7%, and Cluster 4 at 2.3%. Cluster 3's growth variance of 33% is also significantly higher than the variance for the other two clusters - 11% (cluster 2) and 21% (cluster 4).
- The patterns are similar to those in Tables 6.4a and 6.4b for the cross-sectional year 2000, showing that Cluster 2's firms are highly diversified (7.1 grades) compared with Cluster 3 and Cluster 4 (2.5 and 1.4 grades). Cluster 2's firms on average are 4 times larger than Cluster 3's firms, which are 9 times larger than Cluster 4's firms.
- In Cluster 2 79% of capacity is concentrated in the high-growth grades and 21% in low-growth grades. These figures are 66% and 34% for Cluster 3 and 51% and 49%

for Cluster 4 which means that Cluster 2's Large & Diversified firms' capacity is mostly concentrated in the high-growth grades, while Cluster 4's Small & Very Specialized firms tend to have a more uniform capacity distribution across the 10 grades. Cluster 3 Medium & Specialized firms are between the two extremes.

- The 8 Cluster 2 firms have existed for an average of 15 years, which corresponds to the study period, meaning that they are all incumbents; no new firms entered Cluster 2 during this period. The 41 Cluster 3 firms have existed on average for 11.8 years and the 185 Cluster 4 firms have been in existence for 11.4 years, thus both clusters have experienced new firm entry.

Table 6.6 Descriptive statistics of historical data (period 1986-2000) of survivor firms and its three cluster's decomposition

Firm's features			SURVIVORS 1986-2000		CLUSTER 2		CLUSTER 3		CLUSTER 4	
n_firms & n_obs. (n.)			234	2,612	**8**	120	**41**	464	**185**	2,028
growth_av & sd (%) ┬			3.2	21	**3.7**	11	**8.1****	33**	**2.3**	19
size_av & sd (m. tonnes)			0.41	0.99	3.76	2.38	0.94	0.76	0.10	0.15
n_years_av & sd (n.)			11.6	5.1	15.0	0	11.8	4.8	11.4	5.2
n_grades_av & sd (n.)			1.8	1.6	7.1	2.0	2.5	1.6	1.4	0.8
				b		*b*		*b*		*b*
Technology classes cumulative capacity (million tonnes)	high-growth	**gp**	293	26%	177	39%	66	15%	50	24%
		liner	248	22%	99	22%	125	28%	24	12%
		corr	98	9%	35	8%	49	11%	14	7%
		sbb	66	6%	35	8%	25	6%	6	3%
		tissue	51	5%	8	2%	29	6%	13	6%
	subtotal		756	68.1%	355	78.6%	294	65.6%	108	51.2%
	low-growth	news	89	8%	17	4%	54	12%	18	9%
		mp	123	11%	63	14%	27	6%	33	16%
		special	32	3%	2	1%	15	3%	15	7%
		recb	73	7%	3	1%	42	9%	28	13%
		kraft	36	3%	11	2%	17	4%	8	4%
	subtotal		353	31.9%	96	21.4%	154	34.4%	103	48.8%
total cumulative capacity			**1,110**		**451**		**448**		**210**	
% total cumulative capacity			100%		40.6%		40.4%		19.0%	

*** Significant at 1% level for a joint test of growth average and growth average standard dev. difference*

┬ *The two null hypothesis tested are: Ho: growth_av of Cluster 2=Cluster 3=Cluster 4*
Ho: growth_sd of Cluster 2=Cluster 3=Cluster 4
Both null hypotheses are rejected at 1% confidence level.

b Percentage of technology classes cumulative capacity over total cumulative capacity

The most important conclusion from this section is that growth across clusters was heterogeneous over the 15 years study period. Cluster 3 firms showed significantly higher growth performance than Cluster 2 and Cluster 4 firms. The next section investigates the factors that might explain this persistent difference in growth performance among clusters arguing that it is not random but due to conspicuous and internal sources of heterogeneity.

6.3 Factors that explain persistent growth performance heterogeneity among clusters

The previous section showed that there are systematic differences in growth performance across clusters within the US p&p industry. Here, we challenge the hypothesis of random differences in growth arguing that there are factors that explain this systematic heterogeneity. This section investigates the last components of the second research question:

- Are there distinctive firm behaviours associated with each cluster that may explain systematic differences in firm performance across groups?
- What portion of inter-firm difference cannot be explained by these behaviours (and thus may be due to firm-specific fixed effects)?

To investigate these questions the section is organized in two subsections. The first conducts random-walk tests within the three clusters. The second decomposes each cluster into eight subgroups using two variables: technology-class (high v/s low growth grade firms) and type-class (incumbents v/s new-entrants firms). Random-walk test are run within the 8 subgroups and growth performance differences are tested in order to identify conspicuous and internal sources of growth heterogeneity.

6.3.1 Random-walk analysis within clusters

A first step to explore the factors that may explain systematic growth performance heterogeneity among clusters is to conduct a random-walk analysis within clusters. Table 6.7 presents the results of these tests: each of the three charts has 25 data-columns,[90] most of which are self explanatory. However, the three 'capacity' columns warrant some explanation. The 'total' column shows total cumulative capacity for each size-class and for the cluster (last raw of each table) measured in million tonnes; 'H-gth' and 'L-gth' columns show the percentage of total high-growth and total low-growth grades cumulative capacity for each size-class and for the cluster over total cumulative cluster capacity (see Figure 6.1). The last ten columns show the percentages of the cumulative capacity distribution over 10 grades for each size-class and for the cluster (last raw of each table). The percentage figure shown below each chart in the 'total' column corresponds to the percentage of cumulative capacity for each cluster, during the period 1986-2000, over total cumulative capacity of the survivor firms during the same period. This percentage represents the weight of each cluster over the total cumulative capacity of the survivor firms in the period analysed.

- **Cluster 2 Random-walk test analysis** (Table 6.7, first chart)

  The results of this test show clearly that random-walk is operating within the 8 Cluster 2 Large & Diversified firms, which explains 40.6% of the total cumulative capacity of the survivor firms during the period 1986-2000. The growth mean and growth variance of the four smaller firms (mean=4.2 & sd=11) show no significant differences with the four larger firms (mean=3.1 & sd=11). In fact, average growth and average growth variances are quite similar in both size-classes.

  Also, the eight firms in this cluster are incumbents (all existed for the whole 15 year period studied) and no new firms entered during the period; all have a high-growth grades technological configuration with 79% of total cumulative capacity in the five high-growth technological classes and just 21% in the low-growth technological classes. It is interesting that 14% of the 21% of the five low-growth technological classes is concentrated in market-pulp which is the grade that provides vertical integration to the companies. This means that the capacity mix configuration of this cluster is concentrated 93% along the five high-growth technology classes plus market-pulp which is a key input to paper production.

[90] This is the format used to display the results of all the random-walk tests run in this subsection which are shown in the Table 6.7 and in Appendix A6.3 from Table A6.3a to A6.3i.

Table 6.7 Random-walk tests within Clusters 2, 3 and 4, period 1986-2000[91]

CLUSTER 2 — **RANDOM WALK TEST FOR: 8 survivor year 2000 firms (two size classes)**

CONCLUSION: **Random walk,** the 4 smaller firms have not significant growth performance differennce with the 4 larger firms

size-class		# of:		years		size (th.tonnes)		# grades		growth (%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº	limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=3,000	4	60	15	0	**1,903**	668	5.9	1.6	**4.2**	**11**	114	22	4	58	17	11	0	0	6	6	1	1	1
2	>3,000	4	60	15	0	**5,612**	1,983	8.2	1.6	**3.1**	**11**	337	57	18	33	24	7	10	2	3	17	0	1	3
Cluster 2		**8**	120	15	0	**3,757**	2,375	7.1	2.0	**3.7**	**11**	451	79	21	39	22	8	8	2	4	14	1	1	2

40.6 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 — **RANDOM WALK TEST FOR: 41 survivor year 2000 firms (two size classes)**

CONCLUSION: **Not random walk,** the smaller size-class grow faster than larger size-class

NEXT STEP: **Analyse subgroups of:** High v/s Low-growth grades and Incumbents v/s New-entrant firms

Nº	limits	firms	obs.	years av	years sd	size av	size sd	grades av	grades sd	growth av	growth sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=500	21	250	12	4	**568**	438	1.7	1.0	**11.5***	**41**	147	19	14	17	24	14	1	3	20	3	1	18	0
2	>500	20	214	13	5	**1,366**	835	3.5	1.7	**4.7***	**21**	302	47	20	13	31	9	8	8	8	7	4	5	5
Cluster 3		**41**	464	12	5	**936**	763	2.5	1.6	**8.1**	**33**	448	66	34	15	29	11	6	6	12	6	3	9	4

40.4 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 4 — **RANDOM WALK TEST FOR: 185 survivor year 2000 firms (four size classes)**

CONCLUSION: **Not random walk,** growth of firms diminish with size of firms

NEXT STEP: **Analyse subgroups of:** High v/s Low-growth grades and Incumbents v/s New-entrant firms

Nº	limits	firms	obs.	years av	years sd	size av	size sd	grades av	grades sd	growth av	growth sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=30	63	814	13	4	**20**	21	1.2	0.5	**3.0****	**23**	17	4	4	12	7	4	0	25	0	9	19	19	5
2	30-70	50	542	11	5	**62**	36	1.3	0.6	**2.8****	**19**	35	9	8	26	2	17	0	6	3	11	8	24	2
3	70-180	39	370	10	6	**127**	55	1.6	0.7	**1.3****	**15**	49	13	10	32	6	10	0	8	11	6	4	16	7
4	>180	33	302	10	6	**344**	245	1.8	1.3	**-0.2****	**15**	110	26	27	22	18	2	5	3	10	23	7	8	3
Cluser 4		**185**	2,028	11	5	**100**	149	1.4	0.8	**2.3**	**20**	210	51	49	24	11	7	3	6	9	16	7	13	4

19.0 (% of total cumulative capacity of survivor firms period 1986-2000)

*Notes: total cumulative capacity is measured in million tonnes, H-gth and L-gth is measured in %, * significant at 5% level, ** significant at 1% level the columns names in tables of Clusters 3 and 4 are the same as in table of Cluster 2.*

[91] Random-walk test in Clusters 2 and 3 compares two size-classes since they have 8 and 41 firms. In Cluster 4 it compares four size-classes since it has 185 firms.

These antecedents make it possible to deduce that the eight firms in Cluster 2 form a strategic group which is isolated from the other clusters and is composed of firms with similar combination of scope and resource commitments which is a key feature that characterized strategic groups in an industry (Cool and Schendel 1987, p.1106). Within the eight Cluster 2 firms, we can observe both commitments. Scope is reflected by their high diversification (7.1 technological classes compared to 2.5 and 1.4 in Clusters 3 and 4 respectively). This diversification is concentrated in the high-growth rather than the low-growth technological classes (79% v/s 21%). The resource commitment is reflected in their size, since these eight firms are among the 11 largest p&p companies in year 2000; they are 10 times larger than the industry size average, 4 times larger than Cluster 3 firms and 37 times larger than the average size of firms in Cluster 4.

- **Cluster 3 Random-walk test analysis (Table 6.7, second chart)**

The results of this test show a different picture from the Cluster 2 analysis. In this case random-walk is not in operation within the 41 Cluster 3 firms which account for 40.4% of the total cumulative capacity of the survivor firms during the period 1986-2000 (thus the size is similar to Cluster 2 size) since the growth mean of the 21 smaller firms is significantly higher than the growth mean of the 20 larger companies (mean=11.5 & sd=41 compared mean=4.7 & sd=21).

Also, this cluster has new-entrant firms during the study period (average existence of 12 years for all firms), and the 21 smaller firms are much less diversified than the 20 larger firms (an average of 1.7 compared to 3.5 grades). Within this cluster 66% of total cumulative capacity is concentrated in the five high-growth technological classes and 34% in the five low-growth technological classes which mean that it is more distributed than Cluster 2 firms.

- **Cluster 4 Random-walk test analysis (Table 6.7, third chart)**

Within Cluster 4, random-walk is not in operation since the growth mean of its 185 firms which explains 19.0% of total cumulative survivor capacity in the period 1986-2000 diminishes systematically with firm size (growth means = 3.0, 2.8, 1.3, -

0.2).[92] As was the case for Cluster 3, this group has new-entrants firms over the study period with average existence of 11 years for all firms. Within this context of low level of diversification, the smaller size-classes are less diversified than the larger size-classes (1.2 compared with 1.8 grades on average) and capacity along the five high-growth technological classes is very similar to capacity along the five low-growth technological classes (51% v/s 49%).

The main conclusion of this subsection is that random-walk is in operation in Cluster 2 but not in Clusters 3 or 4, where growth diminishes with size. The following subsections deepen this analysis by investigating two possible sources of growth heterogeneity within clusters: technology-class and firm type-class.

6.3.2 Growth comparison and random-walk analysis within cluster subgroups

This subsection investigates two possible sources for the growth performance heterogeneity observed above: firm's technology-classes (high v/s low growth grades) and firm's type (incumbents v/s new-entrants).

Technology-class variable

As explained in subsection 6.1.1 and depicted in Figure 6.1, depending on the capacity mix, firms can be classified as: high-growth technology-class which corresponds to firms with more than 50% of their total capacity in the five high-growth grades (liner board, graphic papers, corrugated boards, solid-bleached boards, and tissue paper) during 1986-2000; or low-growth technology-class which are firms with more or equal than 50% of their total capacity in the five grades with the smallest growth (newsprint, pulp, specialty papers, recovery boards, and kraft paper) during the same period.

There are two special cases that need to be considered when using this classification. Firms that change their technology-class during the study period and firms that have 50% of their total capacity in each of the two technology classes across the 15 years period. Of the 234 firms clustered, 214 were in the same technology class across the whole period 1986-2000 and account for 91.5% of total sample cumulative capacity. 16

[92] Because of the large number of firms in Cluster 4, the random-walk test was conducted comparing four rather than two size-classes as was done in Clusters 2 and 3.

firms, representing 6.8% of total sample cumulative capacity, changed technology class (4 from Cluster 3 and 12 from Cluster 4). In these cases the firms are classified as belonging to the technology-class where they had the most experience (higher number of years). Just 4 firms, all from Cluster 4, had the same high and low technology-class capacity during the 15 years studied, representing 1.7% of total capacity. These 4 firms are classified as low-growth grades since they are all small in size (between 23,000 and 70,000 tonnes) thus more similar to this group rather than to the high-growth grades firms. Appendix A6.2 provides specific information for these 20 special cases' firms.

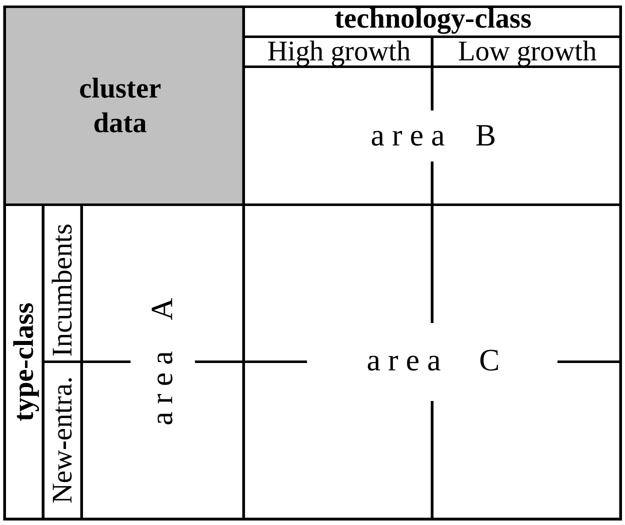
<u>Variable for firm type-class</u>

Firms are classified as incumbents if they existed in 1986 and persisted across the period. Firms are considered new-entrants if they entered the industry after 1986 and survive to year 2000.[93] Using the variables technology-class and firm type-class, the clusters are decomposed into eight subgroups as depicted in Figure 6.4, and two statistical tests were conducted:

(a) random-walk test within each subgroup;

(b) growth performance differences test between subgroups.

Figure 6.4 Firm's subgroups within clusters



These eight subgroups can be subdivided into three areas A, B and C as explained below.

[93] Firms that exited the industry are not considered here since the three clusters were formed by survivor firms in the period 1986-2000. Firms that exit the industry as well as their patterns and determinants are studied in Chapter 7.

Area 'A' examines whether random-walk is in operation within the Incumbents and New-entrants subgroups regardless of the firm's technology-class, and tests whether there are significant differences in the growth-rates of the two groups.

Area 'B' examines whether random-walk is in operation within the High and Low-growth technological classes regardless of firm's type-class, and tests whether there are significant differences in the growth-rates of the two groups.

Area 'C'[94] examines whether random-walk is in operation within the four subgroups resulting from the above two variables, and tests whether there are significant differences in the growth-rates of the four pairs constituting technology-class and type-class subgroups. This area permits to capture possible interaction effects between the two variables. For example, one group formed by a new-entrant's high-growth technological configuration could produce a specific growth performance which would distinguish it from the high-growth technological configuration of the incumbents.

Tables 6.8, 6.9 and 6.10 summarize the main indicators, random-walk test and growth comparison for the eight subgroups within Clusters 2, 3 and 4.[95] The variables displayed are the same for each subgroup. For instance in Table 6.8, column 1 (% cap.) corresponds to the percentage of the subgroup's cumulative capacity over total cumulative capacity for survivor firms along the period 1986-2000. Columns 2 and 3 (# firms and # obs.) are the number of firms and number of observations. Column 4 (size) is average firm size measured in thousand tonnes capacity. Column 5 (# grds) is average number of grades. Columns 6 and 7 are average and standard deviations of annual growth-rates (avge. gth, sd gth). The first row (underlined figures), in Columns 2 to 7, show the subgroup-level results. The figures in the next two rows (in Columns 2 to 7), correspond to the results for the size-classes within cluster's subgroups analysis. The figures in the second row correspond to the subgroup of 4 smaller firms; the figures in the third row correspond to the subgroup of 4 larger firms. The avge. gth comparison between these two rows allows us to test for random-walk within subgroups, denoted RW or Not RW in Column 1.

[94] This is discussed in Appendix A6.3.

[95] These three tables are a resume of the complete output figures shown in the Appendix A6.3 from Tables A6.3a to A6.3h.

Table 6.8 Random-walk test within Cluster 2 with Technology-class and Type-class decomposition
(Cluster 2 figures taken from Table 6.7)

TECHNOLOGY-CLASS: High + Low Growth Grades

CLUSTER 2 (TYPE-CLASS)	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth
Incumbents + New Entrants	**40.6**	8	120	3,757	7.1	3.7	11
	RW	4	60	1,903	5.9	4.2	11
		4	60	5,612	8.2	3.1	11
Incumbets	(idem right data)						
New Entrants	NO FIRMS						

TECHNOLOGY-CLASS: High Growth Grades

CLUSTER 2 (TYPE-CLASS)	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth
Incumbents + New Entrants	(idem below data)						
Incumbets	**40.6**	8	120	3,757	7.1	3.7	11
	RW	4	60	1,903	5.9	4.2	11
		4	60	5,612	8.2	3.1	11
New Entrants	NO FIRMS						

TECHNOLOGY-CLASS: Low Growth Grades

CLUSTER 2 (TYPE-CLASS)	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth
Incumbents + New Entrants	NO FIRMS						
Incumbets	NO FIRMS						
New Entrants	NO FIRMS						

Notes:
For Tables 8, 9 and 10 size is measured in thousand tonnes; avge. and sd growth are measured in %.

Table 6.9 Random-walk test within Cluster 3 with Technology-class and Type-class decomposition
(Cluster 3 figures taken from Table 6.7 and subgroups figures taken from Appendix A6.3 Tables A6.3a to A6.3d)

CLUSTER 3	TECHNOLOGY-CLASS																					
	High + Low Growth Grades							**High Growth Grades**							**Low Growth Grades**							High vs Low avge. growth differences
	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	
TYPE-CLASS: Incumbents + New Entrants	**40.4**	41	464	936	2.5	8.1	33	**29.2**	26	288	1,084	3.0	8.9	37	**11.2**	15	174	690	1.8	6.9	26	NOT significant
	NOT	21	250	568	1.7	11.5*	41	**RW**	13	145	654	2.1	12.2	45	**RW**	8	105	458	1.2	9.2	32	
	RW	20	214	1,366	3.5	4.7*	21		13	143	2	3.9	5.5	25		7	69	1,037	2.6	3.6	14	
TYPE-CLASS: Incumbents	**33.9**	25	375	1,006	2.7	5.5	25	**24.5**	16	238	1,140	3.2	7.4	34	**9.4**	9	135	772	1.9	4.4	16	NOT significant
	RW	13	194	582	1.7	7.8	34	**RW**	8	119	637	2.2	9.1	41	**RW**	5	75	509	1.2	5.3	19	
		12	181	1,462	3.8	4.7	22		8	119	2	4.2	5.8	26		4	60	1,100	2.8	3.2	13	
TYPE-CLASS: New Entrants	**6.5**	16	89	688	1.9	14.3	40	**4.7**	10	50	924	2.3	14.7	46	**1.8**	6	39	444	1.4	14.8	45	NOT significant
	NOT	8	56	525	1.6	18.5*	48	**NOT**	5	26	719	2.0	26.4*	51	(*)	3	30	343	1.3	18.7	50	
	RW	8	33	943	2.3	4.7*	17	**RW**	5	24	1,034	2.6	4.2*	15		3	9	722	1.7	6.2	22	
Inc. vs NewEn. avge. growth differences	significantly different at 1% confidence level							significantly different at 10% confidence level							significantly different at 5% confidence level							

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

(*) Not enough data for testing Gibrat´s Law

Table 6.10 Random-walk test within Cluster 4 with Technology-class and Type-class decomposition
(Cluster 4 figures taken from Table 6.7 and subgroups figures taken from Appendix A6.3 Tables A6.3e to A6.3h)

CLUSTER 4		TECHNOLOGY-CLASS																					
		High + Low Growth Grades							High Growth Grades							Low Growth Grades							High v/s Low avge. growth differences
TYPE-CLASS		% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	% cap.	# firms	# obs.	size	# grds	avge. gth	sd gth	
Incumbents + New Entrants		**19.0**	185	2,028	100	1.4	2.3	20	**10.3**	95	980	112	1.5	2.6	22	**8.7**	90	1,048	89	1.3	2.0	19	NOT significant
		NOT	63	814	20	1.2	3.0**	23	**NOT**	26	348	18	1.3	2.7*	19	**RW**	32	373	19	1.2	2.9	25	
		RW	50	542	62	1.3	2.8**	19	**RW**	23	237	53	1.4	3.3*	26		24	257	44	1.0	2.0	16	
			39	370	127	1.6	1.3**	15		23	191	104	1.3	2.4*	20		22	239	101	1.5	2.1	15	
			33	302	344	1.8	-0.2**	15		23	204	339	2.0	-0.2*	12		12	180	263	1.4	0.1	15	
Incumbets		**14.6**	111	1,664	97	1.4	1.8	18	**7.9**	54	807	109	1.5	2.2	21	**6.6**	57	855	86	1.3	1.7	19	NOT significant
		NOT	37	554	15	1.2	3.2**	21	**NOT**	17	254	14	1.1	2.6*	19	**RW**	20	300	13	1.2	1.5	17	
		RW	28	420	40	1.4	2.4**	21	**RW**	14	208	45	1.7	2.9*	19		12	180	39	1.1	1.5	14	
			23	345	94	1.4	2.1**	17		12	180	94	1.3	1.9*	20		13	195	94	1.5	2.2	13	
			23	345	301	1.8	-0,1**	15		11	165	352	2.2	-0,6*	13		12	180	246	1.6	1.1	15	
New-Entrants		**4.4**	74	364	111	1.2	3.9	19	**2.4**	41	171	123	1.3	4.4	24	**2.1**	33	193	101	1.2	2.8	21	NOT significant
		NOT	21	125	32	1.0	4.8*	21	**NOT**	11	11	26	1.0	7.0*	37	**RW**	12	73	38	1.1	3.6	27	
		RW	18	95	68	1.1	3.4*	20	**RW**	10	10	76	1.2	7.2*	23		12	77	75	1.3	1.9	20	
			18	82	130	1.5	1.2*	16		10	10	109	1.3	1.5*	12		9	44	244	1.1	0.9	14	
			17	62	298	1.3	1.5*	6		10	10	298	1.5	1.6*	8								
	Inc. vs NewEn. avge. growth differece	significantly different at 5% confidence level							NOT significant							NOT significant							

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

The results of the cluster subgroups analysis are discussed below in order of the clusters 2, 3 and 4 (Tables 6.8, 6.9 and 6.10) and the areas A, B and C within each of them.

Analysis of Cluster 2 subgroups (Table 6.8)

As observed in subsection 6.3.1, the eight firms in Cluster 2 are all high-growth grades and all incumbents thus this cluster cannot be decomposed further. The conclusions set out in subsection 6.3.1 apply here.

Analysis of Cluster 3 subgroups (Table 6.9)

As observed in subsection 6.3.1 random-walk is not in operation within the 41 Cluster 3 firms because the 21 smaller companies with an average size of 568 th. tonnes have significantly higher growth rate means compared to the 20 larger firms with an average size of 1,366 th. tonnes. Next we examine the two areas A and B[96] and the four subgroups into which they are decomposed; we run random-walk tests within subgroups and compare their growth performance.

- **area Cluster 3-A** (see detailed statistics in Appendix A6.3, Table A6.3a)
  When the 41 Medium & Specialized Cluster 3 firms are decomposed by type-classes, we observe that 25 are incumbents with an average size of 1,006 th. tonnes and 16 are new-entrants with an average size of 688 th. tonnes, thus the incumbents are in average 1.5 times larger than the new-entrant firms. Three main findings emerge from this subgrouping. Firstly, random-walk is in operation within the 25 incumbents firms since the 13 larger companies have no significant differences in growth-rates compared to the 12 smaller companies (7.8% v/s 4.7%). Secondly, random-walk is not in operation within the 16 new-entrant firms since the 8 smaller companies have significant higher growth-rates compared to with the 8 larger companies (18.5% v/s 4.7%). Thirdly, there is a significant difference in growth performance between the two subgroups. Incumbent firms which are larger in size grew at an average of 5.5% (sd=25), while New-entrant firms which are smaller in size grew at an average of 14.3% (sd=40), thus 2.6 times faster.

[96] Area C is briefly described in appendix A6.3, Tables A6.3c and A6.3d.

The above suggests that the subgrouping 'incumbents + new-entrants' captures two factors that influence the dynamics of the cluster in the same directions, that is type-class and size-class of firms. New-entrants are smaller and faster growing firms while incumbents are larger and slower growing. Although total cumulative capacity of the incumbent firms is five times that of the new-entrants (33.9% v/s 6.5%),[97] the fact that the latter grew 2.6 times faster is an indication that firm's type class is a significant and systematic source of growth heterogeneity within Cluster 3.

- **area Cluster 3-B** (see detailed statistics in Appendix A6.3, Table A6.3b)
  When the 41 Medium & Specialized Cluster 3 firms are decomposed by technology-class, 26 are high-growth with an average size of 1,084 th. tonnes and 15 low-growth grades with an average size of 690 th. tonnes. Thus the average size of the former is 1.6 times the size of the latter which is significant at 5% level. Two main findings emerge from this subgrouping. Firstly, random-walk is in operation within each individual subgroup. Among the 22 high-growth grade firms, the 13 smaller companies show no significant growth differences with the 13 larger companies (12.2% v/s 5.5%).[98] Within the 15 low-growth grade firms, the 8 smaller companies show no significant growth differences compared to the 7 larger companies (9.2% v/s 3.6%). Secondly, there is no significant difference in growth performance between the 26 high-growth and 15 low-growth subgroups (8.9% v/s 6.9%)

There are two main conclusions that can be drawn from the above analysis of Cluster 3 subgroups (Table 6.9). First, a major source of heterogeneity in Cluster 3 growth performance is the significant differences in the growth of the 25 incumbents and the 16 new-entrants firms (5.5% v/s 14.3%). When Cluster 3 is decomposed into these two subgroups, the incumbents' growth process is random-walk, but the new-entrants' is not. This departure from random-walk is also observed in the 10 new-entrant high-growth grade firms. Considering that Cluster 3 has 40.4% of the total cumulative capacity of survival firms during the study period, its decomposition allows us to demonstrate that 33.8% of this cumulative capacity operates under random-walk conditions and the

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[97] Cluster 3 incumbents' cumulative capacity is 376 m. tonnes while new entrants' cumulative capacity is 72 m. tonnes. The factors that explain this large difference are number of firms (25 v/s 16), average firm size (1,006 v/s 688 th. tonnes) and number of years in existence (15 v/s 7).
[98] Because of the subgroupings the number of observations for running the tests has reduced considerable which makes more difficult to reject the null hypothesis of equal growth.

residual 6.5% cumulative capacity does not and therefore might be due to fixed effects (firm's internal sources of heterogeneity) which would need to be investigated in further research based on more specific data.

Second, when applying the technology-class variable to decompose Cluster 3 capacity data in high-growth and low-growth grades, both subgroups operate under random-walk conditions, thus there is no residual. It is interesting that growth difference between these two subgroups is not significant. Contrary to what we observed at Cluster 3 and type-class levels, where smaller firms grew faster than larger firms, here high-growth grade firms which are larger exhibit faster growth than low-growth grade firms which are smaller. This suggests that the technology-class subgrouping is capturing two factors with opposing influences on firm's growth dynamics. On the one hand firm technological configuration effect that pushes larger firms to grow faster, which is in opposite direction to the force detected at Cluster 3 level where smaller firms tend to grow faster.

<u>Analysis of Cluster 4 subgroups</u> (Table 6.10)

As observed in subsection 6.3.1 random-walk is not in operation among the 185 Cluster 4 firms because growth rate diminishes with size. Next we examine the two areas A and B[99] and the 4 subgroups into which they are decomposed; we run random-walk tests within subgroups and compare their growth performance.

- **area Cluster 4-A** (see detailed statistics in Appendix A6.3, Table A6.3e)
  When the 185 Small & Very Specialized Cluster 4 firms are decomposed by type-classes, we observe that 111 are incumbents and 74 are new-entrants. Two main findings emerge from this subgrouping. First, random-walk is not in operation within the 111 incumbents and within the 74 new-entrants because in both cases there is a clear pattern of diminishing firm growth with size. Second, there is a significant difference in the average growth of firms in the two groups. New-entrants, which are larger in size, grew at an average of 3.9% (sd=19), while the

[99] Area C is briefly described in Appendix A6.3, Tables A6.3g and A6.3h.

incumbents, which are smaller in size, grew at an average rate of 1.8% (sd=18), thus the former group grew 2.2 times faster.

Similar to Cluster 3, the total cumulative capacity of the incumbents is 3.3 times that of new entrants (14.5% v/s 4.4%).[100] However, in contrast to Cluster 3, we observe that the new-entrants are larger compared to the average size of incumbents (111 v/s 97 th. tonnes). The reason for this could be related to the age of the firms and technological change in p&p machinery. As we showed in the Industry Chapter 2, p&p machines continue to operate for several decades and newer machines incorporating the latest technology result in significantly higher productivity and production capacity. Cluster 4 new-entrants have an average age of 6 years compared to 15 years for the incumbents and most Cluster 4 firms are single machine producers. This suggests that new-entrants are likely to have newer machinery than the incumbents and the higher production capacity of the latest technology is the reason for the larger average size of new-entrant firms.

The fact that new-entrants grew 2.2 times faster than incumbents, might mean that heterogeneous entry is a source of growth heterogeneity within Cluster 4 and thus within the industry. However, this effect is not so strong as in Cluster 3 due to the smaller sizes of firms.

- **area Cluster 4-B** (see detailed statistics in Appendix A6.3, Table A6.3f)
  When the 185 firms of Cluster 4 are separated by technology-classes we observe 95 high-growth and 90 low-growth firms. There are three main findings. First, random-walk is not in operation within the 95 high-growth grade firms since the 23 largest firms show significantly lower growth than the three smaller size-classes (growth varies from -0.2% to 3.3%). This departure from random-walk is also observed in the 54 high-growth grades incumbents and the 41 high-growth grades new-entrants firms. Second, random-walk was in operation within the 90 low-growth grades firms since there are no significant growth-rate differences among the four size-classes. This is also observed in the 57 low-growth grades incumbents and the 33 low-

[100] Cluster 4 incumbents' cumulative capacity is 162 m. tonnes; new entrants' cumulative capacity is 49 m. tonnes. This is explained mainly by the difference in the numbers of these firms (111 v/s 74) and the number of year in existence (15 v/s 6).

growth grades new-entrants firms. Third, and similar to Cluster 3, there is no significant growth performance difference between technology-classes since the 95 high-growth and the 90 low-growth grades firms show no significant growth performance differences.

Considering that Cluster 4 accounted for 19% of the total cumulative capacity of survival firms during the study period, its decomposition allows us to demonstrate that 8.7% of this capacity operates under random-walk conditions. Thus, there may be some fixed effects (firm's internal sources of heterogeneity) in operation for the 10.2% residual which could be investigated in future research based on more specific data.

6.4 Conclusions

Chapter 6 investigated the second research question in this thesis which is concerned with the existence and form of an association between the technological structure of the capital intensive p&p industry, and its dynamic behaviour in terms of market growth and development, from 1986 to 2000. Technological structure is represented by different configurations of p&p companies' technological specialization at one moment in time (cross-sectional data for year 2000), based on the 10 principal commodity products or technological classes that represent p&p firms' capacity mix. These technological configurations give rise to clusters or strategic groups that suggest a structure within the industry. We investigated the specific research questions:

- Within the US p&p industry are there distinctive configurations of technological specialization of p&p firms at one point in time (year 2000)?

On the basis that it was possible to identify strategic groupings, the additional question was investigated:

- Does firm performance, measured as annual growth-rate, differ systematically across strategic groups?

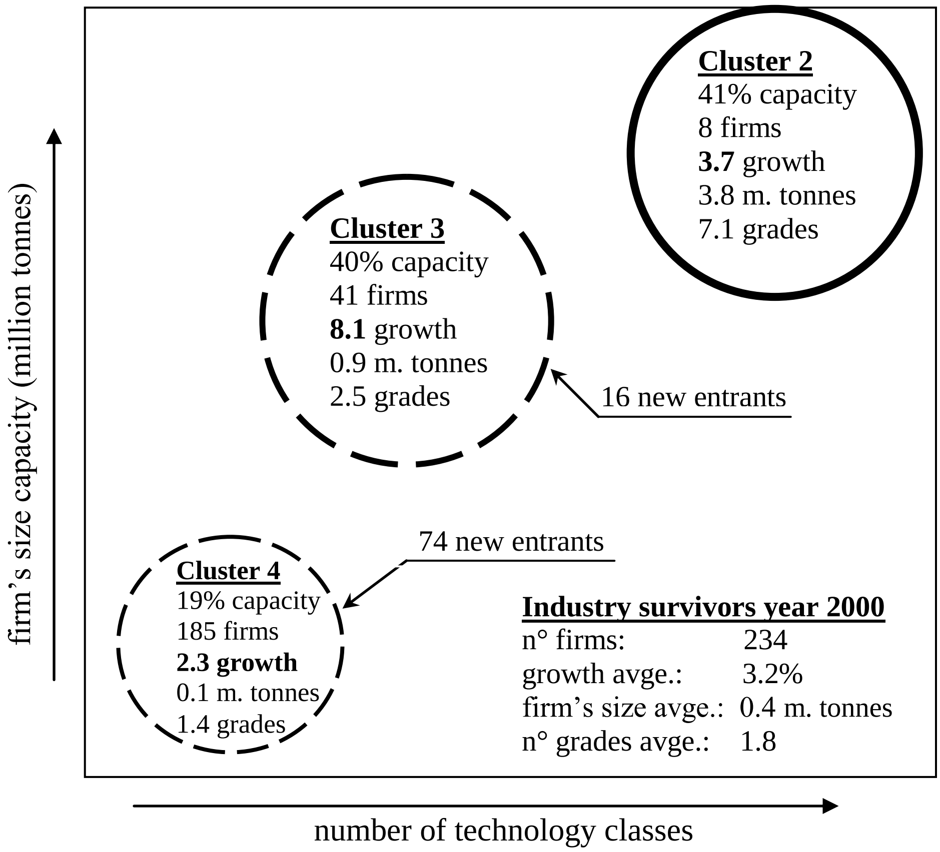
On the basis that we could identify systematic differences in growth performance across strategic groups, we formulated the additional research questions:

- Are there distinctive firm behaviours associated with each configuration that may explain systematic firm performance differences across groups?

- What portion of inter-firm difference cannot be explained by these behaviours (and thus may be due to firm-specific fixed effects)?

There are four main conclusions from this chapter. The first is that there is a structure within the US p&p industry characterized by three different technological configurations that persist over time: i) Large & Diversified firms (8 companies), ii) Medium & Specialized firms (41 companies), iii) Small & Very Specialized firms (185 companies).[101] A cluster algorithm was used to explore and identify these strategic groups. To asses the robustness of the results, reliability and validation techniques were applied and also validated through interviews with industry experts. Figure 6.5 presents a scaled map of the three clusters identified within the p&p industry and their key features. It uses technological diversification (number of technological classes) and firm size (size capacity) as *x*-*y* variables. The size of the circles approximately denotes the total cumulative capacity of each cluster. Cluster 2 thick solid line denotes its high mobility barriers and as a consequence no new firms entered it within the study period.

Figure 6.5 Three clusters identified within the US p&p industry, 1986-00



[101] The number in the brackets corresponds to cross-sectional data for 2000.

Cluster 3 and 4 broken circumferences denote low mobility barriers and consequently new firm entry. The horizontal and vertical distances between clusters denote firm's technological diversification and average differences in size respectively.

The second conclusion is that the three clusters identified within the p&p industry demonstrated systematic heterogeneous growth performance in the period 1986-2000. More specifically the Medium & Specialized firms have grown significantly faster that the other two groups. It grew 2.2 times faster than the Large & Diversified group (8.1% v/s 3.5%), and 3.5 times faster than the Small & Very Specialized cluster (8.1% v/s 2.3%).

The third conclusion is that the differences in growth performance between the three strategic groups are not random. Instead, they were found to be the consequence of at least two factors that influenced the evolution of the p&p industry.

a) The first factor is related to the different strategic choices and resource commitments of the firms in each of the three clusters. Our analysis shows that in order to achieve high growth firms need a degree of specialization in some technological commodity products. This is observed in the Medium & Specialized cluster whose firms are focused on producing between two and four technological classes and since the mid 1980s were systematically the fastest growing group. In addition, we can conclude that being large and diversified such as Cluster 2 firms is associated with medium rather than high growth.[102] This was observed in the Large & Diversified group whose firms are the largest and most diversified in the US p&p industry producing in six to nine technological classes. We can conclude also that being Small & Very Specialized such as Cluster 4 firms is associated with persistently low growth.

b) The second factor is related to the industrial dynamics of the p&p industry whose effect on industry growth was first observed in Chapter 5 subsection 5.2.3. We showed that there are significant and systematic differences in growth-rates between Incumbents, New-entrants and Exiting firms along the size distribution (see Table 5.17 in Chapter 5).

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[102] However this fact does not necessarily mean that these firms do not have a profitable, sustainable and/or persistent strategy. Since this matter exceeds the scope of this thesis we are not going to pursue in this direction and we will keep focused on the technology characteristics.

New-entrants exhibit the highest growth performance and Exiting firms the lowest, which influences the non-stochastic growth process in the sector. In this chapter we have added to the understanding of this phenomenon. Specifically we observed that the effect of firm type-class is not uniform along the size distribution but varies significantly across the three clusters influencing their growth performance unevenly. For example, in 1986-2000 16 new firms entered the Medium & Specialized cluster with an annual average growth rate of 14.3% which is significantly higher than the 5.5% of the 25 incumbents, producing a cluster average growth of 8.1%. This figure is significantly higher than the 3.7% of Cluster 2 Large & Diversified firms where all are incumbents and no new firms entered it. 74 firms entered the Small & Very Specialized cluster with an average growth of 4.4%. The 111 incumbents showed an average growth of 1.8%, producing a cluster growth average of just 2.3% during the study period.

The above indicates that there are two reasons for the significantly higher dynamism of the Medium & Specialized cluster compared to the other two strategic groups:

- First, that the new firms that enter this cluster have the highest average growth-rate among the clusters in the industry: its average growth is near 4 times higher than Cluster 2 firms (14.3% v/s 3.7%), and 3.7 times higher than the new-entrants of Cluster 4 (14.3% v/s 3.9%);
- Second because no firms enter Cluster 2 of Large & Diversified firms during the study period. This strategic group stays with the 8 initial incumbents with medium growth performance.

The fourth conclusion is related to the random-walk tests at different levels of analysis. Through the decomposition of the US p&p industry into clusters and subgroups, we demonstrated that 83% of the total cumulative capacity of survivor firms is under random-walk conditions, while the remainder is not. These inter-firm growth performance differences cannot be explained by distinctive firm behaviours associated with different firm configurations and thus might be due to fixed effects which would require further investigation based on more specific data.

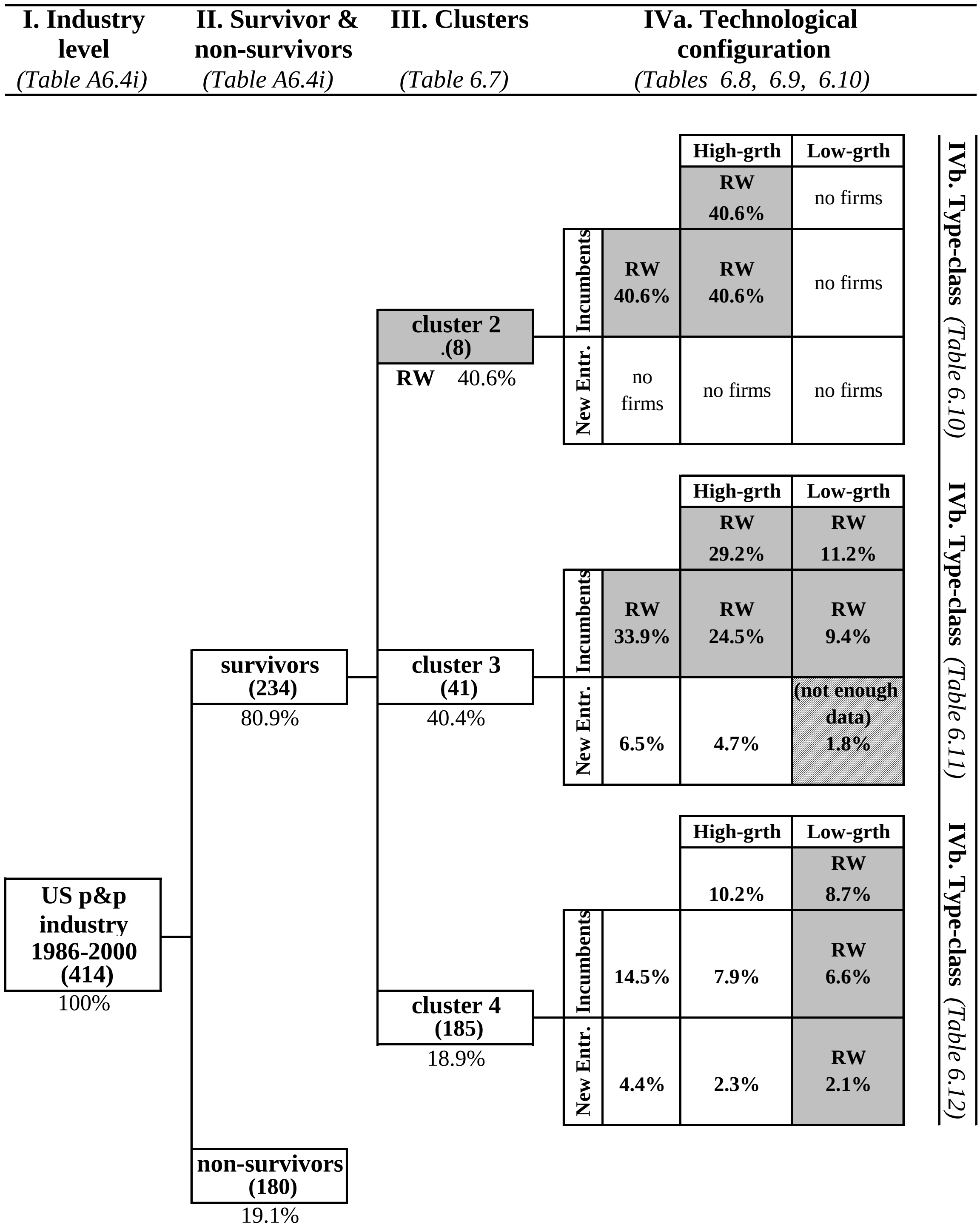
Figure 6.6 shows a synthesis map of random-walk test results at different levels of analysis (numbered I, II, III, IVa and IVb) within the US p&p industry. The first and broader level is Industry which includes all the firms that existed during the period

1986-2000 and it was found that random-walk was not in operation. Chapter 5 also analysed the growth process at this level and found the same results. Since the cluster analysis was based on cross-sectional data for year 2000 (see subsection 6.1.2), the second level of analysis was survivors and not survivors firms of the period 1986-2000. In neither case was random-walk in operation. The third level analysed was the clusters where three distinctive groups of firms where identified, each with different growth performance. Random-walk operates in Cluster 2 formed by 8 Large & Diversified firms but not in Clusters 3 formed by 41 Medium & Specialized firms or Cluster 4 formed by 185 Small & Very specialized firms. The fourth level of analysis uses two variables, technology-class (high v/s low-growth grades) and type-class (incumbents v/s new-entrants firms), to decompose clusters. This four level decomposition process showed that 83% of total cumulative capacity of survivor firms operates under random-walk conditions within their specific group, remaining a residual of 17%.

This research question has provided a deeper understanding of the technological influence in shaping the dynamics and industrial structure of the p&p sector. However the analysis was based exclusively on the US p&p industry. It was not possible to repeat this analysis on a global basis because the disaggregated capacity figures of the 150 largest p&p firms were not available. Nonetheless, it may be possible that the conclusions obtained for the US may apply to the global industry where the world largest 150 firms operate. These reasons include: a) the non situated characteristics of this industry, b) low barriers for the availability of state-of-the-art capital equipment, c) common inputs to the production process, d) the U.S. is by far the largest producer and consumer country of p&p products in the world, accounting for roughly one third of the world p&p production and consumption during the period examined

Based on the fact that the p&p industry has experienced continuous and accelerating technological change that have allowed important increments to production scale and productivity (see Chapter 2 subsection 2.2.2), Chapter 7 investigates whether there are distinctive technology adoption patterns across clusters. This should increase our understanding of the effects of technical advances on p&p firms’ technology adoption and dynamic behaviour throughout the complete size distribution.

Figure 6.6 Random-walk analysis at different US p&p industry levels period 1986-2000



Notes:
- *Figures in parenthesis are the number of firms.*
- *Subgroups where random-walk is in operation are coloured grey.*
- *The % figures of levels I and II are related with total industry cumulative capacity during the period 1986-2000.*
- *The % figures of levels III and IV are related with total cumulative capacity of survivors firms during the period 1986-2000.*

Appendix A6.1 Cluster 2, 3 & 4 firms and capacity data in year 2000

Table A6.1a Cluster 2, 3 & 4 firms and capacity data year 2000

seq #	cluster #	firm name	# of grades	total capacity	technology class capacity (th. tonnes)									
					liner	gp	corr	sbb	tissue	news	mp	special	recb	kraft
1	**2**	International Paper	8	12,235	3,879	3,720	522	2,318	0	0	1,075	181	15	526
2	**2**	Georgia Pacific	8	8,742	2,243	2,064	823	502	697	0	1,932	0	190	292
3	**2**	Weyerhaeuser	5	4,696	1,683	900	631	209	0	0	1,274	0	0	0
4	**2**	Champion International	4	3,255	311	2,489	0	0	0	0	341	0	0	113
5	**2**	Willamette	5	3,132	1,317	1,283	338	0	0	0	148	0	0	45
6	**2**	Boise Cascade	6	2,641	472	1,422	109	0	35	395	209	0	0	0
7	**2**	Mead	4	2,404	0	1,642	649	0	0	0	90	23	0	0
8	**2**	Consolidated Papers	4	1,837	0	1,550	115	0	0	0	27	145	0	0
9	**3**	Fort James	4	3,203	0	585	0	254	2,037	0	327	0	0	0
10	**3**	Westvaco	3	2,224	558	775	0	891	0	0	0	0	0	0
11	**3**	Bowater	3	1,971	0	650	0	0	0	930	392	0	0	0
12	**3**	Gaylord Container	4	1,692	1,198	0	64	0	0	0	0	159	0	272
13	**3**	Kimberly Clark	3	1,595	0	181	0	0	1,372	0	0	43	0	0
14	**3**	Stone Container	3	1,578	1,315	0	0	0	0	0	259	0	4	0
15	**3**	Potlatch	4	1,511	0	349	0	567	141	0	454	0	0	0
16	**3**	Jefferson Smurfit	2	1,374	1,223	0	0	0	0	0	0	0	151	0
17	**3**	Temple Inland Forest Pro	3	1,351	0	113	0	634	0	0	0	603	0	0
18	**3**	Longview Fibre	4	1,329	445	0	123	0	0	0	0	381	0	381
19	**3**	Inland Paperboard & Pac	1	1,318	1,318	0	0	0	0	0	0	0	0	0
20	**3**	Tenneco Packaging	1	1,240	1,240	0	0	0	0	0	0	0	0	0
21	**3**	Inland Container	2	1,126	631	0	494	0	0	0	0	0	0	0
22	**3**	Caraustar Industries	2	1,071	72	0	0	0	0	0	0	0	999	0
23	**3**	SD Warren	1	1,057	0	1,057	0	0	0	0	0	0	0	0
24	**3**	Rock Tenn	2	1,051	0	0	163	0	0	0	0	0	888	0
25	**3**	Donohule Industries	3	934	0	141	0	0	0	730	64	0	0	0
26	**3**	Appleton Papers	1	898	0	898	0	0	0	0	0	0	0	0
27	**3**	Mead Coated Board	1	885	885	0	0	0	0	0	0	0	0	0
28	**3**	Procter Gamble	1	825	0	0	0	0	825	0	0	0	0	0
29	**3**	Packaging Corp. America	2	758	0	0	753	0	5	0	0	0	0	0
30	**3**	MacMillan Bloedel	2	753	494	0	259	0	0	0	0	0	0	0
31	**3**	Riverwood International	3	742	572	0	131	0	0	0	0	0	0	40
32	**3**	North Pacific Paper	1	717	0	0	0	0	0	717	0	0	0	0
33	**3**	St Laurent Paperboard	2	700	548	0	152	0	0	0	0	0	0	0
34	**3**	Rayonier	1	680	0	0	0	0	0	0	680	0	0	0
35	**3**	Sonoco Products	2	671	0	0	168	0	0	0	0	0	504	0
36	**3**	Newark Group	1	671	0	0	0	0	0	0	0	0	671	0
37	**3**	US Alliance Pines	3	635	0	86	0	0	0	304	245	0	0	0
38	**3**	Green Bay Packaging	1	635	635	0	0	0	0	0	0	0	0	0
39	**3**	Crown Vantage	2	535	0	372	0	0	0	0	0	163	0	0
40	**3**	Cedar River Paper	1	535	0	0	535	0	0	0	0	0	0	0
41	**3**	Smurfit Newsprint	1	526	0	0	0	0	0	526	0	0	0	0
42	**3**	PH Glatfelter	1	497	0	497	0	0	0	0	0	0	0	0
43	**3**	Greif Board	2	494	124	0	370	0	0	0	0	0	0	0
44	**3**	US Gypsum	1	486	0	0	0	0	0	0	0	0	486	0
45	**3**	Southeast Paper	1	476	0	0	0	0	0	476	0	0	0	0
46	**3**	Buckeye Florida L P	1	460	0	0	0	0	0	0	460	0	0	0
47	**3**	Blue Ridge Paper Produc	2	452	0	230	0	221	0	0	0	0	0	0
48	**3**	Fraser Paper	1	446	0	446	0	0	0	0	0	0	0	0
49	**3**	Augusta Newsprint	1	436	0	0	0	0	0	436	0	0	0	0
50	**4**	Florida Coast Paper	1	436	436	0	0	0	0	0	0	0	0	0
51	**4**	Blandin Paper	1	431	0	431	0	0	0	0	0	0	0	0
52	**4**	Alabama Pine Pulp	1	397	0	0	0	0	0	0	397	0	0	0
53	**4**	Gilman Paper	3	386	0	0	0	172	0	0	0	124	0	89
54	**4**	Seminole Kraft	1	381	381	0	0	0	0	0	0	0	0	0
55	**4**	Alabama River Pulp	1	366	0	0	0	0	0	0	366	0	0	0
56	**4**	Smurfit Stone Container	3	330	4	0	136	0	0	0	0	0	191	0
57	**4**	Wausau	2	327	0	177	0	0	0	0	0	150	0	0
58	**4**	Simpson Tacoma Kraft	2	322	283	0	0	0	0	0	39	0	0	0
59	**4**	Pulp & Paper of America	3	305	0	145	0	0	48	0	112	0	0	0
60	**4**	Lake Superior Paper Ind.	2	298	0	218	0	0	0	0	80	0	0	0

Table A6.1 Cluster 2, 3 & 4 firms and capacity data year 2000 (continuation)

seq #	cluster #	firm name	# of grades	total capacity	liner	gp	corr	sbb	tissue	news	mp	special	recb	kraft
					technological class capacity (th. tonnes)									
61	**4**	Gulf States Paper	2	295	0	0	0	240	0	0	54	0	0	0
62	**4**	Wausau Mosinee Paper	2	288	0	0	0	0	185	0	0	103	0	0
63	**4**	Inexcon Maine	2	272	0	132	0	0	0	141	0	0	0	0
64	**4**	Menasha	1	264	0	0	264	0	0	0	0	0	0	0
65	**4**	Sappi Fine Paper Americ	1	259	0	259	0	0	0	0	0	0	0	0
66	**4**	Graphic Packaging	1	254	0	0	0	0	0	0	0	0	254	0
67	**4**	Alabama River Newsprin	1	254	0	0	0	0	0	254	0	0	0	0
68	**4**	Pasadena Paper	2	253	0	182	0	0	0	0	72	0	0	0
69	**4**	Interstate Paper	1	251	251	0	0	0	0	0	0	0	0	0
70	**4**	Visy	1	248	248	0	0	0	0	0	0	0	0	0
71	**4**	Ponderay Newsprint	1	240	0	0	0	0	0	240	0	0	0	0
72	**4**	Newsprint South	1	234	0	0	0	0	0	234	0	0	0	0
73	**4**	Port Townsend Paper	3	221	32	0	0	0	0	0	70	0	0	119
74	**4**	Garden State Paper	1	218	0	0	0	0	0	218	0	0	0	0
75	**4**	Simkins Industries	1	217	0	0	0	0	0	0	0	0	217	0
76	**4**	Simpson Paper	1	213	0	213	0	0	0	0	0	0	0	0
77	**4**	FSC Paper	3	207	0	0	0	0	54	127	25	0	0	0
78	**4**	Myllykoski Oy/NY Time	1	204	0	204	0	0	0	0	0	0	0	0
79	**4**	Lin Pac	2	203	143	0	60	0	0	0	0	0	0	0
80	**4**	Visy Recycle	2	203	102	0	102	0	0	0	0	0	0	0
81	**4**	Deferiet Paper	1	201	0	201	0	0	0	0	0	0	0	0
82	**4**	Bear Island Paper	1	200	0	0	0	0	0	200	0	0	0	0
83	**4**	Chesapeake	1	200	0	0	0	0	200	0	0	0	0	0
84	**4**	Louisiana Pacific	1	200	0	0	0	0	0	0	200	0	0	0
85	**4**	Finch Pruyn	1	197	0	197	0	0	0	0	0	0	0	0
86	**4**	Ponderosa Fibres Americ	1	191	0	0	0	0	0	0	191	0	0	0
87	**4**	Buckeye Cellulose	2	191	0	0	0	0	0	0	100	91	0	0
88	**4**	Eastern Paper	2	182	0	147	0	0	35	0	0	0	0	0
89	**4**	Cascades	2	172	0	0	150	0	23	0	0	0	0	0
90	**4**	McKinley Paper	1	167	167	0	0	0	0	0	0	0	0	0
91	**4**	Rand Whitney Paperboar	1	159	159	0	0	0	0	0	0	0	0	0
92	**4**	Great Lake Pulp	1	150	0	0	0	0	0	0	150	0	0	0
93	**4**	Republic Paperboard	2	147	28	0	0	0	0	0	0	0	119	0
94	**4**	IVEX Packaging	2	145	0	0	0	0	0	0	0	56	0	89
95	**4**	Fox River Paper	1	144	0	144	0	0	0	0	0	0	0	0
96	**4**	Shasta	2	141	0	91	0	0	0	0	0	50	0	0
97	**4**	Daishowa America	1	141	0	141	0	0	0	0	0	0	0	0
98	**4**	National Gypsum	1	139	0	0	0	0	0	0	0	0	139	0
99	**4**	Wisconsin Paperboard	1	138	0	0	0	0	0	0	0	138	0	0
100	**4**	Abitibi Consolidated	1	136	0	0	0	0	0	136	0	0	0	0
101	**4**	Field Container	1	133	0	0	0	0	0	0	0	0	133	0
102	**4**	Lafayette Paper	1	130	0	0	130	0	0	0	0	0	0	0
103	**4**	Grays Harbor	1	127	0	127	0	0	0	0	0	0	0	0
104	**4**	Mississippi River	1	127	0	0	0	0	0	0	127	0	0	0
105	**4**	Pomona Paper	2	124	0	59	65	0	0	0	0	0	0	0
106	**4**	Groveton Group	1	124	0	0	124	0	0	0	0	0	0	0
107	**4**	Newark Boxboard	1	118	0	0	0	0	0	0	0	0	118	0
108	**4**	Ohio Paperboard	1	113	0	0	113	0	0	0	0	0	0	0
109	**4**	Global Tissue	1	110	0	0	0	0	110	0	0	0	0	0
110	**4**	Plainwell	1	100	0	0	0	0	100	0	0	0	0	0
111	**4**	Manistique Papers	2	100	0	73	0	0	0	27	0	0	0	0
112	**4**	Cross Pointe	1	100	0	100	0	0	0	0	0	0	0	0
113	**4**	Wausau Papers of NH	1	98	0	98	0	0	0	0	0	0	0	0
114	**4**	American Tissue	1	97	0	0	0	0	97	0	0	0	0	0
115	**4**	Burrows Paper	2	95	0	0	0	0	55	0	40	0	0	0
116	**4**	Bay State Paper	1	91	0	0	91	0	0	0	0	0	0	0
117	**4**	Wisconsin Tissue Mills	1	91	0	0	0	0	91	0	0	0	0	0
118	**4**	Schweitzer Mauduit Inter	2	87	0	54	0	0	0	0	0	33	0	0
119	**4**	The New Group	1	86	0	86	0	0	0	0	0	0	0	0
120	**4**	EB Eddy Paper	2	85	0	43	0	0	0	0	0	43	0	0

Table A6.1 Cluster 2, 3 & 4 firms and capacity data year 2000 (continuation)

seq #	cluster #	firm name	# of grades	total capacity	liner	gp	corr	sbb	tissue	news	mp	special	recb	kraft
					technological class capacity (th. tonnes)									
121	**4**	Jackson Paper	1	83	0	0	83	0	0	0	0	0	0	0
122	**4**	Hammermill	1	82	0	82	0	0	0	0	0	0	0	0
123	**4**	Celotex	1	80	0	0	0	0	0	0	0	0	80	0
124	**4**	Marcal Paper Mills	1	80	0	0	0	0	80	0	0	0	0	0
125	**4**	Mohawk Paper Mills	1	78	0	78	0	0	0	0	0	0	0	0
126	**4**	Corrugated Services	1	73	0	0	73	0	0	0	0	0	0	0
127	**4**	Cascade Auburn Fiber	1	73	0	0	0	0	0	0	73	0	0	0
128	**4**	Fibercorr	1	72	0	0	72	0	0	0	0	0	0	0
129	**4**	Badger Paper	1	72	0	72	0	0	0	0	0	0	0	0
130	**4**	Inland Empire Paper	1	72	0	0	0	0	0	72	0	0	0	0
131	**4**	Fox River Fiber	1	70	0	0	0	0	0	0	70	0	0	0
132	**4**	Lyons Falls Pulp & Paper	1	70	0	70	0	0	0	0	0	0	0	0
133	**4**	Four M Paper	1	70	0	0	70	0	0	0	0	0	0	0
134	**4**	Recycled Paper Board	1	67	0	0	0	0	0	0	0	0	67	0
135	**4**	Newman &	1	65	0	0	0	0	0	0	0	0	65	0
136	**4**	APC of New York	2	64	0	0	0	0	32	0	0	0	0	32
137	**4**	Sorg Paper	2	64	0	0	0	0	27	0	0	36	0	0
138	**4**	Halltown Paperboard	1	64	0	0	0	0	0	0	0	0	64	0
139	**4**	Blue Water Fibre L P	1	64	0	0	0	0	0	0	64	0	0	0
140	**4**	White Pigeon Paper	1	64	0	0	0	0	0	0	0	0	64	0
141	**4**	Portage Paper	1	64	0	0	0	0	0	0	0	0	0	64
142	**4**	Encore Paper	1	64	0	0	0	0	64	0	0	0	0	0
143	**4**	Erving Paper Mills	2	63	0	0	0	0	21	0	42	0	0	0
144	**4**	PCDI Oconto Falls Tissu	1	62	0	0	0	0	62	0	0	0	0	0
145	**4**	US Paper Mills	2	62	0	0	30	0	0	0	0	0	32	0
146	**4**	Crane &	1	61	0	61	0	0	0	0	0	0	0	0
147	**4**	FiberMark	2	60	0	0	0	0	0	0	0	22	38	0
148	**4**	Lydall	2	59	0	0	0	0	0	0	0	10	49	0
149	**4**	Kieffer Paper Mills	2	59	0	0	0	0	0	0	35	0	24	0
150	**4**	Nicolet Paper	1	59	0	0	0	0	0	0	0	59	0	0
151	**4**	Pacific Coast Building Pr	1	54	0	0	0	0	0	0	0	0	54	0
152	**4**	Hollingsworth & Vose	1	51	0	0	0	0	0	0	0	51	0	0
153	**4**	Little Rapids	1	51	0	0	0	0	51	0	0	0	0	0
154	**4**	Nicolaus Paper	1	51	0	51	0	0	0	0	0	0	0	0
155	**4**	Buckeye Lumberton	1	50	0	0	0	0	0	0	50	0	0	0
156	**4**	Irving Tissue	1	50	0	0	0	0	50	0	0	0	0	0
157	**4**	Creative Packaging	1	48	0	0	48	0	0	0	0	0	0	0
158	**4**	Cellu Tissue	1	48	0	0	0	0	48	0	0	0	0	0
159	**4**	Simplex Products Group	2	48	25	0	0	0	0	0	0	0	24	0
160	**4**	Garwood Paperboard	1	48	0	0	0	0	0	0	0	0	48	0
161	**4**	California Paperboard	1	48	0	0	48	0	0	0	0	0	0	0
162	**4**	Schoeller Technical Pape	1	48	0	0	0	0	0	0	0	48	0	0
163	**4**	Riverside Paper	1	46	0	46	0	0	0	0	0	0	0	0
164	**4**	Southern Cellulose Prod.	1	45	0	0	0	0	0	0	45	0	0	0
165	**4**	CityForest	1	45	0	0	0	0	45	0	0	0	0	0
166	**4**	Sealed Air	4	44	7	0	8	0	0	0	0	5	0	23
167	**4**	Climax	1	42	0	0	0	0	0	0	0	0	42	0
168	**4**	beckett paper	1	41	0	41	0	0	0	0	0	0	0	0
169	**4**	Seaman Paper	3	40	0	20	0	0	8	0	0	12	0	0
170	**4**	Fort Orange Paper	1	36	0	0	0	0	0	0	0	0	36	0
171	**4**	Valley Converting	1	35	0	0	0	0	0	0	0	0	35	0
172	**4**	Custom Papers Group	2	35	0	0	0	0	0	0	0	12	24	0
173	**4**	USM	1	35	0	0	0	0	0	0	0	0	35	0
174	**4**	Merrimac Paper	1	33	0	0	0	0	0	0	0	33	0	0
175	**4**	Hennepin Paper	1	32	0	32	0	0	0	0	0	0	0	0
176	**4**	Gilbert Paper	1	32	0	32	0	0	0	0	0	0	0	0
177	**4**	Equitable Bag	1	32	0	0	0	0	0	0	0	0	0	32
178	**4**	Great Lakes Tissue	1	32	0	0	0	0	32	0	0	0	0	0
179	**4**	Rockford Paperboard	1	32	0	0	0	0	0	0	0	0	32	0
180	**4**	Re Box Packaging	1	32	0	0	0	0	0	0	32	0	0	0

Table A6.1 Cluster 2, 3 & 4 firms and capacity data year 2000 (continuation)

seq #	cluster #	firm name	# of grades	total capacity	technological class capacity (th. tonnes) liner	gp	corr	sbb	tissue	news	mp	special	recb	kraft
181	**4**	Mead Specialty Paper	2	30	0	19	0	0	0	0	0	11	0	0
182	**4**	Fletcher	1	27	0	27	0	0	0	0	0	0	0	0
183	**4**	Interstate Container	1	27	0	0	27	0	0	0	0	0	0	0
184	**4**	Perkit Folding Box	1	27	0	0	0	0	0	0	0	0	27	0
185	**4**	Ahlstrom Filtration	1	26	0	0	0	0	0	0	0	26	0	0
186	**4**	Papertech	1	25	0	0	0	0	0	0	0	0	25	0
187	**4**	Crystal Tissue	1	25	0	0	0	0	25	0	0	0	0	0
188	**4**	Sorenson Paperboard	1	25	0	0	0	0	0	0	0	0	25	0
189	**4**	Brownville Specialty	1	24	0	0	0	0	0	0	0	0	24	0
190	**4**	Orchids Paper Products	1	24	0	0	0	0	24	0	0	0	0	0
191	**4**	Banner Fiberboard	2	24	12	0	0	0	0	0	0	0	12	0
192	**4**	Pepperell Paper	1	24	0	0	0	0	0	0	0	24	0	0
193	**4**	Monadnock	1	23	0	0	0	0	0	0	0	23	0	0
194	**4**	Coastal Paper	1	23	0	23	0	0	0	0	0	0	0	0
195	**4**	Paper Pak Products	2	23	0	0	0	0	15	0	0	8	0	0
196	**4**	Putney Paper	1	23	0	0	0	0	23	0	0	0	0	0
197	**4**	Munksjo Paper Decor	1	21	0	0	0	0	0	0	0	21	0	0
198	**4**	Atlas Paper Mills Ltd	1	20	0	0	0	0	20	0	0	0	0	0
199	**4**	Dexter	2	20	0	0	0	0	1	0	0	19	0	0
200	**4**	Beloit Box Board	1	19	0	0	0	0	0	0	0	0	19	0
201	**4**	French Paper	1	17	0	17	0	0	0	0	0	0	0	0
202	**4**	Bio Tech Mills	1	17	0	0	0	0	17	0	0	0	0	0
203	**4**	Laurel Hill Paper	1	16	0	0	0	0	16	0	0	0	0	0
204	**4**	Deerfield Specialty Paper	1	16	0	0	0	0	0	0	0	16	0	0
205	**4**	Ohio Pulp Mills	1	16	0	0	0	0	0	0	16	0	0	0
206	**4**	Columbus Secialty Paper	1	16	0	0	0	0	0	0	0	16	0	0
207	**4**	Edwards Paper	1	15	0	0	0	0	15	0	0	0	0	0
208	**4**	Brandywine Paperboard	1	14	0	0	0	0	0	0	0	14	0	0
209	**4**	Bell Packaging	1	14	0	0	14	0	0	0	0	0	0	0
210	**4**	Gabriel Enterprises	2	13	6	0	6	0	0	0	0	0	0	0
211	**4**	Crocker Technical Papers	1	13	0	0	0	0	0	0	0	13	0	0
212	**4**	Rexam DSI	1	12	0	0	0	0	0	0	0	12	0	0
213	**4**	Simplicity Pattern	1	11	0	0	0	0	11	0	0	0	0	0
214	**4**	Parsons NVF	1	11	0	11	0	0	0	0	0	0	0	0
215	**4**	Cheney Pulp & Paper	1	10	0	0	0	0	0	0	10	0	0	0
216	**4**	Rexam	1	10	0	0	0	0	0	0	0	10	0	0
217	**4**	McIntyre Paper	2	9	0	0	0	0	0	0	0	5	0	5
218	**4**	Geo A Whiting Paper	1	9	0	9	0	0	0	0	0	0	0	0
219	**4**	Paper Service	1	8	0	0	0	0	8	0	0	0	0	0
220	**4**	Shryock Brothers	1	8	0	0	0	0	0	0	0	0	8	0
221	**4**	Esleeck	1	8	0	8	0	0	0	0	0	0	0	0
222	**4**	Southworth	1	8	0	8	0	0	0	0	0	0	0	0
223	**4**	Flower City Tissue Mills	1	7	0	0	0	0	7	0	0	0	0	0
224	**4**	Knowlton Specialty Pape	1	6	0	0	0	0	0	0	0	6	0	0
225	**4**	NVF	1	5	0	0	0	0	0	0	0	5	0	0
226	**4**	Martisco Paper	1	5	0	0	0	0	0	0	0	0	0	5
227	**4**	MH Dielectrics	1	5	0	0	0	0	5	0	0	0	0	0
228	**4**	Red Hook Paper	1	5	0	0	0	0	0	0	0	0	5	0
229	**4**	Gusmer Enterprises	1	4	0	0	0	0	0	0	0	4	0	0
230	**4**	Windsor Stevens	1	4	0	0	0	0	0	0	0	0	4	0
231	**4**	McGoldrick Tissue Mills	1	4	0	0	0	0	4	0	0	0	0	0
232	**4**	US packaging	1	4	0	0	0	0	4	0	0	0	0	0
233	**4**	North End Paper	1	3	0	0	0	0	3	0	0	0	0	0
234	**4**	Penacook Fibre	1	2	0	0	0	0	0	0	0	0	2	0

Appendix A6.2 Firms that changed their technology-class over time

Table A6.2a Firms that changed their technology-class (high or low growth grades) or have equal high/low growth grades capacity over time (1986-2000)

#	Firm name	cluster #	year min	year max	# of years 1986-2000	# of years high / low	size mean (000 tonnes)
1	Crown Vantage	3	1993	2000	8	5 / 3	500
2	Kimberly Clark	3	1986	2000	15	14 / 1	1,226
3	Temple Inland Forest Prod.	3	1993	2000	8	5 / 3	1,269
4	Fort James	3	1997	2000	4	3 / 1	2,016
5	Sealed Air	4	1986	2000	15	5 / 10	32
6	Erving Paper Mills	4	1986	2000	15	8 / 7	51
7	Corrugated Services	4	1986	2000	15	13 / 2	53
8	Riverside Paper	4	1993	2000	8	5 / 3	57
9	US Paper Mills	4	1986	2000	15	4 / 11	62
10	California Paperboard	4	1986	2000	15	5 / 10	66
11	Manistique Papers	4	1986	2000	15	2 / 13	69
12	Rand Whitney Paperboard	4	1987	2000	14	6 / 8	81
13	Lafayette Paper	4	1993	2000	8	6 / 2	112
14	Sorg Paper	4	1986	2000	15	12 / 3	121
15	Bell Packaging	4	1990	2000	11	9 / 2	123
16	Gilman Paper	4	1986	2000	15	7 / 8	282
17	Banner Fiberboard	4	1986	2000	15	equal size	24
18	Simplex Products Group	4	1986	2000	15	equal size	40
19	APC of New York	4	1999	2000	2	equal size	64
20	EB Eddy Paper	4	1986	2000	15	equal size	70

Appendix A6.3 Subgroups random-walk tests results and descriptive statistics

Table A6.3a Growth comparison and random-walk tests for HIGH and LOW-GROWTH grades classes within cluster 3

CLUSTER 3 **26 HIGH vs 15 LOW GROWTH GRADES - GROWTH COMPARISON** cl3_HvsLg

CONCLUSION: **Firms of HIGH & LOW-GROWTH grades configurations have no significant growth performance difference**

NEXT STEP: Explore Random-Walk within the two subgroups HIGH & LOW-GROWTH firm's configurations separately

size-class	# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1=High	26	288	12	5	**1,084**	860	3.0	1.7	**8.9**	**37**	324	61	11	17	37	14	8	9	3	4	3	3	3
2=Low	15	174	11	5	**690**	474	1.8	1.1	**6.9**	**26**	124	4	23	7	5	3	0	0	37	11	5	26	5
	41	462	12	5	**936**	763	2.6	1.6	**8.1**	**33**	448	**66**	**34**	15	29	11	6	6	12	6	3	9	4

40.3 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 **26 HIGH GROWTH GRADES CONFIGURATION - RANDOM WALK TEST** cl3_26Hg_s2

CONCLUSION: **Random Walk**

NEXT STEP: Run random-walk test within the two subgroups INCUMBENTS and NEW-ENTRANTS of HIGH-GROWTH GRADES

size-class	# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 <=580	13	145	12	5	**654**	525	2.1	1.1	**12.2**	**45**	98	29	1	26	41	23	1	4	0	2	1	2	0
2 >580	13	143	12	5	**1,518**	914	3.9	1.8	**5.5**	**25**	226	56	14	14	36	9	11	11	4	5	4	3	5
	26	288	12	5	**1,084**	860	3.0	1.7	**8.9**	**37**	324	**85**	**15**	17	37	14	8	9	3	4	3	3	3

29.1 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 **15 LOW GROWTH GRADES CONFIGURATION - RANDOM WALK TEST** cl3_15Lg_s2

CONCLUSION: **Random Walk**

NEXT STEP: Run random-walk test within the two subgroups INCUMBENTS and NEW-ENTRANTS of LOW-GROWTH grades

1 <=500	8	105	14	3	**458**	233	1.2	0.5	**9.2**	**32**	49	1	39	0	1	1	0	0	41	7	2	48	0
2 >500	7	69	10	6	**1,037**	529	2.6	1.3	**3.6**	**14**	75	15	45	12	9	5	0	0	34	15	7	11	8
	15	174	11	5	**690**	474	1.8	1.1	**6.9**	**26**	124	**16**	**84**	7	5	3	0	0	37	11	5	26	5

11.2 (% of total cumulative capacity of survivor firms period 1986-2000)

Note for all the tables of Appendix A6.3:
*'total cumulative capacity' is measured in million tonnes, 'H-gth' and 'L-gth' in %, * significant at 5% level, ** significant at 1% level*

Table A6.3b Growth comparison and random-walk tests for INCUMBENTS and NEW-ENTRANTS classes within cluster 3

CLUSTER 3 **25 INCUMBENTS v/s 16 NEW ENTRANTS - GROWTH COMPARISON** cl3_IvsNE

CONCLUSION: **New entrants, that are smaller in size, have significantly higher growth performance compared with incumbents**

NEXT STEP: Do Random-Walk test within the 25 INCUMBENTS and the 16 NEW-ENTRANTS firms separately

type-class		# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº	type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1=Incum		**25**	375	15	0	**1,007**	803	2.7	1.7	**5.5***	**25**	377	56	28	16	27	12	5	6	14	4	2	9	4
2=N.Entr.		**16**	89	7	4	**688**	534	1.9	1.2	**14.3***	**40**	72	10	6	7	35	7	7	6	3	15	8	11	1
		41	464	12	5	**936**	763	2.5	1.6	**8.1**	**33**	449	**66**	**34**	15	29	11	6	6	12	6	3	9	4

40.3 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 **25 INCUMBENTS - RANDOM WALK TEST** cl3_25I_s2

CONCLUSION: **Random-Walk**

size-class		# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº	limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=500	13	194	15	0	**582**	380	1.7	0.9	**7.8**	**34**	113	17	13	19	22	16	0	0	26	0	1	16	0
2	>500	12	181	15	0	**1,462**	885	3.8	1.8	**4.7**	**22**	263	49	21	15	29	10	8	9	9	6	3	6	6
		25	375	15	0	**1,006**	803	2.7	1.7	**5.5**	**25**	376	**67**	**33**	16	27	12	5	6	14	4	2	9	4

33.8 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 **16 NEW ENTRANTS - RANDOM WALK TEST** cl3_16NE_s2

CONCLUSION: **Not Random-Walk**, smaller firms grow significantly faster than larger firms

1	<=500	8	56	8	5	**525**	580	1.6	1.3	**18.5***	**48**	33	28	19	11	27	7	2	12	0	15	2	23	0
2	>500	8	33	5	3	**943**	319	2.3	0.9	**4.7***	**17**	39	34	19	4	43	7	11	0	5	16	13	0	2
		16	89	7	4	**688**	534	1.9	1.2	**14.3**	**40**	72	**62**	**38**	7	36	7	7	6	3	15	8	11	1

6.5 (% of total cumulative capacity of survivor firms period 1986-2000)

Table A6.3c Random-Walk tests for INCUMBENTS & NEW-ENTRANTS' HIGH-GROWTH grades classes cluster 3 firms

CLUSTER 3 — **16 INCUMBENTS vs 10 NEW ENTRANTS OF 26 HIGH-GROWTH FIRMS-GROWTH COMPARISON** cl3_26Hg_IvsNE

CONCLUSION: **HIGH & LOW growth grades incumbent firms have no significant growth performance difference**

NEXT STEP: Do the Random-Walk test within both groups HIGH and LOW GROWTH GRADES separately

type-class	# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1=Inc.	16	238	15	0	**1,140**	911	3.2	1.7	**7.4**	**34**	272	71	13	19	35	14	7	9	3	4	1	3	4
2=N.Ent.	10	50	6	3	**924**	605	2.3	1.5	**14.7**	**46**	52	14	3	9	48	9	10	9	0	3	11	1	1
	26	288	12	5	**1,084**	860	3.0	1.7	**8.9**	**37**	324	**85**	**15**	17	36	13	8	9	3	4	3	3	3

29.1 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 — **16 HIGH-GROWTH CONFIGURATION INCUMBENT FIRMS - RANDOM WALK TEST** cl3_16Hg_I_s2

CONCLUSION: **Random-Walk**

size-class	# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 <=580	8	119	15	0	**637**	460	2.2	0.8	**9.1**	**41**	76	27	1	29	42	27	0	0	0	0	0	3	0
2 >580	8	119	15	0	**1,634**	971	4.2	1.8	**5.8**	**26**	196	58	14	15	33	10	10	12	4	6	2	3	5
	16	238	15	0	**1.140**	911	3.2	1.7	**7.4**	**34**	272	**85**	**15**	19	35	14	7	9	3	4	1	3	4

24.4 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3 — **10 HIGH-GROWTH CONFIGURATION NEW ENTRANT FIRMS - RANDOM WALK TEST** cl3_10Hg_NE_s2

CONCLUSION: **Not Random-Walk,** smaller firms have significantly higher growth than larger firms whithin the 10 HIGH-GROWTH grades firms

NEXT STEP: Finish since it is not possible to subdivide more the data

1 <=550	5	26	6	5	**719**	731	2.0	1.8	**26.4***	**51**	22	37	5	16	39	10	4	19	0	7	3	1	0
2 >550	5	24	6	3	**1,034**	329	2.6	0.8	**4.2***	**15**	30	46	11	3	55	9	14	0	0	0	17	1	2
	10	50	6	3	**924**	605	2.3	1.5	**14.7**	**46**	52	**84**	**16**	9	48	9	10	8	0	3	11	1	1

4.7 (% of total cumulative capacity of survivor firms period 1986-2000)

Table A6.3d Random-Walk tests for INCUMBENTS & NEW-ENTRANTS' LOW-GROWTH grades classes cluster 3 firms

CLUSTER 3	**9 INCUMBENTS vs 6 NEW ENTRANTS OF 15 LOW-GROWTH FIRMS - GROWTH COMPARISON**																								cl3_15Lg_IvsNE
CONCLUSION:	**LOW-GROWTH NEW-ENTRANTS have significant higher growth than LOW-GROWTH INCUMBENTS**																								
NEXT STEP:	Do the Random-Walk test within both groups INCUMBENTS & NEW ENTRANTS LOW-GROWTH separately																								
type-class		# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)										
Nº	type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft	
	1=Inc.	**9**	135	15	0	**772**	490	1.9	1.2	**4.4***	**16**	104	15	69	8	6	4	0	0	42	5	6	24	6	
	2=N.Ent.	**6**	39	8	5	**444**	317	1.4	0.7	**14.8***	**45**	20	1	15	2	2	0	0	0	10	47	0	38	0	
		15	174	11	5	**690**	474	1.8	1.1	**6.9**	**26**	124	**16**	**84**	7	5	3	0	0	37	11	5	26	5	

11.2 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3	**9 LOW-GROWTH CONFIGURATION INCUMBENTS - RANDOM WALK TEST**																								cl3_9Lg_I_s2
CONCLUSION:	**Random-Walk**																								
size-class		# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)										
Nº	limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft	
1	<=500	5	75	15	0	**509**	174	1.2	0.5	**5.3**	**19**	38	0	36	0	0	1	0	0	54	0	2	42	0	
2	>500	4	60	15	0	**1,100**	555	2.8	1.2	**3.2**	**13**	66	18	46	13	10	6	0	0	35	7	7	13	10	
		9	135	15	0	**772**	490	1.9	1.2	**4.4**	**16**	104	**18**	**82**	8	6	4	0	0	42	5	6	24	6	

9.4 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 3	**6 LOW-GROWTH CONFIGURATION NEW ENTRANTS - RANDOM WALK TEST**																								cl3_6Lg_NE_s2
CONCLUSION:	It is not possible to compare growth rates because the sample size of the 3 largest firms is too small																								
1	<=500	3	30	11	3	**343**	302	1.3	0.5	**18.7**	**50**	11	2	55	0	3	0	0	0	0	29	0	67	0	
2	>500	3	9	4	4	**722**	142	1.7	1.0	**6.2**	**22**	9	2	41	5	0	0	0	0	24	71	0	0	0	
		6	39	8	5	**444**	317	1.4	0.7	**14.8**	**45**	20	**4**	**96**	2	2	0	0	0	10	47	0	38	0	

1.8 (% of total cumulative capacity of survivor firms period 1986-2000)

<u>Discussion of area Cluster 3-C of Figure 6.4 and Tables A6.3c and A6.3d data:</u>

When the 41 cluster's 3 firms were decomposed by both technology-classes and type-classes, four subgroups were formed. Random-walk test were conducted within each of them and the following results were obtained:

- **16 high-growth grades incumbents firms**
  Random-walk is in operation since there is no significant difference in growth performance between the 8 larger and the 8 smaller companies (9.1% v/s 5.8%).
- **9 low-growth grades incumbents firms**
  Random-walk is in operation since there is no significant difference in growth performance between the 5 larger and the 4 smaller companies (5.3% v/s 3.2%).
- **10 high-growth grades new-entrant firms**
  Random-walk is not in operation since the 5 smaller companies have significant higher growth-rate compared with the 5 larger companies (26.4% v/s 4.2%).
- **6 low-growth grades new-entrant firms**
  There are no enough data to compare growth performance between the 3 smaller companies and the 3 larger companies.

Four between-groups comparisons are conducted in order to test if there are significant average growth differences between subgroups. The followings are the results obtained:

- **16 high-growth grades incumbents v/s 9 low-growth grades incumbents**
  There is not a significant difference in growth performance between the 16 high-growth grades incumbents v/s the 9 low-growth grades incumbents firms.
- **10 high-growth grades new-entrant v/s 6 low-growth grades new-entrants**
  There is not a significant difference in growth performance between the 10 high-growth grades new-entrants v/s the 6 low-growth grades new-entrants firms.
- **16 high-growth grades incumbents v/s 10 high-growth grades new-entrants**
  There is not a significant difference in growth performance between the 16 high-growth grades incumbents v/s the 10 high-growth grades new-entrants firms.
- **9 low-growth grades incumbents v/s 6 low-growth grades new-entrants**
  There is not a significant difference in growth performance between the 9 low-growth grades incumbents v/s the 6 low-growth grades new-entrants firms.

Table A6.3e Growth comparison and random-walk tests for HIGH and LOW-GROWTH grades classes within cluster 4

CLUSTER 4 — **95 HIGH vs 90 LOW GROWTH GRADES - GROWTH COMPARISON.** — cl4_HvsLg

CONCLUSION: Firms of HIGH & LOW-GROWTH grades configurations have no significant growth performance difference

NEXT STEP: **Explore Random-Walk within the two subgroups HIGH & LOW-GROWTH grades firms separately**

configu-ration	# of: firms	obs.	years av	sd	size(th.tonnes) av	sd	# grades av	sd	growth(%) av	sd	cumulat. capacity total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1=High	**95**	980	11	6	**112**	185	1.5	0.9	**2.6**	**22**	114	46	8	44	18	10	3	11	0	7	5	1	2
2=Low	**90**	1,049	12	5	**89**	104	1.3	0.6	**2.0**	**19**	97	5	41	1	3	3	3	1	19	26	11	28	6
	185	2,029	11	5	**100**	149	1.4	0.8	**2.3**	**21**	211	**51**	**49**	24	11	7	3	6	9	16	7	13	4

18.9 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4 — **95 HIGH GROWTH GRADES CONFIGURATION - RANDOM WALK TEST** — cl4_95Hg_s4

CONCLUSION: **NOT Random-Walk, the largest size-class has significantly lower growth performance than the smaller size-classes**

size-class Nº	limits	# of: firms	obs.	years av	sd	size(th.tonnes) av	sd	# grades av	sd	growth(%) av	sd	cumulat. capacity total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<= 35	**26**	348	14	3	**18**	21	1.3	0.7	**2.7***	**19**	6	5	1	18	5	12	0	53	0	3	2	5	3
2	35-65	**23**	237	11	6	**53**	32	1.4	0.8	**3.3***	**26**	13	11	1	55	6	9	0	23	0	1	3	3	0
3	65-150	**23**	191	9	6	**104**	54	1.3	0.5	**2.4***	**20**	21	18	1	47	0	33	0	14	0	1	4	0	1
4	> 150	**23**	204	9	6	**339**	294	2.0	1.4	**-0.2***	**12**	73	52	12	43	27	2	5	4	0	10	5	0	3
		95	980	11	6	**112**	185	1.5	0.9	**2.6**	**22**	114	**85**	**15**	44	18	10	3	11	0	7	5	1	2

10.3 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4 — **90 LOW GROWTH GRADES CONFIGURATION - RANDOM WALK TEST** — cl4_90Lg_s4

CONCLUSION: **Random walk**

Nº	limits	firms	obs.	years av	sd	size av	sd	# grades av	sd	growth(%) av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<= 29	**30**	387	13	4	**19**	21	1.2	0.4	**2.9**	**25**	7	1	7	0	10	0	0	0	0	9	35	38	8
2	29-55	**20**	223	12	5	**44**	16	1.0	0.2	**2.0**	**16**	10	1	9	2	0	9	0	0	0	9	27	48	5
3	55-140	**21**	245	12	5	**101**	41	1.5	0.7	**2.1**	**15**	25	5	22	2	5	7	0	2	14	17	3	44	5
4	> 140	**19**	194	11	6	**263**	111	1.4	0.7	**0.1**	**15**	53	4	51	0	2	1	5	0	27	36	8	16	7
		90	1,049	12	5	**89**	104	1.3	0.6	**2.0**	**19**	97	**11**	**89**	1	3	3	3	1	19	26	11	28	6

8.7 (% of total cumulative capacity survivor firms period 1986-2000)

Table A6.3f Growth comparison and random-walk tests for INCUMBENTS and NEW-ENTRANTS classes within cluster 4

CLUSTER 4 **111 INCUMBENTS v/s 74 NEW ENTRANTS - GROWTH COMPARISON** cl4_IvsNE

CONCLUSION: New entrants, that are smaller in size, have significantly higher growth performance compared with incumbents

NEXT STEP: **Do random walk analysis for the 111 incumbents and the 74 new entants firms separately**

type-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 = Incum	**111**	1,663	15	0	**97**	158	1.4	0.8	**1.8***	**18**	161	38	38	27	8	6	4	6	6	16	9	14	4
2 = N.Ent.	**74**	364	6	4	**111**	106	1.2	0.5	**3.9***	**19**	49	13	10	15	23	9	0	9	16	14	1	9	3
	185	2,027	11	5	**100**	149	1.4	0.8	**2.0**	**19**	210	**51**	**49**	24	11	7	3	6	9	16	7	13	4

18.9 (% of total cumulative capacity of survivor firms period 1986-2000)

CLUSTER 4 **111 INCUMBENTS - RANDOM WALK TEST** cl4_111I_s4

CONCLUSION: **Not random walk**, smaller firms grow faster than large firms within the 111 incumbents

size-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 <= 30	**37**	554	15	0	**15**	18	1.2	0.6	**3.2****	**21**	8	3	2	13	1	8	0	34	0	7	19	15	4
2 30-70	**28**	420	15	0	**40**	24	1.4	0.7	**2.4****	**21**	17	5	5	30	4	9	0	6	0	6	24	19	3
3 70-180	**23**	345	15	0	**94**	43	1.4	0.5	**2.1****	**17**	32	9	11	29	2	7	0	7	11	9	4	27	3
4 > 180	**23**	345	15	0	**301**	249	1.8	1.3	**-0.1****	**15**	104	33	31	27	11	5	6	3	6	21	8	9	5
	111	1,664	15	0	**97**	158	1.4	0.8	**1.8**	**18**	161	**50**	**50**	27	8	6	4	6	6	16	9	14	4

14.5 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4 **74 NEW ENTRANTS - RANDOM WALK TEST** cl4_74NE_s4

CONCLUSION: **Not random walk**, the two smaller size classes grow faster than two larger size classes within the 74 new entrants

1 <= 35	**21**	125	7	4	**32**	30	1.0	0.2	**4.8***	**21**	5	5	4	5	16	0	0	32	0	5	4	30	8
2 35-75	**18**	95	6	4	**68**	30	1.1	0.3	**3.4***	**20**	8	8	7	0	6	36	0	12	0	13	0	32	2
3 75-180	**18**	82	6	4	**130**	46	1.5	0.8	**1.2***	**16**	13	16	11	25	14	10	0	10	24	10	2	2	3
4 > 180	**17**	62	5	5	**298**	90	1.3	0.6	**1.5***	**6**	23	26	22	17	35	1	0	2	21	19	1	2	3
	74	364	6	4	**111**	106	1.2	0.5	**3.9**	**19**	49	**55**	**45**	15	23	9	0	9	16	14	1	9	3

4.4 (% of total cumulative capacity survivor firms period 1986-2000)

Table A6.3g Random-Walk tests for INCUMBENTS and NEW-ENTRANTS' HIGH-GROWTH grades classes cluster 4 firms

CLUSTER 4	**54 INCUMBENTS v/s 41 NEW ENTRANTS OF 95 HIGH GROWTH FIRMS - GROWTH COMPARISON**																							cl4_Hg_IvsNE
CONCLUSION:	Not significant differences between INCUMBENTS and NEW ENTRANTS																							
NEXT STEP:	**Do the random walk test within both groups INCUMBENTS and NEW ENTRANTS separated**																							
type-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)										
Nº type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft	
1 = Incum	**54**	809	15	0	**109**	199	1.5	1.0	**2.2**	**21**	88	64	13	49	13	9	4	9	0	8	6	1	2	
2 = N.Ent.	**41**	172	5	4	**123**	117	1.3	0.5	**4.4**	**24**	26	21	2	27	37	12	0	16	0	3	2	0	3	
	95	980	11	6	**112**	185	1.5	0.9	**2.6**	**22**	114	**85**	**15**	44	18	10	3	11	0	7	5	1	2	

10.2 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4	**54 HIGH GROWTH CONFIGURATION INCUMBENT FIRMS - RANDOM WALK TEST**																							cl4_54Hg_I_s4
CONCLUSION:	**Not random walk,** the largest size class has a significantly smaller growth performance compared with the other three size classes																							
size-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)										
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft	
1 <= 20	**17**	254	15	0	**14**	9	1.1	0.7	**2.6***	**19**	3	4	0	32	2	2	0	55	0	0	4	0	6	
2 20-60	**14**	208	15	0	**45**	36	1.7	0.9	**2.9***	**19**	9	9	1	46	7	12	0	21	0	3	4	7	0	
3 60-140	**12**	180	15	0	**94**	59	1.3	0.4	**1.9***	**20**	17	18	1	56	0	28	0	10	0	1	4	0	0	
4 > 140	**11**	165	15	0	**352**	331	2.2	1.6	**-0.6***	**13**	58	53	14	48	18	3	6	5	0	11	6	0	3	
	54	807	15	0	**109**	199	1.5	1.0	**2.2**	**21**	87	**84**	**16**	49	13	9	4	9	0	8	6	1	2	

7.9 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4	**41 HIGH GROWTH CONFIGURATION NEW ENTRANT FIRMS - RANDOM WALK TEST**																							cl4_41Hg_NE_s4
CONCLUSION:	**Not random walk,** the two smaller size classes grow faster than two larger size classes																							
1 <=35	**11**	54	7	4	**26**	24	1.0	0.1	**7.0***	**37**	2	6	0	1	0	0	0	98	0	0	1	0	0	
2 35-75	**10**	35	5	4	**76**	32	1.2	0.4	**7.2***	**23**	3	13	0	0	13	58	0	27	0	0	0	0	2	
3 75-150	**10**	44	5	4	**109**	25	1.3	0.5	**1.5***	**12**	6	22	1	54	0	19	0	23	0	0	3	0	2	
4 >150	**10**	39	4	5	**298**	100	1.5	0.6	**1.6***	**8**	15	52	7	25	61	0	0	3	0	6	1	0	4	
	41	172	5	4	**123**	117	1.3	0.5	**4.4**	**24**	26	**92**	**8**	27	37	12	0	16	0	3	2	0	3	

2.3 (% of total cumulative capacity survivor firms period 1986-2000)

Table A6.3h Random-Walk tests for INCUMBENTS and NEW-ENTRANTS' LOW-GROWTH grades classes cluster 4 firms

CLUSTER 4 **57 INCUMBENTS v/s 33 NEW ENTRANTS OF 90 LOW GROWTH FIRMS - GROWTH COMPARISON** cl4_Lg_IvsNE

CONCLUSION: Not significant differences between INCUMBENTS and NEW ENTRANTS

NEXT STEP: **Do the random walk test within both groups INCUMBENTS and NEW ENTRANTS separated**

type-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº type	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 = Incum	**57**	855	15	0	**86**	106	1.3	0.5	**1.7**	**19**	74	8	69	1	2	3	3	1	14	26	13	31	7
2 = N.Ent.	**33**	194	7	5	**101**	95	1.2	0.6	**2.8**	**21**	23	3	21	2	7	5	0	0	35	27	1	20	3
Cluster 4	**90**	1,049	12	5	**89**	104	1.3	0.6	**2.0**	**19**	97	**11**	**89**	1	3	3	3	1	19	26	11	28	6

8.7 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4 **57 LOW GROWTH CONFIGURATION INCUMBENTS - RANDOM WALK TEST** cl4_57Lg_I_s4

CONCLUSION: **Random walk**

size-class	# of:		years		size(th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº limits	firms	obs.	av	sd	av	sd	av	sd	av	sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1 <= 25	**20**	300	15	0	**13**	10	1.2	0.4	**2.9**	**25**	4	0	5	0	0	0	0	0	0	9	56	32	3
2 25-50	**12**	180	15	0	**39**	15	1.1	0.4	**1.8**	**15**	7	1	8	0	0	13	0	0	0	13	43	24	7
3 50-100	**13**	195	15	0	**94**	42	1.5	0.6	**2.2**	**13**	18	3	22	3	1	5	0	3	20	14	3	45	5
4 > 100	**12**	180	15	0	**246**	121	1.6	0.7	**0.1**	**16**	44	6	54	0	3	0	6	0	14	34	9	26	8
	57	855	15	0	**86**	106	1.3	0.5	**1.7**	**19**	73	**10**	**90**	1	2	3	3	1	14	26	13	31	7

6.6 (% of total cumulative capacity survivor firms period 1986-2000)

CLUSTER 4 **33 LOW GROWTH CONFIGURATION NEW ENTRANTS - RANDOM WALK TEST** cl4_33Lg_NE_s3

CONCLUSION: **Random walk**

1 <= 35	**12**	73	7	5	**38**	34	1.1	0.2	**3.6**	**27**	3	4	10	7	24	0	0	0	0	8	5	43	13
2 35-100	**12**	77	7	4	**75**	39	1.3	0.8	**1.9**	**20**	7	8	21	0	12	15	0	0	0	26	2	41	4
3 > 100	**9**	44	6	5	**244**	79	1.1	0.3	**0.9**	**14**	13	1	55	1	0	1	0	0	62	32	0	3	0
	33	194	7	5	**101**	95	1.2	0.6	**2.8**	**21**	23	**14**	**86**	2	7	5	0	0	35	27	1	20	3

2.1 (% of total cumulative capacity survivor firms period 1986-2000)

<u>Discussion of area Cluster 4-C of Figure 6.4 and Tables A6.3g and A6.3h data:</u>

When the 185 cluster's 4 firms were separated by both technology-classes and type-classes, four subgroups were formed. Random-walk test was conducted within each of them and the following results were obtained:

- **54 high-growth grades incumbents firms**
  Random-walk is not in operation since the 11 firms of the largest size-class have significant less growth-rate average compared with the three smaller size-classes (growth rate varies from -0.6% to 2.9%).
- **57 low-growth grades incumbents firms**
  Random-walk is in operation since there is no significant difference in growth performance among the four size-classes.
- **41 high-growth grades new-entrant firms**
  Random-walk is not in operation since the two smaller size-classes have significant higher growth-rates compared with the two larger size-classes (7.2% v/s 1.5%).
- **33 low-growth grades new-entrant firms**
  Random-walk is not in operation since there is no significant difference in growth performance among the three size-classes.

Four between-groups comparisons are conducted in order to test if there are significant average growth differences between subgroups. The followings are the results obtained:

- **54 high-growth grades incumbents v/s 57 low-growth grades incumbents**
  There is not a significant difference in growth performance between the 54 high-growth grades incumbents v/s the 57 low-growth grades incumbents firms.
- **41 high-growth grades new-entrant v/s 33 low-growth grades new-entrants**
  There is not a significant difference in growth performance between the 41 high-growth grades new-entrants v/s the 33 low-growth grades new-entrants firms.
- **54 high-growth grades incumbents v/s 41 high-growth grades new-entrants**
  There is a significant difference in growth performance between the 54 high-growth grades incumbents v/s the 41 high-growth grades new-entrants firms, since the latter group has a significant higher growth-rate compared with the former group (4.4% v/s 2.2%).
- **57 low-growth grades incumbents v/s 33 low-growth grades new-entrants**
  There is not a significant difference in growth performance between the 57 low-growth grades incumbents and the 33 low-growth grades new-entrants firms.

Table A6.3i Random-walk tests for: all 414 firms, 234 survivors and 180 not-survivors year 2000, within the period 1986-2000

Random walk test for: 414 FIRMS THAT HAVE EXISTED IN THE INDUSTRY DURING THE PERIOD 1986-2000

CONCLUSION: **Not random walk.** Growth rates are significant different across size-classes.

NEXT STEP: **Separate the data according to the 234 survivors and the 180 non-survivors firms year 2000 and run random-walk test**

size-class		# of:		years		size (th.tonnes)		# grades		growth(%)		cumulat. capacity			cumulative capacity distribution (%)									
Nº	limits	firms	obs.	av	sd	av	sd	av	sd	**av**	**sd**	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=20	80	773	10	6	15	17	1.1	0.5	**3.1****	**23**	11	0	0	18	0	6	0	32	0	6	20	13	5
2	20-60	114	945	9	5	51	74	1.2	0.6	**3.1****	**20**	50	1	2	15	5	10	0	10	0	5	10	43	3
3	60-180	107	916	9	5	117	86	1.4	0.7	**1.9****	**18**	256	5	3	11	5	6	0	4	3	3	3	8	1
4	180-540	64	562	9	6	434	324	1.5	0.7	**4.4****	**23**	256	11	8	17	24	9	3	6	16	11	2	11	1
5	>540	49	489	10	6	1,882	1,730	4.4	2.4	**2.0****	**18**	941	51	18	27	26	8	8	6	5	12	3	3	4
		414	3,685	9	5	359	883	1.7	1.5	**2.9**	**21**	1,372	68	32	24	23	8	6	7	7	11	3	7	3

100 (% of total cumulative industry capacity within the period 1986-2000)

Random walk test for: 234 SURVIVOR FIRMS YEAR 2000, period 1986-2000

CONCLUSION: **Not random walk.** Growth rates are significant different across size-classes.

Nº	limits	firms	obs.	years av	years sd	size av	size sd	grades av	grades sd	growth av	growth sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=20	42	580	14	3	15	18	1.2	0.5	**3.7***	**23**	9	0	0	13	1	8	0	34	0	6	20	14	4
2	20-60	55	608	12	5	54	91	1.3	0.6	**3.1***	**24**	34	1	2	15	6	9	0	8	0	4	12	43	3
3	60-180	60	599	11	5	126	101	1.5	0.7	**2.2***	**18**	79	4	3	29	13	13	0	6	8	9	4	14	4
4	180-540	46	440	10	6	435	352	1.5	0.8	**4.3***	**23**	201	9	9	18	19	9	3	2	20	10	3	13	1
5	>540	31	385	13	5	2,000	1,883	4.6	2.4	**2.8***	**19**	786	53	18	29	25	8	8	4	5	12	2	2	4
		234	2,612	12	5	411	994	1.8	1.6	**3.2**	**21**	1,109	68	32	26	23	9	6	4	8	11	3	6	3

80.9 (% of total cumulative industry capacity within the period 1986-2000)

Random walk test for: 180 NON-SURVIVOR FIRMS YEAR 2000, period 1986-2000

CONCLUSION: **Not random walk.** Growth rates are significant different across size-classes.

Nº	limits	firms	obs.	years av	years sd	size av	size sd	grades av	grades sd	growth av	growth sd	total	H-gth	L-gth	gp	liner	corr	sbb	tissue	news	mp	special	recb	kraft
1	<=20	37	193	6	4	14	13	1.0	0.0	**3.1****	**26**	3	1	0	33	0	1	0	24	0	5	19	10	9
2	20-60	60	341	6	4	45	22	1.1	0.3	**2.6****	**16**	16	3	4	13	2	12	0	16	0	8	5	42	2
3	60-180	47	313	7	5	101	41	1.4	0.6	**1.7****	**14**	33	6	6	17	5	15	0	13	2	5	13	30	0
4	180-540	18	122	7	5	432	193	1.4	0.5	**5.1****	**25**	55	17	4	12	40	9	0	20	2	11	0	5	0
5	>540	18	104	6	4	1,447	852	3.6	2.2	**-0.6****	**14**	155	42	17	17	26	4	8	15	1	14	5	6	3
		180	1,073	6	4	232	492	1.5	1.1	**2.1**	**19**	262	68	32	16	25	7	5	16	2	12	5	11	2

19.1 (% of total cumulative industry capacity within the period 1986-2000)

CHAPTER 7

THE EFFECTS OF TECHNOLOGY ADVANCES ON PAPER AND PULP INDUSTRY DYNAMICS

Chapter 6 demonstrated the existence of technological configurations of p&p firms that give rise to clusters or strategic groups which reveal a particular structure within the industry. These clusters of specific technological configurations have experienced persistent heterogeneous growth performance which explains why the industry does not follow Gibrat's law, as demonstrated in Chapter 5. The central aim of this chapter is to add to the empirical literature on industrial dynamics by providing evidence of the significant influence of p&p industry technology advances on firm survival, as well as on the patterns of firm's technology adoption behaviour, and on the patterns of industry capacity expansion during the period 1970-2000.

The importance of firm entry and exit as determinants of industry dynamics and performance is acknowledged in the literature (Dunne, Roberts et al. 1988). Firms' technology adoption behaviour over time and across the three clusters identified in Chapter 6 is of special interest in the context of the p&p industry because of the significant technological changes described in Chapters 1 and 2 (see Figure 1.2). The increased speed of paper machines has allowed an important increment in production scale and productivity but also considerably increased costs and risks for p&p firms purchasing new equipment. The higher risks are associated with the high investment needed to allocated on one state-of-the-art paper machine and its implications in terms of the large jump in capacity (Diesen 1998) and high sunk costs.[103]

[103] Paper machines are among the world's largest machines. They are 200 m. in length, 9 m. wide and cost more than US$300 million. The increased speed and width of state-of-the-art newsprint machines

How these technology advances have affected the dynamics of the p&p industry and firms' technology adoption behaviour during the period 1970-2000 are investigated in this chapter. More specifically the research questions related to the existence and causality of survival and technology adoption patterns of p&p firms over time that were proposed in Chapter 3 are:

- Within the US p&p industry are there distinctive patterns of non-survivor firms during the period 1970-2000?
- If so, what are their sources?
- Within the US p&p industry are there distinctive patterns of firm's technology adoption behaviour over time and across the three clusters identified in Chapter 6?
- What proportion of the US p&p industry capacity expansion is explained by state-of-the-art technology adoption and what proportion is explained by incremental technology improvements and upgrading?

The availability of production capacity data in the population of US p&p firms over the three decades 1970 to 2000 allows us to study the dynamics and evolution of the industry over a considerable period of time. The chapter is organized in three sections. Section 7.1 investigates the dynamics of the p&p industry over time; it proposes an exit hazard model and examines the determinants of firm survival. Section 7.2 investigates the patterns of firms' technology adoption behaviour and its implications for p&p industry capacity expansion during the study period. Section 7.3 summarizes the results and presents the main conclusions of the chapter.

7.1 Dynamics of the p&p industry in 1970-2000

In order to deepen our investigation of the dynamics of the p&p industry we analyse patterns of firm entry, exit and growth over three decades through the construction of several transition matrixes. We propose an exit hazard model and investigate the determinants of firm survival. Finally in this section we analyse the significant differences in survival hazard functions over time, specifically between the periods 1970-1985 and 1986-2000.

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have increased their production scale from 75,000 to more than 350,000 tonnes/year over the period 1960-2000 (Haunreiter 1997).

7.1.1 Patterns of firm entry, exit and growth (the transition matrixes)

To make a first examination of patterns of entry, exit and growth among US p&p firms, we construct transition matrixes of the complete population of US p&p firms. The transition matrix for the whole period 1970-2000 is presented in Table 7.1 and the transition matrixes for each decade are contained in Appendix A7.1. A transition matrix shows firms' movements in terms of size within specific time periods. We can deduce how many firms entered, exited, persisted or shifted size-position during each period. To construct these matrixes it is necessary to divide the size scale into a number of ranges, each of which forms a size-class. Thus we divide the scale following a geometric progression, with the upper limit of any interval being twice its lower limit. Several authors use similar criteria when analysing the dynamics of firm growth over time (Hart and Prais 1956; Singh and Whittington 1975; Dunne and Hughes 1994). In our analysis the 14 upper limits, measured in '000 tonnes per year are: 2, 4, 8, 16, 32, 64, 128, 256, 512, 1,024, 2,048, 4,096, 8,192 and 16,384. This constant geometric scale allows us to represent firm growth (e.g. firm size in year 2000/firm size in year 1990) as the movement from one size-class to another. The proportionate growth scale used varies in the following ranges: 1/64, 1/32, 1/16, 1/8, 1/4, 1/2, 1, 2, 4, 8, 16, 32 and 64. Thus, if a firm moves upwards four classes, this means its size has increased by approximately 16 times. On the other hand if a firm moves downwards three classes, this means that it has become 8 times smaller.

The matrix in Table 7.1 shows firms' movements along the size-classes axes and across the full historical period 1970-2000. The 'total in 1970' column shows the distribution of firms in year 1970 along the 14 size-classes measured in terms of number and percentage of firms. '# of non-survivors to 2000' shows the distribution of firms that did not survive to year 2000 in terms of number and percentage of firms. 'Survivors to 2000' shows the distribution of firms that survived to 2000 measured in terms of number and percentage. The column 'Size-class of survivor firms to year 2000' (which is subdivided into the 14 size-classes) shows how firms that were positioned in each size-class in year 1970 are distributed along the 14 size-classes in year 2000.

The transition matrix shows that of the 300 firms in existence in 1970, 107 survived to 2000 while 193 did not. The smaller firms tend to have lower survival rates than the

Table 7.1 Transition matrix of p&p firms full period 1970-2000

size class		capacity (th tonnes)	total in 1970		# of non survivors to 2000	survivors to 2000		Size-class of survivor firms to year 2000													
								1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
			#	**%**		**#**	**%**	2	4	8	16	32	64	128	256	512	1,024	2,048	4,096	8,192	8,192
1	<=	2	3	1%	3		0%	**0**													
2	<=	4	20	7%	14	6	30%	1	**1**	1	2	1									
3	<=	8	15	5%	9	6	40%			**3**	3										
4	<=	16	34	11%	22	12	35%			1	**5**	3	3								
5	<=	32	71	24%	46	25	35%				1	**10**	10	2	2						
6	<=	64	41	14%	25	16	39%					1	**5**	8	1		1				
7	<=	128	25	8%	19	6	24%							**3**	2	1					
8	<=	256	36	12%	20	16	44%						1	2	**4**	4	1	3	1		
9	<=	512	28	9%	19	9	32%								2	**3**	3	1			
10	<=	1,024	17	6%	11	6	35%								1		**0**	2	3		
11	<=	2,048	6	2%	4	2	33%											**1**	1		
12	<=	4,096	3	1%	1	2	67%												**0**	1	1
13	<=	8,192	1	0%	0	1	100%													**0**	1
14	>	8,192	0	0%																	**0**
			300	**100%**	**193**	**107**	**36%**	**1**	**1**	**5**	**11**	**15**	**19**	**15**	**12**	**8**	**5**	**7**	**5**	**1**	**2**
			arrivals in the period			127	54%	0	3	2	5	17	20	18	25	16	12	8	1	0	0
			total in 2000:			**234**		**1**	**4**	**7**	**16**	**32**	**39**	**33**	**37**	**24**	**17**	**15**	**6**	**1**	**2**
			% in 2000:					0%	2%	3%	7%	14%	17%	14%	16%	10%	7%	6%	3%	0%	1%

Proportionate growth (size in 2000 / size in 1970)			**1/64**	**1/32**	**1/16**	**1/8**	**1/4**	**½**	**1**	**2**	**4**	**8**	**16**	**32**	**64**	**128**
Number of survivor firms (1970-2000)	**107**	**36%**					2	8	35	39	15	6	2			
% of survivor firms (1970-2000)							2%	7%	33%	36%	14%	6%	2%			

Note: Values in bold in cells are the count of firms who maintain their size class. Those above (below) the diagonal define grow (decline) over the period. Zeroes are entered to fully delineate the diagonal.

larger firms. Of the 107 firms that survived the full period 1970-2000, 35 (33%) firms stayed in the same size class, 62 (58%) grew between 2 to 16 times their initial sizes – e.g. two medium size firms grew approximately 16 times their initial size; and 10 (9%) firms moved down one or two size classes which means that they reached sizes 1/2 to 1/4 that of which they began.

Next we analyse ‘entry’ and ‘exit’ dynamic processes in the US p&p industry, based on the transition matrixes presented in Table 7.1 and Appendix A7.1.

Non-survivors

Table 7.2 provides a view of the non-survivor firms across size classes and over time.[104] During the 1970s, 25% of the firms that existed in year 1970 did not survive to year 1980; the percentage of non-survivors during the 1980s is 30% and during the 1990s is 39% (last row of Table 7.2). In other words, firms’ exit rate increased considerably over time. When the analysis is at size-class level, the percentage of non-survivor small firms per decade (first raw of table 7.2) varies from 27% in the 1970s, to 42% in the 1990s. Among the medium-sized firms the percentage varies between 23% and 38%, and in the large-size class it varies from 0% to 26%. We can conclude that the biggest share of non-survivors is among small firms and the smallest share of exiting firms is in the large firms group.

Table 7.2 Number of non-survivor firms per size-class and per decade

Firms size	1970	1971-1980		1980	1981-1990		1990	1991-2000	
(th. tonnes)	#[1]	#[2]	%[3]	#[1]	#[2]	%[3]	#[1]	#[2]	%[3]
Small (<= 64)	184	50	27%	168	53	32%	135	57	42%
Medium (64-1,024)	106	24	23%	106	30	28%	107	41	38%
Large (> 1024)	10	0	0%	14	4	29%	23	6	26%
All size-classes	300	74	25%	288	87	30%	265	104	39%

Source: own elaboration, data taken from FPL-UW database.

Notes: [1]Number of firms per size-class in specific years. [2]Number of exit firms per size-class per decade. [3]Percentage of non-survivors out of the total number of firms that existed within the size class at the beginning of the decade.

[104] In this case we consider three size classes not five as in Chapter 5 where we test Gibrat’s law. This is, because the analysis in this chapter relates to non-survivor firms with the result that there are fewer data which require a smaller number of size classes and different boundaries.

Table 7.3 shows the distribution of the non-survivors across size classes for the period 1970-2000, and per decade. Of the total number of firms that exited the industry in the full period (265 non-survivors), 60% belong to the small size class, 36% to the medium, and 4% to the large (second column of Table 7.3). The general pattern persists over the three decades but in slightly different proportions.

Table 7.3 Distribution of non-survivor firms per size-class and per decade

Firms size (th. tonnes)	1971-2000	1971-1980	1981-1990	1991-2000
Small (<=64)	160 (60%)	50 (68%)	53 (61%)	57 (55%)
Medium (64-1,024)	95 (36%)	24 (32%)	30 (34%)	41 (39%)
Large (>1,024)	10 (4%)	0 (0%)	4 (5%)	6 (6%)
All size-classes	265 (100%)	74 (100%)	87 (100%)	104 (100%)

Source: own elaboration, data taken from FPL-UW database.
Figures in brackets correspond to the % of non-survivors across the different size-classes per decade.

From the above two tables we conclude that a substantial proportion (25% to 39%) of p&p firms that existed in any of the three decades did not survive and this mortality pattern persists and even increases over time. Also, there is a persistent inverse relationship between size and exit rate since smaller firms display the highest exit rates and while large firms have the best chance of surviving.

<u>New-entrants</u>

The transition matrixes show that a substantial number of firms entered the industry during the three decades studied; however, total new entrants (199) is less than total number of firms that exited (265), thus the number of firms in the industry reduced from 300 in year 1970 to 234 in year 2000. Table 7.4 presents a summary of the new-entrant firms across size classes and over time. During the 1970s, new-entrants that survive to 2000 represent 21% of the firms that existed in year 1970, this figure increased to 22% for the 1980s and to 28% for the 1990s (last row in Table 7.4). In the 1990s, the number of entrants is higher than in the previous two decades (73 firms compared with 64 and 62 firms).

If we base the analysis on size-class level, two patterns emerge. Within the small size-class the number of firms that enter the industry decreases over time from 41 (22%) in the 1970s to 25 (19%) in the 1990s. However, in the medium size-class the number of new entrants increased significantly from 21 (20%) in the 1970s to 44 (41%) in the 1990s, and in the large-size class new-entrants increased from 0 in the 1970s to 4 firms (22%) in the 1990s.

Table 7.4 Number of new-entrant firms per size-class and per decade

Firms size (th. tonnes)	1970	1971-1980		1980	1981-1990		1990	1991-2000	
	#[1]	#[2]	%[3]	#[1]	#[2]	%[3]	#[1]	#[2]	%[3]
Small (<= 64)	184	41	22%	168	33	20%	135	25	19%
Medium (64-1,024)	106	21	20%	106	29	27%	107	44	41%
Large (> 1,024)	10	0	0%	14	2	14%	23	4	17%
All size-classes	300	62	21%	288	64	22%	265	73	28%

Source: own elaboration, data taken from FPL-UW database.
Notes: [1]Number of firms per size-class in specific years. [2]Number of new-entrants per size-class per decade. [3] Percentage of new-entrants out of the total number of firms that existed within the size class at the beginning of the decade.

Table 7.5 shows the distribution of new-entrants across size-classes for the full period, and per decade. Of the total number of new-entrants over the whole period (199), 50% were in the small size-class, 47% in the medium size-class, and just 3% in the large size-class. However, in terms of new-entrants per decade we find that in the 1970s 66% were small firms and 34% were medium sized firms. In the 1990s 34% of new arrivals were small firms, 60% were medium and 6% large firms.

Table 7.5 Distribution of new-entrant firms per size-class and per decade

Firms size (th. tonnes)	1971-2000	1971-1980	1981-1990	1991-2000
Small (<= 64)	99 (50%)	41 (66%)	33 (52%)	25 (34%)
Medium (64-1,024)	94 (47%)	21 (34%)	29 (45%)	44 (60%)
Large (> 1,024)	6 (3%)	0 (0%)	2 (3%)	4 (6%)
All size-classes	199 (100%)	62 (100%)	64 (100%)	73 (100%)

Source: own elaboration, data taken from FPL-UW database.
Figures in brackets correspond to the % of new-entrants across size-classes and decade.

From the above analyses of exit and new entrant firms we can conclude that both processes have been important in shaping the dynamics of the p&p industry during the period 1970-2000. Over the three decades, 265 firms exited the industry and 199 new firms entered and survive to 2000, with a reduction in the total number of companies from 300 to 234. Chapter 6 demonstrated the significant influence of new-entrants on heterogeneous firm growth along the size distributions, and their contribution to explaining the departure from Gibrat's law that was demonstrated in Chapter 5. In the following subsection we propose an exit hazard model in order to investigate more deeply the determinants of firm survival.

7.1.2 Exit hazard model and determinants of firm survival

First, following Kaplan-Meier (1958), we present some basic survival data and estimates (see Figure 7.1) for the cohorts of firms in the period 1970-2000 without consideration of covariates. Figure 7.1 shows that the survival function declines with firm age, however, there are three distinct parts to the survival curve. The highest exit rates occur along the first part of the curve when firms are young (40% of firms exit after less than 25 years). In part II the exit rate moderates for firms up to 100 years old, and in part III for older firms the exit rate curve flattens out (15% of firms exit after more than 100 years). This convex shape is consistent with the selection pattern being more severe during the first years, moderating in the intermediate years and flattening out at the end of the life-cycle.

Figure 7.1 Kaplan-Meier survival estimates US p&p firms, all cohorts period 1970-2000

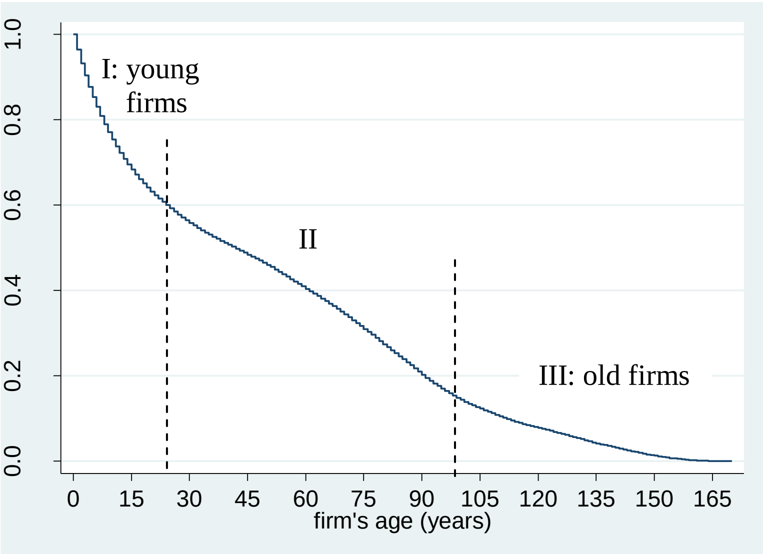
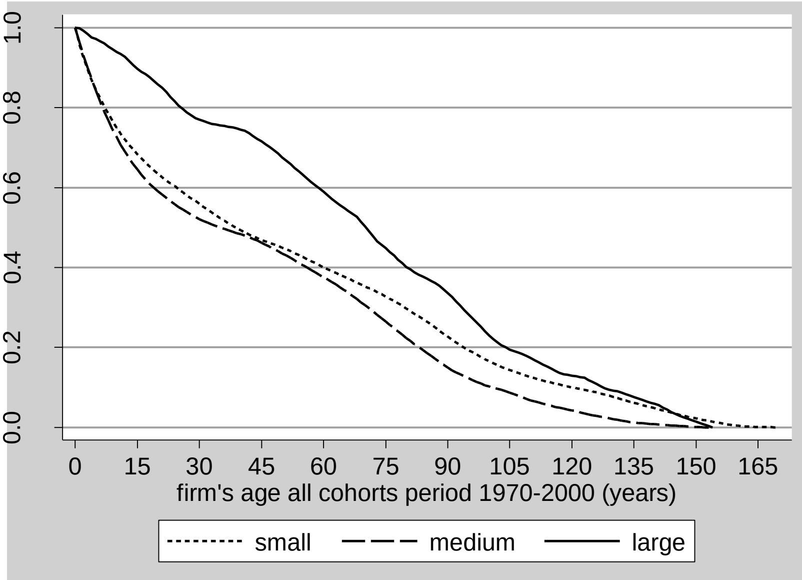


Figure 7.2 illustrate the Kaplan-Meier survival function but in this case separated into size-classes: small (<=64 th.tonnes) medium (>64 and <1,024 th.tonnes) and large firms (>1,024 th.tonnes). Figure 7.2 shows that the firms in the large size-class are more likely to survive than firms in the small and medium size classes. Roughly 90% of large firms

and 65% of small and medium firms survive for at least 15 years. Roughly 78% of large firms and 53% of small and medium firms survive for at least 30 years.

Figure 7.2 Kaplan-Meier survival estimates US p&p firms, all cohorts period 1970-2000 by size-classes



We use a log-rank test to investigate the equality of the three survivor functions between size classes, thus we test the null hypothesis Ho: h1(t) = h2(t)= h3(t). From the results in Table 7.6 we can conclude that the null hypothesis of equality of the three size-class survivor functions is clearly rejected.

Table 7.6 Log rank test for equality of firm's survivors between size-classes

size_class	# of observed events	# of expected events	chi2 test
small	3,948	4,219	Chi2(2) = 165.6
medium	3,263	2,781	
large	565	776	
total	7,776	7,776	Pr>chi2 = 0.000

However, none of the above proves that just being large means a firm is more likely to survive. We need to consider other variables and to adopt a more general hazard model, such as developed below.

Hazard survival model

In order to investigate the determinants of firm survival we use a general hazard model that allows for the explanatory variables to vary across the study period. Hazard function is a statistical technique determining the conditional probability that an individual will experience an event in time t (in our case that a firm will exit the industry), given that the individual was subject to the risk that the event might occur in the past time t (in our case, given survival past time t). Thus the hazard function is defined as:

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \tag{7.1}$$

where:

$f(t)$ is a probability density function which corresponds to a failure density function

$F(t) = \int_0^t f(x)dx$ is the failure distribution, thus a cumulative distribution function

$S(t) = 1 - F(t)$ is a survivor density function or population of survivors

Since the hazard rate is likely to change over time, it is necessary to decide upon the functional form determining whether the hazard depends upon time and the different explanatory variables.[105] Several probability distributions can be used to model the failure distribution. 106 For the present investigation we use the Cox Proportional Hazard Model (Cox 1972) which is a log-linear model given by:

$$h_i(t) = h_0(t)\exp(Z(t)\beta) \tag{7.2}$$

where:

- ***$h_i(t)$***: is the hazard function for firm *i* which indicates the probability that firm *i* exits the industry in the interval *t* to *t+1*, conditional upon having survived until period *t*.

---

[105] In the literature the terms 'explanatory variable', 'time-varying explanatory variable' and 'time-varying covariate' are all used to refer to the same phenomena.

[106] Some distributions are Exponential, Weibull and Log-normal regression models.

- ***$h_0(t)$****:* is the baseline hazard, or hazard for a firm when the value of all the independent variables is equal to zero. We use Cox's (1975) and Audretsch and Mahmood's (1995) method to estimate equation 7.2 using a partial likelihood function which does not require $h_0(t)$ to be specified. Thus, we obtain estimates for β avoiding the risk of mis-specifying the baseline hazard function.[107]

- *t*: is the time since the firm entered the industry (in years)

- ***Z(t)***: is a vector of the independent or explanatory variables that can vary over time. These variables can include: firm specific, market, technology, economic cycle characteristics, etc.

- β : is the vector of the regression coefficients

The Cox Proportional hazard model assumes a log-linear relationship between the hazard function and the explanatory variables; it assumes also that the impact of, say a price shock on the hazard, is the same irrespective of whether the firm is 1 or many years old. We check both assumptions.

This model has been used by several authors since it allows for the explanatory variables to vary during the study period and also it is a semi-parametric model and, thus, does not rely on parametric assumptions for the underlying hazard distribution. This model was used by Disney et al. (2003) to analyse UK manufacturing companies in the period 1986-1991. Mata et al. (1995) studied the survival hazard rates of all companies operating in Portugal from 1983 to 1990. Boeri and Cramer (Boeri and Cramer 1992) estimated the determinants of the hazard rate of survivals and exits using German data and Roberts and Samuelson (1989) studied the determinants of exit rates using several explanatory variables such as size, age, industry, year and ownership type.

The next step in our analysis is to define the explanatory variables. There is extensive discussion in the literature about which variables might be included in an analysis of this type. As a general guide for empirical analysis of entry and exit firms we use Jovanovic's (1982) model of industry evolution. The model is driven by a selection process in which relatively efficient firms prosper and grow, while inefficient ones

[107] Because $h_0(t)$ is an unspecified baseline hazard function this method is described as semi-parametric. See Lancaster (1990) for a further discussion of duration models.

contract and fail. This model focuses on several factors that are likely to be important for an empirical examination of the entry, exit and growth processes. They can be at different levels of aggregation such as: economic context or economic cycle, technology context or technological regime, market/industry level or firm level.[108] The variables considered relevant for our investigation and thus employed in our hazard model are defined and discussed below.

Energy context

- International energy price

The p&p industry is an energy intensive consumer industry and, since the early 1970s energy prices has experienced important changes, thus this variable may have a significant influence on p&p firms' survival rates. The annual average US Retail Prices of Electricity for Industrial Sectors index shown in Appendix A7.2 is used as an instrument for this factor.[109] We expect energy prices to be positively correlated with the hazard rate since the higher the energy costs the higher the probability of exit.

Technology context

- State-of-the-art technology change

This variable is designed to capture the possible impact of exogenous technological change (or technological opportunity) in the p&p industry. For its estimation we use data on the world technology frontier paper machine speeds, during the period 1970-2000 (see Figure 1.2 in Chapter 1). We expect this variable to be positively correlated with the hazard exit rate since higher operating speeds mean bigger and more expensive machines which increase the probability of firms (especially small ones) exiting the industry.

[108] Some authors include plant level variables (Mata, Portugal et al. 1995; Disney, Haskel et al. 2003), however we do not have data disaggregated at plant level.

[109] The cost of electrical energy for p&p operations is influenced by the long-standing use of co-generation in which some of the raw materials and waste heat generated by industrial process is used to offset electrical energy purchase. While this may lower the average cost of electricity at individual plants, the average marginal cost of electrical energy is likely to be closely related to the variable chosen.

Market/industry level[110]

- Industry concentration

This variable is designed to capture the possible impact of changes in industry concentration on firm survival. It is measured using the Herfindahl index explained and calculated in Chapter 2 (subsections 2.2.2 and 2.3.2). It is difficult to anticipate a priori the type of correlation between these two variables.

Firm level

- Current firm size

This is defined as the natural logarithm of firm's annual capacity. This variable is used in several studies of survival and is usually negatively correlated with the hazard rate meaning that the larger the firm the lower the exit risk.

- Initial firm size

This is defined as the natural logarithm of a firm's annual capacity in its entry year or, in 1970 for companies in existence in 1970 or before. This variable is also used in other survival studies (Mata, Portugal et al. 1995; Disney, Haskel et al. 2003) since it provides a way to relate start-up size and survival hazard rate. The two studies referenced here find a positive relationship between these two variables meaning that the exit hazard rate increases with larger initial firm size.

- Firm growth-rate

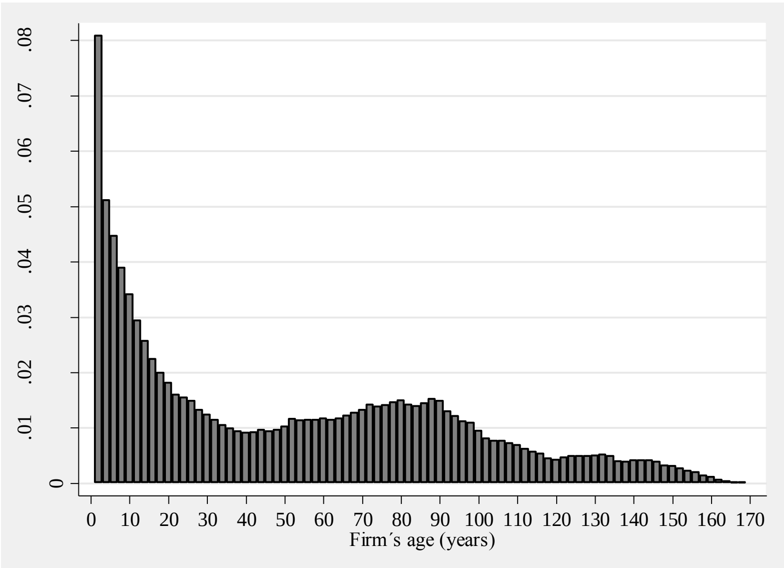
This is defined as the firm's year-to-year capacity growth-rate and captures the influence of year to year changes in firm size on firm survival. This variable is used in several survival studies and is usually negatively correlated to hazard rate, thus, the probability of exiting the industry diminishes with firm growth. Because in this industry changes in firm capacity could be the result of lumpy investments, we prefer not to anticipate the type of correlation.

[110] Some studies include the variable 'market size' to capture the influence of changes in total industry capacity or output on firms. In the present study this is not necessary since we use firm capacity as a proxy for firm size, and industry size is the sum of all individual firm capacities.

- Firm age

To define the variable for firm age we need to specify two situations. For firms that appear for the first time in the database after 1970 (approximately half of the firms in our sample) we can define age as the difference between the current and the entry year. For companies that already existed in 1970, which do not correspond to an entry cohort since they are a mix of entrants in 1970 plus survivors from earlier years, we use start up year.[111] Figure 7.3 shows the distribution of firms by age measured in years. The age distribution is widely spread, since the oldest firm is 170 years and the youngest is 1 year. The average firm is 52 years old with a standard deviation of 43 years and a median of 44 years. The age distribution appears to have two modes. The first for approximately the 8% of the firms that are 1 or 2 years old, and the second for the firms that are around 80 years old.

Figure 7.3 Firms' age distribution



Firm age is a relevant explanatory variable in our Cox model, however it is not possible to include it directly due to collinearity with the base line hazard. Therefore, we limit its use to studying the interaction of firm age with the other firm level explanatory variables such as current size, initial size and growth.[112] According to Jovanovic (1982) we would expect hazard exit rates to decrease with firm age since older firms are able

[111] Of the total population of 566 US p&p firms that existed during the period 1970-2000, we were able to find start up years for 521. The 45 firms whose start up date we could not identify represent less than 8% of the population.

[112] The Weibull parametric model which is run after the Cox model allows us to include age as direct explanatory variable.

more accurately to estimate their features, thus, after a time, future expectations about cost efficiency are less likely to be below the level that would induce exit.

- Technological diversification

The fifth firm level variable that we considered is technological diversification which is defined as the quotient of number of the firm's technological classes divided by total number of possible technological classes which is 13.[113] This variable is used in several survival studies, including Audretsch (1991), since it can be interpreted as the capacity of a firm to innovate. It is generally negatively correlated with the hazard rate meaning that more diversified firms are less likely to exit the industry. However because of the strong co linearity with firm size, we cannot include this variable in the model.

<u>Time-period</u>

A dummy variable for time-period is included in the model which allows comparison of hazard rates across the two periods 1970-1985 and 1986-2000, and investigation of factors that may explain their difference.

Table 7.7a shows descriptive statistics for the explanatory variables used in the model for the full period 1970-2000. There are no missing values for the variables and the number of firm-year observation is 7,776.

Table 7.7a Descriptive statistics for the main explanatory variables, 1970-2000

explanatory variable	unit	mean	median	st.dev.	min.	max.
energy price	USD	5.7	5.6	1.1	3.6	8.0
machine speed	mts/min	1,401	1,372	314	1,067	2,000
industry concentration	herfindhale	0.024	0.023	0.003	0.020	0.034
current firm size	ln(tonnes)	4.4	4.2	1.7	0.6	9.4
initial firm size	ln(tonnes)	4.1	3.9	1.6	0.6	8.5
annual growth-rate	annual %	3.6	0.0	27.1	-92.0	305.0
firm age	years	52	44	43	1	170

Table 7.7b presents the correlation coefficients of the seven explanatory variables during the period 1970-2000 which tend to be low except for the two cases of 'machine

[113] In subsection 2.3.2 Chapter 2, we discussed the technological diversification of US p&p firms during the period 1970-2000.

speed-herfindahl index' and the 'current size-initial size' that are high. We will take account of the possible effects of these high correlations in doing the hazard modelling.

Table 7.7b Correlation coefficient of explanatory variables within the period 1970-2000

explanatory variables	energy price	machine speed	Herfindahl Index	current size	initial size	growth rate	age
energy price	1.000						
machine speed	-0.262	1.000					
herfindahl index	-0.279	0.934	1.000				
current size	-0.021	0.095	0.089	1.000			
initial size	-0.024	0.015	0.015	0.944	1.000		
growth rate	-0.010	0.002	-0.003	0.077	-0.008	1.000	
age	-0.003	-0.019	-0.017	-0.022	-0.008	-0.053	1.000

The Cox proportional model is formulated in terms of the effect of a unit change in a covariate increasing the hazard function (which represents the exit probability) by a factor of exp(β). The sign of the estimated coefficients indicates the direction of the effect of the variable on the hazard function. A positive coefficient implies a higher probability of death, thus shorter durations. A negative coefficient implies a lower probability of death, thus larger duration.

Table 7.8 presents the regression coefficients and the hazard ratio values that result of the application of the Cox Proportional model with nine explanatory variables to our database of 566 US p&p firms that existed during 1970-2000.

Table 7.8 Cox Proportional model results with time varying covariates, 1970-2000

Variable	Coeffient	Std. Err.	Haz.Ratio	Std. Err.	z	P > |z|
energy price	-.0324	.0617	.9682	.0597	-0.52	.600
machine speed	.0020	.0006	1.002	.0006	3.52	.000
herfindahl index	-144.6	51.7	1.61e-63	8.31e-62	-2.80	.005
ln_mppb	-.7016	.2300	.4958	.1140	-3.05	.002
ln_mppb_in	.7075	.2447	2.029	.4965	2.89	.004
growth	-.0030	.0059	.9970	.0059	-0.51	.613
Interaction variables						
ln_mppb-age	.0016	.0039	1.002	.0039	0.42	.677
ln_mppb_in-age	-.0029	.0040	.9971	.0040	-0.72	.474
growth-age	-.0002	.0001	.9998	.0001	-1.67	.094

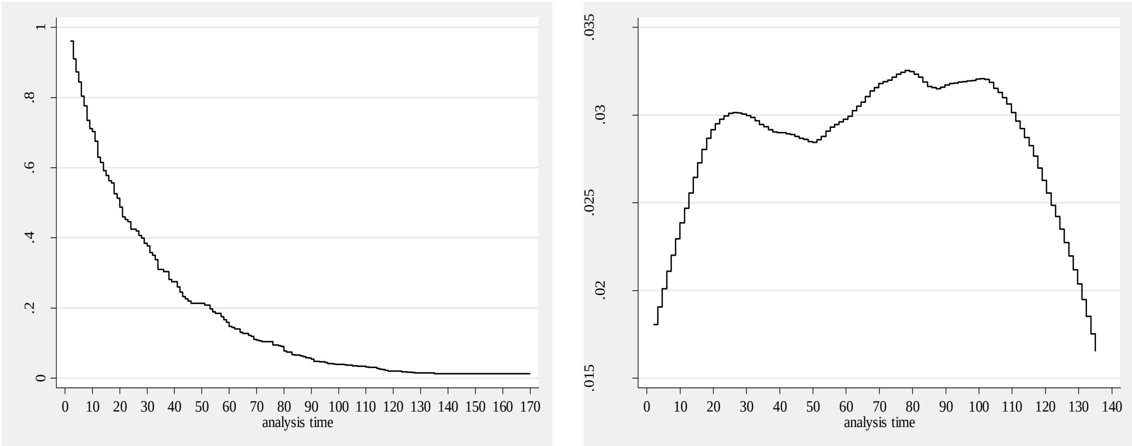
No. of subjects = 486 *No. of obs. = 7,244*
No. of failures = 271 *LR chi2(9) = 54.7*
Log likelihood = -1,163 *Prob > chi2 = 0.000*

The effects of the first contextual variable energy price appears not to be significant, thus changes in energy prices cannot explain changes in the hazard exit rate. The machine speed contextual variable, on the other hand, has a very significant positive coefficient. Considering that the production speed and thus production capacity per unit of time of paper machines have increase significantly, the higher the machine speed, the higher the probability that a p&p firm will exit the industry. At sectoral level, the effect of the industry concentration variable is also significant and negative meaning that an increase in industry concentration reduces the risk of exit.

At firm level, current size has a significant negative coefficient which means that firm size exerts a decisive influence on survival and thus larger firms have a lower risk than smaller firms of exiting the industry. On the other hand, the variable for initial firm size is also significant but its coefficient is positive which means that a larger new-entrant firm has an increased exit hazard rate compared with a start-up of a smaller size. Firm growth is not significant, however the interaction variable ‘growth x age’ has a significant negative coefficient at the 10% confidence level. This means that high growth is not a determinant of firm survival for all types of companies except in the case of the older ones. This could also be interpreted as firms that show persistent growth over long periods have a reduced risk of exit while growth over a short period does not reduce this risk, which would support Jovanovic's (1982) theory that post-entry learning is an important determinant of firm performance. The other two firm level interaction variable current size multiplied by age and initial size multiplied by age are not significant.

The graphs in Figure 7.4 depict the Cox survival and hazard functions. The shape of the survival curve is clearly exponential and more pronounced than the Kaplan-Meier curve in Figure 7.1. The shape of the hazard function is a roughly non-monotonic inverted U, which suggest three phases of exit risk. A first phase for firms between 1 to 25 years old where the exit hazard increases strongly with firm age. A second phase for firms between 25 and 100 years old where the hazard increases more smoothly (on average) with age. A third phase for firms that are more than 100 years old, where the exit risk decreases sharply.

Figure 7.4 Cox proportional hazard regression

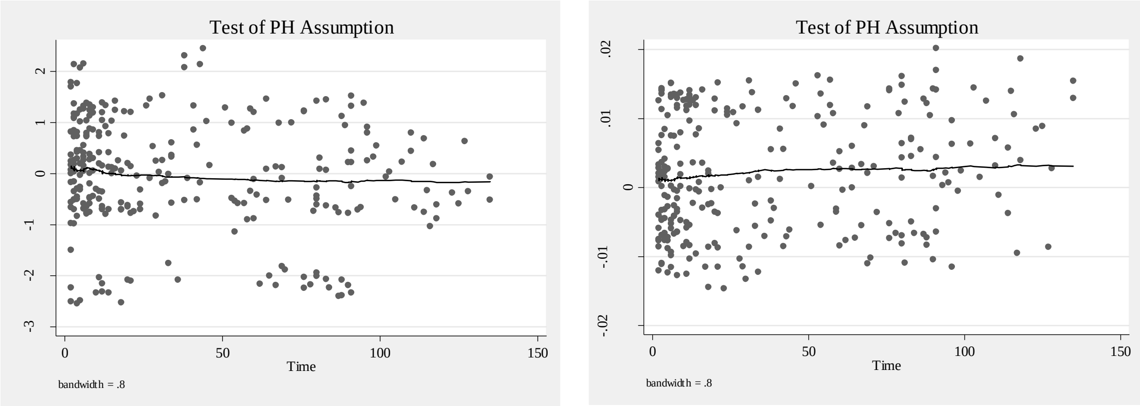


In order to validate the above results we need to check the proportional hazard assumption of the Cox model. We use a test based on Grambsch and Therneau’s (1994) residual linear regression generalization, where the null hypothesis of a zero slope for the individual covariates and globally, is tested. The zero slope is equivalent to testing that the log hazard ratio function is constant over time, thus a rejection of the null hypothesis of a zero slope indicates deviation from the proportional hazard assumption. Table 7.9 presents the results of this test where two explanatory variables ‘energy price’ and ‘machine speed’ violate the assumption, both of which are graphed in Figure 7.5. We observe that the violation occurs because the lines are not horizontal along the first part of the time dimension.

Table 7.9 Cox proportional hazard assumption test

Variable	rho	chi2	df	Prob>chi2
energy price	-0.145	6.49	1	0.011
machine speed	0.151	5.52	1	0.019
herfindahl index	-0.129	3.37	1	0.066
ln_mppb	-0.034	0.30	1	0.582
ln_mppb_in	0.055	0.82	1	0.365
growth	-0.037	0.57	1	0.452
ln_mppb-age	0.012	0.06	1	0.813
ln_mppb_in-age	-0.039	0.57	1	0.452
growth-age	0.051	1.55	1	0.214
global test		23.41	9	0.005

Figure 7.5 Cox proportional hazard assumption test



Bearing in mind the above results demonstrating that the Cox proportional assumption is violated by two explanatory variables, one of which (machine speed) is of particular interest, it is appropriate to consider the parametric distributions proposed in the literature that could be used to model our data and deepen our understanding of the hazard and survival processes. Thus, we conduct a parametric analysis. A better comprehension of the hazard and failure rates may provide better insights into the factors that are more influential in causing the failures.

Use of parametric distribution model

There are several parametric distributions suggested in the literature to model failure times, inlcuding the Wiebull, Log-normal and Log-logistic models. In our case, the selection of the most appropriate parametric distribution is guided by the inverted U-shape exit hazard curve shown in Figure 7.4. The Weibull distribution best accommodates this pattern.[114] This distribution is often used for survival data analysis

[114] The Log-normal hazard and survival functions are defined as:

$$h(t) = \frac{\frac{1}{\sigma t}\phi\left\{\frac{\ln(t)-\mu}{\sigma}\right\}}{\Phi\left\{\frac{-\ln(t)+\mu}{\sigma}\right\}} \qquad s(t) = 1-\Phi\left\{\frac{\ln(t)-\mu}{\sigma}\right\}$$

where ϕ is the probability density function of the normal distribution and Φ is the standard normal cumulative distribution function. The log-logistic is a continuous probability distribution for a non-negative random variable whose logarithm has a logistic distribution. It is similar in shape to the log-normal, but has heavier tails. It is particularly useful for analysing survival data with censoring (Bennett 1983). Log-logistic hazard and survival functions are defined as:

due to its flexibility, since, depending on the values of its parameters, it can model a variety of life behaviours. Its hazard *h(t)* and survival *S(t)* functions are defined as:

$$h(t) = \lambda p t^{p-1} \tag{7.3}$$

$$S(t) = \exp(-\lambda t^{p}) \tag{7.4}$$

Both equations are determined by the value of the shape parameter p and the scale parameter λ. The hazard function is monotonically increasing over time if $p < 1$. It is monotonically decreasing if $p > 1$, and it is constant if $p = 1$. In the Weibull parametric distributions it is possible to include firm age as an explanatory variable since it does not present the co linearity problems that arise in the Cox model. Thus we use seven direct explanatory variables (energy price, machine speed, industry concentration index, current firm size, initial firm size, firm annual growth rate, firm age) and one interaction variable - firm growth-age, which was significant in the Cox model and allows us to check for growth persistence. Since the variable firm age is included in this model, the two interaction variables ln_mppb-age and ln_mppb-age included previously and found not to be significant are omitted here.

Table 7.10 shows the results of applying the Weibull distribution to estimate a hazard model using the maximum likelihood for survival data and the eight explanatory variables. Figure 7.6 shows the Weibull survival and exit hazard regressions.

The results obtained from applying the Weibull model are quite similar to the ones obtained from Cox proportional model. All the coefficients have the same sign and their values are comparables. The two not significant explanatory variables are energy price and firm growth, which means that changes in energy prices or different levels of firm growth during the study period do not explain changes in hazard exit rate.

The new interesting information provided by Table 7.10 is the significant coefficient of the explanatory variables age and the interaction variable growth-age. Age has a negative

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$$h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1+(\lambda t)^{p}} \qquad S(t) = (1+(\lambda t)^{1/p})^{-1}$$

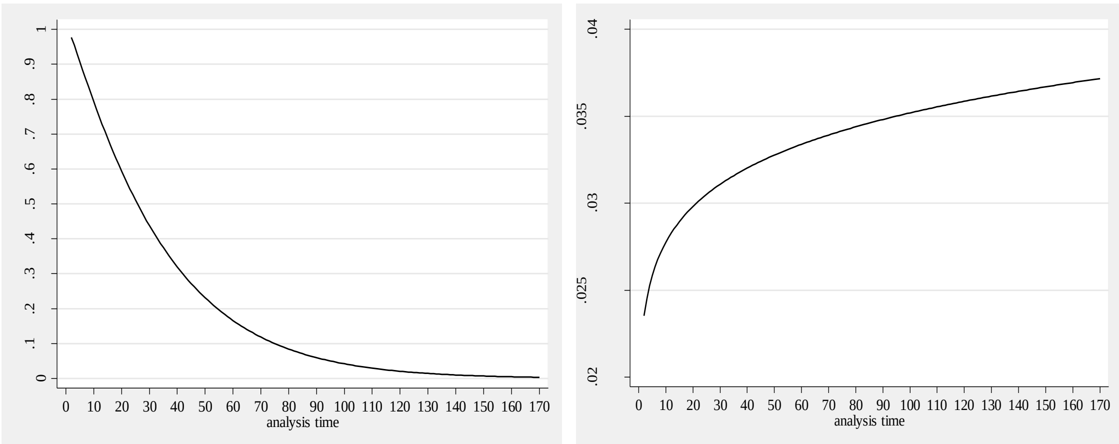
The hazard function is non-monotonic when p > 1 and decreases monotonically when p ≤ 1.

Table 7.10 Weibull model results with time varying covariates, 1970-2000

Variables	Coeffient	Std. Err.	Haz.Ratio	Std. Err.	z	P > |z|
energy price	-.0208	.0614	.9794	.0602	-0.34	0.735
machine speed	.0019	.0005	1.002	.0005	3.48	0.001
herfindahl index	-141.3	51.0	4.5e-62	2.3e-60	-2.77	0.006
ln_mppb	-.6873	.1441	.5029	.0725	-4.77	0.000
ln_mppb_in	.6443	.1515	1.905	.2885	4.25	0.000
growth	-.0014	.0052	.9986	.0052	-0.26	0.793
age	-.0122	.0035	.9879	.0035	-3.45	0.001
Interaction variables						
growth-age	-.0002	.0001	.9998	.0001	-2.39	0.017
constant	-2.044	.8389			-2.44	0.015
/ln_p	.0981	.0934			1.05	0.294
p	1.103	.1031				
1/p	.9066	.0847				

No. of subjects = 486 *No. of obs. = 7,244*
No. of failures = 271 *LR chi2(8) = 65.98*
Log likelihood = -308 *Prob > chi2 = 0.000*

Figure 7.6 Weibull survival and exit hazard functions



coefficient at the 1% confidence level, which means that older firms are less likely to exit the industry than younger firms. The interaction variable growth-age also has a significant negative coefficient at the 2% confidence level (10% in the Cox model). These results confirm that high growth is not a determinant of firm survival for all companies, only for older firms. This could also be interpreted as firms showing persistent growth over long periods reduce their risk of exit but this would not apply to firms showing growth persistence over only short periods of time.

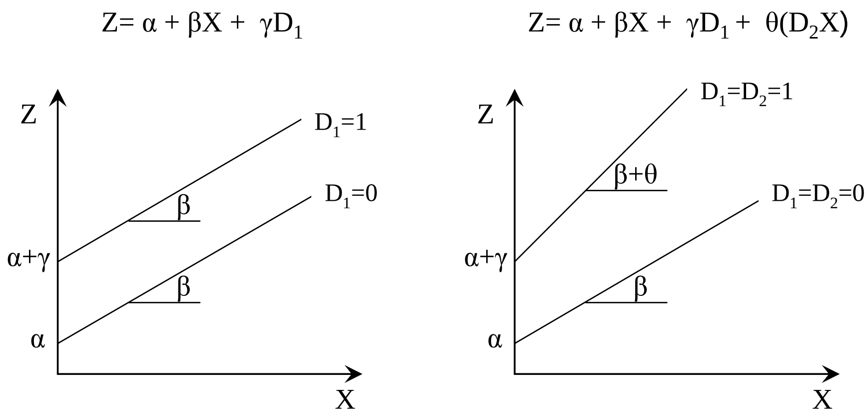
In this subsection we used non-parametric and parametric duration models to estimate the effect of firm, industry and contextual variables on p&p firm survival during the full period 1970-2000. The next subsection analyses firms' hazard exit over time and specifically whether there are differences in survival probabilities for the sub-periods 1970-85 and 1986-00 and if so what are the factors that might explain those differences.

7.1.3 Exit hazard analysis over time using parametric model

In this subsection we are interested in examining p&p firms' survival and exit hazard functions over time. More specifically, we want to compare the periods 1970-1985 and 1986-2000 because of the significant technology change that occurred in the mid 1980s with the introduction of 'automatic process control' technologies which increased the speed of machines significantly.[115]

To conduct this period comparison we use the Weibull model described above and conduct two types of analyses shown graphically in Figure 7.7. First we compare the two periods introducing a dummy variable (D1) as a covariate to model the time-period (left side graph in Figure 7.7). This dummy takes the value 0 if the firm dies during the first period 1970-1985 and value 1 if the firm exits during the second period 1986-2000. This dummy variable captures any possible 'period' effect on the survival and hazard functions keeping the other explanatory variables the same, which means that we assume that the effects of each covariate on the hazard function is the same for both periods. The test that is performed in this first case is H_0: $\gamma = 0$.

Figure 7.7 Graphical interpretation of hazard period comparison[116]



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[115] See section 1.1 in Chapter 1 and section 2.2.1 in Chapter 2.

[116] The equation: $Z = \alpha+\beta X+\gamma D1+\theta(D2X)$ is a re-arrangement of the equation $Z = (\alpha+\gamma D1)+(\beta+\theta D2)X$ where D1 multiplies the axes variable γ and D2 multiplies the slope variable θ.

Table 7.11 shows the Weibull coefficients and hazard ratios and Figure 7.8 shows the survival and exit hazard functions for both periods 1970-1985 and 1986-2000 using a time-period dummy variable and the same eight covariates used before, but not controlling for covariates per period. The null hypothesis Ho of equality of survivor functions is rejected at the 10% significant level, thus both the survival and exit hazard functions are significantly different over time. In the second period, 1986-2000, the firm survival function is significantly lower and firm exit hazard function significantly higher compared with the first period, 1970-1985. Table 7.11 presents the period-dummy coefficient and hazard ratio information and shows that the conditional probability to exit the industry is about 49% higher in the second period than in the first one.[117] The coefficients and hazard ratio values of the significant covariates are similar to those obtained in the previous analysis with no period dummy variable included.

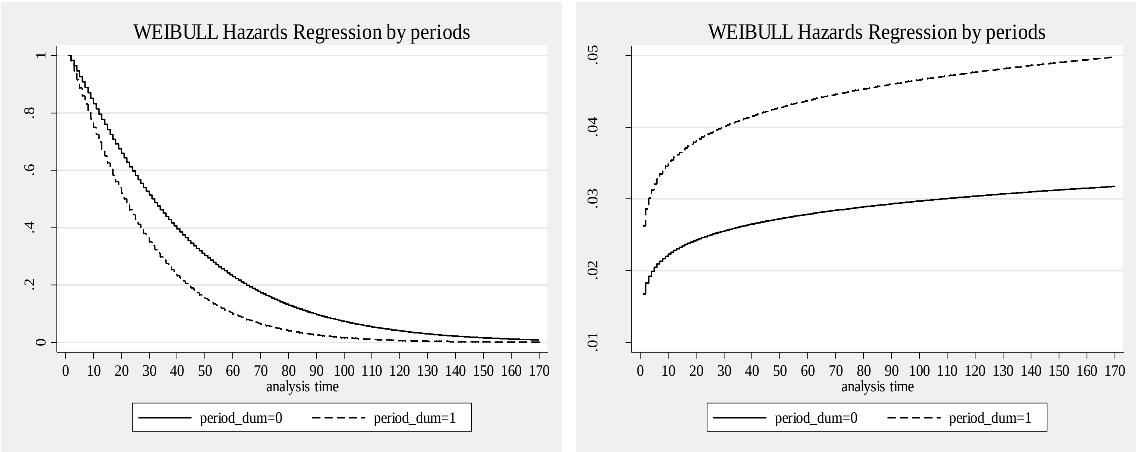
Table 7.11 Weibull coefficients and hazard ratio for 1970-1985 v/s 1986-2000 comparison

Variables	Coeffient	Std. Err.	Haz.Ratio	Std. Err.	z	P > |z|
period_dum	.3979	.2324	1.489	.3460	1.71	0.087
energy price	-.0267	.0627	.9736	.0611	-0.43	0.670
machine speed	.0013	.0006	1.001	.0006	2.10	0.035
herfindahl index	-1,394	51.7	2.9e-61	1.5e-59	-2.69	0.007
ln_mppb	-.6960	.1447	.4986	.0721	-4.81	0.000
ln_mppb_in	.6537	.1522	1.923	.2927	4.29	0.000
growth	-.0015	.0053	.9985	.00527	-0.29	0.775
age	-.0124	.0035	.9877	.0035	-3.52	0.000
Interaction variables						
growth-age	-.0002	.0001	.9998	.0001	-2.38	0.017
constant	-1.503	.9089			-1.65	0.098
/ln_p	.1051	.0929			1.13	0.258
p	1.111	.1031				
1/p	.9002	.0836				

No. of subjects = 521   *No. of obs. = 7,771*
No. of failures = 290   *LR chi2(9) = 68.90*
Log likelihood = -305   *Prob > chi2 = 0.000*

[117] Exp(0.3979)=1.49

Figure 7.8 Weibull survival and hazard regressions for periods 1970-1985 v/s 1986-2000 comparison



The second type of analysis (right hand graph in Figure 7.7) compares both periods keeping the dummy variable ‘period’ (D1) and introducing the interaction of each covariate with the dummy period (D_2X) as explanatory variables in order to investigate whether the covariates show significant differences over the hazard function, between periods. The test that is performed in this second case is H_0: $\theta = 0$.

In this model we use the period-dummy variable, four direct explanatory variables - machine speed, current firm size, initial firm size, firm age, and the interaction of these four variables with the period-dummy. Energy and growth variables are not included since they were not significant in the previous tests. The herfindahl industry concentration is excluded because of its high co linearity with time-period.

Table 7.12 shows the Weibull model coefficients hazard ratios and Figure 7.9 the survival and exit hazard functions for the two periods 1970-1985 and 1986-2000. The null hypothesis Ho of equality of survivor functions h1(t)=h2(t) was rejected at the 10% significant level. The period-dummy coefficient and hazard ratio tell us that the conditional probability to exit the industry is about 4 times higher in the second period compared to the first.[118] This important difference between periods can be observed in Figure 7.9 where the survival and exit hazard curves are clearly different. The three explanatory variables machine speed, current firm size and initial firm size, are the most important determinants of firm exit hazard between periods. The firm age variable does not have a significant heterogeneous effect on firm’s exit hazard between time-periods.

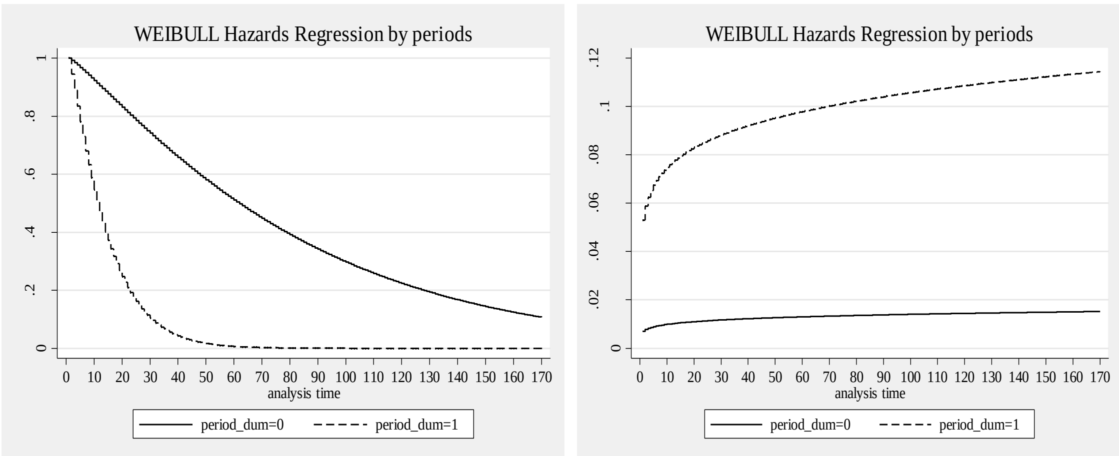
[118] Exp(1.502)=4.49

Table 7.12 Weibull model coefficients and hazard ratio for periods 1970-1985 v/s 1986-2000 comparison with covariates period effects

Variables	Coeffient	Std. Err.	Haz.Ratio	Std. Err.	z	P > |z|
period_dum	1.502	1.295	5.484	9.749	1.56	0.089
machine speed	.0015	.0009	1.002	.0009	1.63	0.093
p_machine speed	-.0018	.0010	.9982	.0010	-176	0.079
ln_mppb	-1864	.2897	.1551	.0449	-6.43	0.000
p_ln_mppb	1.249	.3232	3.487	1.127	3.86	0.000
ln_mppb_in	1.373	.2897	3.947	1.305	6.12	0.000
p_ln_mppb_in	-11.609	.3292	.3132	.1031	-3.53	0.000
age	-.0172	.0037	.9829	.0036	-4.65	0.000
p_age	.0053	.0033	1.005	.0033	1.60	0.179
_constant	-4.579	1.128			-4.06	0.000
/ln_p	.1398	.0632			2.21	0.027
p	1.150	.0727				
1/p	.8695	.0550				

No. of subjects = 521 *No. of obs. = 7,771*
No. of failures = 290 *LR chi2(9) = 86.25*
Log likelihood = -380 *Prob > chi2 = 0.000*

Figure 7.9 Weibull survival and hazard regressions for periods 1970-1985 v/s. 1986-2000 comparison with covariates period effect



The main conclusion of this section is that both the survival and hazard functions are significantly different over time. Firms have a significantly higher risk of exiting the industry in the second period (1986-2000) compared to the first period (1970-1985).

7.2 Patterns of p&p firm's technology adoption behaviour and growth

One of the conclusions from the previous section is that the diffusion of state-of-the-art p&p technology has been a determinant of firm survival and thus an important influence in shaping the dynamics of the industry. The aim of this section is to investigate whether there are distinctive patterns on firm technology adoption behaviour during the period 1970-2000 and its implication on the industry capacity expansion and on the industry dynamics.

As already explained, the increase in the speeds of state-of-the-art p&p machines observed in the mid 1980s (inflection point in Figure 1.2 in Chapter 1) from an evolutionary perspective could be interpreted as a technology regime change,[119] which subjected firms to different kinds of stress. In analysing firms' adoption behaviour, we can investigate the characteristics of firms that benefited from this technological regime change and therefore exhibit high growth, and the characteristics of firms that were negatively affected by it, and thus exhibit low growth and increasing exit.

The adoption of new technology is a key aspect in economic growth. Regardless of the nature of a new technology, its economic impact, such as productivity increase, new product development, better time to market, etc., only becomes clear when it is adopted and used by the productive system (Griliches 1957; Stoneman 2002; Hall and Khan 2003). This implies that different adoption times for production technology have different economics consequences, for example, on market structure, firm performance and, at the aggregate level, economic growth.

In industries such as p&p which are process technology intensive, the benefits of a technological change emerge with the adoption of new capital equipment in which the new technology is embedded. P&p capital equipment is mostly purchased externally rather than being generated in house (Stoneman and Myung Joong 1996). The consequence of this is that R&D is not a good proxy for the use and impact of new p&p process technology. A better proxy is the adoption decision, since the benefit of process

[119] A technological regime is defined as 'the particular combination of technological opportunities, appropriablility of innovations, cumulativeness of technical advances and properties of the knowledge base' (Breschi, Malerba et al. 2000p.388).

technology advances accrue to the firm only when the new technology (new machinery) is adopted and used (Koellinger and Schade 2008).

Investigation of firm-specific characteristics that influence the decisions of firms to adopt innovations (or state-of-the-art capital equipment), has long been recognized as an important area of study (Cabral and Dezs 2008). Mansfield (1968) in his classic work examining the determinants of firm technological adoption argues that the speed with which a firm adopts the new technology, depends on the profitability to be derived from the innovation and some firm characteristics such as relative size. Karshenas and Stoneman (1993) propose a general duration model of technology adoption that incorporates the main factors discussed in different theories of diffusion of new process technologies. They hypothesize that the profit gain to the firm from the adoption of new technology will depend upon the characteristics of the firm (rank effects), number of other adopters (stock effects), and the firm's position in the order of adoption (order effects).

Rank effect derives from the assumption that the potential adopters of a technology have different characteristics and, as a result, obtain different returns from the use of the new technology. These different returns generate different preferred adoption times (Ireland and Stoneman 1986). Firm size is the variable most frequently used as a determinant of technology adoption and the literature proposes two main arguments about its role. On the one hand, large firm size may increase the potential profitability of an innovation and, thus, the likelihood of adoption. Most empirical investigation on inter-firm technological diffusion finds a positive relationship between firm size and frequency of adoption in relation for a wide range of technologies, in different industries (Davies 1979; Hannan and McDowell 1984; Karshenas and Stoneman 1992). An alternative behavioural argument says that large firms, insulated from the market, are less risk-taking, are influenced less by the higher potential profits from the innovation, and thus are slower adopters. A study that confirm this pattern empirically is Oster (1982) which finds a negative correlation between firm size and adoption frequency in a study of the US steel industry.

Stock effect derives from the assumption that the benefit to the marginal adopter of new capital-embodied process technology decreases as the number of previous adopters increases (Reinganum 1981; Quirmbach 1986). Order effect derives from the assumption that the return to a firm from adopting a new technology depends upon its position in the order of adoption, with higher order adopters achieving greater returns than lower order adopters (Fudenberg and Tirole 1985).

In order to investigate this research question within the above conceptual framework, we investigate the patterns of p&p firms' technology adoption behaviour over time (in the periods 1970-1985 and 1986-2000), and across the three clusters identified in Chapter 6. We employ a methodology that allows us to identify state-of-the-art technology adoption decisions elaborated at firm level. Next we conduct a general and aggregated comparison of p&p firm growth deriving from technology adoption (high capacity change) versus growth deriving from technology improvements (incremental capacity change).

7.2.1 Patterns of firm technology adoption behaviour

This subsection studies the patterns of firm technology adoption behaviour at the technology class level. Ideally, we would need a dataset with complete life histories of the population of adopters and potential adopters, and the characteristics of the state-of-the-art p&p machines over a sufficiently long period beginning with their first launch. Such data are rarely available and, in particular, disaggregated data on the adoption of new technologies are scarce. Thus, in the absence of direct observations of the acquisition of new machinery at firm level[120] we need to construct a proxy variable for the technology adoption decision.

Identification of state-of-the-art technology adoption decisions

Cooper et al. (1993) using investment data, define a lumpy investment episode, representing a new technology acquisition decision, when gross investment rate exceeds 20% of total capital plant stock. Thus, this threshold variable separates routine maintenance expenditure, for repairs and improvements to existing machines, from

[120] In Chapter 4, we discuss the fact that our dataset contains annual production capacity at the technology class level; however, we do not have information on type and age of the machinery producing those capacities.

lumpy investment which represents new machine acquisition. The results of their machine replacement model appear to be robust to different threshold values of investment spikes. Power (1998) adopts a similar approach in her study of the relationship between productivity, investment and plant age for over 14,000 plants in the US manufacturing sector, and also Crespi (2004) in his study of the impact of technology adoption on plant level productivity, in Chilean manufacturing industries.

In the absence of specific diffusion and firm technology adoption data, we use a similar approach to those applied by the authors discussed above. However, we need to introduce some specificity. First, due to the idiosyncratic nature of this research which studies a single industry and capacity data for 13 technology classes, high capacity change rather than high investment rate is the appropriate proxy for technology adoption. Because the new p&p technology allows much higher operating speeds and thus higher operating capacity, an indication of adoption is a discontinuity in firm capacity or a lumpy capacity change. Firms that have adopted new capital equipment should show very high relative annual capacity growth in the specific technology class, which could constitute an appropriate index of adoption and could be used as an instrumental variable for analysing patterns of technology adoption over time and among different size classes.

Second, in our case the proxy for technology adoption needs to be capacity change and not the rate of capacity change. The use of capacity change rate would strongly bias the indicator against larger firms. For instance, for a 2 million tonnes capacity firm the adoption of a 0.2 m. tonnes state-of-the-art machine represents a 10% increase capacity while it represents a 100% increase capacity for a 0.2 m. tonnes capacity firm. Thus, in our case, high capacity change in absolute terms provides a more precise estimation of technology adoption at the technology class level. However it is important to be aware that the use of this proxy variable value reduces the possibility for small firms to be identified as new technology adopters since the threshold could be larger than the size of the firm. This occurs because smaller firms, more than medium and large firms, might be less likely to acquire high capacity new machines. This problem affects the comparison of technology adoption patterns across size-classes; we can reduce this data problem by using several threshold values say 0.25, 050, 0.75 and 1.00. The smaller threshold value will work better for the small size-classes and the larger threshold values will work better for the larger size-classes of firms. To study technology adoption patterns over time, which means comparing periods but not size classes, this problem does not arise.

However this index is noisy since it could encompass other things such as increased capacity as a result of learning by doing (important incremental capacity from upgrading an existing machine) or M&A. Also the new machinery adopted might not be state-of-the-art technology and thus the increased capacity of the firms might not appear as a capacity discontinuity. Finally, the discontinuity point might not be clearly identifiable and thus the threshold might not partition incremental versus high capacity growth in a mutually exclusive way.

There is no a priori principle to calculate the appropriate value for the threshold. But by examining the patterns of the data, for various threshold levels we can attempt to understand the patterns of adoption. However, it is important to be aware of the biases and noise that this threshold method introduces when conducting the analysis. A high threshold value tends to exclude adoptions by small firms because their capacity changes may be smaller than the threshold, which would make such changes appear to be incremental improvements. On the other hand, a low threshold value would tend to show incremental capacity improvements in large firms, based on upgrades to existing machines, as technology adoptions.

Considering all of the above we proceed to estimate firm technology adoption decisions at technology class level in the following way:

i) A threshold capacity change value is defined per technology class per decade. These values are obtained from the cumulative capacity change distribution curve for each of the 13 technology classes and decades. Appendix 7.1 provides the threshold values.

ii) There will be a technology adoption (TA) decision if the capacity change of the firm i at time t and technology class j $(CCh_{i,t,j})$ is larger than its corresponding threshold value $(CCh_{t,j}^{threshold})$. In mathematical terms this can be expressed as:

$$TA_{i,t,j} = 1 \quad if: \; CCh_{i,t,j} > CCh_{j,t}^{threshold}$$
$$TA_{i,t,j} = 0 \quad if: \; CCh_{i,t,j} \leq CCh_{j,t}^{threshold} \tag{7.5}$$

<u>Technology adoption frequency (TAF) and technology shut down frequency (TSDF)</u>

Having defined a proxy variable for firm technology adoption we need a technology adoption frequency (TAF) indicator to study and compare firm technology adoption behaviour over time, across size-classes and across the three clusters identified in Chapter 5. We proceed to calculate the TAF average per period and per cluster as follows:

i) We define a technology class variable (TC) per firm *i*, year *t* and technology class *j* where:

$$TC_{i,t,j} = 1 \quad if: \; Capacity_{i,t,j} > 0$$
$$TC_{i,t,j} = 0 \quad if: \; Capacity_{i,t,j} = 0 \tag{7.6}$$

ii) A firm's technology adoption frequency average within a time period *p* and cluster c is defined as:

$$\overline{TAF}_{p,c} = \frac{\sum_{i=1}^{n_c} \sum_{t=1}^{n_p} \left(\frac{\sum_{j=1}^{n_j} (TA_{i,t,j})}{\sum_{j=1}^{n_j} (TC_{i,t,j})} \right)}{\sum_{i=1}^{n_c} \sum_{t=1}^{n_p} \sum_{j=1}^{n_j} (TC_{i,t,j})} \tag{7.7}$$

In the context of a technology regime change during the mid 1980s, it is also interesting to study and compare the machinery shut down frequency over time. To do this we employ the above procedure but using negative threshold values as proxy for significant capacity reduction (or negative capacity change) per technology class and per decade.

There will be a technology shut down (TSD) decision if the negative capacity change of the firm *i* at time *t* and technology class *j* ($CCh_{i,t,j}$) is larger than its corresponding threshold value $(CCh_{t,j}^{threshold})$, thus a technology shut down frequency (TSDF) average variable within a time period *p* and cluster c could be defined as:

$$\overline{TSDF}_{p,c} = \frac{\sum_{i=1}^{n_c} \sum_{t=1}^{n_p} \left(\frac{\sum_{j=1}^{n_j} (TSD_{i,t,j})}{\sum_{j=1}^{n_j} (TC_{i,t,j})} \right)}{\sum_{i=1}^{n_c} \sum_{t=1}^{n_p} \sum_{j=1}^{n_j} (TC_{i,t,j})} \qquad (7.8)$$

Table 7.13 presents and compares technology adoption and technology shut down frequency averages for the two periods 1970-1985 and 1986-2000 for four threshold values (0.25, 0.5, 0.75 and 1.0).

Table 7.13 Technology adoption and technology shut down period's comparison

Threshold	Statistic	Technology adoption frequency (TAF)			Technology shut down frequency (TSDF)		
		1986-00	1971-85	t-test	1986-00	1971-85	t-test
0.25	n	708	534		578	370	
	mean	**0.107**	**0.071**	**0.003**	**0.088**	**0.049**	**0.001**
	st.dev.	0.247	0.194		0.187	0.161	
0.50	n	426	297		424	254	
	mean	**0.065**	**0.039**	**0.022**	**0.064**	**0.034**	**0.005**
	st.dev.	0.187	0.143		0.156	0.122	
0.75	n	256	177		292	160	
	mean	**0.041**	**0.023**	**0.078**	**0.044**	**0.021**	**0.025**
	st.dev.	0.140	0.112		0.133	0.088	
1.00	n	214	123		249	132	
	mean	**0.032**	**0.016**	**0.097**	**0.038**	**0.017**	**0.036**
	st.dev.	0.120	0.085		0.120	0.081	

Two interesting findings emerge from this table.

- both TAF and the TSDF increase significantly for all the threshold values, in the second period 1986-2000 compared to the first period 1970-1985 (in all cases the t-test is significant at the 1% to 10% confidence level). This means that during the second period a larger percentage of capital equipment was renewed through new adoptions and shutting down old equipment.

- for large thresholds such as 0.75 and 1.00 TSDF is higher than TAF in 1986-2000 (292 vs 256 for threshold 0.75 and 249 vs 214 for threshold 1.0) which tells us that a large number of old machinery was shut down but not all was replaced during this period. This result is consistent with the increased number of firms that exited the industry during the second period.

We use the TAF and TSDF variables but now with no threshold (threshold=0) in order to get the statistics for all the positive and negative capacity changes that occurred in the industry at the technology class level, regardless of firm size. Table 7.14 shows both positive (+CChF) and negative (-CChF) capacity change frequencies per period.

Table 7.14 Positive and negative capacity changes period's comparison

Threshold	Statistic	Positive capacity change frequency (+CChF)			Negative capacity change frequency (-CChF)		
		1986-00	1971-85	t-test	1986-00	1971-85	t-test
0	n	1,805	1,455		1,026	763	
	mean	**0.273**	**0.192**	**0.000**	**0.155**	**0.101**	**0.000**
	st.dev.	0.387	0.343		0.287	0.235	

Two interesting findings emerge from this Table:

- incremental capacity changes are very important in this industry taking account that with no threshold a total of 1,805 capacity changes occurred of which 708 (39%) could be considered technology adoptions (using the lowest threshold value of 0.25) and thus 1,097 can be considered technology upgrading (61%). We investigate this comparison further in the following subsection.
- in the cases of both positive and the negative capacity changes their frequency is significantly higher during the second period 1986-2000 compared to the first period 1971-1985. This means that during the latter period a larger percentage of capital equipment was not just renewed as shown in Table 7.13, but also was upgraded through technology improvements;

Here we focus on studying and comparing the technology adoption behaviour of the clusters identified in Chapter 6 (Cluster 2 Large & Diversified firms, Cluster 3 Medium & Specialized firms, Cluster 4 Small and Very Specialized firms). Table 7.15a shows the TAF mean of each cluster comparing the two periods 1970-1985 and 1986-2000, using the same four threshold values (0.25, 0.5, 0.75 and 1.0). Since the threshold method used is biased against smaller firms in favour of the large ones, we exclude from this analysis Cluster 4, thus we focus on the technology adoption patterns of Clusters 2 and 3. Two interesting findings emerge:

- when comparing cluster's TAF mean between the two periods for different threshold values (comparison 'a' and 'b' in Table 7.15a) we see that there is a significant and systematic TAF increase during the second period 1986-2000 compared with the first period 1971-1985, which is another manifestation of the technology regime change that might have occurred in the industry in the mid 1980s;[121]

- however the increase of TAF mean over periods is not uniform across clusters. In Cluster 2 the highest TAF increase occurred for the smaller thresholds (0.25 and 0.5) with increments of 39% and 40% respectively. On the contrary, in Cluster 3 the biggest increase was for the larger thresholds (0.75 and 1.00) with increments of roughly 211% and 259% respectively. TAF increased in Cluster 3 considerably more than in Cluster 2 over time (comparison 'c' in Table 7.15a). For instance, for a 0.5 threshold it increased 4.5 times more (180% versus 40%) than in Cluster 2, and for 1.0 threshold it increased 15 times more (259% versus 17%). This finding is a consistent explanation for the higher growth rate in Cluster 3 compared to Cluster 2 (8.1% vs 3.7%) discussed in Chapter 6 subsection 6.2.2.

Table 7.15b presents the same data as in Table 7.15a, but organized by periods in order to compare and test TAF between clusters within periods. We exclude Cluster 4 data for the same reasons as before, that they are biased against smaller firms. Two findings emerge from this table:

- in the first period 1971-1985 TAF mean for Cluster 2 is significantly higher than for Cluster 3 (comparison 'e' in Table 7.15b) and it increases with larger thresholds (38%, 82%, 100% and 118% for thresholds 0.25, 0.5, 0.75 and 1.0 respectively). We can conclude from this result that the Large & Diversified firms in Cluster 2 adopted new large capital equipment at roughly twice the frequency of Cluster 3's Medium &

[121] The only not significant TAF difference over time is the 17% of Cluster 2 and threshold 1.0, the other seven figures are significant between 0.1% and 10% confidence level.

Specialized firms. However this difference diminishes for the renewal of smaller size capacity capital equipment.

- in the second period 1986-2000 the pattern is reversed. TAF mean for Cluster 2 firms is lower than for Cluster 3 (comparisons ‘d’ in Table 7.15b) and it diminishes with larger thresholds (-2%, -9%, -20% and -29% for the thresholds 0.25, 0.5, 0.75 and 1.0 respectively), though just the -29% TAF difference is significant. The conclusion is that during the second period Cluster 3 firms adopted new large capital equipment at a faster rate than Cluster 2 firms and inverted the pattern observed in the first period. This finding is another manifestation of the effects of the technology regime change that might have occurred in the mid 1980s, discussed in subsection 7.1.3.

The finding of the larger firms showing higher TAF than the medium and small sized firms observed in the period 1970-1985 coincides with most of the empirical investigations on inter-firm technological diffusion which find positive relationships between firm size and frequency of technology adoption in relation to a wide range of technologies in different industries (Davies 1979; Hannan and McDowell 1984; Karshenas and Stoneman 1992). However, during the second period, 1986-2000, the medium sized firms, which are more focused on a few technology classes (2.6 in average) show significantly higher TAF compared with the large and diversified firms (7.1 on average), a finding that is less commonly observed empirically. One of the few studies that documents a similar pattern is Oster (1982) which finds a negative correlation between firm size and adoption frequency in a study of the US steel industry.

Having defined a threshold variable that distinguishes large capacity changes from smaller ones, we next study and compare two different growth types at industry level. One is derived from technology adoption which is observed as a large positive capacity change, and the other is derived from technology improvement, which is observed as incremental positive capacity changes.

Table 7.15a Cluster's TAF over time-periods for different threshold values

		firms			**threshold=0.25**						**threshold=0.5**						**threshold=0.75**						**threshold=1.0**					
cluster #	period	#	size	# of grades	cap. change			TAF			cap. change			TAF			cap. change			TAF			cap. change			TAF		
					#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd
2	1986-00	8	3,757	7.1	153	88	55	**0.181**	**39****	0.158	95	122	58	**0.112**	**40***	0.132	57	159	56	**0.067**	**24***	0.098	62	175	52	**0.056**	**17**	0.089
2	1971-85	8	2,078	7.2	113	88	63	**0.130**		0.145	69	125	69	**0.080**		0.120	47	152	73	**0.054**		0.100	40	168	64	**0.048**	a c	0.089
3	1986-00	41	936	2.6	228	107	85	**0.185**	**97****	0.334	151	143	85	**0.123**	**180****	0.193	103	177	80	**0.084**	**211****	0.244	96	188	77	**0.079**	b **259****	0.121
3	1971-85	24	525	2.8	79	61	49	**0.094**		0.256	47	93	51	**0.044**		0.148	23	110	51	**0.027**		0.181	29	140	55	**0.022**		0.072
4	1986-00	185	100	1.4	176	73	60	0.061		0.215	91	108	69	0.032		0.149	45	149	74	0.016		0.107	37	169	70	0.013		0.100
4	1971-85	110	79	1.3	64	67	47	0.034		0.151	35	98	51	0.018		0.102	23	121	51	0.012		0.084	13	149	55	0.007		0.062

**** significant at 0.1% level   ** significant at 1% level   * significant at 10% level*

Notes: 'a' and 'b' are the TAF comparison between periods within clusters 2 and 3 for different thresholds. 'c' is the TAF % difference comparison between clusters 2 & 3.

Table 7.15b Cluster's TAF comparison within periods for different threshold values

(same data of the above table but organized by periods)

		firms			**threshold=0.25**						**threshold=0.5**						**threshold=0.75**						**threshold=1.0**					
cluster #	period	#	size	# of grades	cap. change			TAF			cap. change			TAF			cap. change			TAF			cap. change			TAF		
					#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd	#	mean	sd	mean	%dif.	sd
2	1986-00	8	3,757	7.1	153	88	55	**0.181**	**-2**	0.158	95	122	58	**0.112**	**-9**	0.132	57	159	56	**0.067**	**-20**	0.098	62	175	52	**0.056**	**-29***	0.089
3	1986-00	41	936	2.6	228	107	85	**0.185**		0.334	151	143	85	**0.123**		0.193	103	177	80	**0.084**		0.244	96	188	77	**0.079**	d	0.121
4	1986-00	185	100	1.4	176	73	60	0.061		0.215	91	108	69	0.032		0.149	45	149	74	0.016		0.107	37	169	70	0.013	f	0.100
2	1971-85	8	2,078	7.2	113	88	63	**0.130**	**38***	0.145	69	125	69	**0.080**	**82***	0.120	47	152	73	**0.054**	**100***	0.100	40	168	64	**0.048**	e **118***	0.089
3	1971-85	24	525	2.8	79	61	49	**0.094**		0.256	47	93	51	**0.044**		0.148	23	110	51	**0.027**		0.181	29	140	55	**0.022**		0.072
4	1971-85	110	79	1.3	64	67	47	0.034		0.151	35	98	51	0.018		0.102	23	121	51	0.012		0.084	13	149	55	0.007		0.062

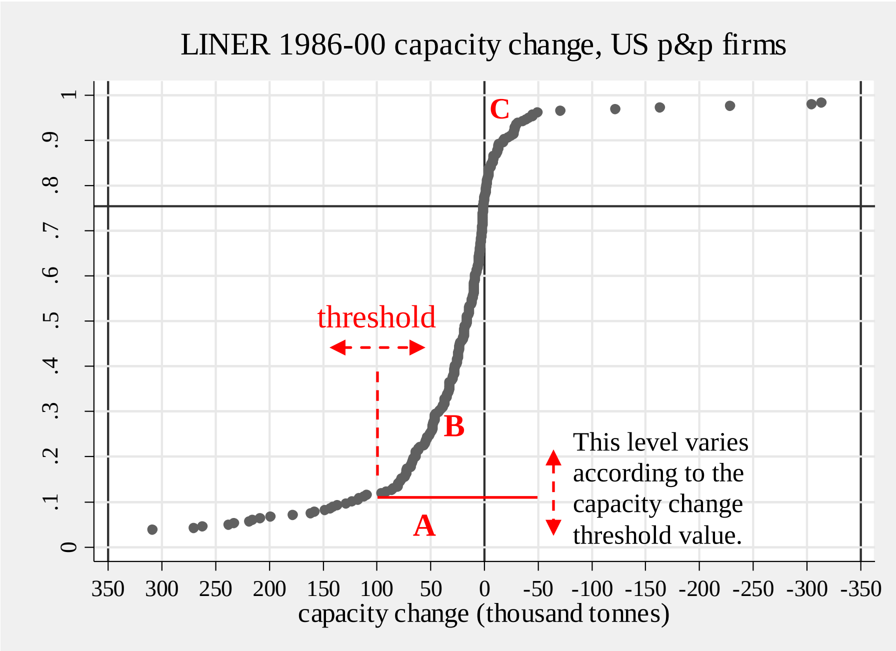
**** significant at 0.1% level   ** significant at 1% level   * significant at 10% level*

Notes: 'd' and 'e' are the TAF comparison between clusters 2 and 3 within periods for different thresholds. 'f' is the TAF % difference comparison between periods.

7.2.2 Technology adoption versus technology improvement capacity changes

For each p&p technology class we can draw a cumulative capacity change distribution curve such as the one depicted in Figure 7.10 for *liner* grade in the period 1986-2000.[122] This is an *x-y* type graph where the *x* axis represents the annual technology class capacity change, going from the highest positive to the highest negative (from left to right). The *y* axis represents the share of firms that show an equal or greater capacity change, and goes from 0 at the bottom of the graph, and ends with 1 at the top of the graph for each technology class. Thus, the capacity change curve has an 'S' shape.[123]

Figure 7.10 Capacity change curve for *liner* technology class and period 1986-2000



Taking this curve as reference, we can distinguish the following types of capacity changes:[124]

- Adoption of a new machine (area 'A' in Figure 7.10)

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[122] Appendix A7.4 shows the cumulative capacity change curves for all the technology classes over the two periods 1970-1985 and 1986-2000.

[123] The points with null capacity changes are omitted from this curve since the aim is to represent either positive or negative technology class capacity changes.

[124] At the production level (not the capacity level), we can distinguish two additional growth dimensions. Firstly the re-starting of an existing machine; secondly an increase in the 'capacity use' of an existing machine that was not used at 100% capacity. Since our analysis is at capacity level these dimensions are not considered.

As explained in Chapter 2 and subsection 7.2.1 in this chapter, it is common in the p&p industry that the introduction of a new machine adds considerable new capacity within the specific technology class of the firm. In order to distinguish this lumpy capacity change from incremental change, a capacity change threshold value per decade and per technology class is defined to identify these 'imputed adopters';[125]

- Upgrading an existing machine or conversion to a different technology class (area 'B' of Figure 7.10).

  As explained in subsection 7.2.1, upgrading an existing machine adds new capacity within the specific technology class but in a smaller amount than the introduction of a new machine; thus it is considered incremental capacity change;[126]

- Shutting down an existing machine (area 'C' of Figure 7.10)

  When a machine is shut down or 'downgraded', there is a negative capacity change within the specific technology class.

There can be a fourth type of capacity change at the technology class level as a result of M&A. However, since we do not consider M&A in this investigation, those cases identified were excluded from the database (and do not appear in the capacity change curve). In order to identify capacity change due to a M&A, we looked for coincidences between a high positive capacity change in one firm and a high negative capacity change in another (the acquired) company in one year or in consecutive years, in the same technology classes. These cases identified were excluded since the capacity changes were not the result of adopting new capital equipment or shutting down old equipment.

From a first observation of the technology class cumulative capacity change curves in Appendix A7.4 the following general patterns emerge:

- incremental capacity changes are more frequent than large capacity changes; however they can be several times larger than the largest incremental change. This is

[125] We are aware that there will be other hidden adopters that will not report high capacity change and thus will follow in the 'incremental improvement' zone. This could occur for instance when a firm replace two or more old machines by a new single one, resulting a comparable capacity change.

[126] We are aware that small firms that acquired new but not state-of–the–art machinery could be wrongly classified in this group because its capacity addition is smaller than the threshold value and thus it is considered incremental capacity change rather than technology adoption.

interesting and shows that firms are reluctant to make other than marginal changes to capacity until they are convinced about the need for a mayor investment in large new capacity;

- there is significant heterogeneity in the technology-adoption versus technology-improvement relationship across different technological classes. For instance, in *newsprint* the incremental improvement area is small compared to adoption, in *liner* the two areas are comparable, and in *kraft paper* incremental improvement area is larger than adoption area. There can be several reasons for this differences which are beyond the scope of this thesis and would require more specific data;
- as expected, the negative capacity change areas are larger in technology classes that show smaller or negative growth (see Figure 6.1) such as *kraft paper* (-29% for 1986-2000) and *recovery board* (-4%), and smaller in technology classes that show high capacity growth such as *liner* (53%) and *corrugated board* (52%) in the same period.

Since we are using a proxy variable based on capacity changes rather than a proper technology adoption database to study adoption patterns, we do not pursue this analysis further as this would require the elaboration of a technology diffusion model which is not possible with our data. However, we can analyse the types of capacity changes at the industry level. We can estimate and compare for different threshold values the percentage of total industry capacity expansion derived from technology adoption versus incremental technology improvement, for both periods 1971-1985 and 1986-2000. The results are presented in Table 7.16.

Table 7.16 Types of p&p industry capacity change
Percentages of incremental versus adoption growth per period and per thresholds

Threshold	1971-1985		1986-2000	
	Capacity change		Capacity change	
	Incremental	Adoption	Incremental	Adoption
0.25	40%	60%	41%	59%
0.50	48%	52%	50%	50%
1.00	68%	32%	62%	38%
1.25	71%	29%	64%	36%

As a general conclusion, it can be said that from figures in Table 7.16 both sources of industry capacity growth - technology adoption and incremental technology improvement - are important and comparable. When a threshold value of 0.5 is used both sources are approximately 50%. For a threshold value of 0.25 adoption capacity change increases up to approximately 60%; for a threshold value of 1.25, however, adoption capacity change explains no more than 35% of industry capacity expansion for 1986-2000. The above findings are interesting since they show that even in one of the most capital intensive industry in the world, a significant proportion of aggregate growth is explained by 'learning-by-doing'[127] efforts and not solely by the adoption of new state-of-the-art technology. In the resource-based view of the firm (Wernerfelt 1984; Rumelt 1994), this learning-by-doing activity could be seen as a valuable resource that is neither perfectly imitable nor substitutable without great efforts of competitors (Barney 1991, p.117).

We can also conclude from the figures in Table 7.16 that for high threshold values, such as 1.0 or 1.25, the percentage capacity change from technology adoption seems to increase over time (32% to 38% for threshold=1; 29% to 36% for threshold=1.25). This means that the importance of adopting state-of-the-art technology compared with the importance of upgrading existing technology is not constant over time: it is higher in second period 1986-2000 compared to the first period 1971-1985. However, for low threshold values, such as 0.25 or 0.50, the percentage of capacity change from technology adoption is fairly constant over time.

7.3 Conclusions

Chapter 7 investigated the third research question in this thesis on the patterns and determinants of p&p firms exiting the industry (and, thus, the patterns and determinants of firm survivors), and patterns of technology adoption behaviour. The aim of this chapter is to contribute to the industrial dynamics empirical literature by providing evidences of the existence of survival and technology adoption patterns in a very capital intensive world industry, i.e. p&p, over three decades when the industry showed an important dynamism as discussed in Chapter 2.

[127] Learning by doing is an economic concept that refers to the capability of firms to improve their productivity through practice, self-perfection and minor but continuous innovations. It was first suggested by Arrow (1962) in his endogenous growth theory that explains the effects of innovation and technical change on aggregate growth.

The specific research questions investigated are:

- Within the US p&p industry are there distinctive patterns of survivors and non-survivor firms during the period 1970-2000?
- If so, what are the causalities of these patterns?
- Within the US p&p industry are there distinctive patterns of firm technology adoption behaviour over time and across the three clusters identified in Chapter 6?
- What proportion of US p&p industry capacity expansion can be explained by state-of-the-art technology adoption and what proportion can be explained by incremental technology improvements and upgrading?

The main findings and conclusions of this chapter are presented and organized according to the order of the above questions:

Patterns and determinants of firm survival

Entry and exit processes are important forces shaping the dynamics of the p&p industry during the period studied, 1970-2000. Along the three decades 265 firms exited the industry and 199 new firms entered, which resulted in a reduction in the total number of companies from an initial 300 in 1970 to 234 in year 2000. Thus, an important proportion of firms that existed in any of the three decades failed to survive to 2000 and the rate of mortality increased over time from 25% in the 1970s, to 30% in the 1980s and 39% in the 1990s.

There is an inverse relationship between size and exit hazard rate since medium and small firms have significant larger hazard exit probability than the larger firms, which have the smallest chances of death. After 15 years of existence, around 90% of large firms and 65% of medium and small firms were still in operation. After 30 years of existence roughly 78% of large firms and 53% of medium and small firms were in operation.

The exit probability declines with firm age. It is highest when firms are young (40% of firms exit after less than 25 years). The exit rate moderate for firms up to 100 years old (45% of firms exit between 25 and 100 years), and for older firms it reduces even further (15% of firms exit the industry with more than 100 years). The exit-age curve is convex, which is consistent with the selection pattern/slope being steep during the first years, moderate during the intermediate years and flattening out towards the end of the life-cycle.

To study the determinant of firm exit (or firm survival) we used a semi-parametric Cox Proportional hazard model (Cox 1972) and a Weibull parametric distribution. Both models allow for different explanatory variables to vary over time: the results obtained from the two models were similar. The Weibull was employed because a key variable, machine speed, violated the proportional hazard assumption of the Cox model. In the Weibull model seven direct explanatory variables at firm, industry and contextual level were used (current firm size, initial firm size, firm annual growth rate, firm age, industry concentration, energy price, p&p machine speed) and one interaction variable - firm growth-age.

The variables energy price and firm growth-rate were not found to be significant determinants of firm survival, which means that changes in energy prices or different levels of firm growth rates do not explain changes in the hazard exit rate. On the contrary the contextual variable, machine speed, has a very significant positive coefficient, which means that the higher the machine speed, the higher the probability that p&p firms will exit the industry. At sectoral level, the effect of industry concentration is also significant and negative, meaning that the increase in industry concentration reduces the risk of exit.

At firm level, current firm size has a significant negative coefficient, which means that firm size exerts a decisive influence on survival and thus larger firms have a smaller risk than smaller firms of exiting the industry. Initial firm size is also significant; however its coefficient is positive, which means that the exit hazard rate for a new and large firm is higher than for a start-up of smaller size. As already mentioned, firm growth is not significant, however its interaction with age has a significant negative coefficient at the 10% confidence level. This means that high growth is not a determinant of firm survival for all types of companies but only for those that show persistent growth over long time periods, thus giving support to theories such as Jovanovic's (1982), which emphasizes post-entry learning as an important determinant of firm performance. Firm age is a significant variable with a negative coefficient, meaning that older firms have a lower risk of exiting the industry than younger ones.

Firm exit hazard over time (two period comparison)

Using a Cox proportional hazard model and a Weibull parametric distribution we demonstrated that both the survival and exit hazard functions varied significantly over time. In the second period 1986-2000 firms' survival rate is significantly lower and firm exit hazard rate significantly higher compared to the first period 1970-1985. This confirms the hypothesis that a technological regime change occurred in the industry in the mid 1980s with the introduction of the automatic process control in p&p production operations.

Depending on how the exit hazard rate is estimated, the conditional probability to exit the industry is 1.5 to 4 times higher in the second period compared to the first one. The three explanatory variables - machine speed, current firm size and initial firm size - are the most important determinants of firm exit hazard between periods. Firm age does not have a significant effect on firms' exit hazard between time-periods.

Technology adoption patterns across clusters and over time

From a methodological perspective, one of the challenges in studying patterns of technology adoption behaviour is to identify a technology adoption decision when there is no information about this in the data. Based on a theoretical discussion we designed a methodology to identify new capital equipment acquisition and develop a technology adoption proxy variable. Since p&p is a very capital intensive industry, the adoption of state-of-the-art capital equipment introduces a large capacity change which is observed as a discontinuity at firm's technology class level. Thus, based on the capacity changes at the level of technology class over time and selecting an arbitrary threshold it was possible to estimate technology adoption decisions and to study firm technology adoption behaviour.

A first general finding is that there is a significant increase in TAF and TSDF during the second period 1986-2000 compared with the first period 1970-1985 at industry level, regardless of the threshold value used to identify lumpy capacity changes or size classes. This means that during the second period a larger percentage of capital equipment was renewed through new adoptions and shutting down old machinery, confirming the technology inflection point (technology regime change) that occurred in the mid 1980s.

The most interesting result is that the relationship between firm size and technology adoption is not linear across size-classes and varies significantly over time. During the first period 1970-1985 the large firms showed significantly higher TAF than the medium and small size firms. This coincide with the results of most of the empirical literature on inter-firm technological diffusion which finds a positive relationship between firm size and technology adoption frequency for a wide range of technologies in different industries. However, in the second period, 1986-2000, the medium sized firms, which are focused on fewer technology classes (2.6 on average) show significantly higher TAF compared with the large and diversified firms (7.1 on average), which is a less common empirical finding. Our data do not allow us to infer the reasons for the different patterns of technology adoption behaviour between these two size-classes. It would be an interesting avenue for future research based on qualitative data.

Types of growth: technology adoptions and technology improvements

P&p firm growth is the result of many incremental but small capacity changes based on technology improvements and machinery upgrade, and a small number of large capacity changes due to the adoption of new capital equipment. Our analysis shows that firms are generally reluctant to make more than marginal changes to capacity until they are sure of the need for major new investment.

Depending on the threshold value used to distinguish between types of capacity change, aggregate incremental growth represents 40% to 60% of total industry growth and, thus, the aggregate lumpy capacity change represents between 60% and 40% of total industry growth. The main inference from these figures is that technology upgrade and improvement on the one hand, and technology adoption on the other, are important and comparable sources of aggregate industry capacity expansion.

The above is especially interesting in the context of the very high capital intensive p&p industry where a significant proportion of aggregate growth is associated with 'learning-by-doing' activities, which correspond to technology improvements and upgrading, and not solely with the adoption of new machinery. From the resource based view of the firm literature this 'learning-by-doing' capability can be seen as a valuable resource that is neither perfectly imitable nor substitutable without great efforts of competitors (Barney 1991). Thus, it could be a source of performance heterogeneity. Future research could explore this hypothesis using firm specific data.

At the technology class level there is an important heterogeneity in the relationship between technology adoption and technology improvement across the different grades. For instance for n*ewsprint* the improvement area is small compared with the adoption area, in l*iner* both areas are comparable and in *kraft* paper improvement are is larger than adoption are. There may be several reasons for this heterogeneity which could be investigated in future research based on more specific data.

Appendix A7.1 Transition matrixes of US p&p firms per decades within the period 1970-2000

Table A7.1a Transition matrix of US p&p firms years 1970 to 1980

size class		**capacity (th tonnes)**	**total in 1970**		**# of non survivors to 1980**	**survivors to 1980**		**Size-class of survivor firms to year 1980**													
								1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
			#	**%**		**#**	**%**	2	4	8	16	32	64	128	256	512	1,024	2,048	4,096	8,192	8,192
1	<=	2	3	1%	1	2	67%	**1**	1												
2	<=	4	20	7%	9	11	55%		**5**	5		1									
3	<=	8	15	5%	4	11	73%			**8**	2	1									
4	<=	16	34	11%	10	24	71%			3	**13**	6	2								
5	<=	32	71	24%	16	55	77%				1	**37**	15	2							
6	<=	64	41	14%	10	31	76%				1	2	**20**	8							
7	<=	128	25	8%	5	20	80%						2	**12**	5	1					
8	<=	256	36	12%	7	29	81%							1	**13**	8	6	1			
9	<=	512	28	9%	8	20	71%						1	1	1	**9**	8				
10	<=	1,024	17	6%	4	13	76%								1		**8**	4			
11	<=	2,048	6	2%	0	6	100%										1	**4**	1		
12	<=	4,096	3	1%	0	3	100%												**3**		
13	<=	8,192	1	0.3%	0	1	100%													**1**	
14	>	8,192	0	0%																	**0**
			300	**100%**	**74**	**226**	**75%**	**1**	**6**	**16**	**17**	**47**	**40**	**24**	**20**	**18**	**23**	**9**	**4**	**1**	**0**
			arrivals in the period:			62	22%	0	2	2	7	13	17	6	6	5	4	0	0	0	0
			total in 1980:			**288**		**1**	**8**	**18**	**24**	**60**	**57**	**30**	**26**	**23**	**27**	**9**	**4**	**1**	**0**
			% in 1980:					0%	3%	6%	8%	21%	20%	10%	9%	8%	9%	3%	1%	0%	0%

Proportionate growth (size in 1980 / size in 1970)			**1/64**	**1/32**	**1/16**	**1/8**	**1/4**	**1/2**	**1**	**2**	**4**	**8**	**16**	**32**	**64**	**128**
Number of survivor firms (1970-1980)	**226**	**75%**				1	3	11	134	63	12	2				
% of survivor firms (1970-1980)						0.4%	1%	5%	59%	28%	5%	1%				

Note: Values in bold in cells are the count of firms who maintain their size class. Those above (below) the diagonal define grow (decline) over the period. Zeroes are entered to fully delineate the diagonal.

Table A7.1b Transition matrix of US p&p firms years 1980 to 1990

size class		capacity (th. tonnes)	total in 1980 #	total in 1980 %	# of non survivors to 1990	survivors to 1990 #	survivors to 1990 %	Size-class of survivor firms to year 1990: **1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
								2	4	8	16	32	64	128	256	512	1,024	2,048	4,096	8,192	8,192
1	<=	2	1	0%	0	1	100%	**1**													
2	<=	4	8	3%	2	6	75%	1	**3**	1		1									
3	<=	8	18	6%	4	14	78%			**9**	3	2									
4	<=	16	24	8%	10	14	58%			1	**9**	3	1								
5	<=	32	60	21%	20	40	67%				1	**29**	8	1				1			
6	<=	64	57	20%	17	40	70%					2	**25**	10	2	1					
7	<=	128	30	10%	8	22	73%					1	1	**14**	5	1					
8	<=	256	26	9%	6	20	77%							3	**14**	2	1				
9	<=	512	23	8%	6	17	74%								3	**8**	4	1	1		
10	<=	1,024	27	9%	10	17	63%									2	**7**	7	1		
11	<=	2,048	9	3%	2	7	78%											**5**	2		
12	<=	4,096	4	1%	2	2	50%												**1**	1	
13	<=	8,192	1	0%	0	1	100%													**1**	
14	>	8,192	0	0%																	**0**
			288	**100%**	**87**	**201**	**70%**	**2**	**3**	**11**	**13**	**38**	**35**	**28**	**24**	**14**	**12**	**14**	**5**	**2**	**0**
			arrivals in the period:			64	24%	0	2	3	1	14	13	11	7	7	4	2	0	0	0
			total in 1990:			**265**		**2**	**5**	**14**	**14**	**52**	**48**	**39**	**31**	**21**	**16**	**16**	**5**	**2**	**0**
			% in 1990:					1%	2%	5%	5%	20%	18%	15%	12%	8%	6%	6%	2%	1%	0%

Proportionate growth (size in 1990 / size in 1980)			**1/64**	**1/32**	**1/16**	**1/8**	**1/4**	**1/2**	**1**	**2**	**4**	**8**	**16**	**32**	**64**	**128**
Number of survivor firms (1980-1990)	**201**	**70%**					1	14	126	46	10	3	0	0	1	
% of survivor firms (1980-1990)							0.5%	7%	63%	23%	5%	1%	0%	0%	0.5%	

Note: Values in bold in cells are the count of firms who maintain their size class. Those above (below) the diagonal define grow (decline) over the period. Zeroes are entered to fully delineate the diagonal.

Table A7.1c Transition matrix of US p&p firms years 1990 to 2000

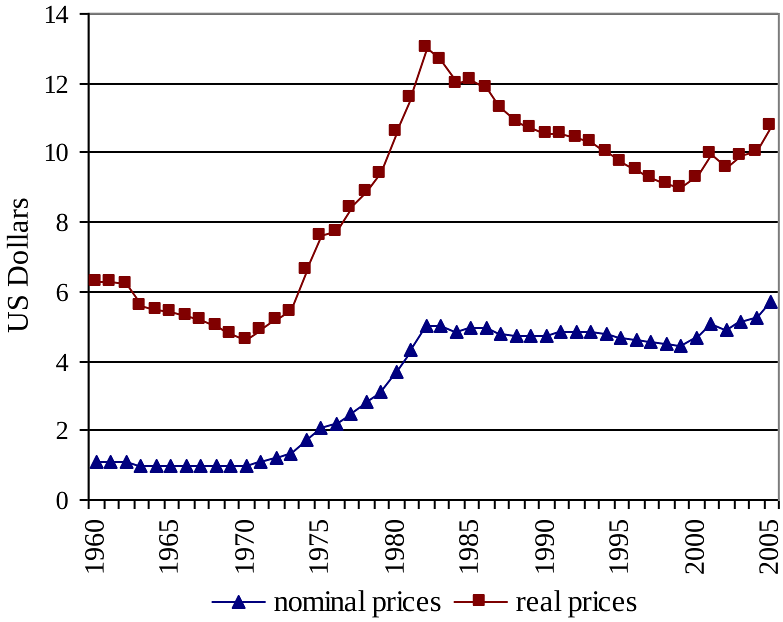
size class		capacity (th. tonnes)	total in 1990 #	total in 1990 %	# of non survivors to 2000	survivors to 2000 #	survivors to 2000 %	Size-class of survivor firms to year 2000													
								1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
								2	4	8	16	32	64	128	256	512	1,024	2,048	4,096	8,192	8,192
1	<=	2	2	1%	1	1	50%	**1**													
2	<=	4	5	2%	1	4	80%		**3**	1											
3	<=	8	14	5%	6	8	57%			**5**	3										
4	<=	16	14	5%	3	11	79%			1	**7**	2	1								
5	<=	32	52	20%	19	33	63%				3	**20**	6	1	3						
6	<=	64	48	18%	27	21	44%						**16**	2	2			1			
7	<=	128	39	15%	19	20	51%				1	1	3	**10**	3	1	1				
8	<=	256	31	12%	9	22	71%							4	**14**	4					
9	<=	512	21	8%	7	14	67%								2	**8**	4				
10	<=	1,024	16	6%	6	10	63%								1	1	**5**	3			
11	<=	2,048	16	6%	5	11	69%								1			**7**	3		
12	<=	4,096	5	2%	1	4	80%											1	**2**	1	
13	<=	8,192	2	1%	0	2	100%													**0**	2
14	>	8,192	0	0%																	**0**
			265	**100%**	**104**	**161**	**61%**	**1**	**3**	**7**	**14**	**23**	**26**	**17**	**26**	**14**	**10**	**12**	**5**	**1**	**2**
			arrivals in the period:			73	31%	0	1	0	2	9	13	16	11	10	7	3	1	0	0
			total in 2000:			**234**		**1**	**4**	**7**	**16**	**32**	**39**	**33**	**37**	**24**	**17**	**15**	**6**	**1**	**2**
			% in 2000:					0%	2%	3%	7%	14%	17%	14%	16%	10%	7%	6%	3%	0%	1%

Proportionate growth (size in 2000 / size in 1990)			**1/64**	**1/32**	**1/16**	**1/8**	**1/4**	**1/2**	**1**	**2**	**4**	**8**	**16**	**32**	**64**	**128**
Number of survivor firms (1990-2000)	**161**	**61%**				2	2	15	98	34	5	4	0	1		
% of survivor firms (1980-1990)						1%	1%	9%	61%	21%	3%	2%	0%	1%		

Note: Values in bold in cells are the count of firms who maintain their size class. Those above (below) the diagonal define grow (decline) over the period. Zeroes are entered to fully delineate the diagonal.

Appendix A7.2 Average US Retail Prices of Electricity

Figure A7.2a Average US Retail Prices of Electricity for Industrial Sectors, 1960-2005



Note: Real prices calculated in chained year 2000 Dollars
Source: Energy Information Administration-EIA. Official Energy Statistics of the US Government.
http://www.eia.doe.gov/emeu/aer/elect.html

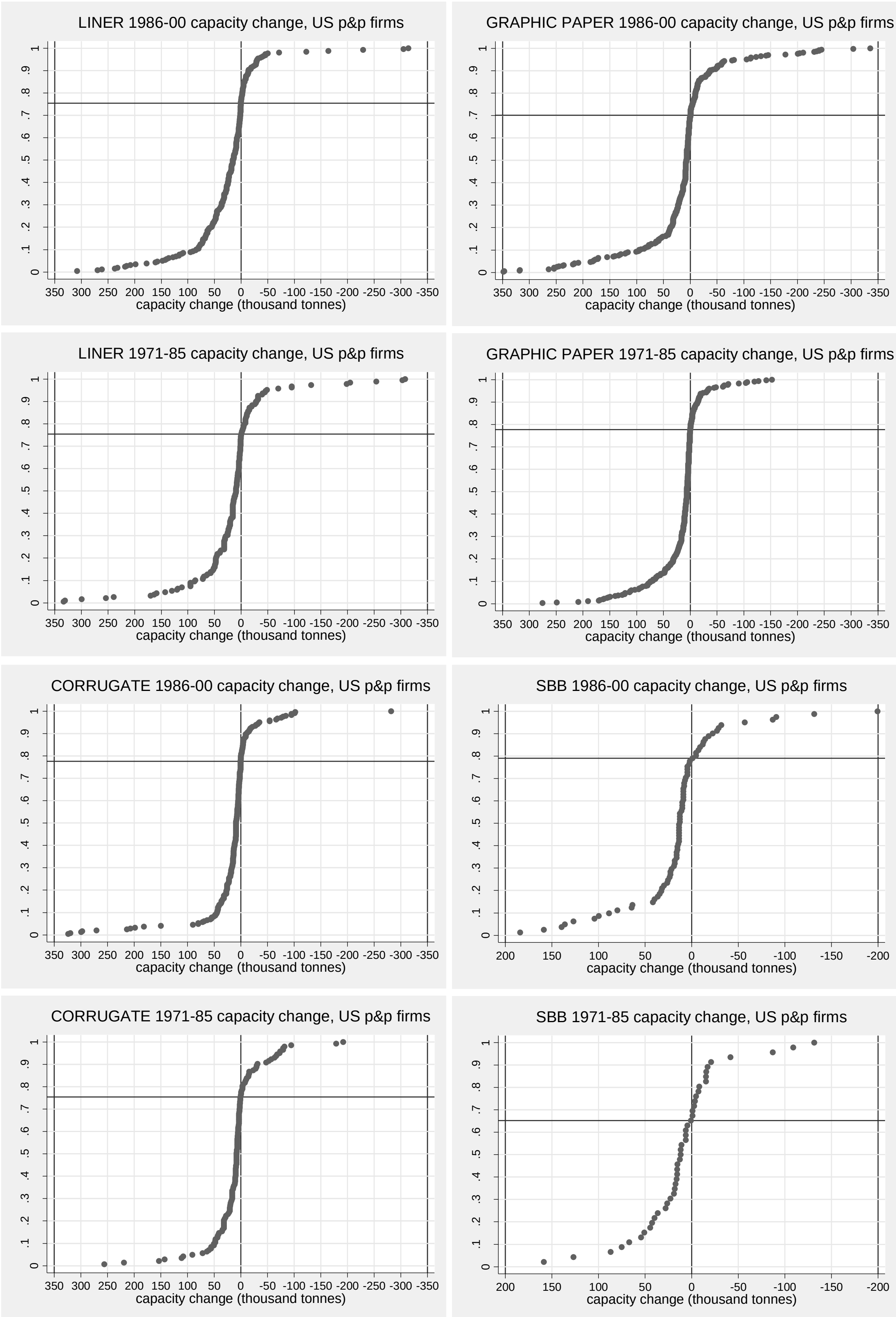
Appendix A7.3 Threshold values of capacity change at the 13 technology classes

Table A7.3a Thresholds values

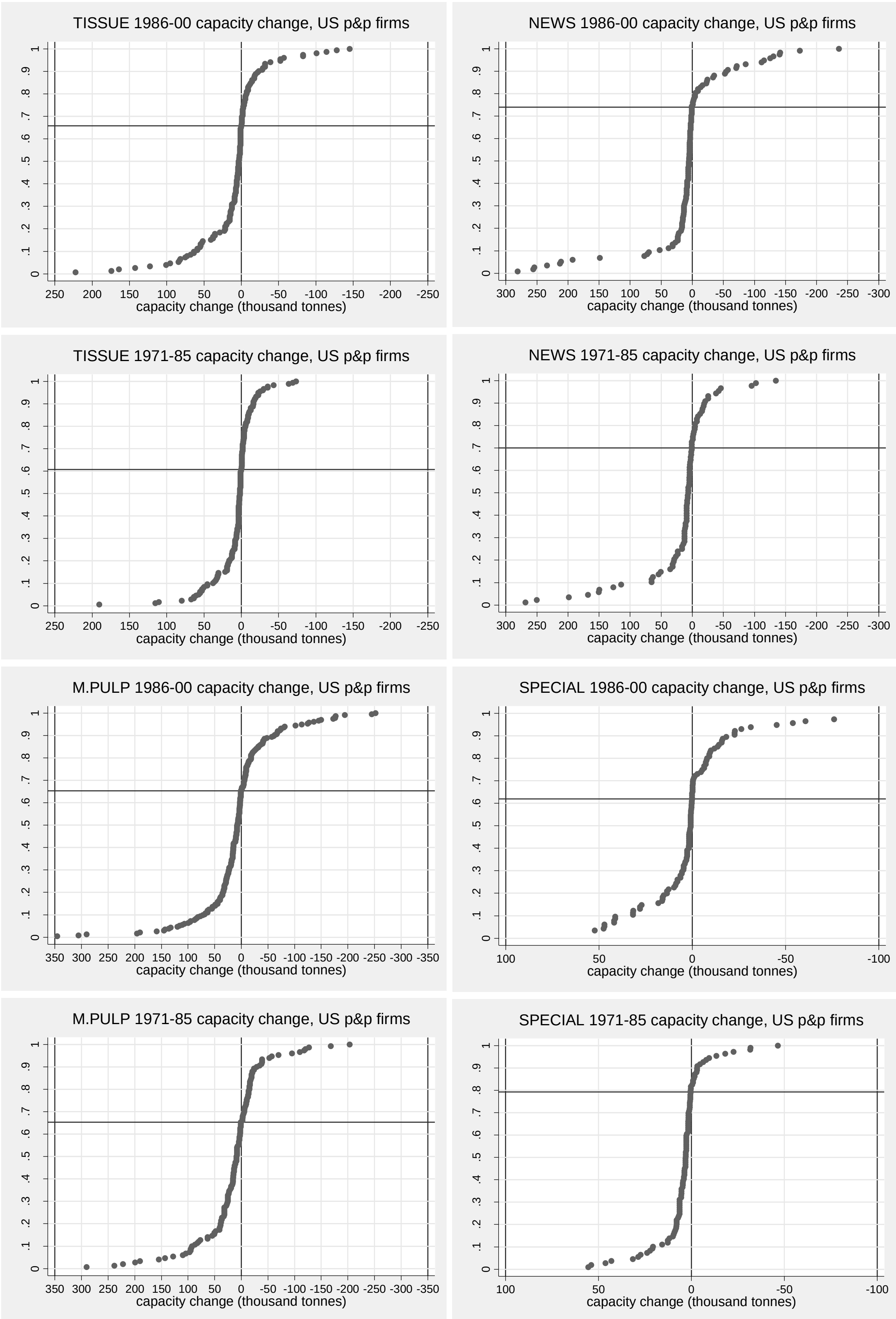
Technology class	Capacity change limits per decade (thousand tonnes)					
	Maximun limit			Minimum limit (1.00 threshold)		
	1970s	1980s	1990s	1970s	1980s	1990s
mp	300	350	400	100	100	120
news	250	250	300	70	70	80
ctfs	200	250	300	90	100	110
ucfs	200	250	300	90	100	110
ctgw	150	200	300	50	60	70
ucgw	150	200	250	80	80	80
tissue	120	150	250	70	70	90
special	110	140	170	60	60	70
kraft	150	150	150	55	55	70
liner	300	400	450	100	100	100
corr	200	250	350	120	125	130
sbb	150	200	200	60	60	60
recb	200	250	300	100	100	100

Note: The minimum capacity limits shown on the above table are used as one threshold. However for the sensitivity analysis these minimum limits are varied according to five different thresholds that take the values of: 1.25, 1.00, 0.75, 0.50, 0.25.

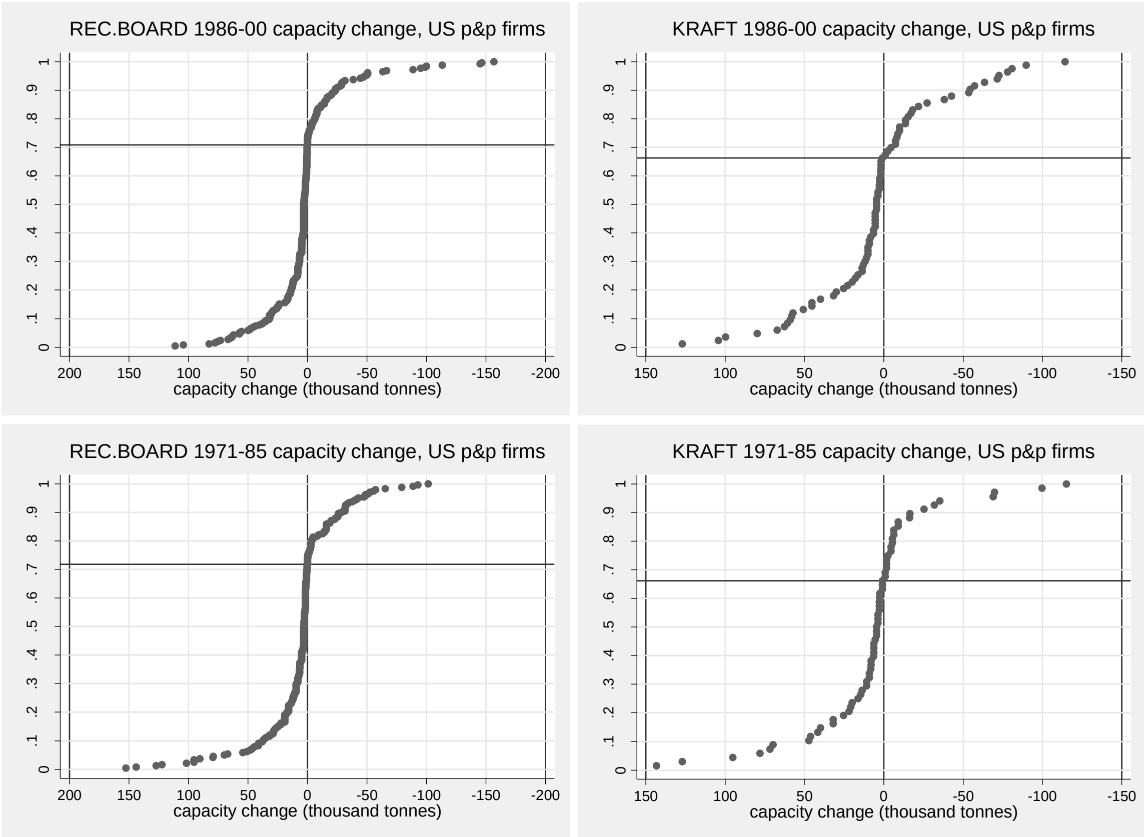
Appendix A7.4 Cumulative capacity change distribution curves for the technology classes over the two periods 1986-2000 and 1970-1985



Appendix A7.4 (continuation)



Appendix A7.4 (continuation)



CHAPTER 8

CONCLUSIONS

This conclusion chapter is organized in three sections. The first provides a summary of the research problem, thesis aims, background and research methodology. Section 8.2 discusses the main findings and contributions of this thesis. Section 8.3 points to the limitations of this study and provides directions for future research.

8.1 Summary of the research

Research problem

The research problem in this thesis is concerned with the existence and form of association between the technological structure of the highly capital-intensive p&p industry, and its dynamic behaviour in terms of market growth and development. Issues related to industrial structure are particularly relevant in studies of highly capital-intensive sectors because of features they commonly exhibit such as strong economies of scale and intense vertical integration.

The p&p industry is considered to be a mature, homogenous and rather static sector and, perhaps because of this, in the past it has been a less interesting arena for the investigation of issues related to changes in industrial structure or the role of technology in influencing these changes. However, the p&p industry has exhibited interesting structural dynamism since the mid-1980s when started experiencing a major transformation that changed its size distribution and concentration. In 1978 the top 20 firms produced 25% of total output; in 2000, this had risen to almost 40%. Also, there has been significant technological advance in this industry since the 1980s, which has allowed significant increments in production scale, productivity and product diversification. P&p firms have responded to these technological opportunities with different strategic choices that have resulted in different outcomes such as systematically dissimilar growth-rates over time.

Overall, p&p industry output has grown at an average compound rate of 4% per year in the period 1950-2000. The industry does not perceive the increasing digitalization of former heavy paper consuming sectors as an important threat since aggregate demand is highly correlated with increasing use of digital technologies and with the degree of national economic development (see Figure 2.6). Thus, it is expected that global consumption of pulp and paper products, in their different forms, will continue to grow at similar rates. However, this could change if the above correlations cease to apply.

The p&p industry is characterized by the following five key economic and technological features: capital and scale intensiveness, energy intensiveness, cyclical market behaviour, technology absorption (supplier dominated) and environmental sensitivity, all of which have influenced the structure and dynamics of the global industry (Carrere and Lohmann 1996; Herbert-Copley 1998; Norberg-Bohm and Rossi 1998; Dijk 2005). The industry became more concentrated in the 30 years from 1970 to 2000 with a significant reduction in the number of firms and a significant increase in average firm production capacity. Thus, in this period, the size distribution curve moved towards the medium and large firm size classes.

The demand side is characterized by increased volume and sophistication of p&p products, which has contributed to increasing market segmentation and the continuous development of new paper related products. There are three main sources of entry barriers to this sector, which limit competition. They are the large initial capital investment needed to capture the benefits of scale economies; financially and practically affordable access to forest resources, the most important p&p industry raw material; and the need to manage and control the complex and expensive production process and operate at near full capacity. International trade in p&p products has been increasing since the mid-1970s with pulp and paper product imports increasing steadily to reach more than 30% of world output in year 2000. These trends suggest that global consumption of paper products in their different forms will continue to grow in succeeding decades.

Research questions

Within this industrial context, this thesis investigates the following three research questions related to two main literatures within which this research is positioned: dynamics of industrial structure (firm's growth size relationship) and heterogeneity within industries (strategic groups). These literatures provide lenses through which the data can be viewed with varying degrees of specificity about the hypotheses emerging from these theories.

- First research question:

Is there a significant relationship between growth-rate and size of p&p producers during the period 1970-2000 (Gibrat's law or random-walk analysis)? If such a correlation exists what is its nature?

Is there a significant relationship between the growth-rate variance among p&p producers and their size? If such a correlation exists what is its nature?

Is there significant serial correlation in the growth-rates of p&p firms? If such a correlation exists what is its nature?

These three parts research question is formulated to investigate whether p&p growth dynamics follows a random walk process, which means that growth is regarded as a pure stochastic phenomenon independent of size, resulting from the cumulative effect of a large number of factors acting independently. In the case that a non-random walk growth process is in operation, we wanted to investigate its main characteristics. It is important to study these growth dynamics features because they contribute to a better understanding of the patterns of corporate growth and industry evolution: the literature often assumes the stylized fact that firms' growth rates follow a random walk (Geroski 1999).

- Second research question:

Within the US p&p industry are there distinctive 'configurations' of technological specialization (strategic groups) of firms at one point in time (year 2000)? On the basis

that we can identify strategic groupings, does firm growth performance differ systematically across strategic groups? On the basis that it is possible to identify systematic differences in growth performance across strategic groups:
Are there distinctive firm behaviours associated with each technological configuration that may explain systematic firm growth performance differences across groups?
What portion of inter-firm difference cannot be explained by these behaviours (and thus may be due to firm-specific fixed effects)?

The aim of these four parts second research question is to deepen the nature of the departure from Gibrat's law. We investigated the hypothesis that firm growth is not a random-walk because firms' technological configurations give rise to strategic groups whose performance is consistently heterogeneous.

- Third research question:

Within the US p&p industry are there distinctive patterns of non-survivor firms during the period 1970-2000?[128] If there are observable patterns, what are their sources and determinants? Within the US p&p industry are there distinctive patterns of firm technology adoption behaviour over time and across the three clusters identified in Chapter 6? What proportion of US p&p industry capacity expansion can be explained by state-of-the-art technology adoption, and what proportion can be explained by incremental technology improvements and upgrading?

These four parts third research question aimed at augmenting the industrial dynamics empirical literature by providing evidence of the existence of survival and technology adoption patterns in one of the most capital intensive industries in the world during the period 1970-2000 when the industry experienced important technology advances that significantly affected its dynamics.

<u>Databases and methodology</u>

The empirical investigation in this thesis was based on two panel databases. A first dataset containing information on key characteristics of the 150 world's largest p&p

[128] Corresponding distinctive patterns and determinants of firm survival.

firms, which account for two-thirds of world output, for the period 1978-2000. This dataset provides an appropriate representation of the global p&p industry. A second dataset contains data of the annual production capacity of the entire population of US p&p companies during the period 1970-2000 including capacity data for each of the 13 principal p&p technological classes. The US is by far the largest producer and consumer of pulp, paper and board, accounting for approximately one third of world production and consumption. The detailed information on capacity for different technology classes allowed careful analysis of the industry dynamics and detailed consideration of the role of technology in these dynamics. In addition to the above, other industry and country level data and qualitative information were gathered via interviews with industry experts and from industry and company reports.

To answer the research questions the thesis used a quantitative hypothesis-deductive approach and specific statistical and econometric tools. To investigate the operation of Gibrat's law (first research question) a dynamic econometric model was applied taking into consideration the several econometric problems often present in dynamic analyses such as serial correlation, heteroskedasticity, sample selection bias and non-linearity. To investigate the second research question that deals with the existence of the technological configuration of firms, we used cluster analysis in order to group and test the existence of different clusters of firms with specific technological characteristics and systematic differences in growth performance. To analyse the third research question relating to the patterns and determinants of p&p firms' survival and technology adoption patterns over time, we used three complementary techniques. Firstly, 'transition matrixes' were constructed for the complete population of US p&p firms to conduct a first examination of their patterns of entry, exit and growth. Secondly, a general hazard rate function was applied to investigate the determinants and patterns of firm survival. We used a semi-parametric (Cox proportional) and a parametric (Weibull) model, which allow contextual, industry and firm level explanatory variables to vary over the study period. Thirdly, a threshold capacity change variable was defined for each technology class per decade in order to distinguish between adoption of new capital equipment and improvement or upgrading of existing machinery.

8.2 Thesis main findings and contributions to the literature

This subsection discusses the theoretical, methodological and empirical contributions of the thesis.

8.2.1 Contribution to the dynamics of industrial structure and heterogeneity within industries literatures

Although this research is empirically driven rather than theoretical based, the findings contribute to the theoretical understanding of the dynamics of industrial structure and heterogeneity within industries literatures.

The first theoretical contribution is related to the identification of three important patterns of long run corporate growth within a very high capital intensive industry context. First, corporate growth is not, as a large body of literature argues, a random walk process. Second, this non-random growth size relationship is not linear along the size distribution. Thus, even when Gibrat's law is not assumed, it is incorrect to suppose that a unique growth-size relationship applies to the whole industry, as is assumed by many studies. Third, corporate growth persistence is heterogeneous along the size distribution and over time. There is a large literature related to growth that sees corporate growth as being driven essentially by several uncorrelated forces, and as being independent of past growth, thus as a random-walk process. We demonstrate that even in a quite mature industry, corporate growth is not random, not linear and not independent of past growth. Our findings imply that the forces ruling the industry dynamics are more complex than those ones suggested by Viner, Bain or Mason[129] and later by Gibrat's tradition (see Chapter 3). The findings from this research give support to the 'evolutionary' and 'resource based' theory of the firm (Nelson and Winter 1982; Teece and Pisano 1994) which conceives firms as historical and social entities in which growth is considered to be path dependent and their heterogeneity an essential aspect of the processes that create economic progress.

[129] As discussed in Chapter 3, they argue that economic forces, such as minimum efficient scale or efficient production function, govern the dynamics of the industry in the long run.

The second theoretical contribution of this thesis is to demonstrate that corporate growth in a high capital intensive and mature industry context (such as the p&p industry described in Chapter 2) does not follow Gibrat's law because of the existence of a within industry structure characterized by three technological configurations of firms which show persistently heterogeneous growth performance over long periods of time. These three distinctive clusters or strategic groups are *'Large & Diversified'*, *'Medium & Specialized'*, and *'Small & Very Specialized'* firms. In contrast to neoclassical theory which predicts that small firms tend to grow faster than medium and large firms in order to reach a 'minimum efficient scale' (Hart 2000), and which see heterogeneous performance of firms as a temporary phenomenon as convergence takes place; our findings show that heterogeneity persists over long periods of time. In addition, we have demonstrated that it is not the small but rather the *'Medium & Specialized'* companies that systematically show the highest growth performance in the size distribution. This heterogeneity is not a random process; rather we would argue that it is the consequence of at least two factors that influence the evolution of the industry. On the one hand, different patterns of technology adoption behaviour associated with each of the strategic groups. On the other hand, different patterns of new entrant firms among strategic groups. New entrants have significantly higher growth performance compared with incumbents and exiting firms, however their entry rate varies significantly across the three clusters, unevenly influencing growth performance.

The third theoretical contribution is demonstration of the important influence of technological change in industry dynamics and as a determinant of performance heterogeneity. We demonstrate that the exit hazard rate among other variables, is strongly correlated to the principal technological advances during the study period 1970-2000, i.e. the rapid increase in paper machine operating speeds. This finding confirms the important effect of technological progress on industry structure (Abernathy, Clark et al. 1983; Baldwin and Scott 1987) as argued by several scholars.

8.2.2 Methodological contributions

This thesis makes three methodological contributions.

The first methodological contribution is related to the in-depth analysis of a single industry that gives the opportunity to observe and understand the forces and patterns of industry structure dynamics that are not observable within a more general approach such as comparing large numbers of industries without understanding their principal technologies and the possible configurations of strategic groups (Porter 1979, p. 220). This in-depth analysis enriches the within industry heterogeneity and strategic group literatures adding new elements and, specifically, on the dynamics of the p&p industry structure which has received little academic research attention in recent decades. Certainly, in high capital intensive industries structural features, such as economies of scale, and entry and exit of firms, are of strategic importance to firms' long run competitiveness.

Second, the literature discusses extensively the need to conduct more appropriate studies of firm growth dynamics since they present several econometric and growth measurement problems (e.g. heteroskedasticity, serial correlation, sample selection bias and linearity assumptions) which bias results (Sutton 1997). This thesis provides a methodological contribution to the literature by conducting a robust analysis of the dynamic growth process of more than 500 firms from a single industry using historical data for a period of 30 years. The robustness of the results is based on the consideration of the econometric and data problems described above that occur in this type of studies. We conducted sensitivity analysis of growth measurements and testing through the use of: i) different times lagged to calculate firm growth; ii) both normalized and non-normalized firm size data across years; iii) two different methods to test Gibrat's law, size class comparisons for growth mean and growth variance analysis, and log linear regression model for growth persistent analysis; iv) use of two different size-class border definitions to compare average growth across the different classes. Most of the literature regarding Gibrat's law uses less robust and less accurate techniques than those proposed in this investigation.

A third methodological contribution is related to defining a proxy variable to represent the technology adoption decision at the different technology class levels. This variable is based on a threshold capacity change value which is defined per technology class per decade. These values are obtained from the cumulative capacity change distribution curve for each of the 13 p&p technology classes and decades. We identify a technology adoption decision if the capacity change of the firm *i* at time *t* and technology class *j* is larger than its corresponding threshold value. Ideally, to study technology adoption patterns we would need a dataset with complete life histories of the population of adopters and potential adopters, and the characteristics of the state-of-the-art p&p machines over a sufficiently long period beginning from their first launch. Such data are rarely available and, thus, in the absence of direct observations of the acquisition of new machinery, we constructed a technology adoption decision variable which allowed us to study and compare firm technology adoption behaviour over long periods of time and across different size-classes of the firm size distribution curve.

8.2.3 Contribution to the empirical understanding of the dynamics and technological structure of the p&p industry

The main findings and contributions of this thesis to the empirical understanding of the dynamics and technological structure of the p&p industry are presented following the order of the three research questions investigated in Chapters 5, 6 and 7.

<u>Empirical contribution of research question 1</u>

The main contribution of the investigation of this research question is the finding that the p&p industry growth dynamics do not follow a ‘random walk’ process or Gibrat’s law. For the US dataset none of the three Gibrat’s law hypotheses were supported; for the dataset of the 150 global firms the first two hypotheses were not supported. For example, first, we found there was a general tendency for smaller firms to grow faster on average than large firms during the study period, which is in line with the findings from several other studies (Mansfield 1962; Kumar 1985; Hall 1987; Evans 1987b; Dunne, Roberts et al. 1989; Mata 1994; Hart and Oulton 1996; Sutton 1997; Caves 1998; Almus and Nerlinger 2000). However a more interesting and somewhat surprising finding is the non-linear growth-size relationship observed along the size distribution. For the five size-classes studied (very large, large, medium, small, and very small firms), firms in the ‘large’ size-class (not in the ‘very large’ size-class) exhibit consistently high growth rates – among the highest in the size distribution. Most Gibrat’s law studies assume linearity and this finding demonstrates that at least in the p&p industry there is important variability in the growth-size relationship along the size distribution and thus the average industry coefficient is not an appropriate indicator.

Second, we demonstrate that the variability in firm growth decreases with size, being larger for small firms than big companies for both datasets which is also in line with several other studies (see recent reviews: Audretsch, Klomp et al. 2002; Lotti, Santarelli et al. 2003). The results of the third Gibrat's law proposition that refers to the existence of growth persistence show that serial correlation is not significant for the global dataset, but we found a positive serial correlation for the US industry during the 1980s, but a not significant correlation for the 1970s and 1990s. The most interesting finding is that growth persistence differs considerably among the different size-classes and also over time. 'Large' firms show positive growth persistence along all three decades studied. 'Medium' and 'small' firms show dissimilar autocorrelation over time, with growth persistence negative during the 1990s, positive during the 1980s, and not significant during the 1970s. We hypothesize that the reason for the positive growth persistence observed for the entire size-distribution over the 1980s, is the important increase in production capacity during that decade (see Table 5.12). This suggests that all firm size-classes reaped some advantage from the aggregate growth in capacity that occurred in the 1980s. We can also hypothesize that the higher machine speeds in the industry after the mid-1980s might explain the significant differences in growth persistence along size-classes observed in the 1990s. While large firms were positively affected by these technological innovations, demonstrated by their strong positive autocorrelation, small and medium sized firms were negatively affected by it (see Table 5.11), explaining their negative autocorrelation and the increased number of small firms that exited the industry in that decade. These hypotheses could be tested in future research using more specific data.

From our analysis of the relationship between firm type-classes (incumbents, new-entrants, and exits) and growth we can conclude that new-entrants show the highest growth-rates on average and also the highest growth-rate variance among both the global and the US p&p firms, which is in line with the Schumpeterian (1912) hypothesis characterized by a major role played by new entrants in innovative activities, and a continuous erosion of the competitive and technological advantages of the established firms in the industry. It is reasonable to assume that this pattern might also explain the non-stochastic nature of p&p growth dynamics, considering that new entrant firms' sizes are not randomly spread along the distribution, but concentrated in the small and medium size-classes as demonstrated in Chapter 6.

<u>Empirical contribution of research question 2</u>

The second research question investigates why random walk is not in operation within the p&p industry and its main contribution is the demonstration that there is a technological structure within the p&p industry which explains this departure from Gibrat's law. In Chapter 6 we demonstrated the existence of distinctive configurations or strategic groups of firms, based on their technological specialization. Specifically, we found there are three distinctive strategic groupings: i) Large & Diversified firms (8 firms with size mean of 3.6 million tonnes during the period 1986-2000 and 7.1 technological classes average), ii) Medium & Specialized firms (41 firms with size mean of 0.9 million tonnes and 2.5 technological classes average), and iii) Small & very Specialized firms (185 firms with size mean of 0.1 million tonnes and 1.4 technological classes average). To assess the robustness of these results, we applied reliability and validation techniques, and we also checked them through interviews with industry experts.

A second finding is that there are systematic differences in firms' growth performance across these three strategic groups, which explain the departure from a random walk process. The 'Medium & Specialized' cluster shows systematically the highest growth rates (8.1% annual growth mean during the period 1986-2000) compared with the other two strategic groups (3.7% for the 'Large and Diversified' firms and 2.3% for the 'Small and very Specialized' firms).

A third finding is that the systematic growth performance differences across clusters is not random, but is the consequence of at least two factors that influenced the evolution of the p&p industry in the 1980s and 1990s. The first factor is related to the different technological choices made by the firms in each of the three clusters. In order to achieve high growth performance firms need to encompass a degree of specialization in some technological commodities. This applies to the 'Medium and Specialized' cluster whose firms are focused on production in between two and four technology classes and from mid 1980s was the fastest growing group. In contrast, being large and diversified such as cluster 2 firms, is associated not with high growth but with medium growth in this sector. This applies to the ‘Large and Diversified’ cluster whose firms are the largest in the US p&p industry and are the most diversified firms, producing six to nine technology classes. We show also that being small and very specialized, such as cluster 4 firms, is associated with low growth performance. This applies to the ‘Small and very Specialized’ cluster whose firms are the smallest in the US p&p industry and also are the most specialized, producing only one or two technology classes.

The second factor is related to the industrial dynamics in the industry. New entrant firms exhibit the highest growth in the industry; however their entry is not uniform along the size distribution: they tend to be medium sized firms on entry, which contributes to the high growth in the ‘Medium & Specialized’ cluster. New entrants tend not to belong to the ‘Large and Diversified’ cluster: thus, this strategic group remained a closed system during the study period with the eight initial incumbents showing medium growth performance.

The fourth contribution is related to the random-walk analysis within clusters and industry subgroups, and its residual for the period 1986-2000, which is the most interesting period for dynamic analysis in this industry. It has been demonstrated that random-walk operates within cluster 2 (8 ‘Large and Diversified’ firms) because the ‘growth rate mean’ and ‘growth variance’ of the four smaller firms (mean=4.2 & sd=11) show no significant differences compared with the four larger firms (mean=3.1 & sd= 11). However, random-walk does not operate within clusters 3 (41 ‘Medium & Specialized’ firms) and does not operate within cluster 4 (185 ‘Small & very specialized’ firms). In both cases the growth mean of the 50% smaller firms was significantly higher than the growth mean of the 50% larger companies. The main reason for this heterogeneity performance is that new entrant firms have systematically higher growth rate means compared with cluster incumbents and they tend to be smaller in size.

Through a process of decomposition within clusters we demonstrated that for 83% of total cumulative capacity of survivor firms (year 2000) random-walk conditions apply. For the 17% residual the inter-firm growth performance differences are not explained by the distinctive behaviours of firms associated with their strategic groups and thus might be related to fixed effects. This requires further investigation using more specific data.

Empirical contribution of research question 3:

A first result from our analysis of this research question is the empirical demonstration of a discernable pattern of p&p firm survival (or exits) over the period 1970-2000 examined. Five variables and one interaction variable were found to be significant determinants of firm exit:

- the contextual variable ‘machine-speed’ has a very significant positive coefficient which means that the higher the machine speed, the higher probability that p&p firms will exit the industry;
- at sectoral level, the effect of industry concentration is significant, but its coefficient is negative meaning that the increase in industry concentration reduces the risk of exit. This variable is highly correlated with machine speed;
- at firm level, current size has a significant negative coefficient, which means that firm size exerts a decisive influence over survival and, thus, larger firms will have a smaller risk of exiting the industry than smaller firms;
- initial firm size has a positive and significant coefficient which means that the exit hazard rate for larger size start-ups is higher than for smaller size start-ups;
- firm age is a significant variable with a negative coefficient which means that older firms are less likely to exit the industry than young firms; this finding is in line with several other empirical studies (e.g. Dunne and Hughes 1994);
- firm growth is not significant; however, its interaction with age has a significant negative coefficient. This means that high growth is not a determinant of firm survival for all types of firms, but only for those that show persistent growth over long periods of time, thus giving support to Jovanovic (1982) and others who emphasize post-entry learning as an important determinant of firm performance.

A second finding from our investigation of this research question is that exit hazard is not constant over time, and increased significantly during the second part of the study period 1986-2000 compared to the first period 1970-1985. The three explanatory variables machine speed, initial and current firm size, are the most important determinants of exit hazard between periods. This result is in line with the hypothesis of a technological regime change that may have taken place in the industry during the mid-1980s as a consequence of a major technological advance: acceleration in paper machine operating speed (Mardon, Vyse et al. 1991; Davy 1997; Haunreiter 1997).

A third result is related to the different patterns of technology adoption over time. We demonstrated that a significant increase in the frequency of technology adoption and technology shut down occurred during the second period 1986-2000 compared to 1970-1985. This means that during the latter period a larger percentage of capital equipment was renewed through purchase of new and shutting down of old machinery, confirming the existence of a technology inflection point (technology regime change) in the mid-1980s.

Our fourth finding is related to the patterns of technology adoption over time, identified in Chapter 6, by firms in the two largest strategic groups. In the first study period, 1971-85, the ‘Large & Diversified’ strategic group adopted new capital equipment at an average annual rate of 4.6%, while the adoption rate for the ‘Medium and specialized’ strategic group was 2.5%. It is interesting that during the next period 1986-2000 the adoption pattern was reversed. Although both strategic groups increased the frequency of their adoption of technology over time, as explained above, for the ‘Medium and Specialized’ firms it increased from 2.5% to 8.6% (by more than three times) while for the ‘Large & Diversified’ firms the increase was only from 4.6% to 6.0% (less than half time). These systematic differences in technology adoption behaviour across clusters, and over time, provide a robust explanation for the heterogeneous growth performance observed between clusters 2 and 3 during the period 1986-2000: the former had an average growth rate of 8.1% while the latter was 3.7%. This systematic heterogeneous growth performance across clusters is also a significant explanation for the departure from Gibrat’s law.[130]

The above suggests that ‘Medium & Specialized’ firms are able to reap more advantage from new technology than the ‘Large and Diversified’ firms and the ‘Small and very Specialized’ firms. There may be several reasons for this asymmetry in technology

[130] As already discussed, other causes are the heterogeneous patterns of firm entry and exit, and the serial correlation differences observed across the size distribution.

adoption behaviour across clusters. One is proposed by Penrose (1959); the 'span of control' of management is constrained, setting a limit to the exploration and exploitation of new technological opportunities among the largest incumbent companies. Medium & Specialized firms on average are three times less diversified than the former group, thus, they are less constrained in terms of the exploration and exploitation of the new opportunities given by the continuous changes in p&p production technology. However this hypothesis needs further investigation using qualitative data at firm level.

The fifth finding of this research question is related to the type of industry capacity expansion. We have demonstrated that both sources of growth - adoption of new capital equipment, which usually produces lumpy capacity changes at firm level, and upgrading of/improvement to existing machinery, which usually produces many incremental capacity changes at the firm level – explain much of the aggregate capacity expansion observed in the industry over the period 1970-2000 analysed.

In summary

As a general conclusion we can say that the p&p industry does not follow a 'random walk' process or Gibrat's law because it is influenced by such factors as technological change and different market conditions. Firms react to these influences in different ways creating distinctive clusters or strategic groupings of firms whose heterogeneous conduct and performance persist over time. Also there is not a linear relation between growth and size distribution, and between time and growth rate, thus we can say that size, technology and time matter.

Size matters because there is a general tendency in the study period, for medium-large firms to grow faster on average than the very large firms. Also, the variability in firm growth decreases with size, being larger for small firms than for big companies. which is in line with many other studies (Sutton 1997; Audretsch, Klomp et al. 2002; Lotti, Santarelli et al. 2003). We found also that the growth-size relationship observed along the size distribution is non-linear. Among the five size-classes studied ('very large', 'large', 'medium', 'small', 'very small') firms in the 'large' size-class exhibit consistent growth rates which are among the highest in the size distribution. Also, there is significant growth persistence in large firms, and null or negative growth persistence in small size firms.

Technology matters because we found that different configurations of technological specialization give rise to clusters or strategic groups that constitute a structure within the industry with persistent growth performance heterogeneity, which explains the departure from Gibrat's law. This means that among medium and large firms, those that have been more specialized in some technological classes have shown significantly higher growth rates than large and more diversified firms working in several different technological classes. However, this applies only to the US firm sample: data limitations prevent us from demonstrating this result for the 150 global firms.

Time matters because the above growth dynamics is not linear over time, in fact there are significant differences between the periods 1971-1985 and 1986-2000. There is robust evidence that during the latter period the dynamics of the industry increased considerably. The exit hazard rate augmented significantly in the latter period, a large number of firms exited the industry, and the technology adoption rate by medium and more specialized firms increased significantly over time.

From the point of view of the firm, the above evidence shows that a production strategy focused on specific subsets of the 13 technology classes studied and being a medium to large size (but not very large) company has been the basis for success in the p&p industry since the mid-1980s when a technology regime change occurred. The group of companies with these characteristics have exhibited consistently higher growth rates during the study period compared with very large and diversified firms and small and very specialized companies. This suggests that, at minimum, careful consideration of product strategy and size are important for success in the future. Of course, future conditions may not reproduce the experience of the 30 years before 2000 and therefore actual changes would need to be taken into account when formulating a specific company strategy.

8.3 Limitations of this study and suggestions for future research

One of the limitations of this research is the data used to investigate the second and third research questions. Both the cluster analysis in Chapter 6 and the analysis of technology adoption in Chapter 7 apply only to the US p&p industry because of lack of data on the 150 world firms. Output or capacity data at the technology class level were not available for the 150 largest world firms. Were these data to become available, it would be an interesting line for future research to compare the results obtained for the US p&p sector with those for the global industry. Due to the unavailability of p&p demand data it was not possible to analyse the influence of demand on firms' growth performance and adoption behaviours. Bottazzi & Dosi *et al.* (2001) provide this type of analysis for the world's 150 largest pharmaceutical firms over a 10 year period.

Nevertheless, there are several reasons to believe that the conclusions obtained for the US in Chapters 6 and 7 could be generalized to the global industry. These include: a) the non-situated characteristics of this industry; b) the fact that the US is the largest producer and consumer country of p&p products in the world, accounting for more than one third of the world p&p production and consumption during the study period; c) there are common inputs to the production process, d) there are low barriers to availability of state-of-the-art p&p capital equipment,

A second limitation of this research is the difficulty of accounting totally for the effects of M&A activity in this industry during the study period. As noted in the thesis, this industry is highly fragmented and region-based, thus it is extremely difficult to gather all the historical information required to eliminate completely the possible M&A effect on the phenomena investigated. Chapters 4 and 7 describe the procedures applied to reduce the effects of the most important M&A activity among the medium and large companies. Many previous studies on growth ignore M&A because of the difficulties of constructing historically comparable data. If more detailed M&A data were to be made available by the industry or governments, we could enhance understanding of the effects.

A third limitation of this research is related to the type of data used for the investigation of technology adoption patterns developed in Chapter 7. This analysis uses secondary data on significant changes in firm capacity, as a proxy for capital equipment adoption.

Considering the highly capital-intensive characteristics of the sector, if primary data on acquisition of new capital equipment by p&p firms, on a year to year basis, for the period analysed in this research, a model could be developed to represent diffusion of the latest technology. This could then be used to trace in more detail the patterns of p&p firms' technology adoption behaviour.

A final comment relates to the possibility of contrasting the results in this research that used quantitative methods to verify the relationship between firm size, growth, technological configuration and adoption, with more specific information that might be gathered using a qualitative approach such as another set of interviews with industry experts. This might provide more detailed information on the hypotheses tested in this thesis.

Further research

This thesis provides an in-depth, single industry investigation which improves our understanding of the forces underlying the dynamics of industrial structure in one of the most capital-intensive sectors in our modern economy. This investigation has raised several additional questions and hypotheses that should become part of a future research agenda and would help to overcome some of the limitations of this research.

Having identified significant growth performance differences over time among the three strategic groups reported in Chapter 6 ('Large & Diversified firms', 'Medium & Specialized firms' and 'Small & very Specialized firms'), a next step could be to study the relationship between these strategic groups and their firms' financial performance over time. Specifically, it would be interesting to investigate whether the fast growing strategic group conformed by the 'Medium & Specialized' firms is also associated with the highest average profits and whether the medium growth group of 'Large & Diversified' firms is associated with lower average profits in the long run. This would require collection of comparable annual financial data.

Another topic for future research is related to the growth persistent analysis conducted in Chapter 5 (section 5.2.2) and specifically with the 'demand shock' and 'technology shock' hypotheses. On the one hand, the high increase in p&p capacity that occurred during the 1980s might explain the positive growth persistence observed in that decade along the entire size distribution. This would suggest that all firm size-classes reaped some advantage from the important jump in US p&p capacity that emerged in the 1980s. On the other hand, the higher speeds of p&p machines that became available in this industry in the mid-1980s (see Figure 1.2) produced important increments in production scale, productivity and machinery costs, which might explain the significant differences in growth persistence across the size-classes observed in the 1990s. We have hypothesized that large firms were positively affected by these significant technological innovations, which explains their strong positive autocorrelation, and that small and medium size firms were negatively affected by it, which explains their negative growth persistence (see Table 5.11), and the increased number of exits among small firms during the 1990s. Thus, demand shocks and technology shocks produce different effects on the industry. While the former benefited the entire size distribution, the latter benefited only the large companies and negatively impacted on the medium and small firms. It would be interesting to test these hypotheses in order to increase our comprehension of the impact of significant demand and technology changes on growth dynamics.

A third avenue for further research agenda is related to the persistent heterogeneous technology adoption behaviour across clusters and over time, discussed in Chapter 7. It would be interesting to investigate its specific causes using more specific data. During the first period studied in this thesis, 1970-1985, the large firms show significantly higher technology adoption frequency than the medium and small size firms which is in line with most empirical investigations of inter-firm technological diffusion which generally find a positive relationship between firm size and frequency of adoption for a wide range of technologies in different industries. However, during the second period studied, 1986-2000, after the technology inflection point (see Figure 1.2), the 'Medium & Specialized' cluster of the firms that are active in only a few technology classes, shows significant and persistent higher technology adoption frequency compared with the 'Large & Diversified' cluster (see Table 7.14b) – a phenomenon that has been rarely observed empirically. We could suggest some reasons for this asymmetry in technology adoption behaviour across clusters. One is in line with Penrose (1959), who argues that the 'span of control' of management is constrained, creating a limit to the exploration and exploitation of new technological opportunities among the largest incumbents companies. Is the span of control of management in the p&p industry a significant factor in explaining the slower adoption of new technology of the 'Large & Diversified' cluster compared with the 'Medium & Specialized' whose firms are on average three times smaller and less diversified than the former group? Does this mean that they are more constrained in terms of exploration and exploitation of new opportunities provided by the accelerated changes in p&p production technology that occurred in the mid-1980s? These are empirical questions that could be investigated in future research in order to test Penrose's hypothesis based on qualitative data at firm level.

A fourth suggestion for future research is related to the random walk residual discussed in Chapter 6, Section 6.3.2. Through a decomposition process within the three clusters identified, we demonstrated that 83% of the total cumulative capacity of year 2000 survivor firms operate under random-walk conditions within their cluster or sub-cluster, but that the 17% residual does not. This inter-firm growth performance difference is not explained by distinctive firm behaviours associated with the different configurations of firms, and thus might be related to fixed effects: this requires a deeper investigation and more specific data.

A fifth area for further research would be a deeper investigation of the roles of the demand-side, foreign trade and regulation and their evolution in the sector and their possible role in shaping p&p industry dynamics. As discussed in Industry Chapter 2, aggregate demand for p&p at country level is highly correlated with the degree of economic development (Diesen 1998). Thus, global consumption of p&p products is expected to continue growing at approximately 4% per year in successive decades. Also, international trade in p&p products has increased steadily since the mid-1970s (see Figure 2.7) to reach approximately 30% of world output in 2000, and is expected to continue increasing in future decades. Finally, environmental aspects are an important dimension of the p&p industry since it is ranked among the top five in terms of quantities of toxic materials generated per unit of output (Herbert-Copley 1998). Concern for the environment has pushed regulations towards promoting more environmentally friendly products and processes and the use of recycled fibre. Further research oriented to study the influence of these three developments on p&p industry dynamics would complement the present investigation.

This thesis does not examine the composition of new capital equipment acquisition due to the absence of data. This absence of data required assumptions to be made about the nature of technical change in the industry. Observation of aggregate indicators shows that there was a major ‘inflection point’ in the frontier speed of paper machine operating technology during the mid-1980s (see Figure 1.2). While the possibility of large scale acquisition of ‘new vintage’ capital equipment with incremental capacity increases might seem to confound the assumption that this inflection point reflects a radical change in the available technology, the interviews provided no evidence of a simultaneous technology adoption. Several interviewees commended on the impressive technical advances that had been made during the period. However, it is possible that some portion of the change observed was based on some firms adopting technology that provided incremental improvements as a response to the adoption by other firms of more radically improved machinery. Data on specific models and the patterns of adoption of new technology during this period would be a useful extension to the research in this thesis.

A final suggestion is related to industry comparisons. It would be interesting to run similar investigations of other industries with comparable characteristics, such as the cement or steel industries. This would provide a better understanding of the how far the findings from this research can be generalized. Similar to the p&p industry, these industries are highly capital-intensive; their production processes are continuous and highly dependent on the location of resource inputs. Generally their production plants are located at a distance from their markets despite the high costs of transport. In all these sectors the technology has changed significantly since the 1980s and the investigation in this thesis would be complemented and extended if other industries with comparable characteristics were similarly analysed.

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