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UNIVERSITE PARIS 1 PANTHEON-SORBONNE
ECOLE DOCTORALE



Scuola Superiore
Sant'Anna
di Studi Universitari e di Perfezionamento

SANT'ANNA SCHOOL OF ADVANCED STUDIES

DOCTORAT
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EMPIRICAL INVESTIGATIONS INTO THE CHARACTERISTICS
AND DETERMINANTS OF THE GROWTH OF FIRMS

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Scuola Superiore
Sant'Anna
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EMPIRICAL INVESTIGATIONS INTO THE CHARACTERISTICS
AND DETERMINANTS OF THE GROWTH OF FIRMS

A DISSERTATION
SUBMITTED TO THE S.ANNA SCHOOL OF ADVANCED STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN ECONOMICS AND MANAGEMENT

Alexander Jean-Luc Coad
April 2007

L'université de Paris 1 n'entend donner aucune approbation ni improbation aux opinions émises dans cette thèse. Ces opinions doivent être considérées comme propres à leur auteur.

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Chapter 1

Introduction

The primary focus of this thesis is to advance our understanding of the phenomenon of firm growth. In our modern economy, industries are becoming more and more turbulent and the struggle between firms for market share is becoming increasingly fierce. The growing importance of innovation, in particular, has been responsible for this. In addition, the development of financial institutions has enabled firms to accelerate their expansion projects with the support of external finance. Globalization has forced firms to become aware of their overseas markets, as the struggle for customers can no longer be confined within national borders. More generally, the fast pace of the information age has changed the way firms operate, bringing customers closer to their suppliers. For all of these reasons, and more besides, we believe it is necessary to take a new look at the growth of firms.

It is instructive to place firm growth in a historical perspective. In the past, a large size was a prerequisite for security. Firms strove to become large in order to guarantee their future. The advantages of a large size were reinforced by the relatively backward state of financial markets. Large firms had the advantage of ‘deeper pockets’ into which they could delve during adverse business conditions. Another factor to be taken into consideration is that at the beginning of the twentieth century, the ‘Fordist’ brand of mass-production techniques was very much in vogue. During this period, the growth of firms was associated with economies of scale and lower unit costs. Furthermore, firms began to question the mono-product business model that had hitherto been the norm. In this vein, Du Pont de Nemours achieved legendary success by engaging in a diversified portfolio of activities arranged in the context of a decentralized and multidivisional organizational form. In addition, it was conjectured (e.g. by Schumpeter) that it was primarily the large firms that were willing and capable of investing in R&D laboratories. Large size was therefore considered to be a sign of the accomplishment of a firm’s aspirations, and as something of an ‘ultimate stage’ in a firm’s development.

In the present business climate, however, there is an emphasis on flexibility and ‘lean’ production. We are now in an age where downsizing and refocusing are celebrated strategies.

A capitalism based on mass production and standardization has given way to an organization of production based on customization and product differentiation. Improvements in financial markets, and the aversion of shareholders to diversified firms (and conglomerates in particular) has brought on the disintegration of the large Chandlerian firm. Information Technology has played a role in this, allowing firms to increase the flexibility of their production lines. Indeed, there is evidence to suggest that the introduction of productivity-enhancing Information Technology has been accompanied by widespread organizational change (Brynjolfsson and Hitt, 2000). Furthermore, Information Technology has helped reduce transaction costs, thereby reducing the incentives for firms to be fully integrated along their respective ‘filières’. In the context of the ‘make-or-buy’ dilemma, firms need to be less cautious about dealing with suppliers through the market mechanism, even if this means the outsourcing of services from far-away continents. The fast pace of change in markets has led to the emergence of a new stereotype – the lean, flexible firm whose competitive advantage rests on a focus on a small number of core competences.

In the light of this discussion, it is evident that we need to reconsider the subject of the growth of firms – a subject which still, arguably, remains dominated by the seasoned works of Gibrat (1931), Penrose (1959) and Marris (1964).

Early theoretical work into the size and growth of firms was placed in a comparative statics framework, and by reason of its static nature did not really deal with the dynamic phenomenon of growth. Firms were supposed to be at their ‘optimal size’; and if they weren’t there already, they were assumed to grow instantaneously to reach it. In this way, firm growth received a cursory treatment as an appendage to the optimal size theory. Firms were considered to grow only inasmuch as this enabled them to reach their optimal size. However, dissatisfaction with this theory of firm behavior has grown in recent decades. Notions of an ‘optimal size’ have been rejected in almost any interpretation of the phrase that one might subscribe to. Similarly, other theoretical contributions surveyed in Chapter 2 have not been helpful in describing the growth of firms. Instead, emphasis has been placed on the prevalence of uncertainty and bounded rationality in the context of a turbulent and restless economy. It is therefore our view that the evolution of the economy cannot be worked out from the armchair. Instead, our understanding of the growth of firms must progress through solid empirical analysis. This necessarily involves ‘getting one’s hands dirty’ and working with data. We feel obliged to reiterate an exhortation that is dated but nonetheless still very relevant: “The subject of organizational growth has progressed beyond abysmal darkness. It is ready for – and badly needs – solid, systematic empirical research directed toward explicit hypotheses and utilizing sophisticated statistical methods” (Starbuck, 1971: 126).

The choice of an empirical approach to research into firm growth has been bolstered by several recent trends in economic research. First, the development of longitudinal datasets,

which allow detailed analysis at the firm level, has been responsible for much of the recent progress in our understanding of firm behavior and industrial development. Second, econometric techniques have kept pace with the availability of increasingly informative datasets. Modern econometric work is able to deal with such complicated issues of endogeneity, unobserved time-invariant effects, and selection bias. The progress that has been made in this domain has been reflected by the number of Nobel memorial prizes awarded to econometricians in recent years. Third, steady increases in computational power have been able to match developments in databases and econometric techniques. Bootstrapping methods, for example, are particularly computationally intensive and their use has only become feasible thanks to developments in the performance of computers.

Care should be taken in choosing our empirical methodology, however. There are certainly many pitfalls and limitations that accompany empirical work. In particular, in this thesis we consider it to be necessary to recognize the great heterogeneity that exists between firms, whether we consider productivity levels, profitability, or a large number of other key dimensions. As Griliches and Mairesse (1995: 23) explain:

“We also thought that one could reduce aggregation biases by reducing the heterogeneity as one goes down from such general mixtures as ‘total manufacturing’ to something more coherent, such as ‘petroleum refining’ or the ‘manufacture of cement’. But something like Mandelbrot’s fractals phenomenon seems to be at work here also: the observed variability-heterogeneity does not really decline as we cut our data finer and finer. There is a sense in which different bakeries are just as much different from each other, as the steel industry is from the machinery industry.”

(See also Dosi and Grazzi (2006) for further evidence of pervasive heterogeneity of firms, even at finely disaggregated levels.) We should be cautious of notions of a ‘representative firm’ which might lead us to overlook this heterogeneity. The assumption of homogenous firms¹ is not innocuous, and in our case it leads to a rather different characterization of the underlying phenomenon. Indeed, the analyses presented in Chapters 4, 7 and 8 yield results that are qualitatively different from those that could be inferred from approaches that deal exclusively with ‘the firm on average’. In an attempt to deal with this issue of heterogeneity, much of our analysis employs quantile regression techniques, that are able to identify differential effects of the explanatory variables across the conditional distribution of

¹Note however that there are subtle differences between the concepts of the ‘representative firm’ in Marshall’s sense, and the concept of ‘representative firm’ employed in other models. Marshall’s ‘representative firm’ refers to one single firm that has the same behaviour as the industrial sector. Other models, however, consider the representative firm to be some sort of ‘average firm’, and model industries as being composed of n such identical firms (i.e. n ‘clones’) that are in competition with each other.

the dependent variable. Our results clearly indicate that a much richer appreciation of the underlying economic relationships is made possible only by allowing for heterogeneous effects.

For these reasons the notion of the ‘representative firm’ has been qualified (if not discredited) in theoretical discourse; however it can still be seen to persist in a nuanced form in empirical work. Although, the hypothesis of the ‘representative firm’ in empirical research has largely escaped attention, it can be found implicitly in conventional regression estimators that focus on summary point estimates corresponding to ‘the average effect for the average firm’. This approach is particularly ill-suited for looking at the relationship between innovation and firm growth, for example, because innovating firms have fundamentally heterogeneous performance differences – a minority of firms doing spectacularly well whilst in most cases R&D efforts will yield nothing substantial. Whilst many economists would question the usefulness of calculating, for example, the average value of a patent (without further investigating the distribution of patents), it seems that empirical work to date has been quite content to consider the ‘average’ influence of innovation on firm growth. In this thesis, however, we consider the influence of innovation on firm growth over the range of the conditional growth rate distribution. More generally, the focus of conventional regression estimators on ‘the average effect for the average firm’ is unhelpful because the ‘average firm’ is not representative. As is evident from the tent-shaped plots of growth rates (introduced into economics by Giulio Bottazzi, Giovanni Dosi, Angelo Secchi and colleagues; see Figures 2.3 and 2.4 on page 21 for an example) we see that the average firm does not grow very much at all. We argue that there is little point in trying to find the determinants of growth for the ‘average firm’, because this latter grows so little that its growth could be due to almost anything (hence the highly idiosyncratic component that is commonly found). Instead, it is just a handful of extreme-growth firms that are responsible for a disproportionate share of the turbulence and reallocation that drives industry dynamics. Focusing on the ‘average firm’ in the case of firm growth rates would be to misplace our attention. One of the main organizing themes of Chapter 7, and perhaps of the thesis in general, is that it is a heterogeneous minority of agents that is driving the process of industrial evolution.

Our empirical analysis is guided by the evolutionary perspective, for several reasons. First, this perspective explicitly recognizes the heterogeneity of firms (Paulré, 1997). At any time, we can expect there to be considerable diversity in the characteristics of firms. Whilst the least viable firms can be expected to be eliminated due to selection pressures, there will remain at any time a marked heterogeneity between the surviving firms, even among dimensions such as productivity and production methods. The importance of such an evolutionary vision of the economy has been further underlined by recent observations (referred to in the thesis) that selection pressures are rather weak. Second, evolutionary economics is based on what Sid Winter has called a ‘*dynamics first!*’ approach. A dynamic view of firms and industries is

obviously an essential ‘point de départ’ for our study of the growth of firms. Third, evolutionary economics embraces the phenomenon of innovation in a way that other perspectives are not able to do. The importance of firm-level innovative activity has grown tremendously over the last decades, and we need a theoretical framework that will take this into account. This is especially true given that Chapters 7 and 8 focus specifically on firm-level innovation. Fourth, the low rationality assumptions that form the basis of the evolutionary framework strike us as simply being far more judicious than the ‘Olympian’ rationality frequently assumed in the neoclassical paradigm. Uncertainty is unquestionably one of the basic features of the modern economy, and it seems to us to be one of the defining characteristics of firm growth. Indeed, in Chapter 5 we criticise the mainstream literature that takes the assumption of infinitely rational profit-maximizing firms as a foundation for its empirical work into firm-level investment patterns. Instead, we delve into evolutionary theory to obtain a guiding theory. In Chapter 6 we investigate the evolutionary principle of ‘growth of the fitter’ and it is astonishing to observe that even this general principle, when taken literally, does not appear to hold. It seems that even evolutionary economics, which has genuinely mild rationality assumptions, may be overstating the capacity of the forces of economic selection.

A final motivation for basing our analysis in the evolutionary perspective is that it appears to be in accordance with the empirical facts. One of the few regularities that has emerged from research into the growth of firms is that Gibrat’s ‘law of proportionate effect’ appears to provide a better description of industrial development than any other alternative theory. Although Gibrat’s law is frequently criticised as having no theoretical content (due to the emphasis on purely stochastic shocks), on the contrary it is our view that Gibrat’s law does have a theoretical basis, and that it is not too far-fetched to consider that this basis is of an ‘evolutionary’ flavour. We have three reasons for making this association. First, Gibrat’s law emphasizes heterogeneity between firms that stems from the variance of the growth shocks. Second, Gibrat’s law accommodates the evolutionary principle of path dependency (i.e. the ‘history matters’ argument) by the fact that a firm’s current size is viewed as the mere amalgamation of all previous growth shocks. Third, the stochastic nature of Gibrat’s law can be seen to emphasize the inherent uncertainty that permeates modern capitalism.

The analysis in this thesis inevitably presents only a partial description of the processes of industrial evolution. Among a large number of limitations, let us mention here three caveats that we believe to be the most important.

First, a major gap in the thesis concerns our deflection of questions relating to entries and exits of firms. These discrete events also have a substantial impact in shaping the evolution of industries. Nonetheless, it is our intuition that there is much that can be learnt just by concentrating the growth of firms. Selection can, in fact, be seen to operate through two mechanisms. One is selection via differential growth (i.e. the principle of ‘growth of the fitter’)

and the other is selection via exit (i.e. ‘survival of the fitter’). The first corresponds to Fisher’s fundamental equation (also known as ‘replicator dynamics’), whereas the second is perhaps closer to Baumol’s vision of contestable markets. The focus of this thesis is on the former. It can be expected that future work will not neglect these issues relating to entry and exit, although it must be acknowledged that a substantial body of literature already does focus on these issues.

A second major omission in our analysis is that we do not deal with growth by merger or acquisition in any great detail. These are rather peculiar modes of growth, corresponding to a transfer of productive capacity, rather than any objective increase in productive capacity. In our analysis of the French manufacturing industry (Chapters 3, 4 and 6), we have the unique possibility of separating these events from internal growth, because M&A events are coded for in the data and can thus be excluded. (In our analysis of US high-tech sectors in Chapters 7 and 8, however, it has not been possible to make the distinction between M&A and organic growth.)

A third caveat we should mention here is that our analysis does not include the very small firms that have only a small number (or indeed zero) employees. It was not possible to look at these cases given the nature of our databases. Although these firms represent a large part of the absolute number of business enterprises, it should be remembered here that their weighted share of economic activity is relatively small. Furthermore, these firms are quite different with respect to attitudes to growth – there is evidence that many small business managers are what we could call ‘lifestylers’², who display a certain aversion to growth. For such individuals, the enterprise is merely the guarantee of an independent way of life rather than being the apparatus of any serious attempt at ‘capitalist profit-maximisation’. As a consequence, the omission of these micro businesses does not appear to be a fatal flaw in our analysis.

Structure of the thesis This thesis is split into 5 parts. Part 1 aims to provide a reasonably comprehensive review of the literature to bring the reader up to date with the current state of knowledge about firm growth. Part 2 contains investigations into some basic features of growth rates and their autocorrelation structure. Part 3 focuses on the relationship between profits and growth. Part 4 attends to the influence of firm-level innovative activity on firm performance, and Part 5 concludes.

The ‘modular’ nature of the thesis is not simply due to the ‘Anglo-Saxon’ thesis design encouraged at many leading universities (including the Sant’Anna School of Advanced Studies, Pisa) whereby a thesis consists of three articles rather than one coherent book. The main reason for the multipronged research strategy is that the growth of firms is very much a multi-

²This expression is borrowed from Hay and Kamshad (1994: 66).

faceted phenomenon, and there are gaps in the literature that are best addressed individually. Indeed, in our analysis we use two completely different databases for precisely this reason. The first database, obtained from the French Statistical Office (INSEE), contains information on virtually all French manufacturing firms with over 20 employees. The second database, which describes large firms in the US high-tech manufacturing industry, was constructed for the purposes of obtaining reliable quantitative indicators of innovation.

Chapter 2 opens the thesis by providing a lengthy survey of the ‘state of the art’ of research into firm growth. It certainly is not merely a perfunctory introductory chapter, but it is essential introduction to the analysis in the rest of the thesis. We need an up-to-date catalogue of empirical work in which we can situate our subsequent analysis. It is necessary to have a feel of what has already been done in order to appreciate the contribution of the following chapters. In addition, the literature review deliberately emphasizes the multifaceted nature of firm growth. The reason for this is that we want the reader to be aware that what we call an ‘observation’ in the ensuing econometric investigations (i.e. a percentage growth rate for a firm in a given year) is not just a ‘statistic’ but actually has a much deeper significance. Chapter 2 therefore aims to emphasize the multidimensional and qualitative aspects of firm growth which risk being overlooked in the subsequent statistical analysis. This is indeed one of the dangers of empirical work – one can get so accustomed to dealing with numbers that one may forget what the numbers actually represent. (This has lead some individuals to be unnecessarily apprehensive about empirical work in general.)

One of the main results that emerges from the literature review is that the random element of growth rates is predominant. Efforts to identify the determinants of firm growth have had a limited success, and the combined explanatory power of the explanatory variables (summarized by the R^2 statistic) is typically low, usually below 10%. It may well be that, after reading the survey of the empirical evidence, both the econometrician and the theorist feel like tearing their clothes in frustration and wailing “random, utterly random, everything is random!” Theory and evidence do not appear to concur, especially concerning the relationships between innovation and growth and financial performance and growth. Whilst theoretical models and survey evidence suggest that innovation has a key role in explaining the growth of firms, it appears that the empirical evidence has difficulty in identifying any such effect. Indeed, some studies fail to find any significant effect of innovation on firm growth. Another puzzling result concerns the relationship between a firm’s financial performance and its growth. Whilst the neoclassical and the evolutionary schools of thought can be considered to offer contrasting interpretations of any relationship between financial performance and growth, the empirical evidence suggests that the two series are, for practical purposes, quite independent. These are some of the issues we explore in the subsequent analysis.

Chapter 3 adds to the literature by presenting an econometric analysis of a recent database

on French manufacturing firms. We observe that firm growth seems to be largely independent of firm size, although the variance of growth rates tends to decrease with size. We also discover that the distribution of growth rates has fatter tails than both the Gaussian and the Laplace densities. This distribution is even fatter tailed than the corresponding distributions observed in the previous literature on Italian and US manufacturing industries.

Chapter 4 follows on from the preceding chapter by taking a closer look at growth rate autocorrelation patterns in the French manufacturing database. Although at the aggregate level we observe a small negative autocorrelation, this is to a certain extent a mere aggregation effect that is specific to the composition of the database. We explore the autocorrelation dynamics of firms along two key dimensions – size and growth rate. Considering first a firm’s size, we show that larger firms seem to experience positive feedback in their growth patterns, while the dynamics of smaller firms tend to display negative autocorrelation. It also appears that extreme-growth firms (that is, the fastest-growing or fastest-shrinking firms) are especially susceptible to negative autocorrelation. This latter result is especially true for small firms, but does not appear to be so important for the largest firms.

Chapter 5 serves as a theoretical discussion in which the empirical analysis in Chapter 6 can be framed. Chapter 5 documents how the mainstream literature, which can be traced back to the q theory of investment, tends to interpret any relationship between investment (which we take as a proxy for growth) and measures of financial performance such as ‘cash flow’ as a sign that financial constraints are preventing the economy from reaching its optimum. Although there are many possible interpretations, the most common way of explaining investment-cash flow sensitivities is in terms of financial constraints. Instead, we argue that the problem of financial constraints for firms has been exaggerated. We suggest that the financial constraints interpretation is an artefact of the modelling assumptions (the perfect rationality and profit-maximization hypotheses in particular). We construct an alternative interpretation basing ourselves on the evolutionary principle of ‘growth of the fitter’. In this view, selective pressures ensure that a firm’s growth depends on its financial performance.

Chapter 6 presents the empirical analysis of the relationship between firm growth and financial performance (or more precisely, scaled gross operating margin). We use a variety of techniques ranging from non-parametric scatterplots to panel data techniques, these latter being able to control for a variety of econometric issues such as endogeneity and unobserved firm-specific effects. Although our regressions yield a positive and significant coefficient, we conclude that the magnitude is small enough to be regarded as inconsequential in economic terms. Interestingly enough, however, we observe that growth has a positive effect on profit rates, and this effect seems to be larger than that of profits on growth.

Chapter 7 investigates the influence of innovation on growth, focusing on high-tech industries in the US manufacturing sector. We begin by creating a composite ‘innovativeness’

variable using information from a firm's recent history of patenting and R&D expenditures. Our analysis shows that the uncertainty of innovation is reflected in the growth patterns of innovating firms. Whilst some firms are seen to experience spectacular growth, this growth is strongly associated with their previous attempts at innovation. For many other firms, however, the influence of innovation on growth seems to be much less impressive.

Chapter 8 follows on from Chapter 7, albeit with a different measure for firm performance. Given that it may take a long time for innovation to materialize into the growth of sales of new products, the choice of a different proxy for firm performance might be warranted. We explain that the time lag between innovation and firm performance is likely to be shorter when a firm's market value is used to measure post-innovation performance. It is nonetheless encouraging that we observe the same qualitative results as in the previous chapter, further emphasizing the heterogeneous effects of innovation on firm performance. Some firms achieve an astonishing success on the stock market, and their market value is strongly associated with their previous investments in innovation. For the firms with the lowest market values, however, it seems that their attempts at innovation are virtually ignored by the stock market.

In Chapter 9 we share some concluding thoughts. Whilst we maintain that this thesis has made an important contribution to the literature, we also outline how future work might shed further light on the phenomenon of firm growth.

Part of this thesis comes from co-authored research. Chapter 3 was written with Giulio Bottazzi, Nadia Jacoby, and Angelo Secchi (see Bottazzi et al., 2005). Chapters 7 and 8 draws from ongoing work with Rekha Rao (see Coad and Rao, 2006a,b,c). In fact, a version of Chapter 8 has already been published in *Economics Bulletin*. Other chapters are currently beyond the initial 'revise and resubmit' stage of publication in journals. Chapter 4 (also available as Coad, 2006b) has received a second round 'revise and resubmit' from the *Review of Industrial Organization*. Chapter 6 (also available as Coad, 2005) has been revised and resubmitted to *Structural Change and Economic Dynamics*. Finally, Chapters 2 and 4 have made previous appearances as Coad (2007b) and Coad (2007a) respectively.

Part I

Literature review

Chapter 2

A survey of facts and theories relating to the growth of firms

In order to appreciate the contribution of this thesis, it is necessary to review the work that has already been done in the domain of the growth of firms. This first chapter aims to provide an up-to-date and reasonably comprehensive survey for such purposes.

The present Chapter explains how theoretical work has often been unhelpful in explaining the growth of firms. Instead, we argue that progress in this particular area requires careful empirical work. In particular, it is emphasized that there are certain gaps in the literature concerning the relationship between innovation and growth, and between financial performance and growth. Although theoretical contributions have made bold claims on the nature of these relationships, empirical work has not risen to the challenge in a satisfactory way.

2.1 Introduction

The aim of this survey is to give an overview of research into the growth of firms, while also highlighting areas in need of further research. It is a multidisciplinary survey, drawing on contributions made in economics, management and also sociology.

There are many different measures of firm size, some of the more usual indicators being employment, total sales, value-added, total assets, or total profits; and some of the less conventional ones such as ‘acres of land’ or ‘head of cattle’ (Weiss, 1998). In this survey we consider growth in terms of a range of indicators, although we devote little attention to the growth of profits (this latter being more of a financial than an economic variable).

There are also different ways of measuring growth rates. Some authors (such as Delmar et al., 2003) make the distinction between relative growth (i.e. the growth rate in percentage terms) and absolute growth (usually measured in the absolute increase in numbers of employees). In this vein, we can mention the ‘Birch index’ which is a weighted average of both relative

and absolute growth rates (this latter being taken into account to emphasize that large firms, due to their large size, have the potential to create many jobs). This survey focuses on relative growth rates only. Furthermore, in our discussion of the processes of expansion we emphasize positive growth and not so much negative growth.¹

In true Simonian style,² we begin with some empirical insights in Section 2.2, considering first the distributions of size and growth rates, and moving on to look for determinants of growth rates. We then present some theories of firm growth and evaluate their performance in explaining the stylised facts that emerge from empirical work (Section 2.3). In Section 2.4 we consider the demand and supply sides of growth by discussing the attitudes of firms towards growth opportunities as well as investigating the processes by which firms actually grow (growth by ‘more of the same’, growth by diversification, growth by acquisition). In Section 2.5 we examine the differences between the growth of small and large firms in greater depth. We also review the ‘stages of growth’ models. Section 2.6 concludes.

2.2 Empirical evidence on firm growth

To begin with, we take a non-parametric look at the distributions of firm size and growth rates, before moving on to results from regressions that investigate the determinants of growth rates.

2.2.1 Size and growth rates distributions

A suitable starting point for studies into industrial structure and dynamics is the firm size distribution. In fact, it was by contemplating the empirical size distribution that Robert Gibrat (1931) proposed the well-known ‘Law of Proportionate Effect’ (also known as ‘Gibrat’s law’).

We also discuss the results of research into the growth rates distribution. The regularity that firm growth rates are approximately exponentially distributed was discovered only recently, but offers unique insights into the growth patterns of firms.

Size distributions

The observation that the firm-size distribution is positively skewed proved to be a useful point of entry for research into the structure of industries. (See Figures 2.1 and 2.2 for some examples of aggregate firm size distributions.) Robert Gibrat (1931) considered the size of French firms in terms of employees and concluded that the lognormal distribution was a valid heuristic. Hart and Prais (1956) presented further evidence on the size distribution, using data on quoted

¹For an introduction to organizational decline, see Whetten (1987).

²See in particular Simon (1968).

UK firms, and also concluded in favour of a lognormal model. The lognormal distribution, however, can be viewed as just one of several candidate skew distributions. Although Simon and Bonini (1958) maintained that the “lognormal generally fits quite well” (1958: p611), they preferred to consider the lognormal distribution as a special case in the wider family of ‘Yule’ distributions. The advantage of the Yule family of distributions was that the phenomenon of arrival of new firms could be incorporated into the model. Steindl (1965) applied Austrian data to his analysis of the firm size distribution, and preferred the Pareto distribution to the lognormal on account of its superior performance in describing the upper tail of the distribution. Similarly, Ijiri and Simon (1964, 1971, 1974) apply the Pareto distribution to analyse the size distribution of large US firms.

Efforts have been made to discriminate between the various candidate skew distributions. One problem with the Pareto distribution is that the empirical density has many more middle-sized firms and fewer very large firms than would be theoretically predicted (Vining, 1976). Other research on the lognormal distribution has shown that the upper tail of the empirical size distribution of firms is too thin relative to the lognormal (Stanley et al., 1995). Quandt (1966) compares the performance of the lognormal and three versions of the Pareto distribution, using data disaggregated according to industry. He reports the superiority of the lognormal over the three types of Pareto distribution, although each of the distributions produces a best-fit for at least one sample. Furthermore, it may be that some industries (e.g. the footwear industry) are not fitted well by any distribution.

More generally, Quandt’s results on disaggregated data lead us to suspect that the regularities of the firm-size distribution observed at the aggregate level do not hold with sectoral disaggregation. Silberman (1967) also finds significant departures from lognormality in his analysis of 90 four-digit SIC sectors. It has been suggested that, while the firm size distribution has a smooth regular shape at the aggregate level, this may merely be due to a statistical aggregation effect rather than a phenomenon bearing any deeper economic meaning (Dosi et al, 1995; Dosi, 2007). Empirical results lend support to these conjectures by showing that the regular unimodal firm size distributions observed at the aggregate level can be decomposed into much ‘messier’ distributions at the industry level, some of which are visibly multimodal (Bottazzi and Secchi, 2003; see also Chapter 3 in this thesis). For example, Bottazzi and Secchi (2005) present evidence of significant bimodality in the firm size distribution of the worldwide pharmaceutical industry, and relate this to a cleavage between the industry leaders and fringe competitors.

Other work on the firm-size distribution has focused on the evolution of the shape of the distribution over time. It would appear that the initial size distribution for new firms is particularly right-skewed, although the log-size distribution tends to become more symmetric as time goes by. This is consistent with observations that small young firms grow faster than

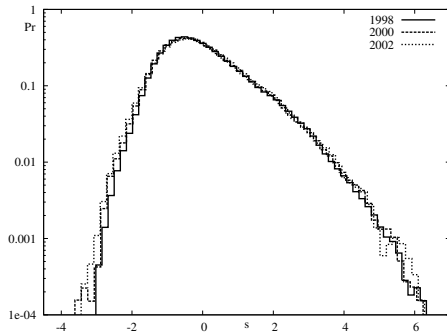


Figure 2.1: Kernel estimates of the density of firm size (total sales) in 1998, 2000 and 2002, for French manufacturing firms with more than 20 employees. Source: Bottazzi et al., 2005.

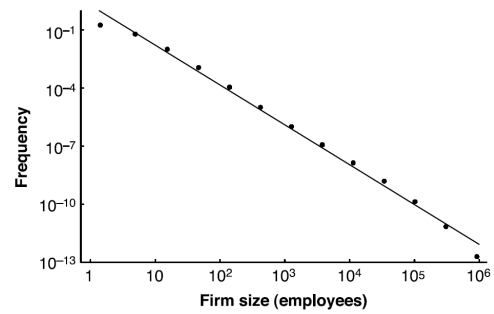


Figure 2.2: Probability density function of the sizes of US manufacturing firms in 1997. Source: Axtell, 2001.

their larger counterparts. As a result, it has been suggested that the log-normal can be seen as a kind of ‘limit distribution’ to which a given cohort of firms will eventually converge. Lotti and Santarelli (2001) present support for this hypothesis by tracking cohorts of new firms in several sectors of Italian manufacturing. Cabral and Mata (2003) find similar results in their analysis of cohorts of new Portuguese firms. However, Cabral and Mata interpret their results by referring to financial constraints that restrict the scale of operations for new firms, but become less binding over time, thus allowing these small firms to grow relatively rapidly and reach their preferred size. They also argue that selection does not have a strong effect on the evolution of market structure.

Although the skewed nature of the firm size distribution is a robust finding, there may be some other features of this distribution that are specific to countries. Table 2.1, taken from Bartelsman et al. (2005), highlights some differences in the structure of industries across countries. Among other things, one observes that large firms account for a considerable share of French industry, whereas in Italy firms tend to be much smaller on average. (These international differences cannot simply be attributed to differences in sectoral specialization across countries.)

Growth rates distributions

It has long been known that the distribution of firm growth rates is fat-tailed. In an early contribution, Ashton (1926) considers the growth patterns of British textile firms and observes that “In their growth they obey no one law. A few apparently undergo a steady expansion... With others, increase in size takes place by a sudden leap” (Ashton 1926: 572-573). Little (1962) investigates the distribution of growth rates, and also finds that the distribution is fat-tailed. Similarly, Geroski and Gugler (2004) compare the distribution of growth rates to the normal case and comment on the fat-tailed nature of the empirical density. Recent

Table 2.1: The importance of small firms (i.e. firms with fewer than 20 employees) across broad sectors and countries, 1989-94

	Absolute number (%)			Share of employment (%)			Ave. No. Employees per firm		
	Total economy	Manufacturing	Business services	Total economy	Manufacturing	Business services	Total economy	Manufacturing	Business services
US	86.7	69.9	87.9	16.6	5.8	20.6	26.4	80.3	21.4
Western Germany	87.9	77.9	90.2	23.6	11.3	33.8	17.0	39.1	11.5
France	78.6	73.6	78.8	13.9	17.0	12.1	33.5	32.1	35.7
Italy	93.1	87.5	96.5	34.4	30.3	46.3	10.5	15.3	6.8
UK	-	74.9	-	-	8.3	-	-	40.7	-
Canada	-	-	-	-	-	-	12.7	40.5	12.0
Denmark	90.0	74.0	90.8	30.2	16.1	33.4	13.3	30.4	12.7
Finland	92.6	84.8	94.5	25.8	13.0	33.0	13.0	27.8	9.9
Netherlands	95.8	86.7	96.8	31.2	16.9	41.9	6.5	18.3	5.3
Portugal	86.3	70.5	92.8	27.7	15.7	39.8	16.8	31.0	11.4

Source: Bartelsman et al. (2005: Tables 2 and 3).

Notes: the columns labelled 'share of employment' refer to the employment share of firms with fewer than 20 employees.

empirical research, from an ‘econophysics’ background, has discovered that the distribution of firm growth rates closely follows the parametric form of the Laplace density. Using the Compustat database of US manufacturing firms, Stanley et al. (1996) observe a ‘tent-shaped’ distribution on log-log plots that corresponds to the symmetric exponential, or Laplace distribution (see also Amaral et al. (1997) and Lee et al. (1998)). The quality of the fit of the empirical distribution to the Laplace density is quite remarkable. The Laplace distribution is also found to be a rather useful representation when considering growth rates of firms in the worldwide pharmaceutical industry (Bottazzi et al., 2001). Giulio Bottazzi and coauthors extend these findings by considering the Laplace density in the wider context of the family of Subbotin distributions (beginning with Bottazzi et al., 2002). They find that, for the Compustat database, the Laplace is indeed a suitable distribution for modelling firm growth rates, at both aggregate and disaggregated levels of analysis (Bottazzi and Secchi 2003a). The exponential nature of the distribution of growth rates also holds for other databases, such as Italian manufacturing (Bottazzi et al. (2007)). In addition, the exponential distribution appears to hold across a variety of firm growth indicators, such as Sales growth, employment growth or Value Added growth (Bottazzi et al., 2007). The growth rates of French manufacturing firms have also been studied, and roughly speaking a similar shape was observed, although it must be said that the empirical density was noticeably fatter-tailed than the Laplace (see Chapter 3).³ Research into Danish manufacturing firms presents further evidence that the growth rate distribution is heavy-tailed, although it is suggested that the distribution for individual sectors may not be symmetric but right-skewed (Reichstein and Jensen (2005)). Generally speaking, however, it would appear that the shape of the growth rate distribution is more robust to disaggregation than the shape of the firm size distribution. In other words, whilst the smooth shape of the aggregate firm size distribution may be little more than a statistical aggregation effect, the ‘tent-shapes’ observed for the aggregate growth rate distribution are usually still visible even at disaggregated levels (Bottazzi and Secchi, 2003a; see also Chapter 3). This means that extreme growth events can be expected to occur relatively frequently, and make a disproportionately large contribution to the evolution of industries.

Figures 2.3 and 2.4 show plots of the distribution of sales and employment growth rates for French manufacturing firms with over 20 employees.

Although research suggests that both the size distribution and the growth rate distribution are relatively stable over time, it should be noted that there is great persistence in firm size but much less persistence in growth rates on average (more on growth rate persistence is presented in Section 2.2.2). As a result, it is of interest to investigate how the moments of the growth rates distribution change over the business cycle. Indeed, several studies have focused

³The observed subbotin b parameter (the ‘shape’ parameter) is significantly lower than the Laplace value of 1. This highlights the importance of following Bottazzi *et al.* (2002) and considering the Laplace as a special case in the Subbotin family of distributions.

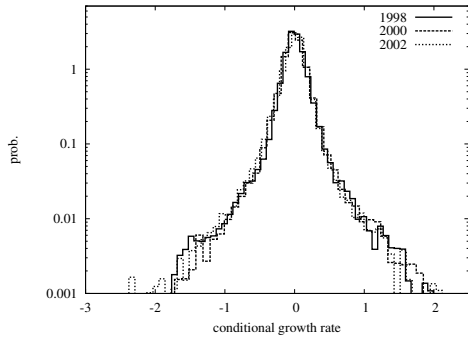


Figure 2.3: Distribution of sales growth rates of French manufacturing firms. Source: Bottazzi et al., 2005.

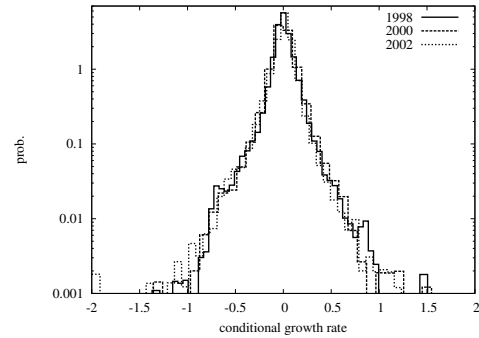


Figure 2.4: Distribution of employment growth rates of French manufacturing firms. Source: Coad, 2006b.

on these issues and some preliminary results can be mentioned here. It has been suggested that the variance of growth rates changes over time for the employment growth of large US firms (Hall, 1987) and that this variance is procyclical in the case of growth of assets (Geroski et al., 2003). This is consistent with the hypothesis that firms have a lot of discretion in their growth rates of assets during booms but face stricter discipline during recessions. Higson et al. (2002, 2004) consider the evolution of the first four moments of distributions of the growth of sales, for large US and UK firms over periods of 30 years or more. They observe that higher moments of the distribution of sales growth rates have significant cyclical patterns. In particular, evidence from both US and UK firms suggests that the variance and skewness are countercyclical, whereas the kurtosis is pro-cyclical. Higson et al. (2002: 1551) explain the counter-cyclical movements in skewness in these words:

“The central mass of the growth rate distribution responds more strongly to the aggregate shock than the tails. So a negative shock moves the central mass closer to the left of the distribution leaving the right tail behind and generates positive skewness. A positive shock shifts the central mass to the right, closer to the group of rapidly growing firms and away from the group of declining firms. So negative skewness results.”

The procyclical nature of kurtosis (despite their puzzling finding of countercyclical variance) emphasizes that economic downturns change the shape of the growth rate distribution by reducing a key parameter of the ‘spread’ or ‘variation’ between firms.

2.2.2 Gibrat’s Law

Gibrat’s law continues to receive a huge amount of attention in the empirical industrial organization literature, more than 75 years after Gibrat’s (1931) seminal publication.

We begin by presenting the ‘Law’, and then review some of the related empirical literature.

We do not attempt to provide an exhaustive survey of the literature on Gibrat's law, because the number of relevant studies is indeed very large. (For other reviews of empirical tests of Gibrat's Law, the reader is referred to the survey by Lotti et al (2003); for a survey of how Gibrat's law holds for the services sector see Audretsch et al. (2004).) Instead, we try to provide an overview of the essential results. We investigate how expected growth rates and growth rate variance are influenced by firm size, and also investigate the possible existence of patterns of serial correlation in firm growth.

Gibrat's model

Robert Gibrat's (1931) theory of a 'law of proportionate effect' was hatched when he observed that the distribution of French manufacturing establishments followed a skew distribution that resembled the lognormal. Gibrat considered the emergence of the firm-size distribution as an outcome or explanandum and wanted to see which underlying growth process could be responsible for generating it.

In its simplest form, Gibrat's law maintains that the expected growth rate of a given firm is independent of its size at the beginning of the period examined. Alternatively, as Mansfield (1962: 1030) puts it, "the probability of a given proportionate change in size during a specified period is the same for all firms in a given industry – regardless of their size at the beginning of the period."

More formally, we can explain the growth of firms in the following framework. Let x_t be the size of a firm at time t , and let ε_t be random variable representing an idiosyncratic, multiplicative growth shock over the period $t - 1$ to t . We have

$$x_t - x_{t-1} = \varepsilon_t x_{t-1} \tag{2.1}$$

which can be developed to obtain

$$x_t = (1 + \varepsilon_t)x_{t-1} = x_0(1 + \varepsilon_1)(1 + \varepsilon_2) \dots (1 + \varepsilon_t) \tag{2.2}$$

It is then possible to take logarithms in order to approximate $\log(1 + \varepsilon_t)$ by ε_t to obtain⁴

$$\log(x_t) \approx \log(x_0) + \varepsilon_1 + \varepsilon_2 + \dots + \varepsilon_t = \log(x_0) + \sum_{s=1}^t \varepsilon_s \tag{2.3}$$

⁴This logarithmic approximation is only justified if ε_t is 'small' enough (i.e. close to zero), which can be reasonably assumed by taking a short time period (Sutton, 1997).

In the limit, as t becomes large, the $\log(x_0)$ term will become insignificant, and we obtain

$$\log(x_t) \approx \sum_{s=1}^t \varepsilon_s \quad (2.4)$$

In this way, a firm's size at time t can be explained purely in terms of its idiosyncratic history of multiplicative shocks. If we further assume that all firms in an industry are independent realizations of i.i.d. normally distributed growth shocks, then this stochastic process leads to the emergence of a lognormal firm size distribution.

There are of course several serious limitations to such a simple vision of industrial dynamics. We have already seen that the distribution of growth rates is not normally distributed, but instead resembles the Laplace or 'symmetric exponential'. Furthermore, contrary to results implied by Gibrat's model, it is not reasonable to suppose that the variance of firm size tends to infinity (Kalecki, 1945). In addition, we do not observe the secular and unlimited increase in industrial concentration that would be predicted by Gibrat's law (Caves, 1998). Whilst a 'weak' version of Gibrat's law merely supposes that expected growth rate is independent of firm size, stronger versions of Gibrat's law imply a range of other issues. For example, Chesher (1979) rejects Gibrat's law due to the existence of an autocorrelation structure in the growth shocks. Bottazzi and Secchi (2006) reject Gibrat's law on the basis of a negative relationship between growth rate variance and firm size. Reichstein and Jensen (2005) reject Gibrat's law after observing that the annual growth rate distribution is not normally distributed.

Firm size and average growth

Although Gibrat's (1931) seminal book did not provoke much of an immediate reaction, in recent decades it has spawned a flood of empirical work. Nowadays, Gibrat's 'Law of Proportionate Effect' constitutes a benchmark model for a broad range of investigations into industrial dynamics. Another possible reason for the popularity of research into Gibrat's law, one could suggest quite cynically, is that it is a relatively easy paper to write. First of all, it has been argued that there is a minimalistic theoretical background behind the process (because growth is assumed to be purely random). Then, all that needs to be done is to take the IO economist's 'favourite' variable (i.e. firm size, a variable which is easily observable and readily available) and regress the difference on the lagged level. In addition, few control variables are required beyond industry dummies and year dummies, because growth rates are characteristically random.

Empirical investigations of Gibrat's law rely on estimation of equations of the type:

$$\log(x_t) = \alpha + \beta \log(x_{t-1}) + \epsilon \quad (2.5)$$

where a firm's 'size' is represented by x_t , α is a constant term (industry-wide growth trend) and ϵ is a residual error. Research into Gibrat's law focuses on the coefficient β . If firm growth is independent of size, then β takes the value of unity. If β is smaller than one, then smaller firms grow faster than their larger counterparts, and we can speak of 'regression to the mean'. Conversely, if β is larger than one, then larger firms grow relatively rapidly and there is a tendency to concentration and monopoly.

A significant early contribution was made by Edwin Mansfield's (1962) study of the US steel, petroleum, and rubber tire industries. In particular interest here is what Mansfield identified as three different renditions of Gibrat's law. According to the first, Gibrat-type regressions consist of both surviving and exiting firms and attribute a growth rate of -100% to exiting firms. However, one caveat of this approach is that smaller firms have a higher exit hazard which may obfuscate the relationship between size and growth. The second version, on the other hand, considers only those firms that survive. Research along these lines has typically shown that smaller firms have higher expected growth rates than larger firms. The third version considers only those large surviving firms that are already larger than the industry Minimum Efficient Scale of production (with exiting firms often being excluded from the analysis). Generally speaking, empirical analysis corresponding to this third approach suggests that growth rates are more or less independent from firm size, which lends support to Gibrat's law.

The early studies focused on large firms only, presumably partly due to reasons of data availability. A series of papers analyzing UK manufacturing firms found a value of β greater than unity, which would indicate a tendency for larger firms to have higher percentage growth rates (Hart (1962), Samuels (1965), Prais (1974), Singh and Whittington (1975)).

However, the majority of subsequent studies using more recent datasets have found values of β slightly lower than unity, which implies that, on average, small firms seem to grow faster than larger firms. This result is frequently labelled 'reversion to the mean size' or 'mean-reversion'.⁵ Among a large and growing body of research that reports a negative relationship between size and growth, we can mention here the work by Kumar (1985) and Dunne and Hughes (1994) for quoted UK manufacturing firms, Hall (1987), Amirkhalkhali and Mukhopadhyay (1993) and Bottazzi and Secchi (2003) for quoted US manufacturing firms (see also Evans (1987a, 1987b) for US manufacturing firms of a somewhat smaller size), Gabe and Kraybill (2002) for establishments in Ohio, and Goddard et al. (2002) for quoted Japanese manufacturing firms. Studies focusing on small businesses have also found a negative relationship between firm size and expected growth – see for example Yasuda (2005) for Japanese manufacturing firms, Calvo (2006) for Spanish manufacturing, McPherson (1996) for Southern African micro

⁵We should be aware, however, that 'mean-reversion' does not imply that firms are converging to anything resembling a common steady-state size, even within narrowly-defined industries (see in particular the empirical work by Geroski et al. (2003) and Cefis et al. (2006)).

businesses, and Wagner (1992) and Almus and Nerlinger (2000) for German manufacturing. Dunne et al. (1989) analyse plant-level data (as opposed to firm-level data) and also observe that growth rates decline along size classes. Research into Gibrat's law using data for specific sectors also finds that small firms grow relatively faster (see e.g. Barron et al. (1994) for New York credit unions, Weiss (1998) for Austrian farms, Liu et al. (1999) for Taiwanese electronics plants, and Bottazzi and Secchi (2005) for an analysis of the worldwide pharmaceutical sector). Indeed, there is a lot of evidence that a slight negative dependence of growth rate on size is present at various levels of industrial aggregation. Although most empirical investigations into Gibrat's law consider only the manufacturing sector, some have focused on the services sector. The results, however, are often qualitatively similar – there appears to be a negative relationship between size and expected growth rate for services too (see Variyam and Kraybill (1992), Johnson et al. (1999)). Nevertheless, it should be mentioned that in some cases a weak version of Gibrat's law cannot be convincingly rejected, since there appears to be no significant relationship between expected growth rate and size (see the analyses provided by Bottazzi et al. (2005) for French manufacturing firms, Droucopoulos (1983) for the world's largest firms, Hardwick and Adams (2002) for UK Life Insurance companies, and Audretsch et al. (2004) for small-scale Dutch services). Notwithstanding these latter studies, however, we acknowledge that in most cases a negative relationship between firm size and growth is observed. Indeed, it is quite common for theoretically-minded authors to consider this to be a 'stylised fact' for the purposes of constructing and validating economic models (see for example Cooley and Quadrini (2001), Gomes (2001) and Clementi and Hopenhayn (2006)). Furthermore, John Sutton refers to this negative dependence of growth on size as a 'statistical regularity' in his revered survey of Gibrat's law (Sutton, 1997: 46).

A number of researchers maintain that Gibrat's law does hold for firms above a certain size threshold. This corresponds to acceptance of Gibrat's law according to Mansfield's third rendition, although 'mean reversion' leads us to reject Gibrat's Law as described in Mansfield's second rendition. Mowery (1983), for example, analyzes two samples of firms, one of which contains small firms while the other contains large firms. Gibrat's law is seen to hold in the latter sample, whereas mean reversion is observed in the former. Hart and Oulton (1996) consider a large sample of UK firms and find that, whilst mean reversion is observed in the pooled data, a decomposition of the sample according to size classes reveals essentially no relation between size and growth for the larger firms. Lotti et al. (2003) follow a cohort of new Italian startups and find that, although smaller firms initially grow faster, it becomes more difficult to reject the independence of size and growth as time passes. Similarly, results reported by Becchetti and Trovato (2002) for Italian manufacturing firms, Geroski and Gugler (2004) for large European firms and Cefis et al. (2006) for the worldwide pharmaceutical industry also find that the growth of large firms is independent of their size, although including smaller

firms in the analysis introduces a dependence of growth on size. It is of interest to remark that Caves (1998) concludes his survey of industrial dynamics with the ‘substantive conclusion’ that Gibrat’s law holds for firms above a certain size threshold, whilst for smaller firms growth rates decrease with size.

Concern about econometric issues has often been raised. Sample selection bias, or ‘sample attrition’, is one of the main problems, because smaller firms have a higher probability of exit. Failure to account for the fact that exit hazards decrease with size may lead to underestimation of the regression coefficient (i.e. β). Hall (1987) was among the first to tackle the problem of sample selection, using a Tobit model. She concludes that selection bias does not seem to account for the negative relationship between size and growth. An alternative way of correcting for sample selection is by applying Heckman’s two-stage procedure. This is the methodology used by Harhoff et al. (1998), who also observe that selection bias has only a small influence on the Gibrat coefficient. In short, the “problem of sample selection does not seem to significantly affect the relationship between growth rate and size of firm” (Marsili, 2001: 15). The possibility of heteroskedasticity is also frequently mentioned, although it can be corrected for quite easily, for example by applying White’s (1980) procedure. In any case, heteroskedasticity does not introduce any asymptotic bias in the coefficient estimates. Serial correlation in growth rates can lead to biased estimates, although Chesher (1979) proposes a simple framework for dealing with this. Finally, Hall (1987) investigates whether ‘errors-in-variables’ may be influencing the regression results, but concludes that measurement error does not appear to be an important factor.

Firm size and growth rate variance

Hymer and Pashigian (1962) were among the first to draw attention to the negative relationship between growth rate variance and firm size. If firms can be seen as a collection of ‘components’ or ‘departments’, then the overall variance of the growth rate of the firm is a function of the growth rate variance of these individual departments. In many cases, the variance of the firm’s growth rate will decrease with firm size. For example, in the case there these departments (i) are of approximately equal size, such that the size of the firm is roughly proportional to the number of components; and (ii) have growth rates that are perfectly independent from each other, then Central Limit Theorem leads us to expect a decrease in growth rate variance that is proportional to the inverse square root of the firm’s size. However, Hymer and Pashigian (1962) were puzzled by the fact that the rate of decrease of growth rate variance with size was lower than the rate that would be observed if large firms were just aggregations of independent departments. At the same time, they found no evidence of economies of scale. They saw this as an anomaly in a world of risk-averse agents. Why would firms want to grow to a large size, if there are no economies of scale, and if the growth rate variance of a large firm is higher than

the corresponding variance of an equivalent group of smaller firms? Subsequent studies did not attempt to answer this question, but they did bear in mind the existence of a negative relationship between growth rate variance and firm size. As a consequence, empirical analyses of Gibrat's law began to correct for heteroskedasticity in firm growth rates (e.g. Hall (1987), Evans (1987a,b), Dunne and Hughes (1994), Hart and Oulton (1996), Harhoff et al. (1998)).

In recent years efforts have been made to quantify the scaling of the variance of growth rates with firm size. This scaling relationship can be summarized in terms of the following power law: $\sigma(g_i) \sim e^{\beta s_i}$; where $\sigma(g_i)$ is the standard deviation of the growth rate of firm i , β is a coefficient to be estimated, and s_i is the size (total sales) of firm i . Values of β have consistently been estimated as being around -0.2 for US manufacturing firms (Amaral et al. (1997, 1998), Bottazzi and Secchi (2004)) and also for firms in the worldwide pharmaceutical industry (Bottazzi et al. (2001), Matia et al. (2004), Bottazzi and Secchi (2006a)). Lee et al. (1998) find that a scaling exponent of -0.15 is able to describe the scaling of growth rate variance for both quoted US manufacturing firms and the GDP of countries. For French manufacturing firms, our analysis in Chapter 3 yields estimates of β of around -0.07, although in the case of Italian manufacturing firms Bottazzi et al. (2007) fail to find any relation between growth rate variability and size.

The discussion in Lee et al. (1998: 3277) gives us a better understanding of the values taken by β , the scaling exponent. If the growth rates of divisions of a large diversified firm are perfectly correlated, we should expect a value of $\beta = 0$. On the other hand, if a firm can be viewed as an amalgamation of perfectly independent subunits, we expect a value of $\beta = -0.5$. The fact that the estimated exponents are between these extreme values of 0 and -0.5 suggest that the constituent departments of a firm have growth patterns that are somewhat correlated.

Matia et al. (2004) and Bottazzi and Secchi (2006) return to the scaling-of-variance puzzle by considering firms as being composed of a certain number of products that correspond to independent *submarkets*.⁶ The average size of the submarkets increases with firm size, but the growth rates are independent across submarkets. These authors provide support for their model by examining evidence from the worldwide pharmaceutical industry, where a firm's portfolio of activities can be decomposed to a fine level of aggregation. As a result, "the explanation of the relationship between the variance of the growth rates distribution and the size of the firm based on the Central Limit Theorem is valid, as long as one considers the actual number of sub-markets a firm operates in, instead of assuming that this number is somehow proportional to the size of the firm" (Bottazzi and Secchi 2006: 860).

⁶Their model bears a certain similarity with the model in Amaral et al. (1998, 2001), who explain scaling of variance in terms of firms being composed of independent 'divisions' in a diversified firm, rather than independent 'submarkets'.

Autocorrelation of growth rates

Early empirical studies into the growth of firms considered serial correlation when growth was measured over a period of 4 to 6 years. Positive autocorrelation of 33% was observed by Ijiri and Simon (1967) for large US firms, and a similar magnitude of 30% was reported by Singh and Whittington (1975) for UK firms. However, much weaker autocorrelation was later reported in comparable studies by Kumar (1985) and Dunne and Hughes (1994).

More recently, availability of better datasets has encouraged the consideration of annual autocorrelation patterns. Indeed, persistence should be more visible when measured over shorter time horizons. However, the results are quite mixed. Positive serial correlation has often been observed, in studies such as those of Chesher (1979) and Geroski et al. (1997) for UK quoted firms, Wagner (1992) for German manufacturing firms, Weiss (1998) for Austrian firms, Bottazzi et al. (2001) for the worldwide pharmaceutical industry, and Bottazzi and Secchi (2003) for US manufacturing. On the other hand, negative serial correlation has also been reported – some examples are Boeri and Cramer (1992) for German firms, Goddard et al. (2002) for quoted Japanese firms, Bottazzi et al. (2007) for Italian manufacturing, and Bottazzi et al. (2005) for French manufacturing. Still other studies have failed to find any significant autocorrelation in growth rates (see Almus and Nerlinger (2000) for German start-ups, Bottazzi et al. (2002) for selected Italian manufacturing sectors, Geroski and Mazzucato (2002) for the US automobile industry, and Lotti et al. (2003) for Italian manufacturing firms). To put it mildly, there does not appear to be an emerging consensus.

Another subject of interest (also yielding conflicting results) is the number of relevant lags to consider. Chesher (1979) and Bottazzi and Secchi (2003) found that only one lag was significant, whilst Geroski et al. (1997) find significant autocorrelation at the 3rd lag (though not for the second). Bottazzi et al. (2001) find positive autocorrelation for every year up to and including the seventh lag, although only the first lag is statistically significant.

To summarize these regression-based investigations, then, it would appear that decades of research into growth rate autocorrelation can best be described as yielding “conflicting results” (Caves, 1998: 1950). It is perhaps remarkable that the results of the studies reviewed above have so little in common. It is also remarkable that previous research has been so little concerned with this question. Indeed, instead of addressing serial correlation in any detail, often it is ‘controlled away’ as a dirty residual, a blemish on the ‘natural’ growth rate structure. The baby is thus thrown out with the bathwater. One reason for this confusion could be that, if indeed there are any regularities in the serial correlation of firm growth, they are more complex than the standard specification would be able to detect (i.e. that there is no ‘one-size-fits-all’ serial correlation coefficient that applies for all firms). A fresh approach is needed.

The analysis in Bottazzi et al. (2002) begins with the observation that the mean auto-

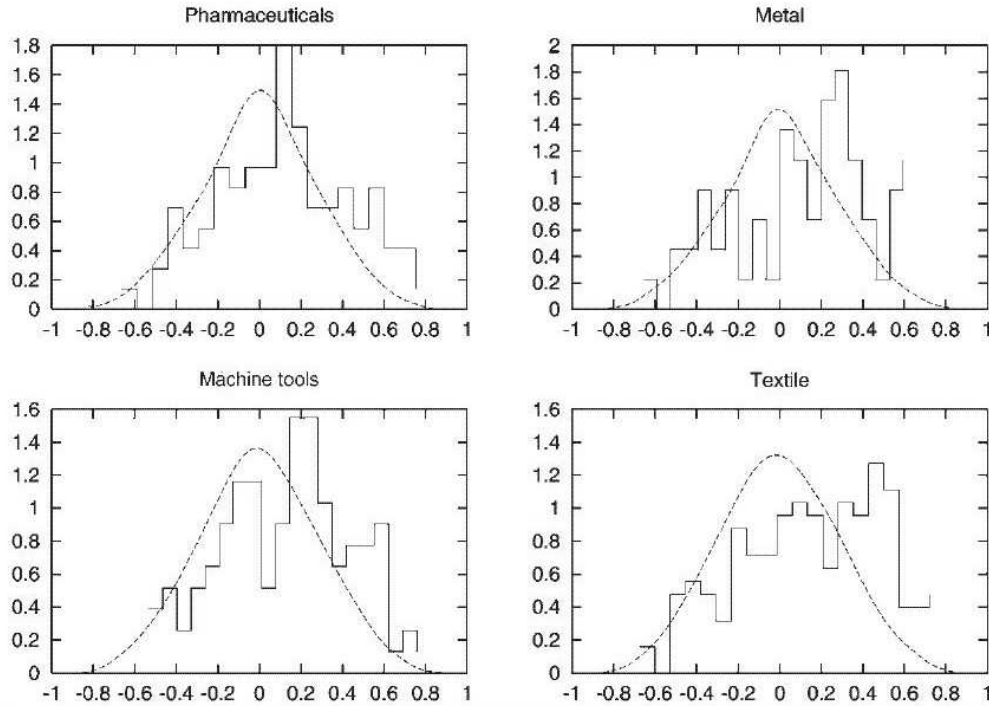


Figure 2.5: Observed empirical frequency for the autocorrelation coefficient of employment growth (steps function) and the associated ‘benchmark’ density distribution generated using bootstrapped time series (dotted line). Source: Bottazzi et al. (2002: Fig. 5).

correlation coefficient for a given industry is either insignificantly different from zero, or else very small in magnitude. However, the authors go on to calculate firm-specific autocorrelation coefficients and observe that firms do in fact have idiosyncratic growth patterns that are not visible simply by looking at averages across firms. They create a purely random ‘benchmark’ case in which the growth rates of all firms are pooled together and then growth rates are extracted randomly to construct growth patterns for ‘artificial firms’. Bootstrap resampling methods allow them to generate a distribution of autocorrelation coefficients for this random scenario. They then compare this stochastic benchmark with the empirical distribution of autocorrelation coefficients (see Figure 2.5 for the case of autocorrelation of employment growth). The differences between the distributions are supported by formal statistical tests (i.e. Kolmogorov-Smirnov tests). The authors conclude that firm growth patterns are indeed idiosyncratic, that they do have a memory process, and that there are indeed persistent asymmetries in growth dynamics across firms.

Chapter 4 also explores the issue of heterogeneous growth profiles across firms and goes some way towards finding regularities in growth rate autocorrelation patterns. A firm’s growth dynamics are seen to depend on two dimensions – a firm’s size and its lagged growth rate. First of all, it is demonstrated that smaller firms are more prone to experience negative autocorrelation, whilst larger firms have a tendency towards positive autocorrelation. This is

consistent with propositions that small and large firms operate on a different ‘frequency’ or time scale, with the actions of large firms unfolding over a longer time horizon. This dependence of autocorrelation on firm size helps to explain why the studies reviewed above yielded different autocorrelation coefficients for databases with different firm-size compositions. Second, Chapter 4 demonstrates that the autocorrelation coefficient depends on the *growth rate*. Firms whose growth rate is close to the average in one year are likely to not experience any autocorrelation in the following year. For those firms that experience extreme growth rates (either extreme positive or negative growth rates), however, these firms are likely to experience considerable negative autocorrelation. This is especially true for fast-growth small firms, whose growth patterns are particularly erratic. Large firms, however, display a smoother dynamics – they are likely to experience positive autocorrelation irrespective of their growth rate in the previous period.

2.2.3 Other determinants of firm growth

Age

The relationship between size and growth has received a great deal of attention in empirical work, as we discussed above in Section 2.2.2. Relatedly, the relationship between a firm’s age and its growth rate has also been frequently investigated. Age and size are certainly closely related, and indeed, in some cases, they are both taken to represent what is essentially the same phenomenon (see e.g. Greiner’s (1972) model). One of the earliest investigations of the influence of age on growth was made by Fizaine (1968), who examined the growth of establishments from the French region of Bouches-du-Rhone. She observed that age has a negative effect on the growth of establishments, and also that the variance of growth rates decreases with age. Fizaine (1968) also argued that the correct causality runs from age to growth, rather than from size to growth as supposed by many investigations into firm growth based on Gibrat’s law (this argument was subsequently reiterated by Evans 1987b). Dunne et al. (1989) analyse US establishments and concur with Fizaine’s findings that both the expected growth rate and also the growth variance decrease with age. Age is also observed to have a negative effect on growth at the firm level, as a large number of studies have testified – see *inter alia* Evans (1987a,b) for US manufacturing firms, Variyam and Kraybill (1992) for US manufacturing and services firms, Liu et al. (1999) for Taiwanese electronics plants, Geroski and Gugler (2004) for large European companies, and Yasuda (2005) for Japanese manufacturing firms.

Generally speaking, then, the negative dependence of growth rate on age appears to be a robust feature of industrial dynamics. This is not always observed, however. Das (1995) examines the growth of firms in a young, fast-growing industry in a developing economy

(i.e. the computer hardware industry in India) and obtains the unusual results that that growth increases with age. Another exception to the general rule is in Barron et al. (1994), who observe a non-monotonic relationship between age and growth for New York Credit Unions. They observe that older firms grow faster than adolescent firms, although it is the very young firms that experience the fastest growth.

Innovation

Innovation and sales growth The relationship between innovation and sales growth can be described as something of a paradox – on the one hand, a broad range of theoretical and descriptive accounts of firm growth stress the important role innovation plays for firms wishing to expand their market share. For example, Carden (2005: 25) presents the main results of the McKinsey Global Survey of Business Executives, and writes that “[e]xecutives overwhelmingly say that innovation is what their companies need most for growth.” Another survey focusing on SMEs (Small and Medium Enterprises) reports that investment in product innovation is the single most popular strategy for expansion, a finding which holds across various industries (Hay and Kamshad, 1994). Economic theorizing also recognizes the centrality of innovation in growth of firm sales (see for example the discussion in Geroski (2000, 2005) or the theoretical models in Dasgupta and Stiglitz (1980) or Aghion and Howitt (1992)). On the other hand, empirical studies have had difficulty in identifying any strong link between innovation and sales growth, and the results have often been modest and disappointing. Indeed, some studies fail to find any influence of innovation on sales growth at all. Commenting on the current state of our understanding of firm-level processes of innovation, Cefis and Orsenigo (2001) write: “Linking more explicitly the evidence on the patterns of innovation with what is known about firms growth and other aspects of corporate performance – both at the empirical and at the theoretical level – is a hard but urgent challenge for future research” (Cefis and Orsenigo, 2001: 1157).

A major difficulty in observing the effect of innovation on growth is that it may take a firm a long time to convert increases in economically valuable knowledge (i.e. innovation) into economic performance. Even after an important discovery has been made, a firm will typically have to invest heavily in product development. In addition, converting a product idea into a set of successful manufacturing procedures and routines may also prove costly and difficult. Furthermore, even after an important discovery has been patented, a firm in an uncertain market environment may prefer to treat the patent as a ‘real option’ and delay associated investment and development costs (Bloom and Van Reenen, 2002). There may therefore be considerable lags between the time of discovery of a valuable innovation and its conversion into commercial success.⁷ Another feature of the innovation process is that there is uncertainty at

⁷However, it is reasonable to assume that the time lag from innovation to superior firm-level performance

every stage, and that the overall outcome requires success at each step of the process. In a pioneering empirical study, Mansfield et al. (1977) identify three different stages of innovation that correspond to three different conditional probabilities of success: the probability that a project's technical goals will be met (x); the probability that, given technical success, the resulting product or process will be commercialized (y); and finally the probability that, given commercialization, the project yields a satisfactory return on investment (z). The overall success of the innovative activities will be the product of these three conditional probabilities ($x \times y \times z$). If a firm fails at any of these stages, it will have incurred costs without reaping benefits. We therefore expect that firms differ greatly both in terms of the returns to R&D (measured here in terms of post-innovation sales growth) and also in terms of the time required to convert an innovation into commercial success. However, it is anticipated that innovations will indeed pay off on average and in the long term, otherwise commercial businesses would obviously have no incentive to perform R&D in the first place.

How then do firms translate innovative activity into competitive advantage?⁸ Our gleaning of this literature of the influence of innovative activity on sales growth yields a sparse and rather motley harvest. (This may be due to difficulties in linking firm-level innovation data to other firm characteristics.) Mansfield (1962) considers the steel and petroleum sectors over a 40-year period, and finds that successful innovators grew quicker, especially if they were initially small. Moreover, he asserts that the higher growth rate cannot be attributed to their pre-innovation behavior. Another early study by Scherer (1965) looks at 365 of the largest US corporations and observes that inventions (measured by patents) have a positive effect on company profits via sales growth. Furthermore, he observes that innovations typically do not increase profit margins but instead increase corporate profits via increased sales at constant profit margins. Mowery (1983) focuses on the dynamics of US manufacturing over the period 1921-1946 and observes that R&D employment only has a significantly positive impact on firm growth (in terms of assets) for the period 1933-46. Using two different samples, he observes that R&D has a similar effect on growth for both large and small firms. Geroski and Machin (1992) look at 539 large quoted UK firms over the period 1972-83, of which 98 produced an innovation during the period considered. They observe that innovating firms (i.e. firms that produced at least one 'major' innovation) are both more profitable and grow faster than non-innovators. Their results suggest that the influence of specific innovations on sales growth are nonetheless short-lived (p81) – “the full effects of innovation on corporate growth are realized very soon after an innovation is introduced, generating a short, sharp one-off increase in sales

is shorter when this latter is measured in terms of stock market valuation – this line of reasoning is pursued in Chapter 8.

⁸This is not the place to consider how innovative activity affects other aspects of firm performance such as stock market success. For a survey of the literature on innovation and market value appreciation, see Chapter 8. For a survey of the relationship between innovation and employment growth (i.e. the 'technological unemployment' literature, see the following section.

turnover.” In addition, and contrary to Scherer’s findings, they observe that innovation has a more noticeable influence on profit margins than on sales growth. Geroski and Toker (1996) look at 209 leading UK firms and observe that innovation has a significant positive effect on sales growth, when included in an OLS regression model amongst many other explanatory variables. Roper (1997) uses survey data on 2721 small businesses in the U.K., Ireland and Germany to show that innovative products introduced by firms made a positive contribution to sales growth. Freel (2000) considers 228 small UK manufacturing businesses and, interestingly enough, observes that although it is not necessarily true that ‘innovators are more likely to grow’, nevertheless ‘innovators are likely to grow more’ (i.e. they are more likely to experience particularly rapid growth). Finally, Bottazzi et al. (2001) study the dynamics of the worldwide pharmaceutical sector and do not find any significant contribution of a firm’s ‘technological ID’ or innovative position⁹ to sales growth.

One observation that emerges from the preceding survey is that innovation can be measured in several ways, although the most common approach is to use R&D statistics or patent counts. However, each of these indicators has its drawbacks. R&D statistics are typically quite smoothed over time, which contrasts with the lack of persistence frequently observed in patent statistics. Furthermore, R&D expenditure is an innovative input and it gives only a poor indication of the value of the resulting innovative output that a firm can take to market. Patent statistics are very skewed in value, with many patents being practically worthless whilst a fraction of patents generate the lion’s share of the economic value. Another limitation is that many previous studies have lumped together firms from all manufacturing sectors – even though innovation regimes (and indeed appropriability regimes) vary dramatically across industries.¹⁰ To deal with these difficulties of quantifying firm-level innovative activity, our analysis in Chapter 7 combines information on a firm’s recent history of R&D expenditures as well as patenting activity to create a synthetic ‘innovativeness’¹¹ variable for each firm-year. In this way we extract the common variance associated with each of these indicators while discarding the idiosyncratic noise and measurement error. We also focus on four two-digit ‘complex technology’ manufacturing industries that were hand-picked because of their relatively high intensities.

Using semi-parametric quantile regressions, we explore the influence of innovation at a range of points of the conditional growth rate distribution. Our results indicate that most firms don’t grow very much, and their growth is hardly related to their attempts at innovation.

⁹They measure a firm’s innovative activity by either the discovery of NCE’s (new chemical entities) or by the proportion of patented products in a firm’s product portfolio

¹⁰Patenting is an effective means of protecting innovations in the pharmaceutical industry, for example, although it is not very effective in the steel, glass or textile industries (Cohen et al., 2000). Therefore, it is problematic to compare one patent for a pharmaceutical firm with one patent for a steel, glass or textile firm.

¹¹Note that our use of the word ‘innovativeness’ does not correspond to Mairesse and Mohnen’s (2002) use of the same word.

Nevertheless, innovation is seen to be of critical importance for a handful of fast-growth firms. This emphasizes the inherent uncertainty in firm-level innovative activity – whilst for the ‘average firm’ innovativeness may not be very important for sales growth, innovativeness is of crucial importance for the ‘superstar’ high-growth firms. Standard regression techniques which implicitly give equal weights to both high-growth and low-growth firms, and that yield a summary point estimate for the ‘average firm’, are unable to detect this relationship.

Innovation and employment growth Whilst firm-level innovation can be expected to have a positive influence on sales growth, the overall effect on employment growth is *a priori* ambiguous. Innovation is often associated with increases in productivity that lower the amount of labour required for the production of goods and services. In this way, an innovating firm may change the composition of its productive resources, to the profit of machines and at the expense of employment. As a result, the general public has often expressed concern that technological progress may bring about the ‘end of work’ by replacing men with machines. Economists, on the other hand, are usually more optimistic.

To begin with, it is useful to decompose innovation into product and process innovation. Product innovations are often associated with employment gain, because the new products create new demand (although it is possible that they might replace existing products). Process innovations, on the other hand, often increase productivity by reducing the labour requirement in manufacturing processes. Thus, process innovations are often suspected of bringing about ‘technological unemployment’.

The issue becomes even more complicated, however, when we consider that there are not only direct effects of innovation on employment, but also a great many indirect effects operating through various ‘substitution channels’. For example, the introduction of a labour-saving production process may lead to an immediate and localized reduction in employees inside the plant (the ‘direct effect’), but it may lead to positive employment changes elsewhere in the economy via an increased demand for new machines, a decrease in prices, and increase in incomes, an increase in new investments, or a decrease in wages (see Spiezia and Vivarelli, 2000). As a result, the overall effect of innovation on employment needs to be investigated empirically.

Research into technological unemployment has been undertaken in different ways. As a consequence, the results emerging from different studies are far from harmonious – “[e]mpirical work on the effect of innovations on employment growth yields very mixed results” (Niefert 2005:9). Doms et al. (1995) analyse survey data on US manufacturing establishments, and observe that the use of advanced manufacturing technology (which would correspond to process innovation) has a positive effect on employment. At the firm-level of analysis, Hall (1987) observes that employment growth is related positively and significantly to R&D intensity in

the case of large US manufacturing firms. Similarly, Greenhalgh et al. (2001) observe that R&D intensity and also the number of patent publications have a positive effect on employment for British firms. Nevertheless, Evangelista and Savona (2002, 2003) observe a negative overall effect of innovation on employment in the Italian services sector. When the distinction is made between product and process innovation, the former is usually linked to employment creation whereas the consequences of the latter are not as clear-cut. Evidence presented in Brouwer et al. (1993) reveals a small positive employment effect of product-related R&D although the combined effect of innovation is imprecisely defined. Relatedly, work by Van Reenen (1997) on listed UK manufacturing firms and Smolny (1998) for West German manufacturing firms shows a positive effect on employment for product innovations. Smolny also finds a positive employment effect of process innovations, whereas Van Reenen's analysis yields insignificant results. Harrison et al. (2005) consider the relationship between innovation and employment growth in four European countries (France, Italy, the UK and Germany) using data for 1998 and 2000 on firms in the manufacturing and services industries. Whilst product innovations are consistently associated with employment growth, process innovation appears to have a negative effect on employment, although the authors acknowledge that this latter result may be attenuated (or even reversed) through compensation effects. To summarize, therefore, we can consider that product innovations generally have a positive impact on employment, whilst the role of process innovations is more ambiguous (Hall et al., 2006).

Financial performance

Research into the relationship between financial performance and firm expansion has traditionally taken the view that any sensitivity between financial performance and investment signals the problem of 'financial constraints' and 'information asymmetries'. We begin by explaining how this interpretation became predominant. However, we prefer what we might call here an 'evolutionary' interpretation of the relationship between financial performance and growth. In any case, it is clear that financial performance is not a major determinant of firm growth rates.

Mainstream research into the expansion of firms has based itself on the q -theory of investment. (Note however that the literature does not elaborate upon the distinction between replacement investment and expansionary investment.)¹² If some initial assumption are satisfied (including the assumption that firms are rational profit-maximizers, and that financial markets are efficient), then a firm's growth prospects can be entirely summarized by the stock market's expectations concerning a firm's expected future profits. In other words, the only

¹²The author is not aware of any relevant empirical work that distinguishes replacement investment and expansionary investment. In the present discussion, we place more emphasis on the latter when we speak of 'investment'. In any case, the distinction between the two may not be very clear-cut in the first place, especially when we consider that firms tend to replace their exhausted capital stock with more recent vintages.

predictor of firm-level investment should be the marginal change in the ratio between the market value of the firm and the replacement value of the firm's existing assets. This latter ratio is known as marginal q . Empirical investigations of q models, such as Blundell et al. (1992), have not had great success, however. Tobin's q does not seem to explain a great deal of investment behavior. One possible interpretation is that profit-maximization on an infinite horizon is not a useful explanation for firm's investment decisions. Furthermore, and contrary to theoretical predictions, other variables are significant, such as lagged q , output, or cash flow.

Following on from the literature on the 'q-theory of investment', Fazzari et al. (1988) demonstrate that the investment behavior of US listed manufacturing firms depends not only on q but also on cash-flow. They interpret this as evidence that capital markets are imperfect, and that firms cannot rely on external finance but instead they must finance their investment using internal funds. In their view, investment should not be related to cash flow, and if it is, this indicates that firms are receiving insufficient external finance for their investment plans. Although this 'financial constraints' interpretation of investment-cash flow sensitivities has been quite influential and has generated a large following, there are also several major flaws in this interpretation. Kaplan and Zingales (1997, 2000), for example, examine the firms that were classified *a priori* as financially constrained according to the methodology of Fazzari et al. (1988, 2000), but they find, upon closer inspection using annual reports, that these firms are actually in good financial standing.¹³ Further evidence against the 'financial constraints' interpretation of investment-cash flow sensitivities is provided by Levenson and Willard (2000) who analyze survey data on small businesses in the US in 1987-88. They estimate that an upper bound of 6.36% of firms were credit-rationed. This leads them to conclude that "the extent of true credit rationing appears quite limited" (2000: 83).

The main prediction for firm expansion coming from the evolutionary approach (surveyed in Section 2.3.4) is that investment or firm growth can be expected to respond to financial performance. This is due to the principle of 'growth of the fitter'. In this view, firms fight for growth opportunities, they are in a continual struggle to grow, and only those with superior financial performance will be able to gain additional market share. Empirical research in this evolutionary context is sparse, however. Coad (2005, reproduced here as Chapter 6) finds a statistically significant relationship between financial performance and sales growth for French manufacturing firms. Nevertheless, the magnitude of the coefficient is so small that he concludes "it may be more useful to consider a firm's profit rate and its subsequent growth rate as entirely independent" (2005: 15). Bottazzi et al. (2006) find similar results in their analysis of Italian firms.

A common finding in these approaches, however, is that financial performance does not

¹³One notable example mentioned by Kaplan and Zingales (2000) is that, in 1997, Microsoft would have been labelled as 'financially constrained' according to the classification schemes of Fazzari et al. (1988, 2000) even though it had almost \$9 billion in cash, corresponding to eighteen times its capital expenditures!

seem to be an important determinant of firm growth, whether this latter is measured in terms of investment or sales growth. Although the coefficients on financial performance are often statistically significant, there is a large amount of unexplained variation in growth rates. Firms appear to have a large amount of discretion in their growth behaviour.

A further discussion of financial performance and growth can be found in the survey in Chapter 5.

Relative productivity

It is perhaps quite natural to assume that the most productive firms will grow while the least productive will decrease in size. However, this assumption does not seem to be borne out by empirical work. A number of studies have cast doubt on the validity of the evolutionary principle of ‘growth of the fitter’, when relative productivity is taken as a proxy for fitness. One explanation for this is that while some firms become more productive through expansion, others become more productive through downsizing. An illustration of this is provided by Baily et al. (1996) who observe that, among plants with increasing labour productivity between 1977 and 1987, firms that grew in terms of employees were balanced out by firms that decreased employment. They find that about a third of labour productivity growth is attributable to growing firms, about a third to downsizing firms, and the remaining third is attributable to the processes of entry and exit. Similarly, Foster et al. (1998) also fail to find a robust significant relationship between establishment-level labour productivity or multifactor productivity and growth (see also the review in Bartelsman and Doms (2000: 583-584)). In addition, using a database of Italian manufacturing firms, Bottazzi et al. (2002, 2006) fail to find a robust relationship between productivity and growth. (Notwithstanding this latter result, Bottazzi et al. (2006) observe a strong positive relationship between productivity and profitability.) Perhaps more worrying is the evidence reported for US and UK manufacturing establishments in Disney et al. (2003: 683) revealing a *negative* between-effect in allocation of market share between establishments according to productivity.

While there is ample evidence suggesting that low productivity helps to predict exit (see e.g. Griliches and Regev (1995), Foster et al (1998)), productivity levels are not very helpful in predicting growth rates. Put differently, it appears that selection only operates via *elimination* of the least productive firms or establishments, while the mechanism of selection via *differential growth* does not appear to be functioning well. As a result, the mechanism of selection appears to be rather ‘suboptimal’ in the sense that its effectiveness is lower than it could conceivably be. For Baily and Farrell (2006), the lack of a positive relationship between relative productivity and growth corresponds to a lack of competition. In an ideal scenario, firms would compete for growth opportunities, and selective pressures would attribute these growth opportunities discriminating in favour of the most productive firms. In this way, there would be some

sort of dynamic efficient reallocation at work, whereby an economy's scarce resources are redistributed to those firms that are able to employ them most efficiently. In reality, however, this mechanism does not seem to be operating. Instead, the evidence is consistent with the hypothesis that many of the more productive firms may not actually seek to grow, or may be unable to grow. As a consequence, the absence of selection via differential growth testifies of missed productivity growth opportunities for the economy as a whole. Whilst we can put forward here that stimulating the growth of high-productivity firms might constitute an objective for policy, it is evident that there are large question marks surrounding how such a policy intervention might be engineered.

Other firm-specific factors

A number of other firm-specific variables have been associated with growth rates. Ownership structure appears to be a relevant factor because there is evidence that multiplant firms have higher growth rates, on average, than single-plant firms. This appears to be the case for US small businesses (Variyam and Kraybill, 1992; Audretsch and Mahmood, 1994), large European corporations (Geroski and Gugler, 2004), and also Italian manufacturing firms (Fagiolo and Luzzi, 2006). In their analysis of West German firms, Harhoff et al. (1998) identify that subsidiary firms grow faster than non-subsidiaries in construction and trade industries, although no difference can be found for manufacturing and services. Furthermore, a plant-level analysis reveals that plants which belong to large companies are observed to have higher growth than stand-alone plants (Dunne et al., 1989). Whilst there is weak evidence that foreign-owned firms experience faster growth rates, government-owned firms seem to grow more slowly (Beck et al., 2005). A firm's legal status is also proposed as a determinant of its growth rate. Harhoff et al. (1998), among others, examine the growth of West German firms and observe that firms with limited liability have significantly higher growth rates in comparison to other companies. However, these firms also have significantly higher exit hazards. These results are in line with theoretical contributions, along the lines of Stiglitz and Weiss (1981), that emphasize that the limited liability legal form provides incentives for managers to pursue projects that are characterized by both a relatively high expected return and a relatively high risk of failure.

Another approach has been to consider the characteristics of the management. The 'managerial' theory (surveyed in Section 2.3.3) suggests that managers attach utility to the size and growth of their firms, such that they will pursue growth above the shareholder-value-maximizing level. This leads to the hypothesis that owner-controlled firms will have lower growth rates (and perhaps higher profits) than manager controlled firms. Whilst Radice (1971) and Holl (1975) find no support for this claim in their analyses of large UK firms, Hay and Kamshad (1994) find that owner-controlled SMEs have lower growth rates than non-owner-

controlled SMEs. The human capital embodied in the proprietor has also been suspected of having an effect on firm growth, although the evidence is mixed. Whilst Almus (2002) identifies a positive effect of human capital (i.e. university degree or above) on growth for fast-growing German firms, Robson and Bennett (2000) fail to find a significant effect of skill level in explaining employment or profitability growth in their sample of UK small businesses. McPherson (1996) observes that the level of human capital embodied in the proprietor has a positive and significant influence on the growth of micro and small businesses in five Southern African nations. He also observes that firms owned by female persons have lower growth rates for the businesses in his sample.

It has also been shown that characteristics relating to the nature of the firm's activity have an influence on firm growth. The level of diversification appears to have a negative overall influence on the growth of large European corporations (Geroski and Gugler, 2004), although a positive and significant influence can be detected in the particular cases of advertising intensive industries (Geroski and Gugler, 2004) and the life insurance industry (Hardwick and Adams, 2002). Advertising intensity is another factor that is associated with sales growth, according to Geroski and Toker's (1996) analysis of leading UK firms. In addition, whilst previous firm-level analyses have mainly associated exporting activity to increases in productivity, some authors have identified a positive relationship between exports and firm growth (Robson and Bennett, 2000; Beck et al., 2005). The degree of centrality, or the amount of experience in a network of firms also contributes to a firm's (employment) growth rate, according to Powell et al. (1996).

Threshold effects of various kinds are also thought to dampen the growth of firms. In the past, when antitrust legislation was relatively obsessed with firm size *per se*, large firms sought to limit their growth to avoid antitrust intervention. Furthermore, large firms may be reluctant to implement a strategy of rapid growth (and especially forward integration) because of the threat of a reaction from competitors (see for example Penrose's (1960) biography of the Hercules powder company). In developed countries, there is often a size threshold above which firms face a sudden increase in firing costs. As a result, there may be a slight self-imposed restriction on growth for small firms whose size is close to this threshold. This usually affects firms whose size is somewhere in the range of 8-15 employees range, depending upon the country (see Schivardi and Torrini, 2004). In developing countries, firms can avoid or evade taxes by remaining small and informal. Larger firms, on the other hand, can effectively lobby governments to reduce their tax burden. As a result, the size distribution has a lot of weight corresponding to small firms and large firms, and with a 'missing middle' which testifies to the disadvantages associated with a medium-sized scale of operations (Tybout, 2000). In this case, small firms will tend to allay their growth aspirations, while medium-sized firms will have incentives to grow.

Still other determinants of firm growth can be mentioned here. Almus (2004) observes that German small firms have lower growth rates when there is “the shadow of death sneaking around the corner” (Almus, 2004: 199). Employment growth rates are observed to be significantly lower up to three years before a firm’s exit. There is also some evidence that uncertainty may dampen a firm’s investment. Guiso and Parigi (1999) present convincing evidence that uncertainty of demand plays a significant role in reducing firm-level investment in the case of Italian manufacturing firms. Their measure of demand uncertainty is constructed by referring to the subjective probability distribution of future demand for firm’s products according to the firm’s leading managers. Relatedly, Lensink et al. (2005) use survey data on Dutch SMEs to show that uncertainty has a mixed effect on investment. They observe that uncertainty increases the *probability* of investing (in the context of a binary ‘invest or not’ model), it is seen to reduce the overall *amount* of investment. Finally, Robson and Bennett (2000) show that the use of external business advice is also associated with superior growth. They also present evidence that firms with an ‘established reputation’ experience lower employment growth and higher turnover growth.

Industry-specific factors

There are several reasons to expect that the growth of firms varies across sectors. Firms in mature industries are likely to have lower average growth rates, *ceteris paribus*, because of the lower level of opportunity in mature industries. Firms in high-technology industries may have high growth rates due to the rapid pace of technological progress and the apparition of new products. Innovation regimes are also known to differ considerably across sectors (Pavitt, 1984), which may have an impact on the growth patterns of firms in different industries. In addition, it is reasonable to expect that the growth of firms is somehow linked to sector-specific degrees of competition and concentration. More generally, the population ecology literature (surveyed in section 2.3.5) emphasizes the prevalence of industry-specific factors in explaining growth of firms, because they share the same resource pool.

In most empirical research into firm growth, industry-specific factors are controlled away by using industry dummies that take into consideration the total combined influence of all industry-specific variables put together. The list of industry dummy variables are not usually reported alongside the main regression results, partly because of space limitations, and partly because these industry-specific effects are amalgamations of many industry-specific factors, which makes their interpretation difficult. In any case, the inclusion of industry-specific dummy variables does little to improve the overall explanatory power of the regression model (i.e. the R^2 statistic). However, some efforts have been made to identify the sources of industry-wide differences in firm growth rates. Audretsch (1995) report a positive correlation between the minimum efficient scale (MES) and growth of new firms. It appears that the post-entry

growth rate of surviving firms tends to be spurred on by the extent to which there is a gap between the MES and the size of the firm. Similarly, Gabe and Kraybill's (2002) analysis of 366 Ohio establishments provides (albeit inconclusive) evidence that the growth of firms is positively associated with the average size of plants in the same 2-digit industry. Industry growth, perhaps unsurprisingly, is observed to have a positive effect on firm growth (Audretsch and Mahmood, 1994; Audretsch, (1995)). Geroski and Toker (1996) examine the growth of firms that are leaders in their respective industries and find that growth of industry sales has a positive effect on firm growth. Nonetheless, total industry innovation does not appear to have a significant effect. Furthermore, Geroski and Toker observe that the degree of market concentration is positively related to the growth of these firms. Finally, Geroski and Gugler (2004) consider the impact on firm growth of the growth of rivals, where rivals are defined as other firms in the same 3-digit industry. Firm growth seems to be negatively related to rival's growth, an observation that is especially true for differentiated good industries and advertising intensive industries.

Macroeconomic factors

Although it has been observed that more of the variation in firm growth rates is between industries rather than across countries (Geroski and Gugler, 2004), it is nonetheless instructive to continue our literature review by considering the influence of macroeconomic factors on firm growth rates.

Several studies have discussed how firm growth varies over the business cycle. In this vein, Higson et al. (2002, 2004) analyse US and UK firms over periods of 30 years and above and observe that the mean growth rate is indeed sensitive to macroeconomic fluctuations. Furthermore, higher moments of the growth rate distribution appear to be sensitive to the business cycle (more on this in Section 2.2.1). Hardwick and Adams (2002) investigate changes in the Gibrat Law coefficient over the business cycle (i.e. the coefficient β in equation (2.5)), and they obtain some evidence of a countercyclical variation of this coefficient. In other words, smaller firms appear to grow relatively faster during booms, whereas larger firms grow faster during recessions and recoveries.

Gabe and Kraybill (2002) consider the role of regional factors in explaining the growth of plants in Ohio. However, both the county growth rate and a metropolitan area dummy do not appear to have a statistically significant effect on growth rates. Contrasting evidence can be found in McPherson (1996), however, who reports that Southern African small businesses grow faster in urban areas than in rural areas.

Bartelsman et al. (2005) explore differences in firm growth in developed countries, and observe that the post-entry growth of successful entrants is much higher in the USA than in Europe. In particular, they observe that “[a]fter 7 years of life, the average cohort of firms in

manufacturing experience more than 60% growth in employment, while in European countries the increase is in the 5-35% range” (Bartelsman et al., 2005: 386). This is partly because new firms tend to be relatively smaller upon entry in the US, thus having a larger gap between their entry size and the industry minimum efficient scale (MES). The authors suggest that this difference in post-entry growth rates is due to institutional barriers to growth that are in place in Europe, such as the lack of market-based financial systems, relatively high administrative costs that may deter smaller firms at entry, and tighter hiring-and-firing restrictions.

Several interesting results relating to cross-country differences in firm growth rates can be found in the study by Beck et al. (2005), which analyzes a size-stratified firm-level survey database covering over 4000 firms in 54 countries. They observe that firms in richer, larger, and faster-growing countries have significantly higher growth rates. The growth rate of GDP is positively correlated with firm growth, which indicates that firms grow faster in an economy with greater growth opportunities. Inflation appears to have a positive impact on growth rates, although the authors admonish that this most likely reflects the fact that firm sales growth is given in nominal terms. Furthermore, indicators of financial and legal obstacles, as well as the prevalence of corruption, are obtained from the questionnaire data. These obstacles vary in importance across countries and are observed to be negatively correlated with firm growth rates.

2.2.4 Conclusion

Without doubt, the main result that emerges from our survey of empirical work into firm growth is that it is the stochastic element is predominant. “In short, the empirical evidence suggests that although there are systematic factors at the firm and industry levels that affect the process of firm growth, growth is mainly affected by purely stochastic shocks,” according to Marsili (2001: 18). Geroski (2000: 169) makes an even bolder statement: “The most elementary ‘fact’ about corporate growth thrown up by econometric work on both large and small firms is that firm size follows a random walk.” The R^2 statistic in growth rate regressions is characteristically low, especially for databases containing many small firms whose growth is particularly erratic. Including a long list of explanatory variables and lags does little to help raise the R^2 value, as is evident from the survey provided in Table 2.2. Firm growth thus appears to be remarkably idiosyncratic, even if the assumption of a purely stochastic process of firm growth is often rejected on purely statistical grounds.

It is also fitting for us to make a statement with regard to validity of Gibrat’s law. The question of whether or not we should reject Gibrat’s law has indeed been hotly debated. Whilst Mansfield (1962), for example, voiced strong opposition to Gibrat’s law, Ijiri and Simon (1964) take a much more favourable approach. These latter consider that although Gibrat’s law does

Table 2.2: A survey of R^2 values obtained from regressions where the dependent variable is the growth rate of a firm or plant

Study	Data	Control variables	R^2
Kumar (1985)	Around 700-800 quoted UK companies	Size, lagged growth	1-4%
Variyam & Kraybill (1992)	422 small businesses in Georgia, USA	Size, age, multiplant firms, industry	11-17%
Geroski & Toker (1996)	209 leading UK firms	Size, innovation, advertising, industry growth, industry concentration	32%
MacPherson (1996)	1671 small firms in 5 Southern African countries	Firm age and size, dummies for sector and location, human capital and socio-economic variables	13-20%
Harhoff et al. (1998)	About 10'000 West German firms	Age, age, subsidiary, diversification, legal status, industry	8%
Liu et al. (1999)	Over 900 Taiwanese manufacturing plants	Age, size, industry dummies, capital-labour ratio, sales per worker, dummies for R&D and exporting activity	19-22%
Robson & Bennett (2000)	Over 1000 SMEs in Britain in 1997	Size, age, exports, profits, industry, innovation and technology, use of external advice, strategy variables	4-8%
Geroski & Gugler (2004)	Large firms in 14 European countries, over 100'000 obs. 1994-98	Size, age, subsidiaries, diversification, growth of rivals	5-6%
Beck et al. (2005)	Survey data covering over 4000 firms of all sizes, in 54 countries	Dummies for government/foreign ownership, export status, subsidies, sector of activity; controls for number of competitors, GDP, GDP per capita, GDP growth, financial/legal/corruption obstacles	2-3%
Coad (2005)	8405 French manufacturing firms, 1996-2004	Gross operating margin, lagged growth, lagged size, industry and year dummies	4-8%
Calvo (2006)	About 1000 Spanish firms	Size, age, legal liability, product/process innovation, technology, sample selection	9%
Fagiolo & Luzzi (2006)	14'277 Italian firms 1995-2000	Size, age, cash flow, dummies for multiplant firms, year and industry dummies	2-3%

Notes: Control variables include the constant term (though this is not mentioned above). Where fixed-effect regressions have been employed, we refer to the overall R^2 and not the within R^2 or between R^2 . Where we have the choice, we prefer the adjusted R^2 . Although growth rates are mostly obtained by measuring size at annual intervals, this is not always the case. For example, McPherson (1996) takes the average annual growth rate for the whole of the period since start-up, whereas Liu et al. (1999) take a yearly average of the growth rate over 4 years.

not hold with perfect accuracy, it is a useful first approximation, just as Galileo's law is approximately correct in describing the motion of balls rolling down inclined planes (albeit without taking into account such factors as friction, air resistance and magnetic fields). This seems to us to be a sensible position to take.

Our survey has also emphasized two other surprising and perhaps counterintuitive findings. First, an examination of the evidence reveals that financial performance and productivity do not predict growth. Selection by differential growth does not seem to work very effectively at all. Instead, selection appears to operate via exit of the weaker only – this considerably reduces the power of selective forces. Although there are strong implications hinging on the relationship between 'fitness' (usually profits or productivity) and growth, there is nonetheless a remarkable lack of empirical research that has been done in this domain. As a result, I feel obliged to reiterate Caves' (1998: 1977) recommendation: "Because reallocations of activity from the less efficient to the more efficient are so important for the optimal use of resources, more evidence is needed on how competitive conditions within an industry affect the speed with which the more efficient displace the less efficient."

Second, another large gap in the literature concerns the link between innovation and firm growth. While much theoretical work, as well as questionnaire evidence from managers, stresses the crucial role of innovation in explaining growth, empirical studies have not really picked up on this in a satisfactory manner. This may well be because the standard regression approach, which focuses on 'the average effect for the average firm', is ill-appropriate for analyzing a phenomenon by which a minority of firms will grow very fast while the average firm will barely grow at all. The semi-parametric quantile regression approach employed by Chapter 7 is much more suitable in circumstances where firms are *a priori* heterogeneous.

By and large, therefore, we put forward that empirical work seeking the determinants of firm growth has made limited progress. Instead, firm growth appears to be an idiosyncratic and fundamentally random process. It appears that the majority of the total variation in firm growth rates is within firms over time (Geroski and Gugler, 2004). As a result, it makes sense for future empirical work to attempt to explain growth by referring to variables that vary more over time within particular firms than they vary between firms (in the cross-section) at any given time. Unfortunately, however, firm-specific variables that display such properties are not easy to find.

A long literature has thus tried to find general determinants of growth rates, with limited avail. However, fresh insights into the processes of firm growth can be gained by looking at the autocorrelation structure of growth rates. Although this topic has long escaped any detailed empirical analysis, Chapter 4 analyses growth rate autocorrelation taking into account heterogeneity between firms along the dimensions of firm size and growth rate. The results are promising, giving a deeper comprehension of growth process and also allowing to distinguish

between competing theories of firm growth. Our understanding of firm growth can also be improved by applying new statistical tools to the data. Chapter 7 applies quantile regression techniques to obtain insights into the relationship between innovation and firm growth that cannot be observed by using more conventional regressions.

2.3 Theoretical contributions

In the following we briefly present five distinct theoretical perspectives, discussing their predictions for firm growth and judging them according to the available empirical evidence. These five theories are the neoclassical theory (in particular, propositions based on the notion of an ‘optimal size’), Penrose’s (1959) ‘theory of the growth of the firm’, the managerial approach, evolutionary economics and its principle of ‘growth of the fitter’, and also the population ecology approach.

2.3.1 Neoclassical foundations – growth towards an ‘optimal size’

Although the term ‘neoclassical’ encompasses a large and vaguely defined body of literature, for the purposes of our discussion on firm growth we consider that the main prediction emerging from the traditional neoclassical perspective is that firms are attracted to some sort of ‘optimal size’ (Viner, [1931] 1952). This optimal size is the profit-maximizing level of production, in which economies of large scale production are traded off against the costs of coordinating large bureaucratic organizations. In this view, firm growth is merely a means of attaining this ‘optimal size’, and it is of no interest *per se*. Once firms have reached their optimal size, they are assumed to grow no more.¹⁴

It is relevant to mention here the well-known transaction costs theory of the firm, which began with the Coase’s (1937) seminal article. To summarize briefly, this theory considers that the optimal boundaries of the firm are determined in a trade-off between the advantages of coordination via authority in a hierarchy versus the advantages of coordination through the price mechanism. If transaction costs are relatively large, then firms will find it worthwhile to expand upstream or downstream in order to acquire strategic assets. In this way, the production chain can be coordinated by the use of authority in the context of a hierarchical organization. If transaction costs are low, however, the optimal boundaries of the firm are smaller because the firm can interact with suppliers and customers via the market mechanism. Factors affecting the desirability of integration are the frequency of transactions, uncertainty, the degree of asset specificity, and the possibility of opportunistic behaviour. We observe that the predictions made by the transaction costs literature most often concern growth by

¹⁴One might see a resemblance here with some theories to be found in the Vatican, which consider that people only have sex because they intend to reach an ‘optimal’ family size...

acquisition in the context of vertical integration (Kay, 2000). As a result, transaction cost economics appears to have a limited scope in explaining other aspects of firm growth.

Another variation on the optimal size theme is in Lucas (1978), who ‘explains’ the log-normal distribution of firm sizes by assuming a log-normal distribution of managerial talent. These managers are then assumed to be successfully matched to firms with a size that corresponds to their skill level. Large firms are large because their managers are particularly talented and can accomplish the difficult task of running a large organization with reasonable success. On the other hand, small firms are supposed to remain small because of the relative incompetence of their managers. Although managers of large firms would be happy to endorse this idea, we consider that the practical value of such a model is questionable.

The concept of an optimal size has received (and still receives) a great deal of attention, despite a blatant lack of empirical support. The notion of an industry-specific optimal size is at odds with observations on the wide support and the prominent skewness of the firm size distribution which can be found even at finely disaggregated levels of analysis. Even the concept of a firm-specific optimal size appears to be inconsistent with time-series analysis of the patterns of firm growth (Geroski et al., 2003; Cefis et al., 2006). In contrast, Gibrat’s model of stochastic drift in firm size performs much better in empirical analysis of firm growth rates than do the neoclassical optimizing models we have mentioned. By way of conclusion to this section, therefore, we suggest that the notion of ‘optimal size’ is of little use in understanding why firms grow, and that it would be better to un-learn it quickly.

2.3.2 Penrose’s ‘Theory of the Growth of the Firm’

Penrose’s (1959) seminal book contains several important contributions to our discussion on firm growth. We first present her idea of ‘economies of growth’ before moving on to the ‘resource-based view’ of the firm.

Penrose’s (1959) fundamentally dynamic vision of firms holds that firm growth is led by an internal momentum generated by learning-by-doing. Managers become more productive over time as they become accustomed to their tasks. Executive functions that initially posed problems because of their relative unfamiliarity soon become routinized. As managers gain experience, therefore, their administrative tasks require less attention and less energy. As a result, managerial resources are continually being released. This excess managerial talent can then be used to focus on value-creating growth opportunities (and in particular, the training of new managers). Firms are faced with strong incentives to grow, because while “the knowledge possessed by a firm’s personnel tends to increase automatically with experience” (1959: 76), there is a challenge to take full advantage of this valuable firm-specific knowledge.

It takes time and effort to successfully integrate new managerial resources within the firm,

but once this is done these new recruits will be able to execute managerial tasks and, in turn, train managers themselves. In this way, a firm will grow in order to create value from its unused resources, which in turn will create new resources.¹⁵ Growth in any period is nonetheless limited by the amount of available managerial attention. Managers who spend too much time focusing on the firm's expansion divert their attention from operating efficiency. As a result, above a certain point corresponding to what we might call an 'optimal growth rate' (Slater, 1980), increases in growth will lead to higher operating costs. Although 'economies of growth' provide incentives for firms to grow, fast-growing firms will have higher operating costs than their slower-growing counterparts. This latter proposition is commonly known as the 'Penrose effect'.

Another key concept in Penrose's theory of firm growth is that firms are composed of idiosyncratic configurations of 'resources'. These resources can play a role in ensuring durable competitive advantage if they are valuable, rare, inimitable and nonsubstitutable (Dierickx and Cool 1989; Eisenhardt and Martin, 2000). Examples of resources are brand names, in-house knowledge of technology, employment of skilled personnel, trade contracts, machinery, and efficient procedures (Wernerfelt, 1984).¹⁶ A firm can decide upon the direction of a growth project by examining the strengths and weaknesses of its existing resource base (Barney, 1986). Economies of growth may emerge from exploiting the strengths associated with the unique collection of productive opportunities available to each firm. The indivisible and interdependent nature of these resources can also be seen to add impetus to a firm's growth (Coad, 2006a). In fast-changing markets, however, a firm's competitive advantage may erode if it relies too heavily on certain specific resources. In such circumstances, a firm's performance depends on its abilities to create or release resources and to reconfigure their resource portfolio. These abilities are known as 'dynamic capabilities' (Teece et al., 1997; Eisenhardt and Martin, 2000; Winter, 2003).

Penrose's vision of firm growth considers that firms grow because of 'economies of growth' that are inherent in the growth process, and not because of any advantage linked to size *per se*.¹⁷ A firm's size is merely a by-product of past growth. Although there may be limits to firm growth, there is no limit to firm size *a priori*. Penrose's approach therefore contrasts greatly with the mainstream neoclassical perspective, in which firms only grow in order to reach an 'optimal size' in static equilibrium, and in which there are limits to firm size (on this last point,

¹⁵Jacques Lesourne puts it this way - "L'entreprise cherchera à employer ces ressources inutilisées, mais en le faisant en créera d'autres, en ne réussissant jamais à atteindre un état d'équilibre complet dans l'utilisation de ses ressources" (Lesourne 1973: 92).

¹⁶Other examples of 'resources' have also been put forward. Montgomery (1994) suggests that Disney's cast of animated characters can be viewed as a resource, that has been observed to fuel diversification. Somewhat more unusual is Feldman's (2004: 304) affirmation that even emotions such as anger and frustration can be considered to be organization-specific 'resources'.

¹⁷Penrose's analysis considers that firms operate in a world of constant returns to scale.

see for example the model in Williamson, 1967). It is perhaps because of this that Penrose's contribution has, unfortunately, been marginalized in the industrial organization literature – as Montgomery (1994: 167) notes, “[a]lthough The Theory of the Growth of the Firm was published in 1959, it has not had a strong impact on the direction of economic discourse.” Nonetheless, Penrose's resource-based perspective has been quite influential in the strategic management literature.

2.3.3 Marris and ‘managerialism’

The fundamental observation of the ‘managerial’ theory of the firm is that managers attach utility to the size of their firms (for pioneering work on the ‘managerial’ perspective, see Marris (1963, 1964) and also the books by Baumol (1959) and Williamson (1964)). A manager's compensation, bonuses, and other perquisites are very often increasing with firm size.¹⁸ Furthermore, non-pecuniary incentives such as prestige, likelihood of promotion, social status, and power are also associated with firm size. As a result, firm size (and firm growth) are seen to be important factors in the ‘managerial utility function’, alongside the financial performance of the firm. For some firms, such as young small firms, the pursuit of growth maximization may coincide with that of profit maximization, so that a manager has no conflict of interest between his duties to shareholders and his own objectives (Mueller, 1969). In other cases, however, managers have to choose between fulfilling their mandate of profit-maximization (in service of shareholders) or pursuing their own interests of growth-maximization. According to the managerial theory, utility-maximizing managers are assumed to maximize the growth rate of the firm subject to the constraint of earning a satisfactory profit rate, which should be large enough to avoid being dismissed by shareholders or being taken over by stock-market ‘raiders’.

In the influential managerial model developed by Marris (1963, 1964), firms are assumed to grow by diversification only. Above a certain level of growth, additional diversification has a lower expected profitability because managers have less time and attention to devote to the operating efficiency of existing activities and the development of new activities. The managerial theory has also been extended to the case of growth by conglomerate merger (Mueller, 1969). Mergers are a faster (and more expensive) way of growth than internal growth – so managerial arguments are *a fortiori* relevant for this type of growth.

Testing the ‘managerial hypothesis’ is a difficult task because the theoretical models (e.g. Marris, 1964) propose a non-linear hump-shaped relationship between growth rate and

¹⁸Commenting on the contemporary business climate of the 1960's, when managerial theories were first hatched, Mueller (1969: 644) ventures to say that “[m]anagerial salaries, bonuses, stock options, and promotions all tend to be *more* closely related to the size or changes in size of the firm than to its profits” [emphasis added].

profit rate, with additional growth having a negative effect on profits only beyond a certain ‘profit-maximizing’ growth rate. Nonetheless, one basic prediction that emerges is that the growth rates of manager-controlled firm will be higher than those of owner-controlled firms, whilst profit rates are likely to be lower. Some early studies thus tried to find performance differences between owner-controlled and manager-controlled firms. The results, however, did not offer unequivocal support in favour of the theoretical predictions. Radice (1971) tests the hypothesis that owner-controlled firms have lower growth rates and higher profit rates than management-controlled firms, using a sample of 89 large UK firms over the period 1957-67. Perhaps surprisingly, he observes that owner-controlled firms have both higher growth rates and profit rates. Holl’s (1975) analysis also focuses on large UK firms, but he fails to detect any significant difference in performance between owner-controlled and manager-controlled firms. If SMEs are considered, however, there is some survey evidence that management-controlled firms have stronger preferences for growth than owner-controlled firms (Hay and Kamshad, 1994). More specifically, it appears that the largest difference between the strategies of management-controlled and owner-controlled firms concerns the area of geographical expansion.

Another body of research, predominantly from the financial economics literature, has investigated the managerial hypothesis by evaluating the performance of diversifying firms. This is a meaningful way of investigating managerialism because the original model proposed by Marris (1963, 1964) considers that growth takes place exclusively through diversification. The theoretical prediction, then, is that high levels of diversification are associated with lower performance. These studies are surveyed in more detail in Section 2.4.2, which focuses on growth by diversification. In general, diversification is often detrimental to overall financial performance, which provides some indirect support for the managerial hypothesis. This evidence comes from both ‘event studies’ of the stock market’s response to diversification announcements, and also analysis of *ex post* profits of diversifying firms. Conversely, over-diversified firms that subsequently refocus are seen to improve their performance. Furthermore, growth by acquisition appears to be negatively related to a firm’s financial performance (Dickerson et al., 2000).

2.3.4 Evolutionary Economics and the principle of ‘growth of the fitter’

The modern economy is increasingly characterized by turbulent competition and rapid technical change, and as a consequence a dynamic theory of competitive advantage may well be more relevant to understanding the economics of industrial organization than the more neoclassical concepts of equilibrium and static optimization. Evolutionary economics has thus been able

to make a significant impact on IO thinking, because it proposes a *dynamics first!* conceptualization of the economy. Evolutionary theory has its foundations in Schumpeter's vision of capitalism as a process of 'creative destruction', and borrows the notions of diversity creation and selection to account for the dynamics of economic development. Alchian's (1950) theoretical paper argues that the evolutionary mechanism of selection sets the economy on the path of progress, as fitter firms survive and grow whilst less viable firms lose market share and exit.¹⁹ The notion of selection via differential growth is also a central theme in the books by Downie (1958) and Nelson and Winter (1982). Downie (1958) models industrial development by assuming that firms grow by reinvesting their earnings. Growth rates thus rise with profitability. Nelson and Winter's (1982) influential book contains a formal microfounded simulation model in which firms compete against each other in a turbulent market environment. In this model, firms can gain competitive advantage through either the discovery of cost-reducing innovations or by imitating the industry best practice. Firms that are more profitable are assumed to grow, whilst firms that are less successful are assumed to lose market share. Agent-based simulation modeling has since remained a dominant tool in the evolutionary literature (see, among others, Chiaromonte and Dosi (1993), Dosi et al. (1995), Marsili (2001) and Dosi et al. (2006); see also Kwasnicki (2003) and Dawid (2006) for surveys). In addition to computer simulation models, the principle of 'growth of the fitter' has also formed the foundations of analytical evolutionary models (see, for example, Winter (1964, 1971), Metcalfe (1993, 1994, 1998)).

The evolution of industries in this family of models is generally guided by the mechanism of 'replicator dynamics', by which growth is imputed according to profitability. This mechanism can be presented formally by Fisher's 'fundamental equation', which states that:

$$\delta M_i = \rho M_i (F_i - \bar{F}) \quad (2.6)$$

where δ stands for the variation in the infinitesimal interval $(t, t + \delta t)$, M_i represents the market share of firm i in a population of competing firms, F_i is the level of 'fitness' of the considered firm, ρ is a parameter and \bar{F} is the average fitness in the population, i.e. $\bar{F} = \sum M_i F_i$. It is straightforward to see that this equation favours the 'fitter' firms with increasing market share, whilst reducing that of 'weaker' firms.

This 'replicator dynamics' does sound intuitively appealing, because implicit in it is the idea that selective pressures act with accuracy, that financial constraints prevent inefficient firms from growing, and that the economic system adapts so as to efficiently allocate resources amongst firms, such that firms 'get what they deserve'. However, these assumptions may not

¹⁹Somewhat more far-fetched is Milton Friedman's (1953) reiteration of Alchian's (1950) original idea, which supposes that the mechanisms of growth of the fitter and exit of the weaker will lead the economy to the neoclassical 'optimum', thereby vindicating the predictions of neoclassical theory.

find empirical validation for a number of reasons. First of all, it cannot be assumed that all firms have the same propensity to grow. Some high-profit firms may not be interested in business opportunities that are instead taken up by less demanding firms. Freeland (2001), for example, documents how GM's shareholders resisted investing in additional business opportunities and sought to restrict growth expenditure even when GM was a highly profitable company. If this is the case, then stricter internal selection will cause high-profit firms to overlook opportunities that are instead taken up by less profitable competitors. In this way, growth may be negatively related to profitability. An extension of this idea is presented by the managerial literature (see Section 2.3.3), which identifies a tension between profits and growth – this arises when managers seek to grow at a rate higher than that which would be 'optimal' for the firm as a whole, with the resulting growth rate being limited by shareholder supervision. If shareholders monitor management closely, growth rates are predicted to be low and profit rates high. If shareholders are ineffective at monitoring and discipline, however, the growth rate may be high and profit rates low. Second, high profits may be made by firms that can exercise market power by restricting their production to obtain a higher price per unit sold. In this case, a firm which has sufficiently inelastic demand for its goods would have a higher profit rate if it reduces its capacity. In this case too, increases in profits would be associated with negative growth. Third, if a firm occupies a highly profitable niche market, it may not have opportunities to expand despite its high profits. Fourth, a firm may experience a higher profit rate due to efficiency gains by downsizing and concentrating on its core competence. Here again, we have no reason to suppose a positive association between profits and firm growth. (Further reasons why firms may not all want to grow are discussed in Section 2.4.1 on 'Growth strategies'.) As a result, the existence of a relationship between profitability and growth is an empirical question.

The principle of 'growth of the fitter', despite its eloquence, does not appear to receive much support from empirical analyses. Let us consider the two usual candidates for 'fitness', namely profitability and productivity, in the light of the survey of empirical work in Section 2.2.3. To begin with, we observed that profitability and sales growth appear to be largely independent from each other, when we consider the available evidence from studies of French and Italian manufacturing industries. Similarly, research based on data for US, UK and Italian manufacturing firms fails to find that the more productive firms grow faster than the others. Although profitability and productivity are perhaps the most obvious indicators of 'fitness', others such as product quality or cost levels have also been suggested. These latter variables are usually more difficult to observe, and so they are not often used in empirical work (although it can be anticipated that they should be positively correlated with both profitability and productivity). However, we can mention here the work by Hardwick and Adams (2002). Whilst these authors fail to find any effect of profitability on firm growth, they do observe a

negative influence of the input cost ratio on growth, for UK life insurance companies (i.e. that high-cost firms have lower growth rates). Weighing up the available evidence, though, we must acknowledge that empirical work on the principle of ‘growth of the fitter’ does not provide encouraging results. It may be better to suppose that selection works only by elimination of the weaker, with growth not being related to any notion of ‘viability’ but instead being at the discretion of managers. In this view, we have ‘survival of the fitter’ without ‘growth of the fitter’ (as in the simulation model of van Dijk and Nomaler (2000)).

There are also welfare implications attached to the failure of the principle of ‘growth of the fitter’ (Baily and Farrell, 2006). If high performance firms were observed to have the fastest growth rates, then selective processes would bring about some sort of efficient dynamic allocation of the economy’s resources between firms. Scarce productive resources would be attributed to those firms who can best exploit them. However, since ‘growth of the fitter’ is generally not observed, economies may be far from achieving their full productive potential. This may be an opportunity for policy intervention.

2.3.5 Population ecology

The ‘population ecology’ or ‘organizational ecology’ perspective hails from sociology and follows on from the seminal contribution of Hannan and Freeman (1977). (More on population ecology approach can be seen in the surveys by Geroski (2001) and Hannan (2005), and some recent developments can be found in the special issue of *Industrial and Corporate Change* (Vol. 13, No. 1, 2004).) The basic theoretical prediction pertaining to the growth of organizations is that these latter require resources which are specific to niches, and these niches have a particular ‘carrying capacity’. If a firm has discovered a new niche with a rich resource pool, then this firm will be able to grow without hindrance. The number of firms in the niche will also grow, due to entry of new organizations. If the population grows to a level where the niche’s resource pool is saturated, however, then competition between firms will limit the growth rates of firms. This relationship between the growth of organizations and the competition for resources in a particular niche is known as ‘density dependence’.

The population ecology perspective thus places the growth of organizations in the context of niche-specific growth patterns without focusing as much on heterogeneity between organizations occupying the same niche. This should not be taken to mean that the scholars deny the existence of differences between organizations.²⁰ Instead, this is due to the fact that the fundamental unit of analysis here is the population of organizations within a niche, rather

²⁰There is ample evidence that the population ecology perspective explicitly acknowledges interorganizational heterogeneity. For example, in the seminal article by Hannan and Freeman (1977: 956), they write “[f]or us, the central question is, why are there so many kinds of organizations?” Furthermore, Hannan (2005) opens his literature review with this very same question.

than the individual organizations that make up the population. As a consequence, population ecologists tend to explain the performance of organizations by referring to features common to all organizations within the same niche, rather than firm-specific factors.²¹ Of course, there are clear limits to a theory of firm growth rates based solely on industry-wide characteristics, because large differences in growth rates can be observed between firms in the same industries. Notwithstanding the analytical starting point, however, some efforts have been made to relate the performance of organizations to idiosyncratic rather than environmental factors.

Broadly speaking, the empirical strategy in the ‘population ecology’ literature takes place by gathering life-history data on populations of organizations that are arguably in the same ‘niche’. This niche may refer to specific industries (e.g. automobile producers (Hannan et al., 1995)), niches within industries (such as biotechnology drug discovery companies (Sørensen and Stuart, 2000)), or even non-commercial ideological organizations (Minkoff, 1999). Most studies focus on the effects of characteristics of organizations²², populations, and the environment on organizational performance by examining birth and death rates of organizations. However, efforts have been made to explain differences in growth rates between firms in the same industry. Baron et al. (1994) analyse data on New York Credit Unions over the period 1914-1990 and observe that larger firms have lower expected growth rates than their smaller counterparts. The interpretation they offer is that larger organizations have become less efficient and less well adapted to the current business environment, thus being more vulnerable to young competitors. This builds upon a key population ecology tenet that firms are fundamentally inert (Hannan and Freeman, 1984), being both averse to and relatively incapable of strategic or organizational change.

2.3.6 Conclusion

The theories we have surveyed above are certainly diverse and sometimes they are contradictory. For example, while neoclassical theory considers that growth is only a means to an end, Penrose considers that growth is an end in itself, and that it may occur even if the firm is beyond an ‘optimal size’ threshold, in the case where ‘economies of growth’ of exploiting a marginal growth opportunity offset the diseconomies of the resultant size.

It is also striking that the theories, though intuitively appealing, do sometimes yield predictions that are quite false. The neoclassical proposition that firms grow in an attempt to reach an ‘optimal size’ is unhelpful at best. The evolutionary principle of ‘growth of the fitter’ consistently fails to receive empirical support. Furthermore, the main prediction from the population ecology perspective (i.e. that firm growth should be modelled by considering industry-specific components) seems rather weak when it is confronted to the empirical test.

²¹As Geroski (2001: 535) notes, there is a “heavy reliance on density dependence to drive dynamics.”

²²Organizational heterogeneity is usually modelled using variables such as age, size, and organizational form.

In our view, it is meaningful to follow Penrose and suppose that growth is not just a means to obtain a certain size, but rather it is an end in itself, a constructive application of spare resources. Indeed, in the presence of learning-by-doing and dynamic increasing returns, a lack of growth would be akin to stagnation.

2.4 Growth strategies

In the following we will first discuss the attitudes of firms towards growth, and then the available means of achieving growth (such as diversification and acquisition). It appears useful to relate these two topics to the distinction between ‘demand’ for growth and ‘supply’ of growth opportunities, respectively. Firm growth requires both a willing attitude to take up growth opportunities, and also the availability of suitable opportunities. However, in the long-run, the distinction between supply and demand determinants of growth may become blurred (Penrose, 1960). Managers with a strong desire to grow will surely find suitable growth opportunities if they search for them. Correspondingly, even firms with a marked aversion to growth will eventually take up additional growth opportunities if these are attractive enough.

2.4.1 Attitudes to growth

As firms get older, they generally increase in size. However, growth is neither irresistible nor inevitable. Indeed, some firms may not wish to pursue growth even if the opportunity presents itself. We observed in Section 2.2.3 that a firm’s growth rate is largely independent of its financial performance. This is consistent with suspicions of a disconnect between a firm’s ability to grow and its desire to grow. In this section we attempt to expound why firms may or may not want to grow, as well as discussing the intentionality of growth.

The desirability of growth

Advantages of growth Growth of an organization can be seen as a means of alleviating tensions in its internal management. Employees appreciate the opportunities for promotion as well as the higher salaries and prestige that accompany growth. Aoki (1990) writes that employees may even be willing to forego current earnings in exchange for future benefits made possible by promotion in an expanding hierarchy. In addition, work is likely to become more challenging as the firm ‘breaks from its routines’ and expands into new business areas. “Work is more fun in a growing company” as Roberts (2004: 243) bluntly puts it. Conversely, a lack of growth can create an uninspiring and stultifying business environment which depresses managerial efficiency (Hay and Morris, 1979). As a result, in growing firms it is “easier to obtain commitment to organizational goals and priorities from various factions and to resolve

conflicts between those factions” (Whetten, 1987: 340). An organization may thus seek a positive growth rate in order to keep its members satisfied. Indeed, it has been conjectured that firms that take their employees interests seriously are likely to have higher growth rates (Aoki, 1990).

The managerial vision of the firm can be considered as an extension of this line of reasoning. Managers attach positive utility to the growth rate of the firm, because an increase in firm size is associated with increases in compensation, power, prestige, bonuses and perquisites. One difference is, however, that managers have the power to determine a firm’s growth strategy themselves, and so they can pursue a growth rate above that which would be optimal for the shareholders. For more on the managerialist theory of the firm, see Section 2.3.3.

Firms may also seek growth as a means of attaining other objectives related to its production of goods and services. Lower production costs may be achieved if expansion leads to economies of scale (due to a larger scale of production), or economies of scope (because of a wider range of products or services). Growth may also take place if firms wish to expand their productive capacity or boost their output so as to deter entry from potential competitors (Dixit, 1980).²³ Furthermore, a larger, more diversified firm is better able to spread its risk among its various activities. (This will be an advantage for managers whose fortunes are tied to those of the firm (Amihud and Lev, 1981), although it is not necessarily an advantage for shareholders because they can reduce their risk by investing in a diversified portfolio including other firms.) In this way, growth can be considered to be a basis for security (Whetten, 1987).

Other reasons have also been advanced to suggest why firms might want to grow. One reason might be because growth is sometimes a more suitable metric of performance than profits – this is particularly true for high-volatility markets. A firm’s management may thus set its performance goals in terms of percentage increases in sales rather than profit margins or share prices. Other firms may grow for want of a better alternative. This might be the case for firms who grow by reinvesting profits in the company, as a means of avoiding heavy taxes (on dividends, for example).

There is some empirical evidence that demonstrates the positive effect of growth on firm performance. Chapter 6 analyzes a large sample of French manufacturing firms and observes that growth is associated with increases in profits, whether growth is measured in terms of employment, sales, or value added. Perhaps surprisingly, there seems to be a larger effect of growth on profits than that of profits on growth.

Disadvantages of growth Despite the aforementioned advantages linked to growth, some managers or owner-managers may be wary of increasing the size of their firm. One major

²³The ‘entry deterrence’ argument is of limited relevance, because entrants are usually too small to pose a serious threat. However, the argument may hold as long as large firms in other industries are deterred from diversifying into the sector under consideration.

reason for this is what we could call the ‘control-loss’ argument. Loss of control may originate from the increased size or the rate of growth. As a firm increases in size, as employees are added and the number of hierarchical levels increases, the manager has less control of the firm and is less well informed of its current state (Williamson, 1967). Problems of control and coordination are also increasing functions of the growth rate. Whilst it has been advanced that problems of coordination vanish under truly static conditions (Kaldor, 1934), fast-growth firms may experience difficulties in coordinating operations in a complex and changing environment.²⁴

Family-owned and traditional firms may have an especially cautious approach to growth if they are keen to keep the firm under tight control or if they are reluctant to integrate a large number of employees and managers from outside the family. Furthermore, they may be particularly risk-averse because failure of the enterprise may take on connotations of ruining the family tradition. Managers whose training and experience have been confined to a single industry are also characteristically timid when it comes to growth, especially growth by diversification (Ansoff, 1987). This is also true for managers approaching retirement. In these cases, firms may prefer not to expand, and instead remain in a ‘comfort zone’.

Larger firms are less attractive environments than smaller firms for a number of reasons. Large firms are less adaptable and less responsive than their smaller counterparts. Routinization replaces initiative, and bureaucratic ossification replaces the dynamism associated with small firms. Large organizations tend to become less motivating environments for employees. Furthermore, the initial energy and motivating enthusiasm of the founding entrepreneur is replaced by a manager whose role is to monitor and coordinate a more routinised method of production (Witt, 2000). A common ideology and a cooperative working environment is substituted by an organizational culture in which employees are more concerned with personal and self-centered goals. However, it should be emphasized that a distaste for organizations of large size does not necessarily preclude a firm’s growth. Because of ‘economies of growth’, firms may still benefit from taking up marginal growth opportunities even if there are diseconomies of large size (Penrose, 1959). Indeed, growth should not be seen as merely a means of attaining a larger size.

A firm’s attitude to growth may also be influenced by the existence of a certain size threshold. Schivardi and Torrini (2004) demonstrate that Italian firms close to the threshold of 16 employees are reluctant to expand because this would be associated with an increase in their employment protection responsibilities. Although statistically significant, this effect can only be detected using large databases, however, and so its economic importance should not be exaggerated. Tybout’s (2000) survey of manufacturing firms in developing countries describes how small firms have incentives to stay small and informal to avoid taxes. In contrast, medium-

²⁴Using survey evidence for Dutch SMEs, Lensink et al. (2005) observe that higher growth firms perceive that they have more idiosyncratic uncertainty than other firms.

sized firms have incentives to grow in order to become large enough to be able to lobby the government. It has also been suggested that large firms whose sales account for a significant fraction of the market may also restrain their own growth in order to keep prices high and avoid ‘spoiling the market’ (see e.g. Nelson (1987)).

Some empirically-minded papers have found negative attitudes to growth in a range of situations. A lack of desire for growth has been found by Tether (1997) in the case of UK high-tech firms as well as by Audretsch et al. (2004) for family-owned hospitality industries in the Netherlands. Hay and Kamshad (1994) present evidence from a survey of UK SMEs. They find that many software firms encounter limits to growth imposed by the scarcity of first-class programmers. In the instruments industry, the scientists that founded the firms are often not well prepared for the management roles that larger firms require. In the printing sector, many firms choose not to grow simply because the owners use their business as a means to support a relaxed and independent lifestyle. More generally, Greiner (1998) provides the following description of the ‘lifestyler’ manager’s attitude to growth: “Top management that is aware of the problems ahead [linked to organizations of a large size] could well decide not to expand the organization. Managers may, for instance, prefer to retain the informal practices of a small company, knowing that this way of life is inherent in the organization’s limited size, not in their congenial personalities. If they choose to grow, they may actually grow themselves out of a job and a way of life they enjoy” (Greiner, 1998: 67).

Is growth intentional or does it ‘just happen’?

Are growth opportunities to be passively seized or are they to be built? Is firm growth intentional and proactive, or does it ‘just happen’? Some perspectives on firm growth, such as Gibrat’s law, view it as a passive absorption and accumulation of growth opportunities. Other authors, however, talk of ‘growth strategies’, and sometimes firms include growth rate targets among their explicit performance objectives. In this section, we discuss different perspectives on the intentionality of firm growth.

Gibrat’s (1931) ‘law of proportionate effect’, in its simplest form, considers that the growth of firms is best modelled as a stochastic process in which the magnitude of a random ‘growth shock’ over a specific period is independent of a firm’s size. Relatedly, the ‘island models’ developed by Ijiri and Simon (1977), Sutton (1998) and Bottazzi and Secchi (2006) present statistical processes in which firms are seen as ‘islands’, or independent entities, whose resultant growth is simply a cumulation of the stochastic opportunities they receive in any period. These growth opportunities are supposed to be exogenously created and upon arrival they are randomly allocated across firms. Firms are required to have minimal rationality, and, more generally, these statistical models can be said to have a minimal recourse to any economic theory because growth is entirely explained by random factors. One advantage of this class of

models, however, is that they can explain the observed size distribution whilst demonstrating both simplicity and generality. Whilst Gibrat's law appears to be one of the more useful approaches to modelling firm growth and the evolution of industries, it should nonetheless be remembered that there is a certain rationality and intentionality in the process of firm growth.

Another early model considered that the size of an organization has an inherent and quasi-automatic tendency to drift upwards (Parkinson, 1957; see also Starbuck, 1971: 16-17). The rationale of this model is that members of an organization, at all hierarchical levels, are guided by motives of prestige, power, and security. Consider the case of an employee, A, who considers herself overworked. She has three options – she may resign, she may ask to halve her work with a colleague called B, or she may ask the assistance of two subordinates, C and D. In fact, the third option is the only serious one. If she were to resign, she would lose her job and all associated privileges. Were she to ask for B to be appointed, she would merely introduce a rival into her level of the hierarchy (which would also reduce her chances of promotion). As a result, she asks for two assistants. These assistants improve her status in the organization, and furthermore, by dividing her work into two categories (for C and D) she will become entrenched in a position of power because she is the only person who understands the work of both of the assistants. In turn, when C and D consider themselves to be overworked, A will be more than happy to introduce further insubordinated employees. These later additions will improve her standing in the hierarchy, and make her more eligible for promotion and salary increases. As we have seen, in this particular model, the growth of the organization has little to do with 'decisions taken at the top' but instead it is due to the behavior of people throughout the hierarchy.

Some authors, mainly from Penrose's camp, explain growth as being due to the build-up of internal pressure. As time goes by, managerial resources are continually being released as managers become more accustomed to their work and become more productive. (More on Penrose's 'Theory of the Growth of the Firm' can be found in Section 2.3.2.) As a result, managers can divert their attention from routine operations to planning and carrying out growth projects. Unused managerial services are a key determinant in a firm's capacity to expand. Firms must then decide upon the direction for growth. Managers must search for potential growth opportunities and draw up growth plans. As a result, growth is an informed and intentional process (Penrose, 1955).²⁵ Growth is seen primarily as a result of managerial decision and 'human will' rather than being a response to technological factors.²⁶ If, on the other hand, these unused managerial services are involved in growth projects that are

²⁵In fact, it is precisely because of the intentionality attributed to the growth of firms that Penrose (1955) rejects biological analogies as valid descriptions of firm growth.

²⁶An unpublished comparison of sectoral growth rate distribution parameters (at the 3-digit level) for Italy and France reveals that there is very little in common in the growth rate distributions for same sectors across countries. This hints that the underlying sector-specific production technology does not go far in explaining growth rates – instead it may well be that human factors play a major role.

unstructured or ill-prepared, then they are unlikely to succeed (Penrose, 1955; Dixon, 1953).

In neoclassical work, even stronger rationality is attributed to firms that grow. In this perspective, growth is the result of a forward-looking process in which firms adjust their current scale of production to anticipate future market trends. According to neoclassical q -theory, firms are assumed to have rational anticipations, and their size is determined as the solution to an intertemporal profit-maximization problem on an infinite time horizon (see Section 2.2.3).

By way of conclusion, then, we consider that firms do have some rationality in their growth, although assuming perfect rationality is certainly taking things too far. For some firms, such as small firms struggling to reach the MES (minimum efficient scale of production), growth is very much an intended outcome. This is in spite of what a simplistic and literal interpretation of Gibrat's law might suggest – firm growth is not just an ‘organizational drift’, but instead there is some rationality and planning involved.

2.4.2 Growth strategies – replication or diversification

“[G]rowth is not for long, if ever, simply a question of producing more of the same product on a larger scale; it involves innovation, changing techniques of distribution, and changing organization of production and management” (Penrose 1959: 161). Although in some cases firms may be able to expand by producing ‘more of the same’ using the same resources, the time will come when further expansion will require them to take on new employees, build new production plants, or even diversify into new markets. There are thus a number of issues and complications that accompany a firm's decision to grow. These issues are discussed in the following sections.

Growth by replication

In traditional economic theory, firms decide how much to produce by selecting a profit-maximizing output level determined by the demand curve. It is supposed that the firm operates in a homogenous product market and can easily expand or contract to arrive at the optimal output level. While this may be an acceptable description of the output of one particular factory floor, it is unhelpful in describing more significant growth events such as the hiring of new employees or the setting up of new production plants.

One caveat of this primitive vision of firm growth is that the production of goods and services requires the application of a certain amount of tacit knowledge. This tacit knowledge is difficult to transfer from one individual to another, or from one locus of production to another. As a firm grows, problems may arise because of the difficulty in transferring this tacit knowledge. Although the firm may have enjoyed successful production in the past, it may be

non-trivial to replicate this past success with newly-introduced additional productive capacity, especially where production processes are characterized by a high degree of complexity (Rivkin, 2001). In other words, businesses may fail when they try to reproduce a best practice because the in-house ‘experts’ don’t truly know why it worked in the first place (Szulanski and Winter, 2002).

Indeed, the extensiveness of tacit knowledge and the difficulty of replication may go some way in explaining the persistent heterogeneity in profitability and also productivity levels that are visible even between firms in the same narrowly-defined industrial sectors.²⁷

How then can a firm replicate its superior performance? A firm’s replication strategy is more likely to be successful if a few guidelines are followed (Winter and Szulanski, 2001; Szulanski and Winter, 2002). First, the template should be kept in mind throughout the replication process, and even after acceptable results have been obtained by the new unit. This template should be copied as closely as possible. Changes can be introduced only after decent results have been obtained. Managers should focus on the activity they are trying to replicate, rather than on what the documentation or the experts say. Finally, it is important that managers have a meek attitude and a keenness to copy the template faithfully rather than to attempt to improve upon it.

A more extreme approach to technology transfer, applied by Intel, is known as the ‘copy **EXACTLY!**’ policy (MacDonald, 1998). Semiconductor manufacturing is characterized by very complex production processes in which the process steps have low tolerances and have complex interactions. In addition, this complexity has increased with successive generations of semiconductors. Precision in replication is thus of paramount importance. If variables such as barometric pressure, ultra pure rinse water temperature and the length of the electrode cooling hose are not copied with utmost accuracy, the results can be catastrophic. After a period in which new plants exhibited a dismal performance, Intel developed the ‘Copy **EXACTLY!**’ philosophy according to which “‘everything which might affect the process, or how it is run’ is to be copied down to the finest detail, unless it is either *physically impossible* to do so, or there is an *overwhelming competitive benefit* to introducing a change” (MacDonald, 1998: 2 (emphasis in the original)). Furthermore, if a modification has been suggested and is applied, this idea is simultaneously implemented at all other sites as well. As a result of this replication strategy, it is now common for Intel’s new production plants to meet best-practice performance standards from the very first day of production.

²⁷For empirical evidence on the heterogeneity of firm productivity levels, even within narrowly-defined industrial sectors, see Dosi and Grazzi (2006). See also Dosi (2007) for evidence on the dispersion of profit margins within industries.

Growth by diversification

Theoretical perspectives An early view of diversification considered that managerial competences were the key to superior firm performance, irrespective of the sector of activity. In other words, this perspective holds that “management is an amorphous substance which can be applied with equal success to totally unrelated lines of business” (Mueller 1969: 651). In order to take full advantage of these scarce assets, successful firms sought to spread their superior management capabilities across several different industries. In this way, diversification was guided by a logic of synergies of managerial competence as opposed to synergies of a technological nature. As a result, the large diversified conglomerate became a popular organizational form, especially in the 1950s and 1960s.

Penrose’s (1959) vision of firm growth by diversification can be placed within this context. Managerial attention is seen to be the main factor limiting firm growth. As a firm continues its operations, incumbent managers gradually gain experience, and new managers can be trained and integrated into the firm, thus expanding the firm’s resource base. In this way, managerial resources are continually being freed up over time. Growth thus constitutes a responsible use for excess managerial attention – it challenges managers to focus their attention on generating profits in new activities. However, Penrose also gives clear recommendations as to the direction of diversification. A key element of Penrose’s theory of firm growth is that firms are composed of indivisible resources, which are specialized and specific to the firm. A firm’s diversification strategy should therefore focus on how to best exploit the idiosyncracies of the firm’s current resource base. In other words, growth by diversification is most effective when the new activities are related to the existing resource base.

The notion of related or ‘synergistic’ diversification is central to Igor Ansoff’s [1965] (1987) celebrated book. Ansoff advocated a prudent approach for diversification at a time when, in retrospect, it appears that general management synergies were overestimated. According to him, firms should only consider diversification when there is no other option for a firm of realizing its growth objectives – “if a firm can meet all of its objectives by measures short of diversification or internationalization, it should do so” (Ansoff 1987: 131). Indeed, in many cases a firm can discover growth opportunities by re-evaluating and re-formulating its strategies within its present portfolio of activities, instead of expanding the portfolio by commencing new activities. Firms that choose to diversify, however, can do this in one of three ways: by exporting the firm’s traditional products or services into new markets (which constitutes the “highest synergy move” (Ansoff 1987: 125)), or by diversifying according to synergies of demand or synergies of technology. In each case, attention must be paid to the coherence of the diversified firm’s portfolio of activities. Candidate new businesses must display synergies with the existing portfolio of activities along dimensions such as operations, R&D, or marketing and distribution. These synergies may be due to lower expected fixed costs

of starting-up, or alternatively due to anticipated operating economies. Furthermore, efforts should be made to convert the *ex ante* ‘potential synergy’ into ‘realized synergy’, by actively seeking to integrate the new activity alongside the firm’s existing activities. If these guidelines are successfully applied, synergistic diversification allows firms to earn superior profits by leveraging their capabilities, know-how and general experience in new markets. It should be pointed out that synergistic diversification is not incompatible with corporate refocusing, but is instead closely related (Batsch, 2003). Both of these view the firm as a coherent portfolio of related activities based on a small number of core competences. Refocusing can be seen as a corrective strategic measure undertaken after excessive unrelated diversification – it is a modification (but not necessarily a reduction) in a firm’s activities as the firm seeks to focus on exploiting certain specific capabilities. Refocusing should not be seen as a ‘return’ to the firm’s previous condition, however, but as a strategic reevaluation of a firm’s core competences in an ever-changing business environment (Paulré, 2000).

‘Managerial’ or ‘agency’ theories of firm growth, as presented above in Section 2.3.3, have also made a considerable impact on research into diversification. (In fact, empirical work on diversification has mainly focused on testing the hypothesis that diversification is detrimental to firm performance.) The decision to diversify is usually taken at the initiative and the discretion of managers, and managers have strong incentives to diversify even when this is not in the best interests of shareholders. On the one hand, standard economic theory predicts that diversification will be in the best interests of the firm as a whole when expansion into new activities promises relatively high profit levels. Diversification was also historically encouraged for other reasons pertaining to the business environment around the time of the 1960s – the multidivisional firm (i.e. the ‘M-form’) was lauded as an effective organizational innovation, underdeveloped financial markets meant that there were advantages of having an internal capital market (i.e. the ‘deep pockets’ argument), and the prevailing anti-trust legislation limited growth prospects in any one industry. On the other hand, however, diversification also offers at least four other advantages that are more specific to managers. First, managers of large and growing firms receive higher pay (as well as increases in bonuses, ‘perks’, prestige, and “the pure pleasures of empire-building” (Montgomery, 1994: 166)). This point is clearly illustrated by Hyland and Diltz (2002), who compare managerial compensation for a group of diversifying firms with a similar matched sample of undiversifying firms – “the mean compensation increase over the time interval between proxy statements for diversifying firms is \$84,397 and the median is \$57,133. . . . For matched-sample firms, the mean compensation increase is \$22,642 and the median is \$18,128” (Hyland and Diltz 2002: 64). Second, managers who have vested interests in the performance of their firm (or who are merely concerned about their reputations) may attempt to lower the firm’s volatility by spreading the risk and diversifying into new activities, even if this does not improve the firm’s average rate of return (Amihud

and Lev, 1981). This is against the interests of shareholders, because these latter usually prefer to reduce risk by including diverse specialized firms in their investment portfolio, rather than by investing in one diversified firm. Third, managers may diversify in order to ensure that the firm will require their personal skills and services in the future – this is known as the ‘managerial entrenchment’ argument (Shleifer and Vishny, 1989). Fourth, managers may be reluctant to distribute any spare cash-flow back to shareholders in the form of dividends, and instead they may prefer to spend it on pet projects even if these have a low expected return (Jensen, 1986).

Empirical evidence A large body of research in the financial economics literature has focused on the relative performance of diversified firms vis-à-vis stand-alone firms or less-diversified firms, generally using data on large US firms. The general message that emerges is that diversification is associated with inferior performance. In some cases, diversification behavior is examined via ‘event studies’ of stock market reactions to diversification or refocusing. It appears that the stock prices respond negatively to diversification announcements (see e.g. Hyland and Diltz, 2002) but positively to refocusing announcements (Berger and Ofek, 1999; Markides, 1992). Others have analyzed the effects of diversification on *ex post* realized profits, again finding that diversification exerts a negative pressure on profits (Doukas and Kan, 2004). Conversely, there is evidence that corporate refocusing is associated with increases in *ex post* profits (Markides, 1995). The distinction between related and unrelated diversification has also received attention from empirical work. Whilst unrelated diversification is often detrimental to firm performance, related diversification is more successful. As a result, despite the negative tone of research into the performance of diversified companies, it is likely that the ‘optimal level of diversification’ for large firms is above the minimum of one industry (Montgomery, 1994).

A historical perspective on diversification is also of interest. In the 1950s and 1960s, diversification was actually a popular strategy, for several reasons. First, capital markets were relatively undeveloped and firms had incentives to organize several businesses around an ‘internal capital market’. (This is also known as ‘deep pockets’ argument.) Second, antitrust law imposed limits on the market shares of firms in specific industries, which meant that firms who were willing to grow had to do so in new industries. Third, the multidivisional or ‘M-form’ organization was growing in popularity. Fourth, there is evidence that early diversification announcements actually received a positive stock market reaction. As a result, the 1960s have been described as a ‘wave of unrelated acquisitions’ (Montgomery 1994: 170). The 1970s were also characterised by unrelated acquisitions and overdiversification. The 1980s, however, correspond to a ‘return to corporate specialization’ (Bhagat et al., 1990). During this time, changes in the business environment made diversification less appealing (in particular, financial

markets became more developed, and antitrust law changed its stance on measures of absolute market share). Furthermore, the poor financial performance of large diversified conglomerates had become widely recognized.

2.4.3 Internal growth vs growth by acquisition

Internal growth, also known as ‘organic growth’, is usually associated with non-diversifying firms, while growth by acquisition is usually associated with diversifying firms. However, both internal growth and acquisition can be used as means of either expanding market share in a particular industry or of diversifying into new industries.

Internal growth is a preferable means of diversifying when there are strong synergies between the firm’s existing activities and the target industry. These synergies may take the form of reduced entry costs or reduced operating costs, or both. Furthermore, internal growth is particularly attractive if firms can develop and integrate their new capabilities in an environment where time pressures are not too great. In this way they can steadily cultivate a sound base of in-house competences that will be a source of enduring competitive advantage. Internal growth is also a relevant option when there are no suitable target firms available for acquisition at a reasonable price.

Growth by acquisition of other businesses, on the other hand, is most effective when a firm must rapidly acquire new capabilities, production capacity or good managerial resources. Similarly, acquisition is a preferred means of entry into industries in which market shares are already stable and there is little space for a new entrant. Furthermore, acquisition is more appropriate if synergies with the new activity are not expected to be significant.

Nevertheless, a strategy of growth by diversification is particularly difficult to make good. “There are more unsuccessful acquisitions than there are successful ones” according to John Harvey-Jones, former Chairman of ICI (cited in Ansoff 1987: 10). In reality, acquisitions are rather expensive growth strategies. According to one (admittedly dated) estimate, the typical premium paid by an acquiring firm is 10-30% above the market price of the acquired firm’s stock before the merger (Mueller 1969:652). To this must be added the costs of assimilating the target firm, in order to convert the ‘potential synergy’ into ‘realized synergy’.

Acquisitions have been attributed a noble character by some economists because, in effect, they introduce an element of competition into the ‘market for corporate control’. The possibility of takeover can act as a disciplining device that gives incentives for management to run a company with efficiency and due responsibility (see e.g. Marris (1964)). In reality, however, the ‘market for corporate control’ is very imperfect, takeovers are very rare, and inefficient management can continue for long periods. The disciplining device of takeovers is rather weak. In contrast, it seems that acquisitions are often a source of inefficiency in the

economic system – indeed, “quite a bit of evidence points to the dominance of managerial rather than shareholder motives in firms’ acquisition decisions” (Shleifer and Vishny, 1997: 747). For example, acquisitions may take place because managers act in their own interests rather than those of the firm as a whole (Mueller 1969). This conflict of interests may arise if pay increases, bonuses, perquisites, or prestige are associated with the size of the firm. In addition, managers of mature firms (often having high cash flow but few growth prospects) may choose to acquire businesses because they are reluctant to distribute the earnings to shareholders (Jensen, 1986). Furthermore, managers may undertake acquisitions because they are overconfident of their managerial abilities – this is the essence of Roll’s (1986) ‘hubris hypothesis’. As a result, empirical evidence suggests that “acquisitions, in general, have a deleterious effect on company performance as measured by profitability” (Dickerson et al., 2000: 424). Acquisitions may also be socially harmful if a firm acquires a competitor as a way of obtaining market power in a particular industry. For all of these reasons then, and perhaps more, acquisitions are often associated with decreases rather than increases in social welfare.

2.5 Growth of small and large firms

There are fundamental differences between small and large firms that it would not be appropriate to neglect. Indeed, in Section 2.2 we observed that small firms do have different growth patterns from larger firms. The aim of this section is to elaborate upon these differences. We begin by focusing on the dichotomous distinction between small and large firms, before taking a more detailed look at organizational stresses that accompany the growth process in our discussion of the ‘stages of growth’ models.

Firms that are small (large) very often correspond to firms that are young (old). Although this is not always the case,²⁸ in the following small (large) and young (old) can be taken as more or less synonymous adjectives of firms.

2.5.1 Differences in growth patterns for small and large firms

The growth of small firms is a particularly erratic phenomenon. Entry rates of new firms are high, regardless of the industry, and a large number of these entrants can be expected to fail within a few years. For example, Bartelsman et al. (2005) examine the post-entry performance of new firms in 7 OECD countries and observe that about 20-40% of entering firms fail within the first two years, while only about 40-50% survive beyond the 7th year. A small proportion of these entrants are actually innovators, as highlighted by Santarelli and Vivarelli (2006: 5) – “one has to recognize that when dealing with gross entry across all economic sectors

²⁸It may be that small firms are nonetheless relatively old, if they have a history of aversion to growth.

we encounter a huge multitude of ‘followers’ and very few ‘real’ entrepreneurs.” Instead, overconfidence and the escape from unemployment are often key characteristics of new firms.

These firms enter on a small scale relative to incumbents – around 40-60% of the average size of incumbents (Bartelsman et al., 2005). Their small size puts them at a disadvantage vis-à-vis their larger counterparts, and so they must expand rapidly, as if their life depended on it. The larger they grow, the smaller their cost disadvantage relative to firms above the MES, and thus the higher their chances of survival. For such firms, the growth objective coincides with survival and the pursuit of profits. These firms tend to have a higher average growth rate than larger firms, despite the difficulties they may face in financing their expansion.

According to Penrose (1959), small firms can thrive in the ‘interstices’ of major markets, in submarkets that are not large enough to support large firms. As a result, they are often sheltered from direct competition with large firms. This is not to say that they are entirely protected from the competition however. In fact, survey evidence for small businesses indicates that competitive pressures are a major factor inhibiting their growth (Hay and Kamshad, 1994; Robson and Bennett, 2000).

The growth of large firms is different in several respects. While small firms’ survival depends to some extent on their growth, for large firms above the MES the objectives of survival, growth and profits become separated and may even conflict. Growth of large firms takes on a new meaning as ‘economies of growth’ become more relevant than ‘economies of scale’. If these firms grow to become very large, they begin to resemble financial investment trusts composed of relatively autonomous divisions (Penrose, 1959). These firms have a decentralized structure because the firm is too large for the top management to play an active role in the activities of each division. This decentralized structure has been observed to facilitate spinoffs of the weakest divisions (Penrose, 1959).

Empirical evidence presented in Chapter 4 provides unique insights into differences in the growth of small and large firms. The growth of small firms appears to be marked by a negative autocorrelation which becomes very strong for the fastest-growing small firms. This is consistent with observations on the erratic nature of growth for small firms. Larger firms, on the other hand, have a much smoother growth pattern, with a small positive autocorrelation of one year’s growth onto the next. It appears that larger firms enjoy greater stability and are able to plan their growth over a longer time horizon.

Some influential theoretical models have attempted to describe the chaotic process of small firms growing larger. Jovanovic (1982) presents what is known as the ‘passive learning’ model, in which small firms have a fixed firm-specific productivity level. Their growth and survival prospects are bound to this productivity variable. Although firms do not know how productive they are upon entry, they learn about their relative productivities once they have entered. It is shown that this model is able to account for the faster growth and also the higher exit hazards

associated with small firms. Hopenhayn (1992) presents a similar model in which a firm's productivity level evolves according to a Markov process. Finally, the 'active learning' model (Ericson and Pakes, 1995; see also Pakes and Ericson, 1998) investigates the evolution of a competitive industry when firms can influence their specific productivity levels by investing in R&D.

The growth of small firms is often seen as having a beneficent character, often being taken as a goal for policy intervention. Small firms are often portrayed as being dynamic and innovative, playing a key role in generating new employment opportunities. In contrast, it appears that the growth of large firms is often implicitly put in a bad light – questions of market power, unfair competition, or managerialist 'empire-building' are frequently raised. In our view, this conception of the growth of firms is not very helpful. In reality, only a fraction of small firms are truly innovative, their ability to generate jobs is limited, and the jobs they create often disappear shortly afterwards (see Santarelli and Vivarelli, 2006). It might be better to characterize the entry of small firms by phenomena of excessive entry, high exit rates, and a large amount of waste of economic resources. Larger firms, on the other hand, have the ability to generate jobs in large absolute numbers, and these jobs appear to correspond to relatively stable positions. Furthermore, it has been argued that the ability of large firms to diversify into new markets helps to ensure that markets are reasonably contestable.²⁹

2.5.2 Modelling the 'stages of growth'

As we have seen from the previous section, small and large firms grow for different reasons and in different ways. Indeed, it has been observed that the firm undergoes a radical metamorphosis as it grows, with the entrepreneur's vision and dynamism gradually being replaced by a more bureaucratic structure (see e.g. Witt 2000). A body of research along these lines, guided by "common sense views of youth, adolescence, maturity, and old age" (Whetten 1987: 337), has culminated in theoretical models of regularities in the stages of firm growth. The main thrust of these models is the goals, priorities and issues faced by firms change considerably along their respective trajectories of development.

The 'stages of growth' models view firms as growing through successive stages of roughly sequential ordering as they evolve from birth to maturity. These stages correspond to configurations of problems, strategies, and priorities that firms are likely to face as they grow, as well as describing the level of owner involvement and the organizational structure. The resolution of one set of problems allows a firm to enjoy a period of steady growth and prosperity, but as the firm continues to grow it encounters new difficulties. Typically, these models contain 3-6 stages of firm development, with some models focusing in particular on the early stages

²⁹Bain, quoted in Penrose (1959: 256).

of firm growth. Although the unit of analysis is usually the firm, it could also plausibly be taken to be a subsystem of a firm in the case of a mature organization with loosely-coupled divisions.

A prominent and early contribution to this literature was made by Greiner [1972] (1998). In Greiner's model, presented in Figure 2.6, firms progress through episodes of evolution and revolution, with growth stages corresponding to a series of internal crises related to leadership, control, and organizational coordination. The resolution of one crisis is seen to sow the seeds for the next crisis. Thus, a small young firm, characterized as a creative enterprise, will have to deal with a crisis of leadership as it grows too big to be managed single-handedly by the founding entrepreneur (see Figure 2.6). If the firm succeeds in introducing a capable business manager, it will typically enjoy a period of growth characterized as the 'direction' stage. However, a crisis of autonomy looms as employees are torn between following procedures and taking their own initiative – this crisis is resolved by promoting delegation in the context of a decentralized organizational structure. As the firm puts delegation into practice, however, top management may feel as though it is losing control. To deal with this control crisis, the firm enters the 'coordination' phase as formal coordination systems are introduced. These latter help to alleviate control problems but they create a gap between headquarters and operating workers. This is the bureaucratic 'red tape' crisis, which occurs when the organization becomes too large to be managed using rigid, formal techniques. Spontaneous managers capable of creating teams and encouraging teamwork help the firm move into the final stage, the stage of 'collaboration'.

Churchill and Lewis (1983) also present a five-stage 'stages of growth' model, although their perspective is quite different. The five stages are those of existence, survival, success, take-off, and resource maturity. At the existence stage, the young firm faces problems of obtaining customers and delivering the product. The firm requires financial resources to take it to the 'survival' stage, at which the firm must demonstrate the quality of its personnel and operating efficiency. The following stage is the 'success' stage, at which the firm must decide whether it wants to expand or just maintain the status quo. At this stage, the owner still has a considerable degree of control over the business, but will forfeit this control if the firm expands further. If the firm does not grow, it remains at what they call the 'success-disengagement' stage. If the firm decides to grow, however, it experiences a 'take-off' and must deal with issues of decentralization and delegation before reaching the ultimate stage, 'resource maturity'. Churchill and Lewis (1983) also emphasize a fundamental transformation that takes place in growing firms – the fact that although the owner's abilities are important at the start of the enterprise, they become less so as the firm becomes mature. Conversely, delegation is not important in small firms but it becomes increasingly important as the firm grows. It follows that the "inability of many founders to let go of doing and begin managing

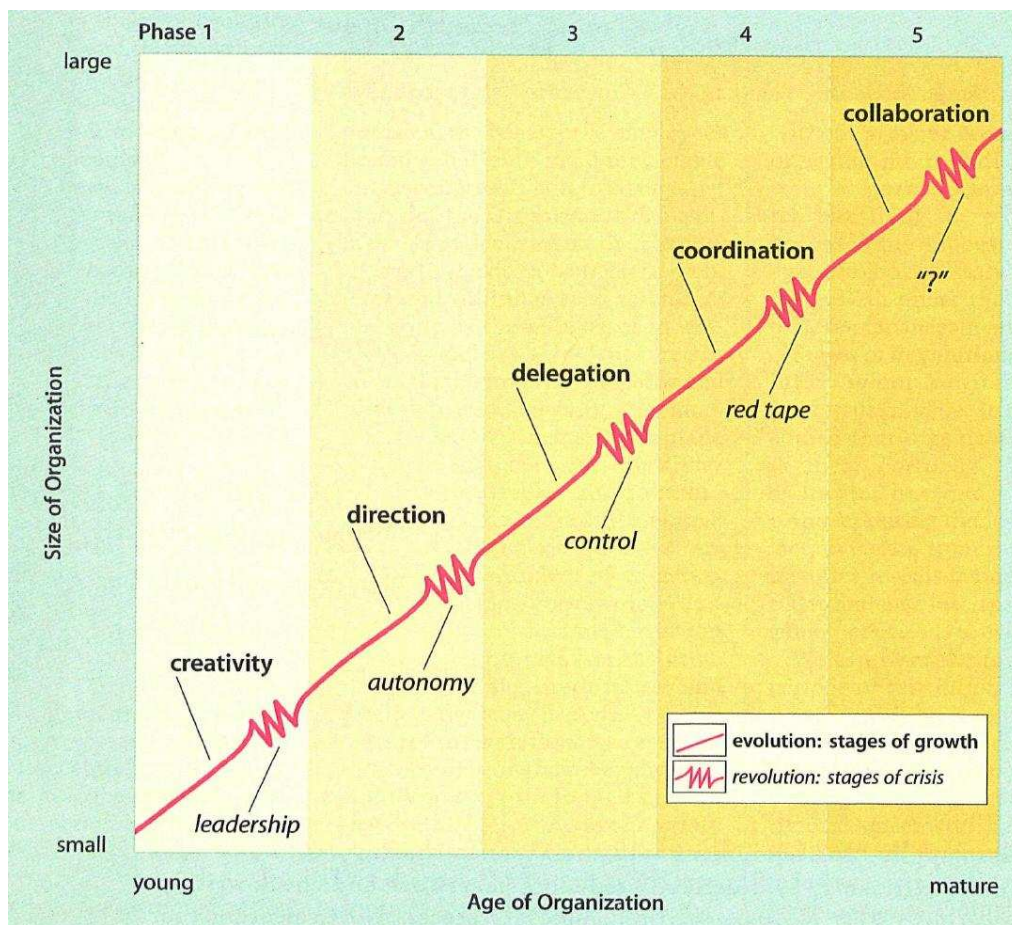


Figure 2.6: Evolution and revolution in a model of growth stages (Source: Greiner (1998:58))

and delegating” (1983: 42) is a major obstacle to the development and growth of small firms.

The model developed by Garnsey (1998) is similar to that of Churchill and Lewis (1983) although it focuses more on the early stages of growth in new firms. She places emphasis on the high hazard rates that confront new firms, and their effort and struggle to quickly access, mobilize and deploy resources before they can generate resources for growth. Once a firm’s operations are set up, however, the initial burst of energy required to get things going is no longer required, and resources are released for growth. Garnsey (1998) also discusses the phenomenon of routinization of operations in “small growing firms. To begin with, “[n]ew firms are hampered by their need to make search processes a prelude to every new problem they encounter” (1998: 541). As time goes by, however, firms learn about their business and develop problem-solving repertoires that make demanding situations appear more routine. Problems can be identified as recurrent and require less time and energy, and “early challenges are replaced by repetitive grind” (1998: 542). As a consequence, this routinization found in growing small firms can engender disillusionment, and growth can be hindered by morale problems (which may even lead to spin-outs of new ventures).

Although the ‘stages of growth’ models have largely escaped empirical attention, it is worthwhile to mention here the work by Kazanjian and Drazin (1989).³⁰ The essence of their test is to observe how small new firms evolve through four discrete growth stages – Conception & Development, Commercialization, Growth, and Stability. Firms are sorted into growth stages by a self-categorization exercise in which CEOs were requested to select from among four alternative, unlabeled organizational descriptions that best described their firm’s current situation. Using a longitudinal sample of 71 technology-based new ventures, they present evidence in support of the sequential ‘stages of growth’ model, although the statistical evidence is rather weak.³¹ Their results therefore suggest that, although the evolution of firms along a ‘stages of growth’ schema is often observed, this schema does not have strict deterministic or uni-directional properties because, in some cases, organizations may revert to an ‘earlier’ set of problems.

There are, however, many skeptics of ‘stages of growth’ models. For example, these models have often been criticised because they are too deterministic, too simple, and because they have little predictive power (Whetten, 1987). One particular group of discontents includes those who affirm that organizational change is a pervasive and continuous rather than discrete and episodic. Tsoukas and Chia (2002), for example, dismiss the notion of episodic change and

³⁰For another (perhaps less convincing) example of empirical research into ‘stages of growth’ models, see Mitra and Pingali (1999). These authors apply Churchill and Lewis’ (1983) model to an analysis of 40 automobile ancillaries in India.

³¹The authors use the ‘del’ statistic, which is preferable to the χ^2 statistic because it tests for directionality. They obtain a del statistic (analogous to the R^2 coefficient) of 0.65 (with $p < 0.001$). In other words, knowing the ‘stages of growth’ rule (whereby firms advance 0 or 1 stages over an 18 month period) leads to a 15% proportionate reduction in error over not knowing the rule in predicting stage transitions.

argue that “[w]e should rather start from the premise that change is pervasive and indivisible” (2002: 569). In this view, change is viewed as a permanent feature of organizations, without beginning or end, emerging from the complex interaction of individuals within an organization and the evolving environment. Even organizational routines can be said to contain the seeds of change, because they are performed by individuals who experiment and improvise as they apply routines to novel situations (Feldman and Pentland, 2003). How then can these two different views of organizational change be reconciled? Is organizational change continuous or episodic? How can some sociologists (e.g. Tsoukas and Chia, 2002) view change as a pervasive feature of organizations whilst others (e.g. Hannan and Freeman, 1984) view organizations as being fundamentally inert? (To complicate matters further, other authors take an intermediate position and view organizational dynamics as occurring in a context of punctuated change – see for example Sastry (1997).) The survey by Weick and Quinn (1999) focuses on precisely this question. For them, organizational change can be either episodic or continuous depending on the vantage-point of the social scientist. If we consider the entire life span of organizations, it is possible to pick out certain points, describe the characteristics of these points and compare them. On the other hand, a more detailed look reveals “all the subterranean, microscopic changes that always go on in the bowels of organizations” (Tsoukas and Chia, 2002: 580). ‘Stages of growth’ models, therefore, characterize organizational growth and change as episodic because they take a distant perspective of organizations and focus on general trends in their long-term development over their life span.

2.6 Conclusion

We have observed that theoretical predictions have been of limited use in understanding the growth of firms, if not downright misleading. Notions of a firm-specific ‘optimal size’ can be rejected without further ado. Furthermore, the evolutionary principle of ‘growth of the fitter’ fails to find much empirical validation. Given the strong implications of the principle of ‘growth of the fitter’, however, it seems that theorists are finding it difficult to digest the fact that growth and ‘fitness’ are largely unrelated. Indeed, some prefer to ignore the available evidence. Nonetheless, it seems to us that the way forward is through empirical analysis. We recommend a Simonian methodology (Simon, 1968) whereby facts are first pursued through empirical investigations, and in a second stage theories are formulated as attempts to explain these ‘stylised facts’.

Empirical research into firm growth has also come up against some major obstacles. The main message that seems to emerge is that growth is largely a random process. There seems to be little value added by the multiplication of investigations into Gibrat’s law. Furthermore, there seems to be limited use in trying to find the determinants of growth rates in a standard

regression framework, because the combined explanatory power of the independent variables is remarkably low – the R^2 coefficients are usually around 4-10%, although in rare cases rising to about 30%.

A fresh approach is needed. Progress has been made in the last decade by examining the distribution of growth rates. This leads to a better direct understanding of firm growth, and it has also led to the formation of new theories of firm growth (Bottazzi and Secchi, 2006; Coad, 2006a). Another promising avenue seems to be quantile regression, which allows us to focus on the determinants of growth for fast-growth firms. The average firm does not grow very much, and so the standard regression estimators that focus on ‘the average effect for the average firm’ are not very informative. Quantile regressions, however, allow us to observe the characteristics of fast growth firms, which make a disproportionately large contribution to the turbulence and growth within industries. Preliminary results from quantile regressions do indeed find that these fast-growth firms do have distinguishing characteristics (see Chapters 4 and 7).

Part II

Regularities in the growth process

Chapter 3

Corporate growth and industrial dynamics: some preliminary investigations

To begin our empirical analysis, we explore some general properties of firm size and growth using our dataset on French manufacturing firms. We look at the distributions of firm size and growth rates, at an aggregated and also a disaggregated analysis. Our analysis of the distribution of growth rates complements a sparse literature by showing that the distribution is even fatter-tailed for French firms than for their Italian and US counterparts. We also investigate Gibrat's 'law of proportionate effect' by seeing how a firm's average growth rate and growth rate variance can be expected to vary with size. Although we fail to find clear-cutting evidence against the hypothesis that average growth is invariant to firm size, we observe a negative dependence of growth rate variance on size.

3.1 Introduction

A number of early studies into industrial structure focused on the adequation of theoretical distribution functions (in particular the Pareto, the Yule, and the log-normal) to aggregate distributions of firm size. This pioneering line of research began with Gibrat's (1931) investigation of the French manufacturing sector, and was later applied to the UK manufacturing (Hart and Prais, 1956) and also to US (Simon and Bonini, 1958; Quandt, 1966) and Austrian data (Steindl, 1965).

Another strand of literature has focused on the well-known 'Law of Proportionate Effect', a statistical process formulated by the engineer Gibrat as he attempted to explain the emergence of the aggregate size distribution. This 'law' states that, in a context of constant returns to scale, firm growth follows a purely stochastic process, with growth rates being independent

of firm size. Although it is often criticized as lacking any theoretical foundation, Gibrat's law is nonetheless very useful, as it provides a sort of 'null hypothesis' against which corporate growth can be compared. A large body of research (see for example Mansfield (1962), Evans (1987), Hall (1987), and Dunne et al. (1988); see also Sutton (1997) for a review) generally seems to suggest that the 'Gibrat Law' benchmark can be taken as a rough first approximation of firm growth. However, a closer inspection reveals that firm size usually experiences a slight reversion to the mean (i.e. small firms having higher average growth rates than larger ones), and that several other econometric issues require special attention (such as heteroskedasticity, autocorrelation, and a sampling bias due to higher exit rates of small firms). As a further investigation of the topic of firm growth, several recent contributions have explored the distribution of growth rates (Stanley et al. (1996); Amaral et al. (1997)). Using data on US manufacturing firms, they observe that the distribution is 'tent-shaped' on log-log plots and closely resembles the Laplace. This line of research has been extended to consider the Subbotin family of distributions, of which the Laplace is a special case. Growth rate distributions close to the Laplace have been observed using US data (Bottazzi and Secchi, 2004), Italian manufacturing data (Bottazzi *et al.* (2002)), and also data from the worldwide pharmaceutical industry (Bottazzi et al. (2001)).

Concerning the comparison between aggregate and disaggregate properties, recent theorizing (Dosi et al. (1995)) and evidence from disaggregated analysis (Bottazzi et al. (2002)) suggests that the characteristics of the size distribution are not a robust feature of the different industries but appear, instead, as a mere statistical effect of aggregation. As a result, the distribution of firm size seems to be of limited interest to economists. On the other hand, the Laplace distribution of growth rates appears to be an extremely robust characteristic of industrial dynamics, with a high degree of homogeneity of the distribution which holds at various levels of aggregation. Speculation emerging from the findings on US, Italian and pharmaceutical databases suggests that the Laplace distribution of corporate growth rates seems to be something of a 'stylized fact'. In this vein, Bottazzi and Secchi (2006) and Coad (2006a) construct theoretical models capable of reproducing a Laplace distribution of growth rates.

More than 70 years after Gibrat's seminal book, we return to the study of the French manufacturing sector. The timing of our work is important because it helps in understanding the degree of generality and the robustness of previous results. For instance, contrary to prior results, the present analysis provides evidence that the Laplace distribution of growth rates cannot be considered as a universal property of industrial dynamics. Looking at French manufacturing, we observe growth rates distributions with tails that are consistently fatter than those of the Laplace.

In many respects, the statistical characteristics which emerge from the present analysis seem to arbitrate between previous findings. For example, whilst variance of growth rates

decreased with size in the American case (Bottazzi and Secchi, 2003), it did not for Italian firms (Bottazzi et al. (2007)). Here we find that a negative, though weak, relationship does exist. Also, whilst previous research had found growth rate autocorrelation that was either positive (for US data (Ijiri and Simon, 1967)) or negative (for Italian data (Bottazzi et al., 2007)), the evidence presented here suggests that French firms experience a slight negative autocorrelation in their growth patterns. After a brief description of the data (Section 3.2), Section 3.3 provides the results at the aggregate level on firm size distribution and growth rates distributions while Section 3.4 focuses on a sectoral analysis. Section 3.5 summarizes our findings and sketches several future directions of research.

3.2 Data description

This research draws upon the EAE databank collected by SESSI and provided by the French Statistical Office (INSEE).¹ This database contains longitudinal data on a virtually exhaustive panel of French firms with 20 employees or more over the period 1989-2002. We restrict our analysis to the manufacturing sectors. For statistical consistency, we only utilize the period 1996-2002 and we consider only continuing firms over this period. Firms that entered midway through 1996 or exited midway through 2002 have been removed. Since we want to focus on internal, ‘organic’ growth rates, we exclude firms that have undergone any kind of modification of structure, such as merger or acquisition. Because of limited information on restructuring activities and in contrast to some previous studies (e.g. Bottazzi et al., 2001), we do not attempt to construct ‘super-firms’ by treating firms that merge at some stage during the period under study as if they had been merged from the start of the period. Firms are classified according to their sector of principal activity.² To start with we had observations for around 22 000 firms per year for each year of the period.³ In the final balanced panel constructed for the period 1996-2002, we arrive, somewhat serendipitously, at exactly 10 000 firms for each year.

3.3 Aggregate properties

This section is devoted to the statistical analyses of the firm size distribution and of firm dynamics considering data aggregated over all the industrial sectors. We use the firms’ total sales as a measure of size and we define $S_i(t)$ the size of firm i at time t .

¹The EAE databank has been made available under the mandatory condition of censorship of any individual information.

²The French NAF classification matches with the international NACE and ISIC classifications.

³22 319, 22 231, 22 305, 22 085, 21 966, 22 053, and 21 855 firms respectively

Year	Std. Dev.	Skewness	Kurtosis
1996	1.11	1.04	1.47
1997	1.12	1.03	1.42
1998	1.12	1.01	1.37
1999	1.12	0.99	1.35
2000	1.14	0.96	1.32
2001	1.14	0.94	1.31
2002	1.16	0.91	1.25

Table 3.1: Descriptive statistics of $s_i(t)$ in different years. Size measured in terms of Total Sales.

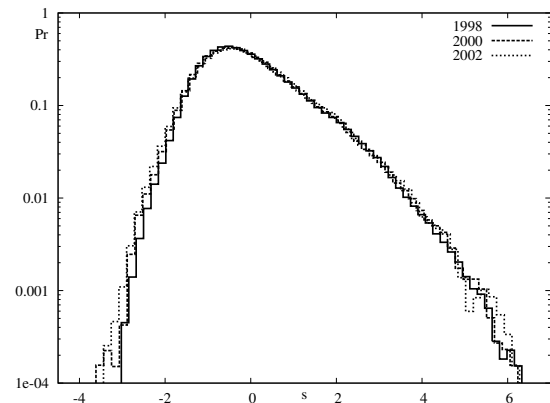


Figure 3.1: Kernel estimates of the density of firm size in 1998, 2000 and 2002. Densities are computed in 64 equispaced points using an Epanechnikov kernel. Note the logarithmic scale on the y-axis.

3.3.1 Size distribution

We develop our analysis of firm size along different but complementary directions. To begin with, we explore the firm size distribution, studying its stationarity and its shape, paying particular attention to the shape of the upper tail for which we have more reliable data. We then focus on the autoregressive structure of firm size by investigating how the French data measures up to Gibrat's Law. Finally we explore the existence of relations between size and growth.

In order to eliminate the common trend in the average size we define the normalized (log) size $s(t)$ as

$$s_i(t) = \log(S_i(t)) - \frac{1}{N} \sum_{i=1}^N \log(S_i(t)) \quad (3.1)$$

where N stands for the total number of firms.

Table 3.1 presents some summary statistics for the rescaled sizes $s_i(t)$ over the period 1996-2002 clearly suggesting that their distribution is remarkably stationary. There are at least two other properties of firms size deserving to be highlighted. First, we confirm once again (among many others see Hart and Prais (1956), Ijiri and Simon (1977), and Bottazzi et al. (2007)) that the distribution of firm sizes is right-skewed as indicated by the positive values for the skewness. Second, the high values for the excess kurtosis statistics provide evidence of distribution tails fatter than in the Gaussian case.

Figure 3.1 presents the kernel density estimate⁴ of firm size in three different years, at the

⁴These estimates are built following Silverman (1986).

Year	OLS		Chesher Regression							
			OLS		LAD					
	α_{OLS}		β	ρ	β	ρ				
1998	0.9807	0.0019	0.9907	0.0013	-0.251	0.025	0.9941	0.0011	-0.0710	0.005
1999	0.9845	0.0019	0.9893	0.0014	-0.166	0.024	0.9967	0.0011	-0.0082	0.006
2000	0.9965	0.0019	1.0005	0.0015	-0.194	0.024	1.0062	0.0011	-0.0535	0.006
2001	0.9869	0.0018	0.9945	0.0014	-0.202	0.023	0.9976	0.0011	-0.0572	0.006
2002	0.9926	0.0020	0.9978	0.0015	-0.222	0.029	1.0036	0.0011	-0.0532	0.006

Table 3.2: Gibrat law regression coefficients using OLS (see equation (3.2)) and also Chesher’s (1979) method (equation (3.4) estimated using OLS and LAD).

beginning, middle and end of the period confirming again that the size distribution presents a strong right-skewed shape that does not seem to change over time. Bearing in mind that the data is truncated and excludes firms having less than 20 employees, we then focus our attention on the upper tail only, beyond the mode. We observe the existence of a power-like tail which can be seen as a roughly straight line of negative slope linking the density (on a log scale) with size. This simple visual inspection reveals the coexistence of many relatively small firms coexisting with a few very large ones. As noticed by many authors (see for example Dosi (2007)), the naïve notion of an ‘optimal size’ around which firms will fluctuate does not sit comfortably with empirical results.

Investigating Gibrat’s law – The autoregressive structure of firm size

How does the French dataset compare to the Gibrat Law benchmark? We investigate this by regression analysis. To begin with, we use normalized (log) sales to estimate an AR(1) model

$$s(t) = \beta s(t - 1) + \epsilon(t) \quad (3.2)$$

where ϵ is an error term. Note that we have no need for a constant term, because we have already normalized the observations, removing their mean. Gibrat’s law is usually said to hold if β has a value not different from 1. Values smaller than 1 imply that small firms grow faster, on average, than large firms, whilst values larger than 1 imply the opposite.

The results of the OLS estimation of equation (3.2) are reported in Table 3.2 (errors are corrected for heteroskedasticity using the jackknife method described in MacKinnon and White (1985)). It is apparent that even if the coefficient β is very close to 1 it is always statistically different from it. However, Chesher (1979) shows that OLS estimation of the Gibrat Law coefficient may imply an estimation bias, if autocorrelation is present in the error term. He

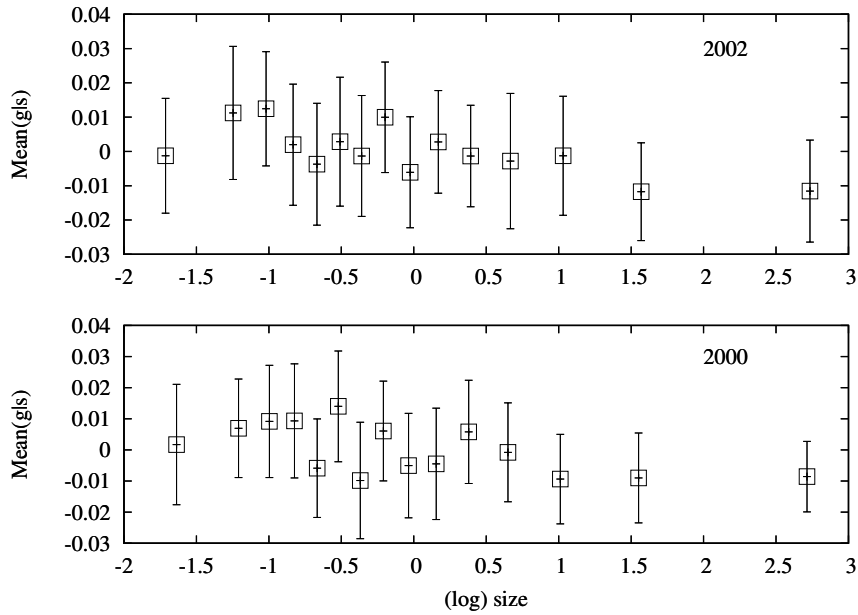


Figure 3.2: Scaling relation of the conditional mean growth rate with respect to firms' (log) size computed using 15 equipopulated bins in 2000 and 2002. Confidence intervals are reported as two standard errors.

also advances that the Gibrat Law cannot be said to hold if this autocorrelation exists, because size and growth are no longer independent. In order to correct for such autocorrelation, he proposes to fit the following system

$$\begin{cases} s(t) = \beta s(t-1) + \epsilon(t) \\ \epsilon(t) = \rho \epsilon(t-1) + u(t) \end{cases} \quad (3.3)$$

where $\epsilon(t)$ is an autocorrelated error term and $u(t)$ is an *i.i.d.* error term. (A more thorough examination of growth rate autocorrelation is provided in the following chapter.) Noting that $\epsilon(t)$ may be expressed in terms of $s(t-1)$ and $s(t-2)$, we can rewrite the above system as the equivalent equation:

$$s(t) = \gamma_1 s(t-1) + \gamma_2 s(t-2) + u(t) \quad (3.4)$$

where $\gamma_1 = \beta + \rho$ and $\gamma_2 = -\beta\rho$. We estimate β using OLS estimation of the parameters γ_1 and γ_2 in equation (3.4), and obtain the results reported in Table 3.2.⁵ There is, however, a further problem affecting our estimates. The procedure just applied assumes $u(t)$ to be an *i.i.d.* Gaussian error term which, as we will show later, is not the case here. Indeed the analyses of the next sections will suggest that the Laplace distribution would be a far better

⁵In estimating equation (3.4) we checked for possible autocorrelation in the error term $u(t)$, but we did not find any. Had it been present, such autocorrelation would have given us unreliable results.

assumption. In order to take the non-normality of the error term into account we also estimate equation (3.4) using the Least Absolute Deviation (LAD) approach assuming that the error term is distributed according to the Laplace. These results are reported again in Table 3.2.

The main finding of our analyses of the Gibrat's regression on French data is that the coefficient β , even if still statistically different from 1, becomes closer to one when one uses a regression technique that takes explicitly into account the possible existence of autocorrelation in the $\epsilon(t)$ error term. Indeed, this autocorrelation is actually present in our data. The ρ statistics presented in Table 3.2 are all significantly negative (though not very large), and roughly speaking they suggest that French firms, on average, experience a negative growth rate autocorrelation of magnitude no larger than around 7%. (Strictly speaking, the ρ coefficients correspond to the magnitude of growth rate autocorrelation once the dependence of growth on size has been controlled for.) These preliminary results suggests the need for further investigations of this issue allowing in equation (3.3) for a more general AR structure of the error term ϵ .

Exploring non-linearities and the Scaling Effect

In this section we continue our analysis investigating the existence of non-linear relations between firm size and characteristics of growth rates. Accordingly with what done in the previous section we define firms growth shocks as the residuals of regression equation (3.3), $\hat{u}(t)$. Our search for relations between $s(t)$ and $\hat{u}(t)$ is organized in two steps. First, we use a graphical analysis to obtain some hints on the existence and on the shape of such relations. Second we assess the robustness of any observed relationship applying regression techniques.

Since any linear relationship between firm size and growth rates has been captured by (3.3), it only remains to assess if any residual non-linear effect is present. To explore this issue we group our observations into 15 bins according to firm size and we plot in Figure 3.2, for two different years chosen as examples, the average growth rate in each bin against the (log) size. As expected we do not observe evidence of any linear relation between size and average growth. Moreover the visual inspection of Figure 3.2 rules out also the possibility that such a relation presents a nonlinear nature.

Next we consider the question of whether or not the variance of growth rates is related to firm size. Some previous studies (e.g. Amaral et al. (1997)), although not all (e.g. Bottazzi et al, 2002), have observed a significant negative exponential relationship between $s(t)$ and the standard deviation of $\hat{u}(t)$. To investigate this for the French data we group again our observations into 15 bins according to size and we plot the conditional standard deviation of growth rates in each bin against the (log) size. Figure 3.3 shows that also for French firms a clear negative relationship emerges: the standard deviation of growth rates decreases with size suggesting that bigger firms present lower variability in their growth rates compared with

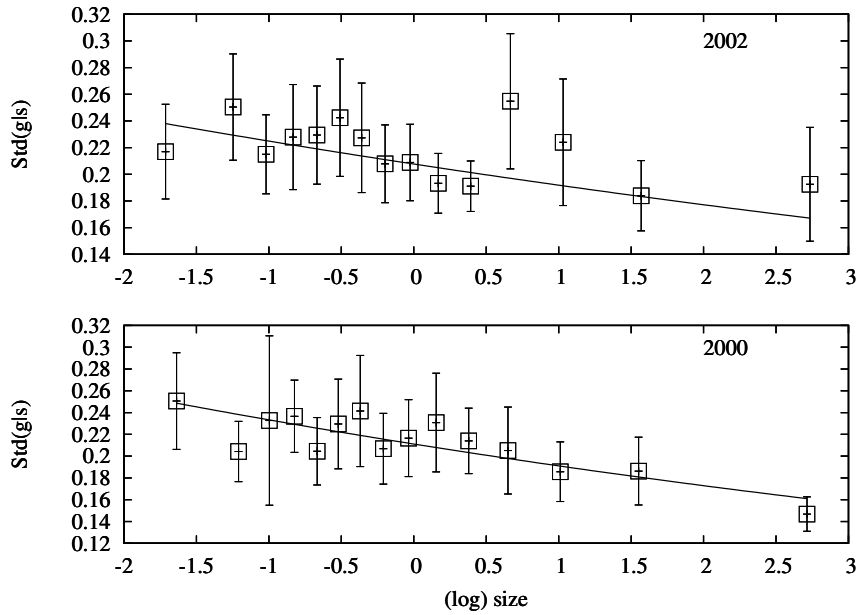


Figure 3.3: Scaling relation of the conditional standard deviation of growth rate with respect to firms' (log) size computed using 15 equipopulated bins in 2000 and 2002. Confidence intervals are reported as two standard errors.

the smaller ones.

In order to assess the statistical significance of the apparent nonlinear relation between $s(t)$ and the standard deviation of $\hat{u}(t)$ we opt for a nonlinear regression. In order to provide comparability with previous works (Amaral et al. (1997), Bottazzi et al. (2002) and Bottazzi and Secchi (2004)), we estimate the model:

$$\hat{u}(t) = e^{-\alpha s(t-1)} g(t) \quad (3.5)$$

where $\hat{u}(t)$ is the residual of the regression in (3.3) and $g(t)$ is an error term. Equation (3.5) describes a regression model with a heteroskedastic error term $e^{-\alpha s(t-1)} g(t)$ which, in line with our visual inspection of Figure 3.3, assumes that the variance of growth rates is greater among smaller firms. We fit the data to this econometric specification to estimate the value of α . First we estimate the model in (3.5) assuming the normality of the error term $g(t)$, using a standard OLS approach. Furthermore we perform a LAD regression under the assumption that error terms are distributed according to the Laplace distribution.⁶ Again the results are reported in Table 3.3. In all cases we observe a small though statistically significant negative relationship between size and growth rate variance, independently of the estimation method adopted.

⁶We will argue in the next section why this second assumption is much more appropriate in this case.

Year	Scaling Relation		Subbotin fit	
	Type of regression	α	b coefficient	a coefficient
1998	non-linear OLS	-0.077 0.019		
	non-linear LAD	-0.075 0.004	0.774 0.176‰	0.110 0.137‰
1999	non-linear OLS	-0.060 0.020		
	non-linear LAD	-0.068 0.004	0.763 0.176‰	0.111 0.138‰
2000	non-linear OLS	-0.098 0.020		
	non-linear LAD	-0.074 0.004	0.800 0.177‰	0.115 0.136‰
2001	non-linear OLS	-0.072 0.022		
	non-linear LAD	-0.062 0.004	0.790 0.177‰	0.111 0.137‰
2002	non-linear OLS	-0.038 0.024		
	non-linear LAD	-0.055 0.004	0.807 0.178‰	0.119 0.136‰

Table 3.3: Estimated coefficient α in (3.5) obtained with non linear regressions under the assumption of a Gaussian (OLS) and Laplacian (LAD) error term. Standard errors are also reported. We also report the maximum likelihood estimate (and coefficient of variation) of the Subbotin density (see equation (3.6)) on firms growth rates rescaled as in (3.5).

3.3.2 Growth rates distribution

In this section, we analyze the shape and the evolution in time of the growth rates density, adopting a non-parametric approach. In the previous section we showed that the variance of growth rates decreases with firms size following an exponential decay. We use this finding to define a rescaled version of the growth rate $\hat{g}(t)$ obtained as the residual in the estimation of equation (3.5). Notice that the statistical properties of $\hat{g}(t)$ are by construction independent of firm size. One important implication of this rescaling is the possibility of pooling together growth rates of firms belonging to different size bins.

Figure 3.4 reports, on a log scale, the kernel estimates of the empirical density of $\hat{g}(t)$ in three different years. We observe a characteristic tent-shape, although the fat tails make the tent-shape appear rather ‘droopy’. This fat-tailed distribution of growth rates corresponds to a high frequency of extreme growth events for French manufacturing firms.

Previous studies have considered growth rates as being distributed according to the Laplace (Stanley et al. (1996)) which can be considered as a special case of the Subbotin family of distributions (Bottazzi et al. (2002)). Having observed the growth rate distribution in Figure 3.4 we now turn to parametric methods of quantifying the distribution. To do this, we estimate the Subbotin parameters of the growth rates distribution.

The Subbotin distribution can be formally presented by the following equation:

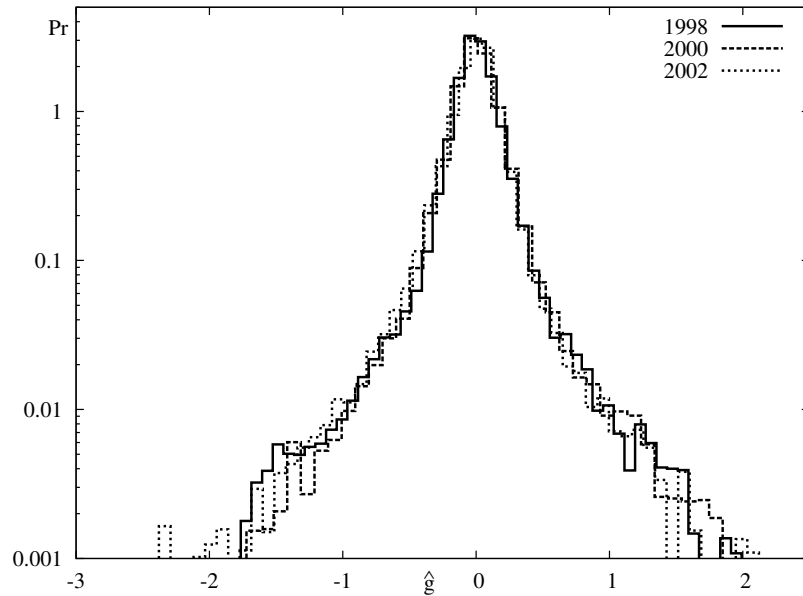


Figure 3.4: Kernel estimates of the growth rates density in 1998, 2000 and 2002. Densities are computed for 64 equispaced points using an Epanechnikov kernel. Note the logarithmic scale on the y-axis.

$$f_s(x) = \frac{1}{2ab^{1/b}\Gamma(1/b+1)} e^{-\frac{1}{b}|\frac{x-\mu}{a}|^b} \quad (3.6)$$

where $\Gamma(x)$ is the Gamma function. The distribution has three parameters - the mean μ , the dispersion parameter a and the shape parameter b . As the shape parameter b decreases, the tails of the density become fatter. The density is leptokurtic for $b < 2$, and platykurtic for $b > 2$. Two noteworthy special cases of the Subbotin family of distributions are the Gaussian distribution (for which $b = 2$) and the Laplace distribution (with $b = 1$).

We estimate the values of the parameters using the maximum likelihood procedure discussed in Bottazzi and Secchi (2006). Results are reported in Table 3.3. The robust conclusion is that the distribution of growth rates appears to be even more heavy-tailed than the Laplace distribution (for which b would equal 1). This surprising result distinguishes growth patterns of French firms from those observed elsewhere, where distributions close to the Laplace are observed (Stanley et al. (1996), Bottazzi et al. (2002), Bottazzi and Secchi, 2003). This fat-tailed distribution of growth rates corresponds to a higher frequency of extreme growth events. Compared to results reported for Italian or US manufacturing firms, French firms are much more likely to undergo significant positive or negative changes in size.

3.4 Sectoral properties

The preceding analysis can be repeated at a disaggregated level. We consider this to be a worthwhile enterprise because there may well be a tension between regularities observed in aggregated data and much ‘messier’ results at a disaggregated level (see Dosi et al. (1995) for a discussion). Our results show that some properties of industrial dynamics, such as the growth rates distribution, survive disaggregation i.e. are present also at a sectoral level. However, for the firm size distribution, the smooth shape that emerges from aggregated data disappears, and we observe that significant multimodality is rife at the sectoral level. Looking at the 2-digit level of ISIC industry classification, we retain sectors 17-36 which correspond to manufacturing activities.⁷ Table 3.4 gives a description of these sectors. Note that sectors 23 and 30 have only a small number of observations, which disqualifies them from detailed quantitative analysis.

3.4.1 Size distribution

We start by looking at the size distribution, using a non-parametric method to explore the shape of the firm size distribution at the disaggregate level. We test the size distribution for multimodality, and then present concentration statistics based on the properties of the distribution’s upper tails. We present some kernel density plots of exemplary sectors, that have been chosen to highlight inter-sectoral diversity. We also look at Gibrat’s law statistics for each sector.

Firm size distribution

Similar to the previous methodology, we take the log of sales and then normalize the observations by deducting the sectoral mean. The normalized sectoral (log) sales of firm i in sector j can thus be defined as

$$s_{ij}(t) = \log(S_{ij}(t)) - \frac{1}{N_j} \sum_{i=1}^{N_j} \log(S_{ij}(t)) \quad (3.7)$$

where N_j is the number of firms in the j -th sector.

We use these normalized observations to examine the size distribution of firms in the same sectors. Although at the aggregate level we observe a rather regular unimodal distribution, previous studies suggest that this unimodality may not hold at a finer level of analysis (see for example Bottazzi and Secchi, 2003). To begin with, we build a kernel estimate (Silverman, 1986) of the probability density of firm size, in order to visualize the shape of the sectoral-level

⁷Strictly speaking, the 2-digit sector ‘37’, which corresponds to the recycling industry, is also included in the manufacturing sector. However, only a small number of firms are reported in this sector. As a consequence, it was dropped from the analysis.

Table 3.4: Description of the manufacturing sectors studied

ISIC class	Description	No. obs.	Mean size €'000 in 2002	Bimodality test (<i>p</i> -values)	D_{20}^4
17	Manuf. of textiles	730	9703	0.594	0.3892
18	Manuf. of wearing apparel, dressing and dyeing of fur	498	9623	0.000	0.5461
19	Tanning and dressing of leather, manuf. of luggage, handbags, ...	205	14629	0.045	0.5995
20	Manuf. of wood and products of wood and cork, except furniture; ...	314	9083	0.002	0.3269
21	Manuf. of paper and paper products	364	22428	0.031	0.3938
22	Publishing, printing and reproduction of recorded media	820	13745	0.022	0.4173
23	Manuf. of coke, refined petroleum products and nuclear fuel	19	73547	-	-
24	Manuf. of chemicals and chemical products	496	52378	0.003	0.3819
25	Manuf. of rubber and plastics products	685	17964	0.000	0.4676
26	Manuf. of other non-metallic mineral products	426	21624	0.052	0.5093
27	Manuf. of basic metals	265	34411	0.006	0.3475
28	Manuf. of fabricated metal products, except machinery and equipment	2276	8041	0.001	0.4174
29	Manuf. of machinery and equipment n.e.c.	987	19343	0.040	0.4374
30	Manuf. of office, accounting and computing machinery	23	39850	-	-
31	Manuf. of electrical machinery and apparatus n.e.c.	357	26740	0.000	0.4216
32	Manuf. of radio, television and communication equipment and apparatus	218	25159	0.000	0.7194
33	Manuf. of medical, precision and optical instruments, watches and clocks	354	12452	0.008	0.3988
34	Manuf. of motor vehicles, trailers and semi-trailers	280	49195	0.022	0.5796
35	Manuf. of other transport equipment	137	68192	0.000	0.7149
36	Manuf. of furniture; manufacturing n.e.c.	546	14411	0.000	0.3870

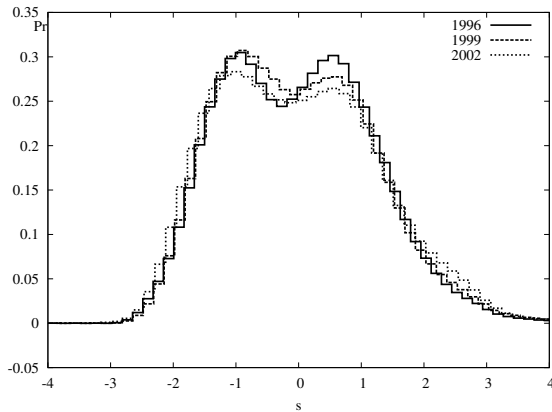


Figure 3.5: Size distribution of ISIC sector 18 (Manuf. of wearing apparel, dressing and dyeing of fur)

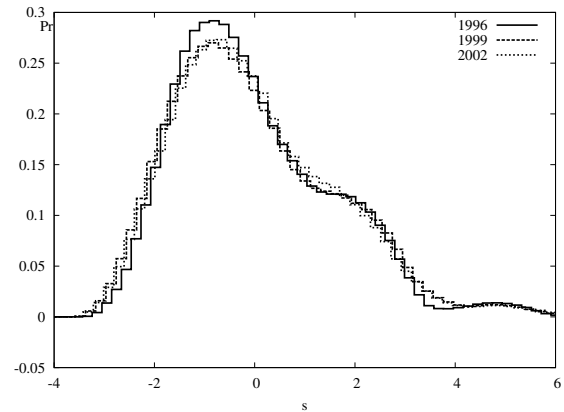


Figure 3.6: Size distribution of ISIC sector 35 (Manuf. of other transport equipment)

size distribution.

Intuitively, a kernel density estimate can be considered to be a smoothed version of the histogram, obtained by counting the observations in the different bins as the width of the bins varies. This estimate requires the provision of two objects: the kernel function K and the bandwidth h of the bin. Formally, we have

$$\hat{f}(x, t; h) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - s_i(t)}{h}\right) \quad (3.8)$$

where $s_1(t), \dots, s_N(t)$ are the number of observations n in each sector, h is a bandwidth parameter controlling the degree of smoothness of the density estimate, and where K is a kernel density, i.e. $K(x) \geq 0, \forall x \in (-\infty, +\infty)$ and $\int dx K(x) = 1$.⁸

Although we observe stationarity of the sectoral size distribution over the 7-year time period, the shape of the distribution varies greatly across sectors. In particular, we may observe multimodality and/or different shapes and gradients for the upper tails. The presence of multimodality is not unusual. In their study of the worldwide pharmaceutical industry, for example, Bottazzi and Secchi (2005) observe significant bimodality in the size distribution and relate this to a cleavage between the industry leaders and fringe competitors. Figures 3.5 and 3.6 present some kernel density plots of exemplary sectors that have been chosen to highlight inter-sectoral diversity (subsequent tests reveal these sectors to be significantly multimodal).

In an attempt to quantify this inter-sectoral heterogeneity, we will use the non-parametric multimodality test presented in Silverman (1981), which is constructed as follows. Consider a dataset made of n observations independently drawn from a common density f . Suppose

⁸Throughout this paper the kernel function will always be the Gaussian density. The use of different kernels, such as the Epanechnikov or the Triangular, does not change noticeably our results. Where not specified otherwise, the bandwidth h has been chosen according to Silverman (1986: Section 3.4).

that we wish to test the null hypothesis that the density f possesses at most k modes against the alternative that the same f possesses more than k modes. First, we need to compute the ‘critical value’ h^* for the bandwidth parameter, defined as the largest value of the parameter h that guarantees a kernel density estimate $\hat{f}(h^*)$ as defined in equation (3.8) with at least k modes. This definition is meaningful since the number of modes is a decreasing function of the bandwidth parameter: for $h > h^*$ the formula in equation (3.8) would give an estimated density with less than k modes while for $h \leq h^*$ the estimated density would have at least k modes.⁹ Note also that, as the sample size n tends to infinity, h^* will tend to zero if the distribution is unimodal, but will be bounded away from zero otherwise.

Second, once the value h^* has been found, we need to assess its significance. Assuming known the true density f , one can repeatedly draw n observations from the true density f and count the modes of the kernel density estimate $\hat{f}(h_0)$ obtained from these observations. The fraction of times in which these modes are greater than k is an estimate of the p -value associated with h^* . The problem of this method is that, in general, the underlying true density is not known. Silverman (1981) suggests the natural candidate density function to use in the simulations is a rescaled version of $\hat{f}(s; h_0)$, derived from data equating the variance of \hat{f} with the sample variance. Hall and York (2001) show that this choice is biased towards conservatism and propose an improved procedure to achieve asymptotic accuracy. Following their suggestion, we compute in each year the critical bandwidth h^* and the p -values of the test where the null is ‘the (log) size distribution is unimodal’ and the alternative is ‘the (log) size distribution presents more than one mode’.

Column 5 in Table 3.4 reports the results of the bimodality tests (at the 5% significance level for the Hall-York procedure). Unimodality can be rejected in an overwhelming 18 out of 20 sectors, if we look at the 5% significance level. We conclude that the rather ‘regular’ shape of the aggregate size distribution does not hold at a finer, sectoral level of analysis, and is primarily a result of statistical aggregation. This finding is in line with Hymer and Pashigian (1962) on UK data, and more recently with the results of Bottazzi et al. (2007) on Italian data and Bottazzi and Secchi (2003) on US data.

Sectoral concentration

Another way of comparing the size distributions of the different sectors is by looking at the upper tail of the distribution. We do this by calculating the concentration statistics. This can be done by using data on the upper tail of the distribution. Although we do not have reliable information on the market share of the largest firms (because the dataset is incomplete in the sense that it excludes firms with less than 20 employees), we can nonetheless investigate

⁹The result has been proved for a small family of kernels of which the Gaussian kernel is a member. See Silverman (1981).

ISIC class	1998			2000			2002					
	β	Std. Error	ρ	Std. Error	ρ	Std. Error	β	Std. Error	ρ	Std. Error		
17	0.9962	0.0042	0.0529	0.0190	0.9980	0.0047	0.0148	0.0232	1.0036	0.0042	-0.0902	0.0202
18	0.9878	0.0042	-0.0736	0.0212	1.0129	0.0050	-0.1005	0.0296	1.0073	0.0049	0.0063	0.0254
19	0.9956	0.0055	-0.5304	0.0298	1.0070	0.0074	0.0001	0.0348	0.9931	0.0078	0.0085	0.0397
20	1.0090	0.0066	0.0570	0.0274	1.0028	0.0068	0.0299	0.0380	1.0065	0.0071	-0.0317	0.0423
21	0.9951	0.0039	-0.0439	0.0264	1.0140	0.0046	0.0273	0.0287	0.9980	0.0041	-0.1433	0.0246
22	0.9933	0.0041	-0.1215	0.0169	0.9987	0.0039	-0.0342	0.0178	0.9971	0.0037	-0.0088	0.0178
24	0.9919	0.0040	-0.0124	0.0244	1.0076	0.0034	-0.1081	0.0216	0.9939	0.0048	0.0402	0.0284
25	0.9847	0.0046	-0.0391	0.0221	1.0002	0.0043	-0.0286	0.0207	1.0018	0.0047	-0.0082	0.0241
26	0.9954	0.0042	-0.0174	0.0247	1.0011	0.0048	0.0137	0.0294	0.9969	0.0044	0.0136	0.0244
27	1.0002	0.0043	-0.0999	0.0273	1.0150	0.0044	-0.1318	0.0490	1.0029	0.0060	0.0990	0.0454
28	0.9925	0.0032	-0.1006	0.0120	1.0010	0.0030	-0.0919	0.0123	1.0055	0.0029	-0.1161	0.0136
29	0.9985	0.0036	-0.1325	0.0178	1.0009	0.0044	-0.0021	0.0190	1.0092	0.0039	-0.1220	0.0203
31	0.9870	0.0047	-0.0073	0.0340	0.9997	0.0050	-0.1395	0.0367	1.0017	0.0053	-0.0433	0.0296
32	0.9917	0.0079	-0.0279	0.0324	1.0207	0.0097	-0.0564	0.0504	0.9897	0.0125	0.0366	0.0560
33	0.9946	0.0075	-0.1082	0.0349	1.0199	0.0079	-0.1176	0.0338	1.0044	0.0081	-0.1275	0.0495
34	0.9987	0.0052	-0.1931	0.0359	0.9988	0.0058	0.0182	0.0398	1.0053	0.0064	-0.0932	0.0426
35	1.0141	0.0096	-0.0822	0.0650	0.9944	0.0080	-0.1358	0.0565	0.9804	0.0069	-0.0572	0.0563
36	1.0030	0.0047	-0.1426	0.0231	1.0086	0.0046	-0.0552	0.0290	1.0010	0.0046	-0.0378	0.0298

Table 3.5: Sectoral analysis: Estimation of the Gibrat law coefficients, using Chesher's (1979) procedure (estimation of equation (3.4) using LAD).

sectoral concentration using the following concentration index:

$$d_{20}^4(t) = \frac{C_4}{C_{20}} \quad t = 1996, \dots, 2002 \quad (3.9)$$

where C_4 and C_{20} are the sums of the market shares of the top 4 and top 20 firms in a sector, respectively. It is trivial to see that this simplifies to the ratio between the combined sales of the largest 4 and largest 20 firms in a sector. Notice that the possible values range from 0.2 (i.e. many firms of equal size) to 1.0 (i.e. 4 firms totally dominate the sector), with higher values of d_{20}^4 for more concentrated sectors. In order to obtain a more robust indicator of sectoral concentration, we take the average value of d_{20}^4 over the 7 years from 1996-2002:

$$D_{20}^4 = \frac{1}{7} \sum_{t=1996}^{2002} d_{20}^4(t) \quad (3.10)$$

The values of D_{20}^4 have been calculated and reported in column 6 of Table 3.4. Whilst the support of possible values ranges from 0.2 to 1.0, we observe that the sectoral concentration indices vary greatly from 0.33 to 0.72. This provides further evidence of heterogeneity of the firm-size distribution across sectors. However, we observe that the average firm size of a sector does not bear any close relationship to the shape of the upper tail.

Gibrat's law – autoregression of size

Using a similar methodology to that described above, we extend our investigation of Gibrat's law to the sectoral level. We perform Chesher's (1979) calculations and report the results in Table 3.5. Again, we observe heterogeneity as the sectoral results fluctuate around the values obtained in the aggregate analysis. Generally speaking, the β values are close to the Gibrat value of 1, whilst the ρ values (which carry information on growth rate autocorrelation) are mostly negative, though often not statistically significant.

3.4.2 Distribution of growth rates

The methodology presented in section 3.3.2 is now extended to the disaggregated level. All sectors have growth rates distributions that are particularly fat-tailed, although we do observe some heterogeneity between sectors.

We estimate the parameters of the sectoral growth rates distribution as follows. To begin with, we investigate the possibility of a relationship between growth rate variance and size, and correct for such 'scaling effects'. The results are reported in Table 3.6. We observe that scaling effects are not significant in each sector. We then estimate the subbotin distribution b parameters on the basis of these rescaled error terms. These values are also shown in Table 3.6.

ISIC class	1998			2000			2002					
	Scaling	Std. Error	<i>b</i>	Std. Error	<i>b</i>	Std. Error	Scaling	Std. Error	<i>b</i>	Std. Error		
17	-0.0330	0.0180	0.931	2.506	-0.0854	0.0161	0.937	2.509	-0.0642	0.0149	0.791	2.426
18	0.0315	0.0174	0.849	3.605	0.0441	0.0169	0.717	3.493	0.0540	0.0176	0.697	3.476
19	-0.0429	0.0296	0.757	8.568	-0.1018	0.0286	0.892	8.845	-0.1216	0.0295	0.860	8.780
20	-0.0547	0.0359	0.990	5.903	-0.1624	0.0346	0.786	5.633	-0.1700	0.0302	0.720	5.544
21	-0.1845	0.0226	0.705	4.764	0.0062	0.0233	1.078	5.189	-0.2158	0.0198	0.685	4.741
22	-0.1385	0.0156	0.578	2.048	-0.1116	0.0154	0.633	2.077	-0.1708	0.0157	0.696	2.110
24	-0.1607	0.0138	0.606	3.411	-0.1005	0.0146	0.813	3.589	-0.1556	0.0128	0.673	3.469
25	-0.1728	0.0183	0.719	2.541	-0.1196	0.0186	0.805	2.594	-0.1786	0.0174	0.811	2.597
26	-0.1043	0.0195	0.837	4.203	-0.1082	0.0216	0.718	4.085	-0.1627	0.0181	0.801	4.167
27	-0.0413	0.0197	0.876	6.817	0.0247	0.0207	1.154	7.242	-0.1106	0.0217	0.949	6.930
28	-0.0190	0.0125	0.813	0.782	-0.0921	0.0122	0.860	0.791	-0.0602	0.0113	0.921	0.802
29	-0.0515	0.0140	0.818	1.806	-0.0492	0.0127	0.776	1.788	0.0292	0.0133	0.880	1.832
31	-0.0832	0.0169	0.862	5.044	-0.2109	0.0192	1.003	5.207	-0.0736	0.0204	1.067	5.278
32	0.0077	0.0296	1.141	8.779	0.0831	0.0296	1.163	8.818	0.1090	0.0256	1.000	8.520
33	-0.1029	0.0276	0.738	4.940	-0.0446	0.0215	0.683	4.873	0.0251	0.0203	0.851	5.074
34	-0.0471	0.0216	1.011	6.649	-0.1462	0.0219	0.805	6.346	-0.0699	0.0229	0.797	6.334
35	-0.1455	0.0315	0.710	12.675	0.0473	0.0308	0.859	13.136	0.0006	0.0275	0.791	12.927
36	-0.0722	0.0210	0.769	3.227	-0.1312	0.0194	0.660	3.141	-0.0617	0.0196	0.919	3.341

Table 3.6: Sectoral analysis: Scaling coefficients (relation between size and growth rate variance) and estimated Subbotin *b* parameters (with coefficients of variation).

Again, sectoral-level heterogeneity is observed, with most of the values being smaller than the Laplace value of 1.00.

How can we account for the differences in growth rate profiles for different sectors? There appears to be no relation between the growth rate distribution coefficients and average firm size. Also, distinguishing between upstream and downstream sectors does not help us to better understand differences in growth rate distributions (results not shown). Furthermore, grouping the sectors according to a Pavitt-type taxonomy of industries (Pavitt, 1984; see also Marsili, 2001) does not help to explain the differences in the estimated coefficients. A deeper understanding of the economic significance of growth rate distribution coefficients is clearly warranted.

3.5 Conclusion

In this study we have investigated some of the key quantities of the structure and dynamics of the French manufacturing industry, using an extensive longitudinal database for the period 1996-2002. We examined the size distribution, Gibrat's law, the growth rates distribution, and growth rate autocorrelation at both an aggregate and disaggregate level. Our findings corroborate well-known stylized facts already observed with Italian and US data, but they also highlight some particularities of the French manufacturing industry.

Gibrat's law appears to be a useful summary metric, although technically speaking it does not appear to hold for our database. Growth rate autocorrelation is observed to be negative and statistically significant (although rather small in practical terms), and this leads us to reject the proposition that growth is independent of size (following Chesher, 1979). Another main finding is the peculiar shape of the growth rate distribution of French manufacturing firms. Whilst the Laplace distribution of growth rates was repeatedly found in previous studies and appeared to be emerging as something of a 'stylised fact', we observe here that the growth rates of French firms are even fatter-tailed than expected, a property which holds with disaggregation. The variance of these growth rates decreases with size, which corroborates many, though not all, previous findings.

It is of interest to contrast the growth rate distribution with the size distribution. Whilst we observe that the former is a very robust property of industrial dynamics, the same cannot be said of the size distribution, which is fairly ordered at the aggregate level but quite disorganized as we move down to analyze individual sectors. Of course, there is a strong link between growth rates and the resulting size. This tension between the two serves to emphasize that firm size is not only due to growth rates but to the *initial size distribution* - size and date of entry, and also due to mergers and acquisitions. These factors are outside the scope of this study, although their effect on economic *dynamics* does not appear to be so important.

Although we de-emphasize the need to explain the aggregate firm size distribution, it seems that the distribution of growth rates is a subject ripe for future investigation. The analysis of growth rates presented here gives us important insights into the competitive process, emphasizing the importance of extreme growth events in the French manufacturing industry. However, we had difficulty in finding a connection between the growth rate distribution coefficients and other economic characteristics. For example, at a sectoral level, there appears to be no relation between the distribution parameters and average firm size. Also, our dataset suggests that there is no relationship between the distribution parameters and the distinction between upstream and downstream sectors. In addition, variation in the growth rate distribution coefficients does not seem to correspond to a Pavitt-type taxonomy (1984) of industrial sectors. Mapping the growth rate distribution coefficients to economic concepts would merit further work. Furthermore, this paper provides results that would be useful in the context of a more detailed international comparison.

Chapter 4

A closer look at serial growth rate correlation

“[S]erial correlation in firm growth rates ... is of considerable economic interest and deserves to be examined in its own right.” Singh and Whittington (1975, p. 17)

In the previous chapter we considered the possibility of an autocorrelation structure in the growth of firms, although our analysis was admittedly cursory. Indeed, as we argued in the literature review in Chapter 2, previous studies have not really looked at growth rate autocorrelation with the attention we feel it deserves. This is in spite of the fact that autocorrelation processes provide useful insights into the processes of how firms actually grow. This chapter therefore takes a closer look at serial growth rate autocorrelation.

4.1 Introduction

A lot of information on the processes of firm growth can be obtained by studying serial correlation in growth rates. At first glance, it allows us to directly observe the evolution of industries by better understanding patterns of year-on-year growth at the firm-level. Such research may have policy implications if, for example, it is desirable to prevent large firms from experiencing cumulative growth, or if one should want to investigate the ability of small firms to generate durable employment, i.e. jobs that have not disappeared by the following year.

Another more subtle motivation for studying serial correlation is that it allows us to judge between theories by comparing the hypothetical predictions with the empirically-observed regularities. First of all, if it were observed to be significant, the existence of serial correlation would lead us to reject Gibrat’s ‘law of proportionate effect’ 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 previous growth shocks. Following Sutton (1997), we define the size of a firm at time t by x_t , and represent growth by the random variable ε_t (i.e. the 'proportionate effect') to obtain:

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

whence:

$$x_t = (1 + \varepsilon)x_{t-1} = x_0(1 + \varepsilon_1)(1 + \varepsilon_2) \dots (1 + \varepsilon_t) \quad (4.1)$$

According to equation (4.1), a firm's size can be seen as the simple multiplication of independent growth shocks. This simple model has become a popular benchmark for modelling industrial evolution because, among other properties, it is able to generate the observed log-normal firm-size distribution, and also the proposition that expected growth is independent of size does find empirical support (roughly speaking). However, such a model would be inappropriate if the assumption of serial independence of growth rates does not find reasonable empirical support.

Second, the notion of a firm- or industry-specific 'optimal size' and the related 'adjustment cost' hypothesis of firm growth can be rejected by looking at the characteristics of serial growth correlation. The traditional, static representation of the firm considered it as having an 'optimal size' determined in a trade-off between production technology and decreasing returns to bureaucratization. This conceptualization of firms having an 'optimal size' was then extended to the case of growing firms. According to this approach, firms have a target size that they tend towards, but the existence of non-linear adjustment costs prohibits them from instantly attaining their ideal size. Instead, they grow gradually by equating at the margin the gains from having a larger size and the costs of growing. If this theory is to be believed, we should expect to find a positive autocorrelation in growth rates as firms approach their 'optimal size'. However, in reality we do not always observe positive autocorrelation in annual growth rates which leads us to doubt the validity of this theory.

Third, looking at autocorrelation statistics will allow us to judge between the different models that attempt to explain the heavy-tailed distribution of annual firm growth rates. The explanation offered by Bottazzi and Secchi (2006) hinges on the notion of increasing returns in the growth process, which would lead us to expect positive autocorrelation in annual growth rates. The explanation offered by Coad (2006a), however, considers that firms grow by the addition of lumpy resources. It follows from the discrete and interdependent nature of these resources that the required additions in any one year are occasionally rather large. In this case, we would not expect a positive autocorrelation of annual growth rates.

Another motivation for this study is to observe what happens to those firms that grow extremely fast. Indeed, a robust 'stylised fact' that has emerged only recently is that annual firm

growth rates distributions are remarkably fat-tailed and can be approximated by the Laplace distribution (Stanley et al., 1996; Bottazzi and Secchi, 2003; Bottazzi et al., 2005; Bottazzi et al., 2007). A considerable proportion of employment creation takes place within just a handful of fast-growing firms. Conventional regression techniques that focus on what happens to the ‘average firm’, and that dismiss extreme events as ‘outliers’, may thus be inappropriate. In this study we therefore include semi-parametric regression techniques (i.e. quantile regression) to tackle this issue.

This paper provides several novel results. In particular, we observe that autocorrelation dynamics vary with firm size, such that whilst large firms experience positive feedback in year-to-year growth rates, the growth of smaller firms is marked by an erratic, ‘start-and-stop’ dynamics. Indeed, small and large firms appear to operate on different ‘frequencies’. For those small firms that experience extreme growth in one year, significant negative correlation indicates that they are quite unlikely to repeat this performance in the following year. Larger firms undergoing extreme growth events, however, do not experience such strong negative autocorrelation.

Section 4.2 reviews the previous literature relating to this subject, and section 4.3 presents the database. In section 4.4, we begin with some summary statistics and results using conventional regressions, and then apply quantile regression techniques in Section 4.5. Section 4.6 concludes with a discussion of our findings.

4.2 Literature review

The relevant empirical questions in this section are the sign, the magnitude, and also the time-scale of serial correlation in the growth rates of firms.

Early empirical studies into the growth of firms measured serial correlation when growth was measured over a period of 4 to 6 years. Positive autocorrelation of 33% was observed by Ijiri and Simon (1967) for large US firms, and a similar magnitude of 30% was reported by Singh and Whittington (1975) for UK firms. However, much weaker autocorrelation was later reported in comparable studies by Kumar (1985) and Dunne and Hughes (1994).

More recently, availability of better datasets has encouraged the consideration of annual autocorrelation patterns. Indeed, persistence should be more visible when measured over shorter time horizons. However, the results are quite mixed. Positive serial correlation has often been observed, in studies such as those of Chesher (1979) and Geroski et al. (1997) for UK quoted firms, Wagner (1992) for German manufacturing firms, Weiss (1998) for Austrian farms, Bottazzi et al. (2001) for the worldwide pharmaceutical industry, and Bottazzi and Secchi (2003) for US manufacturing. On the other hand, negative serial correlation has also been reported – some examples are Boeri and Cramer (1992) for German firms, Goddard et

al. (2002) for quoted Japanese firms, Bottazzi et al. (2007) for Italian manufacturing, and Bottazzi et al. (2005) for French manufacturing. Still other studies have failed to find any significant autocorrelation in growth rates (see Almus and Nerlinger (2000) for German start-ups, Bottazzi et al. (2002) for selected Italian manufacturing sectors, Geroski and Mazzucato (2002) for the US automobile industry, and Lotti et al. (2003) for Italian manufacturing firms). To put it mildly, there does not appear to be an emerging consensus.

Another subject of interest (also yielding conflicting results) is the number of relevant lags to consider. Chesher (1979) and Bottazzi and Secchi (2003) found that only one lag was significant, whilst Geroski et al. (1997) find significant autocorrelation at the 3rd lag (though not for the second). Bottazzi et al. (2001) find positive autocorrelation for every year up to and including the seventh lag, although only the first lag is statistically significant.

To summarize, it would appear that decades of research into growth rate autocorrelation can best be summarized as yielding “conflicting results” (Caves, 1998: 1950). It is perhaps remarkable that the results of the studies reviewed above have so little in common. It is also remarkable that previous research has been so little concerned with this question. Indeed, instead of addressing serial correlation in any detail, often it is ‘controlled away’ as a dirty residual, a blemish on the ‘natural’ growth rate structure. The baby is thus thrown out with the bathwater. One reason for this confusion could be that, if indeed there are any regularities in the serial correlation of firm growth, they are more complex than the standard specification would be able to detect (i.e. that there is no ‘one-size-fits-all’ serial correlation coefficient that applies for all firms). A fresh approach is needed.

The analysis in Bottazzi et al. (2002) begins with the observation that the mean autocorrelation coefficient for a given industry is either insignificantly different from zero, or else very small in magnitude. However, the authors go on to calculate firm-specific autocorrelation coefficients and observe that firms do in fact have idiosyncratic growth patterns that are not visible simply by looking at averages across firms. They create a purely random ‘benchmark’ case in which the growth rates of all firms are pooled together and then growth rates are extracted randomly to construct growth patterns for ‘artificial firms’. Bootstrap resampling methods allow them to generate a distribution of autocorrelation coefficients for this random scenario. They then compare this stochastic benchmark with the empirical distribution of autocorrelation coefficients (see Figure 2.5 in Chapter 2 for the case of autocorrelation of employment growth). The differences between the distributions are supported by formal statistical tests (i.e. Kolmogorov-Smirnov tests). The authors conclude that firm growth patterns are indeed idiosyncratic, that they do have a memory process, and that there are indeed persistent asymmetries in growth dynamics across firms.

The work of Bottazzi et al. (2002) obtains new insights into the growth of firms by exploring the heterogeneity of firm growth patterns. We believe that further work in this direction is

warranted. Whilst many previous studies have been content with a focus on ‘the average effect for the average firm’, in this Chapter we explore the heterogeneity of autocorrelation profiles along two key dimensions – the firm’s size and its previous growth rate.

4.3 Database

In this chapter, we will use the same dataset as in the previous chapter. In brief, this database was provided by the French Statistical Office (INSEE) and is the fruit of a virtually exhaustive survey of French firms with 20 employees or more. We use a balanced panel of exactly 10 000 French manufacturing firms. Mergers and acquisitions have been identified and are excluded. More details can be found in Section 3.2.

4.4 Analysis

4.4.1 Summary statistics

We begin by looking at some summary statistics of firms in our database (see Table 4.1). First, in keeping with the elementary ‘stylized facts’ of industry structure, we observe that the firm-size distribution is right-skewed (compare the mean and the median, look also at the skewness and kurtosis statistics). Second, whilst the distribution appears to be roughly stationary, a closer inspection reveals subtle shifts in the sample characteristics over time, with firms on average getting bigger but at a decreasing rate. Indeed, one caveat of working with balanced panels is that the characteristics of the firms may change slightly as we move from the beginning to the end of the period under consideration.

Our two measures of size and growth are sales and number of employees, which are highly correlated with each other.¹ Figures 4.1 and 4.2 present the distributions of sales and employment growth rates, where these growth rates are cleaned of size dependence, serial correlation and heteroskedasticity effects according to the procedure described in Chapter 3. The main point of interest here is that the distribution is fat-tailed and resembles the Laplace (i.e. it appears to be approximately ‘tent-shaped’ on logarithmic axes). This testifies that relatively large growth events in any year occur not altogether infrequently. It also indicates that regression estimators based on the assumption of normally distributed errors (such as OLS) may be unreliable.

¹The correlation between sales and number of employees is 0.8404 (with $N=70\,000$), and the correlation between sales growth and employment growth is 0.3903 (with $N = 59\,967$; taking logs of employment we lose firms who at some point in time had 0 employees). Both are very highly significant.

Table 4.1: Summary statistics of the firm size distribution

year	obs.	mean	std. dev.	skewness	kurtosis	median	1%	99%
SALES (FF '000)								
1996	10000	93622	324276	14.80	316.24	29660	5640	1149076
1997	10000	98792	364255	19.44	618.02	30815	5665	1179687
1998	10000	104734	383413	19.38	611.57	33117	5960	1227714
1999	10000	107321	381536	17.15	456.54	34080	6042	1318392
2000	10000	117369	424978	17.27	473.09	36617	6044	1429880
2001	10000	121774	445042	17.33	463.25	37845	6009	1548911
2002	10000	120637	456510	18.56	515.27	37091	5638	1502079
EMPLOYMENT								
1996	10000	97.07	225.30	14.78	398.26	44	19	885
1997	10000	97.40	223.16	14.54	386.69	45	20	868
1998	10000	98.41	222.91	14.47	385.01	45	19	889
1999	10000	99.20	222.55	14.32	376.92	45	20	894
2000	10000	101.41	224.41	13.54	328.31	46	20	909
2001	10000	103.47	230.70	13.29	307.61	47	19	925
2002	10000	102.55	233.19	13.97	339.49	46	19	922
SALES GROWTH								
1997	10000	0.0359	0.2337	0.1410	25.74	0.0317	-0.6858	0.7689
1998	10000	0.0665	0.2163	0.0311	22.33	0.0592	-0.6030	0.7516
1999	10000	0.0257	0.2155	-0.0998	23.40	0.0278	-0.6206	0.6695
2000	10000	0.0647	0.2160	0.8329	27.06	0.0569	-0.5604	0.7088
2001	10000	0.0308	0.2114	-0.5049	24.65	0.0351	-0.6677	0.6045
2002	10000	-0.0252	0.2206	-0.3137	22.09	-0.0091	-0.7216	0.5864
EMPLOYMENT GROWTH								
1997	9990	0.0094	0.1359	0.1746	21.79	0.0000	-0.4199	0.4394
1998	9989	0.0143	0.1368	0.1673	18.54	0.0000	-0.4387	0.4199
1999	9989	0.0083	0.1464	4.3251	181.57	0.0000	-0.4162	0.3895
2000	9999	0.0225	0.1451	-0.8492	59.09	0.0118	-0.3947	0.4595
2001	10000	0.0116	0.1380	-0.1701	31.84	0.0000	-0.4480	0.4055
2002	10000	-0.0147	0.1386	-0.7697	32.14	0.0000	-0.4788	0.3460

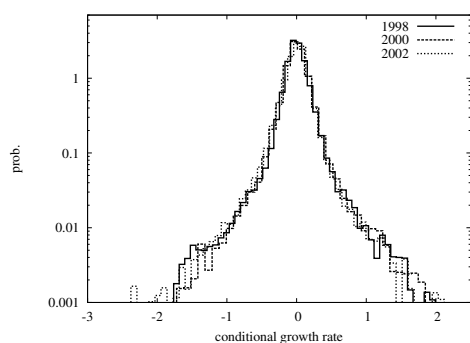


Figure 4.1: Distribution of sales growth rates (source: Bottazzi et al., 2005)

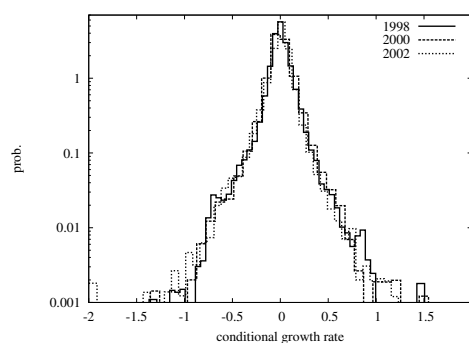


Figure 4.2: Distribution of employment growth rates (source: author's elaboration)

4.4.2 Regression analysis

To begin with, we apply regression analysis to obtain point estimates for autocorrelation coefficients, although the main results of this paper come from the quantile regressions.

In keeping with previous studies, we define our dependent variable *GROWTH* as the log-difference of size:

$$GROWTH_{i,t} = \log(SIZE_{i,t}) - \log(SIZE_{i,t-1}) \quad (4.2)$$

for firm i at time t , where $SIZE_{i,t}$ is measured either in terms of sales or employees. We then estimate the following regression equation:

$$GROWTH_{i,t} = \alpha_0 + \alpha_1 \log(SIZE_{i,t-1}) + \sum_{k=1}^K \beta_k GROWTH_{i,t-k} + \epsilon_{i,t}. \quad (4.3)$$

Given that the Gibrat Law literature has identified a dependence of growth rates upon firm size, we introduce lagged size as a control variable.

To begin with, we estimate equation (4.3) by OLS but, since the residuals are known to be approximately Laplace-distributed, OLS is likely to perform relatively poorly. Similarly, many other estimators, including the Binder-Hsiao-Pesaran (2005) short-panel VAR estimator, require normality of residuals and are thus inappropriate in this particular case. Instead, we follow on from Chapter 3 by preferring the results obtained by Least Absolute Deviation (LAD) estimation of equation (4.3). The LAD estimator is to be preferred on theoretical grounds because it provides reliable results for Laplace-distributed residuals. Regression results are reported in Tables 4.2 and 4.3. When growth is measured in terms of sales, we observe a small negative autocorrelation for the first lag, in the order of -5%. The second lag is smaller, sometimes significant, but variable across the three years; and the third lag is small and positive. Regarding employment growth, we observe a small yet positive and statistically significant correlation coefficient for the average firm, for each of the first three lags.

However, it has previously been noted that one calendar year is an arbitrary period over which to measure growth (see the discussion in Geroski, 2000). We will now look at growth rate autocorrelation over periods of two and three years, by LAD estimation of equation (4.3). The results are presented in Tables 4.4 and 4.5. When we measure growth over periods of two or three years, we obtain quite different results. Regarding autocorrelation of sales growth, we obtain a positive and significant coefficient when growth is measured over a three-year interval, which contrasts with the results presented in Table 4.3 for annual data. In addition, the coefficients for employment growth autocorrelation are much larger when growth is measured over two or three years. In showing these results, we are not trying to confuse the reader by showing that the autocorrelation coefficients vary wildly for different specifications. Rather,

Table 4.2: OLS estimation of equation (4.3), taking 3 lags. Coefficients significant at the 5% level appear in bold.

t	α_1	β_1	β_2	β_3
SALES				
2000	0.0026	-0.2136	-0.0995	-0.0231
(SE)	(0.0017)	(0.0239)	(0.0195)	(0.0172)
2001	-0.0055	-0.2119	-0.0533	0.0029
(SE)	(0.0017)	(0.0237)	(0.0192)	(0.0149)
2002	0.0016	-0.2523	-0.1294	-0.0357
(SE)	(0.0018)	(0.0294)	(0.0238)	(0.0168)
EMPL				
2000	-0.0105	-0.1110	0.0361	0.0452
(SE)	(0.0015)	(0.0286)	(0.0163)	(0.0172)
2001	-0.0017	-0.1185	0.0174	0.0430
(SE)	(0.0015)	(0.0373)	(0.0139)	(0.0148)
2002	-0.0055	-0.1042	-0.0084	0.0448
(SE)	(0.0015)	(0.0253)	(0.0285)	(0.0180)

Table 4.3: LAD estimation of equation (4.3), taking 3 lags. Coefficients significant at the 5% level appear in bold.

t	α_1	β_1	β_2	β_3
SALES				
2000	0.0066	-0.0501	0.0018	0.0207
(SE)	(0.0012)	(0.0066)	(0.0068)	(0.0062)
2001	-0.0028	-0.0530	0.0180	0.0359
(SE)	(0.0012)	(0.0064)	(0.0064)	(0.0063)
2002	0.0025	-0.0568	-0.0336	0.0082
(SE)	(0.0014)	(0.0076)	(0.0076)	(0.0074)
EMPL				
2000	-0.0015	0.0123	0.0588	0.0476
(SE)	(0.0014)	(0.0076)	(0.0088)	(0.0088)
2001	0.0039	0.0045	0.0109	0.0163
(SE)	(0.0004)	(0.0025)	(0.0025)	(0.0026)
2002	-0.0004	0.0003	0.0007	0.0008
(SE)	(0.0000)	(0.0001)	(0.0001)	(0.0001)

we are trying to demonstrate that an autocorrelation coefficient is only ever meaningful when it refers to a specific time period.

These results highlight some important features that should be kept in mind when investigating serial correlation. First, both the magnitude and even the sign of the observed autocorrelation coefficients are sensitive to the accounting period used. We should be reluctant to speak of ‘mean reversion’ in the growth process generally, for example, if we observe negative autocorrelation in annual growth rates, because these findings may not be robust to changes in time periods. Second, the conventional accounting period of one year is arbitrary and does not correspond to any meaningful duration of economic activity. Given these important qualifications, our following analysis is nonetheless able to provide useful insights into the growth process because it explores systematic variation in serial correlation patterns, conditional on firm size and conditional on growth rates.

4.4.3 Does autocorrelation vary with firm size?

As firms grow, they undergo many fundamental changes (Greiner, 1998). Whilst smaller firms are characteristically flexible, larger firms are more routinized, more inert and less able to adapt. In large firms, everything takes place on a larger scale, there is less reason to fear a ‘sudden death’, and the time-scale of strategic horizons extend much further than for a smaller counterpart. Larger firms may well have longer-term investment projects that unfold over a period of several years, whereas smaller firms can adjust much more rapidly. It is therefore

Table 4.4: LAD estimation of equation (4.3), with sales growth measured over different periods. Coefficients significant at the 5% level appear in bold.

t	α_1	β_1	β_2
<i>00-02</i>		<i>98-00</i>	<i>96-98</i>
	0.0023 (0.0013)	0.0043 (0.0055)	0.0062 (0.0055)
<i>99-01</i>		<i>97-99</i>	
	-0.0029 (0.0012)	0.0306 (0.0047)	
<i>98-00</i>		<i>96-98</i>	
	0.0062 (0.0013)	0.0205 (0.0055)	
<i>99-02</i>		<i>96-99</i>	
	0.0024 (0.0013)	0.0126 (0.0045)	

Table 4.5: LAD estimation of equation (4.3), with employment growth measured over different periods. Coefficients significant at the 5% level appear in bold.

t	α_1	β_1	β_2
<i>00-02</i>		<i>98-00</i>	<i>96-98</i>
	-0.0006 (0.0000)	0.0010 (0.0001)	0.0005 (0.0001)
<i>99-01</i>		<i>97-99</i>	
	0.0038 (0.0005)	0.0135 (0.0021)	
<i>98-00</i>		<i>96-98</i>	
	-0.0016 (0.0014)	0.0522 (0.0065)	
<i>99-02</i>		<i>96-99</i>	
	-0.0005 (0.0000)	0.0006 (0.0001)	

meaningful to suppose that differences in the behavior of large firms and smaller firms will also be manifest in their respective growth processes. It has previously been conjectured that large and small firms operate on a different ‘frequency’ or time-scale, and respond to different stimuli (Hannan and Freeman, 1984).² However, to my knowledge, no empirical study has explicitly considered this relationship. The results in Dunne and Hughes (1994: Table VI) and in Wagner (1992: Table II) might appear to lean in this direction, but the authors fail to comment upon this possibility. The aim of this section is thus to compare growth rate autocorrelation among firms of different sizes.

We sort firms into 20 equipopulated bins according to their Sales in 1996,³ and calculate their growth rate autocorrelation by LAD estimation of equation (4.3). The evidence presented in Figures 4.3 and 4.4 would seem to support the hypothesis that annual growth rate autocorrelation varies with size, being negative, on average, for small firms and positive for larger ones. Further evidence in support of this hypothesis will also be presented in what

²To be precise, Hannan and Freeman write about: “the proposition that time-scales of selection processes stretch with size. . . One way to visualize such a relationship is to consider environmental variations as composed of a spectrum of frequencies of varying lengths - hourly, daily, weekly, annually, etc. Small organizations are more sensitive to high-frequency variations than large organizations. For example, short-term variations in the availability of credit may be catastrophic to small businesses but only a minor nuisance to giant firms. To the extent that large organizations can buffer themselves against the effects of high-frequency variations, their viability depends mainly on lower-frequency variations.” Hannan and Freeman, 1984:161

³The issue of ascribing growing firms to different size classes is not as easy as one could imagine. A drawback of sorting firms in this way is that their size in the initial period could be a poor proxy for their longer-term characteristics (this is commonly known as the problem of the ‘regression fallacy’ – see Friedman (1992) for a discussion). In the Appendix we develop an alternative methodology for sorting firms according to size (by taking their mean size over the 7-year period), and we obtain qualitatively similar results.

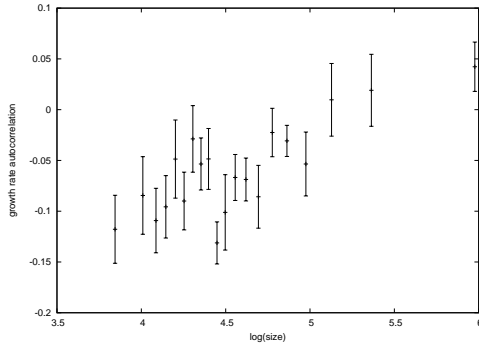


Figure 4.3: Autocorrelation of annual sales growth

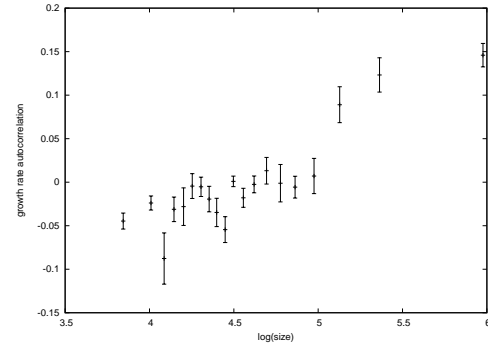


Figure 4.4: Autocorrelation of annual employment growth

follows.

We should be careful how we interpret these results. It may not be meaningful to say that large firms have positive feedback and smaller firms have negative feedback in their growth dynamics because, as discussed previously, it is possible that the magnitudes and signs of the autocorrelation coefficients would change if we were to measure growth over a different time period. However, one thing that we can infer from these results is that large firms and small firms operate on different time scales.

4.5 Quantile regression analysis

In this section we begin by explaining why we believe quantile regression techniques to be a useful tool to this study. First we describe the intuition of quantile regression analysis, and then we present the quantile regression model in a few introductory equations. We then present the results.

4.5.1 An introduction to quantile regression

Standard least squares regression techniques provide summary point estimates that calculate the average effect of the independent variables on the ‘average firm’. However, this focus on the average may hide important features of the underlying dynamics. As Mosteller and Tukey explain in an oft-cited passage:

“What the regression curve does is give a grand summary for the averages of the distributions corresponding to the set of x ’s. We could go further and compute several regression curves corresponding to the various percentage points of the distributions and thus get a more complete picture of the set. Ordinarily this is not done, and so regression often gives a rather incomplete picture. Just as the mean gives an incomplete picture of a single distribution, so the regression curve

gives a correspondingly incomplete picture for a set of distributions.” Mosteller and Tukey (1977: 266).

Quantile regression techniques can therefore help us obtain a more complete picture of the underlying dynamics of firm growth processes.

In our case, estimation of linear models by quantile regression may be preferable to the usual regression methods for a number of reasons. First of all, we know that the standard least-squares assumption of normally distributed errors does not hold for our database because growth rates follow a heavy-tailed distribution. Whilst the optimal properties of standard regression estimators are not robust to modest departures from normality, quantile regression results are characteristically robust to outliers and heavy-tailed distributions. In fact, the quantile regression solution $\hat{\beta}_\theta$ is invariant to outliers on the dependent variable that tend to $\pm \infty$ (Buchinsky, 1994). Another advantage is that, while conventional regressions focus on the mean, quantile regressions are able to describe the entire conditional distribution of the dependent variable. In the context of this study, high growth firms are of interest in their own right, we don't want to dismiss them as outliers, but on the contrary we believe it would be worthwhile to study them in detail. This can be done by calculating coefficient estimates at various quantiles of the conditional distribution. Finally, a quantile regression approach avoids the restrictive assumption that the error terms are identically distributed at all points of the conditional distribution. Relaxing this assumption allows us to acknowledge firm heterogeneity and consider the possibility that estimated slope parameters vary at different quantiles of the conditional growth rate distribution.

The quantile regression model, first introduced by Koenker and Bassett (1978), can be written as:

$$y_{it} = x'_{it}\beta_\theta + u_{\theta it} \quad \text{with} \quad \text{Quant}_\theta(y_{it}|x_{it}) = x'_{it}\beta_\theta \quad (4.4)$$

where y_{it} is the growth rate, x is a vector of regressors, β is the vector of parameters to be estimated, and u is a vector of residuals. $Q_\theta(y_{it}|x_{it})$ denotes the θ^{th} conditional quantile of y_{it} given x_{it} . The θ^{th} regression quantile, $0 < \theta < 1$, solves the following problem:

$$\min_{\beta} \frac{1}{n} \left\{ \sum_{i,t:y_{it} \geq x'_{it}\beta} \theta |y_{it} - x'_{it}\beta| + \sum_{i,t:y_{it} < x'_{it}\beta} (1 - \theta) |y_{it} - x'_{it}\beta| \right\} = \min_{\beta} \frac{1}{n} \sum_{i=1}^n \rho_\theta u_{\theta it} \quad (4.5)$$

where $\rho_\theta(\cdot)$, which is known as the ‘check function’, is defined as:

$$\rho_\theta(u_{\theta it}) = \left\{ \begin{array}{ll} \theta u_{\theta it} & \text{if } u_{\theta it} \geq 0 \\ (\theta - 1)u_{\theta it} & \text{if } u_{\theta it} < 0 \end{array} \right\} \quad (4.6)$$

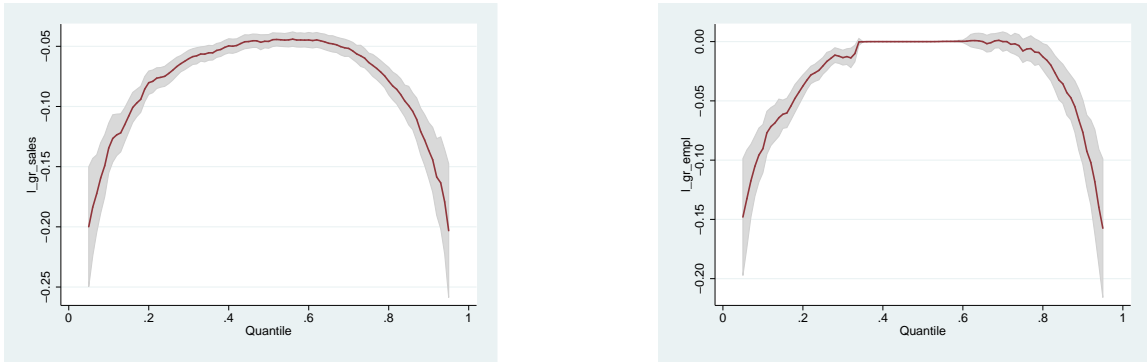


Figure 4.5: Regression quantiles for sales (left) and employment (right) autocorrelation coefficients, with 95% confidence intervals.

Table 4.6: Quantile regression estimation of equation (4.7) for the 10%, 25%, 50%, 75% and 90% quantiles, allowing for only one lag in serial correlation. Coefficients significant at the 5% level appear in bold.

	10%	25%	50%	75%	90%
Sales gr.					
β_1	-0.1354	-0.0725	-0.0449	-0.0596	-0.1267
(<i>t</i> -stat)	-12.35	-17.79	-15.63	-14.15	-10.49
Pseudo- R^2	0.0294	0.0259	0.0189	0.0237	0.0294
Empl. gr.					
β_1	-0.0924	-0.0206	0.0000	0.0034	-0.0547
(<i>t</i> -stat)	-8.45	-5.11	0.00	0.71	-4.00
Pseudo- R^2	0.0091	0.0041	0.0007	0.0121	0.0237

Equation (4.5) is then solved by linear programming methods. As one increases θ continuously from 0 to 1, one traces the entire conditional distribution of y , conditional on x (Buchinsky, 1998). More on quantile regression techniques can be found in the surveys by Buchinsky (1998) and Koenker and Hallock (2001); for applications see the special issue of *Empirical Economics* (Vol. 26 (3), 2001).

4.5.2 Quantile regression results

As an extension to the observation that the distribution of growth rates is heavy-tailed, in this section we ask the question: “how does serial correlation affect the growth processes of these extreme-growth firms?” Conventional regression techniques such as OLS are not appropriate here, because they focus on the ‘average firm’, assume normally-distributed residuals and are not robust to outliers. In fact, extreme observations are frequently dropped from the analysis. In our case, however, the distribution of firm growth rates is fat-tailed, resembling the Laplace density rather than the Gaussian. Furthermore, we explicitly want to focus on those few firms that experience extreme growth events because they make a disproportionate contribution to

employment growth and market share turnover. As opposed to standard regression techniques, quantile regression analysis appears appropriate here because it provides a parsimonious description of the entire conditional growth rate distribution. It will thus be possible to examine serial correlation patterns for firms of all quantiles, including autocorrelation dynamics of extreme growth firms.

The regression equation that we estimate is:

$$GROWTH_{i,t} = \alpha_0 + \alpha_1 \log(SIZE_{i,t-1}) + \beta_1 GROWTH_{i,t-1} + y_t + \epsilon_{i,t}. \quad (4.7)$$

where y_t are yearly dummies. The quantile regression results are presented in Table 4.6, and a summary representation is provided in Figure 4.5. The coefficients can be interpreted as the partial derivative of the conditional quantile of the dependent variable with respect to particular regressors (Yasar et al., 2006b). Evaluated at the median, we observe that there is only slight negative autocorrelation in sales growth and totally insignificant autocorrelation in employment growth. (In fact, the median quantile regression corresponds to the LAD regression estimate.) The story does not end here, however, because the serial correlation coefficient estimates vary considerably across the conditional growth rate distribution. For firms experiencing dramatic losses in sales or employment at time t , the sharply negative coefficient implies that in the previous period $t - 1$ these firms were probably experiencing above-average growth. Similarly, for those fastest-growing firms at time t , the negative coefficient estimate indicates that these firms probably performed relatively poorly in the previous period $t - 1$. It would appear then that, although in any one year there are some firms that undergo significant growth events, these firms are unlikely to repeat this performance.⁴ According to this evidence, it would appear that the better analogy would probably be that of the ‘hare and tortoise’ rather than notions of cumulative ‘snowball effect’ dynamics or even serial independence of growth rates.

4.5.3 Robustness across size groups

Are the previous results robust across size? Or is the relationship displayed in Figure 4.5 just the result of aggregating firms of different sizes – where smaller firms are the extreme growers and it is these same firms that experience the negative autocorrelation? It does not appear, for this dataset, that growth rate variance decreases dramatically with size (see our analysis in Chapter 3). Nevertheless, in this section we will investigate possible heterogeneity across

⁴One potential problem that we thought deserved investigation was the possibility of data entry errors. Despite the INSEE’s reputation for providing high-quality data, we were concerned that there could be cases of omitted numbers in which a firm’s sales (or employees) were observed to shrink by tenfold in one year and grow by tenfold in the next. Where we found such cases, we checked for consistency with other corresponding variables (e.g. value added, employees etc). As it happens, the database appeared consistent under scrutiny and we are pleased to acknowledge that our suspicions were a waste of time.

Table 4.7: Quantile regression estimation of equation (4.7) for the 10%, 25%, 50%, 75% and 90% quantiles for 10 size groups (**1** = smallest), allowing for only one lag in serial correlation. The size groups are sorted according to sales in 1996. Coefficients significant at the 5% level appear in bold.

	10%	25%	50%	75%	90%
Sales gr.					
1: β_1	-0.1694	-0.1420	-0.0847	-0.0810	-0.1427
(<i>t</i> -stat)	-4.74	-10.98	-8.92	-6.23	-4.17
2: β_1	-0.1507	-0.1295	-0.0942	-0.1147	-0.1601
(<i>t</i> -stat)	-4.12	-8.58	-8.21	-7.47	-4.26
3: β_1	-0.1337	-0.0989	-0.0630	-0.0718	-0.1447
(<i>t</i> -stat)	-4.05	-6.96	-4.62	-4.19	-3.00
4: β_1	-0.0375	-0.0336	-0.0456	-0.0701	-0.1381
(<i>t</i> -stat)	-1.06	-2.09	-3.71	-3.93	-2.95
5: β_1	-0.1356	-0.0832	-0.0876	-0.0971	-0.2052
(<i>t</i> -stat)	-3.79	-6.24	-9.89	-6.85	-4.62
6: β_1	-0.0984	-0.0808	-0.0706	-0.1248	-0.1960
(<i>t</i> -stat)	-2.72	-6.16	-7.15	-7.42	-5.15
7: β_1	-0.1366	-0.0584	-0.0574	-0.0997	-0.2218
(<i>t</i> -stat)	-3.38	-3.86	-5.52	-7.26	-6.22
8: β_1	-0.0797	-0.0292	-0.0287	-0.0795	-0.1689
(<i>t</i> -stat)	-2.21	-2.35	-3.84	-5.59	-3.07
9: β_1	-0.0150	-0.0009	-0.0018	-0.0476	-0.1271
(<i>t</i> -stat)	-0.41	-0.07	-0.19	-3.79	-2.95
10: β_1	0.0662	0.0786	0.0641	0.0526	-0.0055
(<i>t</i> -stat)	1.71	5.36	6.07	3.35	-0.13
Empl. gr.					
1: β_1	-0.1837	-0.1051	0.0000	-0.0390	-0.0918
(<i>t</i> -stat)	-5.61	-6.80	0.00	-3.64	-1.90
2: β_1	-0.2002	-0.1016	-0.0196	-0.0354	-0.1544
(<i>t</i> -stat)	-5.72	-5.45	-5.88	-4.10	-3.24
3: β_1	-0.1039	-0.0296	0.0000	-0.0247	-0.0624
(<i>t</i> -stat)	-4.17	-2.66	0.00	-1.19	-1.19
4: β_1	-0.0709	-0.0128	0.0000	0.0006	-0.0184
(<i>t</i> -stat)	-1.92	-1.01	0.00	0.04	-0.46
5: β_1	-0.1355	-0.0734	-0.0248	-0.0660	-0.1367
(<i>t</i> -stat)	-3.67	-5.27	-6.75	-4.08	-3.13
6: β_1	-0.1067	-0.0331	0.0000	-0.0002	-0.0740
(<i>t</i> -stat)	-3.21	-2.46	0.00	-0.01	-2.44
7: β_1	0.0141	0.0381	0.0000	0.0131	-0.0673
(<i>t</i> -stat)	0.49	2.77	0.00	0.79	-1.47
8: β_1	-0.0395	0.0078	0.0063	0.0149	-0.0679
(<i>t</i> -stat)	-1.09	0.59	2.07	1.10	-1.71
9: β_1	0.0528	0.0550	0.0668	0.0848	0.0582
(<i>t</i> -stat)	1.29	3.95	9.77	5.37	1.51
10: β_1	0.1094	0.1361	0.1890	0.1975	0.1780
(<i>t</i> -stat)	2.64	11.92	33.19	18.30	7.70

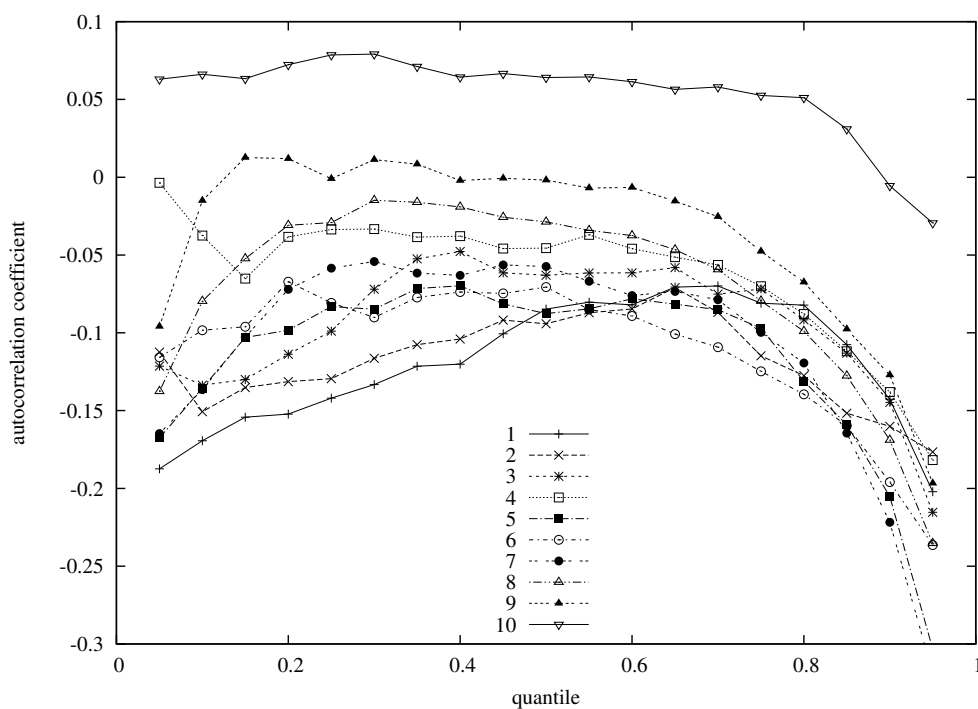


Figure 4.6: regression quantiles for sales growth autocorrelation coefficients across the 10 size groups (group '1' = smallest group)

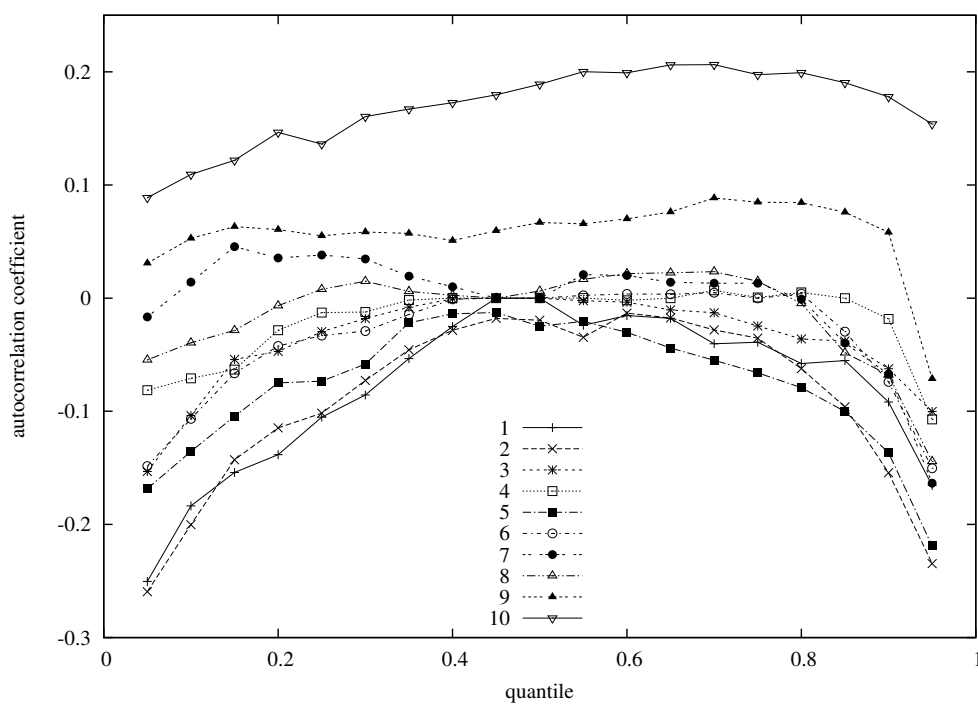


Figure 4.7: regression quantiles for employment growth autocorrelation coefficients across the 10 size groups (group '1' = smallest group)

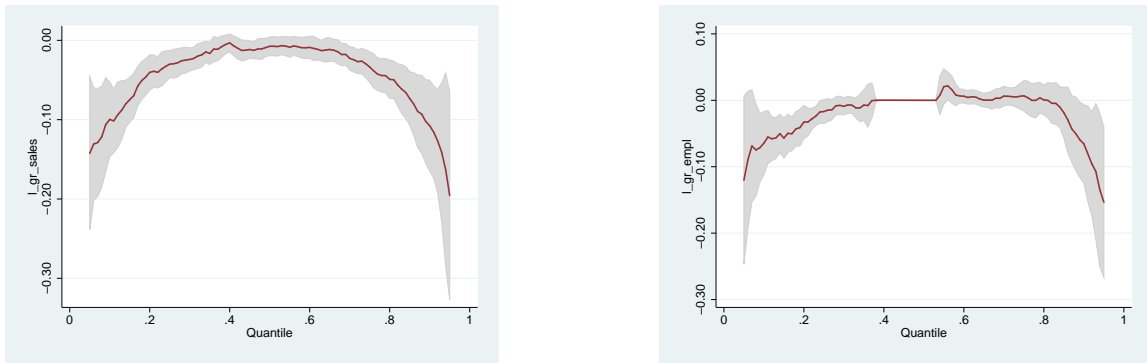


Figure 4.8: Regression quantiles for sales (left) and employment (right) autocorrelation coefficients for $t=1999$, with 95% confidence intervals.

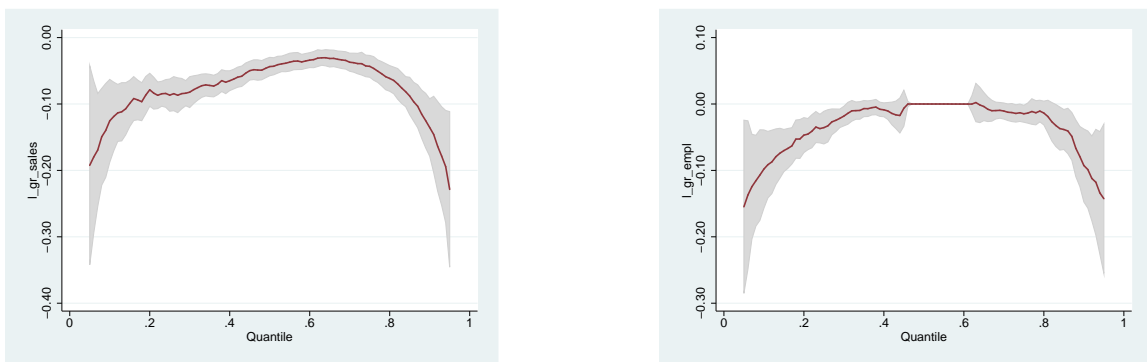


Figure 4.9: Regression quantiles for sales (left) and employment (right) autocorrelation coefficients for $t=2002$, with 95% confidence intervals.

size classes by applying quantile regression analysis to different size groups. We sort and split the firms into 10 size groups according to their initial size (sales in 1996). We then explore the regression quantiles for each of these 10 groups. Results are presented in Table 4.7 and Figures 4.6 (sales growth) and 4.7 (employment growth).

The results are reasonably consistent whether we consider sales growth or employment growth. For the larger firms, the results support the previous finding that, on average, these firms experience a slightly positive autocorrelation in annual growth rates. Even as we move to the extremes of the conditional distribution, the autocorrelation coefficient does not change too dramatically. This may be because diversification has a stabilizing effect on growth rates. Smaller firms, however, typically experience negative correlation which is moderate near the median but quite pronounced towards the extreme quantiles. This is in line with previous observations on “the prevalence of interruptions to growth” for small firms (Garnsey and Heffernan (2005: 675)). For these firms, prolonged periods of high growth are quite unusual.

4.5.4 Robustness to temporal disaggregation

Up until now, we have pooled together the observations from all of the years of the panel database. However, it might not be a valid methodology to pool together observations from

Table 4.8: Quantile regression estimation of equation (4.7) for the 10%, 25%, 50%, 75% and 90% quantiles for 20 2-digit sectors (17-36), allowing for only one lag in serial correlation. Coefficients significant at the 5% level appear in bold.

	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
	Sales gr.					Empl. gr.				
17: β_1	0.0588	0.0221	0.0003	-0.0094	-0.0303	-0.0217	0.0128	0.0003	0.0294	-0.0191
(<i>t</i> -stat)	2.24	1.69	0.02	-0.57	-0.66	-0.50	0.92	1.33	1.85	-0.45
18: β_1	-0.1438	-0.0392	-0.0284	-0.05	-0.1170	-0.0907	-0.0312	0.0000	-0.0699	-0.1097
(<i>t</i> -stat)	-3.30	-2.56	-2.21	-2.38	-2.10	-2.13	-1.86	0.00	-4.52	-1.82
19: β_1	-0.1227	-0.0296	-0.0032	-0.0967	-0.1718	-0.2684	-0.1256	-0.0379	-0.0727	-0.1550
(<i>t</i> -stat)	-2.56	-1.42	-0.22	-4.95	-2.08	-3.08	-5.19	-2.98	-2.00	-1.67
20: β_1	-0.0458	-0.0188	0.0144	0.0383	-0.1454	-0.1578	-0.0531	-0.0019	-0.0319	-0.0896
(<i>t</i> -stat)	-1.09	-0.98	0.68	1.63	-1.86	-2.92	-1.80	-0.79	-0.88	-1.12
21: β_1	-0.2197	-0.0961	-0.0563	-0.1180	-0.2096	-0.1027	-0.0304	-0.0001	0.0018	-0.0531
(<i>t</i> -stat)	-5.86	-4.39	-4.01	-5.80	-3.46	-1.80	-1.74	-1.29	0.12	-0.82
22: β_1	-0.1691	-0.0574	-0.0194	-0.0374	-0.0903	-0.1506	-0.0753	0.0000	-0.0507	-0.1484
(<i>t</i> -stat)	-4.12	-4.95	-2.85	-3.57	-2.48	-2.84	-5.32	0.00	-3.20	-3.72
23: β_1	0.0961	0.1317	0.1883	0.1523	0.1098	-0.0899	0.0683	0.1788	0.1926	0.0678
(<i>t</i> -stat)	0.20	1.80	9.09	5.16	0.12	-0.22	0.80	2.52	1.98	0.27
24: β_1	-0.0667	-0.0155	-0.0100	-0.0272	-0.0558	0.0634	0.0550	0.0587	0.0818	0.0068
(<i>t</i> -stat)	-1.46	-1.01	-0.84	-1.48	-1.14	1.34	3.40	7.66	4.79	0.10
25: β_1	-0.1346	-0.0582	-0.0246	-0.0440	-0.1126	-0.1009	-0.0262	0.0000	0.0091	-0.0361
(<i>t</i> -stat)	-2.50	-3.93	-2.34	-2.87	-3.05	-2.06	-1.50	0.00	0.46	-0.82
26: β_1	-0.0685	-0.3990	-0.0239	-0.0686	-0.1429	-0.1252	-0.0216	-0.0003	-0.0689	-0.1483
(<i>t</i> -stat)	-1.30	-2.31	-2.20	-3.31	-2.60	-1.77	-1.13	-0.56	-3.34	-2.45
27: β_1	-0.1552	-0.1052	-0.0189	0.0094	0.0096	-0.0744	0.0194	0.0115	0.0455	0.0176
(<i>t</i> -stat)	-2.42	-5.02	-0.79	0.29	0.19	-3.05	2.02	3.24	3.58	0.60
28: β_1	-0.1801	-0.1219	-0.1003	-0.1153	-0.1748	-0.1262	-0.0485	-0.0005	-0.0353	-0.1284
(<i>t</i> -stat)	-7.71	-13.85	-14.57	-12.46	-7.07	-6.97	-5.73	-6.37	-3.14	-4.27
29: β_1	-0.2043	-0.1438	-0.1062	-0.1354	-0.1874	-0.0909	-0.0084	0.0006	-0.0028	-0.0758
(<i>t</i> -stat)	-4.91	-8.98	-12.20	-9.37	-4.34	-2.91	-0.77	2.21	-0.18	-1.87
30: β_1	0.0074	-0.0959	0.0194	0.0593	-0.1050	-0.3232	-0.0403	0.1071	0.1416	0.2377
(<i>t</i> -stat)	0.30	-0.70	0.14	0.33	-0.31	-0.86	-0.20	1.49	1.23	0.22
31: β_1	-0.0551	-0.0749	-0.0437	-0.0602	-0.1216	-0.0490	0.0227	0.0172	0.0735	0.1041
(<i>t</i> -stat)	-1.00	-2.69	-2.91	-2.39	-2.11	-0.87	1.09	1.26	3.07	1.57
32: β_1	-0.1094	-0.0904	-0.0610	-0.0228	-0.0538	-0.0106	-0.0138	0.0384	0.0692	0.1172
(<i>t</i> -stat)	-1.31	-2.42	-1.88	-0.93	-0.91	-0.14	-0.62	1.66	1.87	1.16
33: β_1	-0.1573	-0.1179	-0.0763	-0.0779	-0.1457	-0.1160	0.0053	0.0000	0.0895	0.0967
(<i>t</i> -stat)	-2.60	-5.47	-5.33	-2.63	-1.87	-2.03	0.22	0.00	3.45	1.37
34: β_1	-0.0696	-0.0472	-0.0193	-0.0386	-0.0438	-0.1472	-0.0298	0.0245	0.0592	0.0715
(<i>t</i> -stat)	-1.09	-1.98	-0.92	-1.83	-0.51	-2.51	-1.12	1.09	1.75	0.83
35: β_1	-0.2325	-0.1190	-0.1097	-0.1439	-0.2830	-0.0719	0.0036	0.0443	0.0228	-0.1280
(<i>t</i> -stat)	-2.52	-3.53	-4.51	-3.74	-1.90	-0.59	0.15	2.09	0.61	-0.89
36: β_1	0.0052	-0.0304	-0.0172	-0.0588	-0.1527	0.0113	0.0087	0.0039	-0.0482	-0.1278
(<i>t</i> -stat)	0.17	-2.51	-1.53	-3.25	-2.60	0.32	0.61	1.40	-1.87	-2.48

different years if the autocorrelation structure varies with time (e.g. over the business cycle). We now check how our results stand up to temporal disaggregation by estimating the quantile regressions for individual years. We are effectively moving from a panel dataset to five yearly cross-sections. However, our findings appear to be robust to temporal disaggregation. The quantile regression plots for the years 1999 and 2002 (for sales and employment growth) are shown in Figures 4.8 and 4.9.

4.5.5 Robustness to sectoral disaggregation

Rigorous empirical methodology requires us to also ensure that these results are not due to aggregation over heterogeneous industries. In this section, we report quantile regression

results for 20 2-digit industries. Summary information on these sectors has been provided in the previous chapter (see Table 3.4) and the results are presented in Table 4.8.

Generally speaking, the properties that were visible at the aggregate level are also visible for 2-digit industries. Firms near the median experience only moderate autocorrelation (either positive or negative), whereas firms at the extreme quantiles of the conditional growth rate distribution experience much stronger forces of negative autocorrelation. Although sectoral disaggregation does not qualitatively change our key findings, there are a few sectors in which the results are rather ‘ugly’. This may be because we aggregate over firms from the same industry but of different sizes. One interpretation would be that, in determining autocorrelation in growth processes, the most relevant dimension is size and conditional growth rate, rather than sector of activity.

4.6 Summary and Conclusions

We began by exploring serial correlation in annual growth rates using standard regression techniques, and in some cases detected a statistically significant influence of past growth even for the third lag. When sales growth was considered, the coefficient on the first lag was typically around -5%, whereas for employment growth it was generally positive although smaller in magnitude. We also found evidence that growth rate autocorrelation varied with firm size, consistent with the hypothesis that small firms operate on a different time scale (i.e. a shorter ‘frequency’) than larger ones. In the case of annual growth rates, we obtained negative coefficients for groups of smaller firms and positive ones for larger firms. This systematic variation of autocorrelation coefficients across firm size helps explain why previous studies using different databases (reviewed in Section 4.2) found such inconclusive results.

An important recent discovery in the industrial organization literature is that firm growth rates are fat-tailed and follow closely the Laplace density. This means that we can expect that, in any given year, a significant proportion of turbulence in market share or employment is due to a minority of fast-growing firms. Although small in number, these firms are of special interest to economists. What are the characteristics of these firms? Standard regression techniques, that focus on the ‘average effect for the average firm’, are of limited use in this case, because the average firm doesn’t grow much at all. Instead, we apply quantile regression techniques that explicitly recognise heterogeneity between firms, and present results from various quantiles of the conditional growth rates distribution. Although we find a small negative annual autocorrelation at the aggregate level, there exist more powerful autoregressive forces for those firms that matter the most - the extreme-growth firms. These firms may grow a lot in one period, but it is unlikely that the spurt will last long. We also observed an interaction between the characteristics of the extreme-growth firms and size. Whilst smaller fast-growth

firms are much more prone to dramatic negative autocorrelation, larger firms seem to have much smoother growth dynamics.

Our results can be related to some well-known theories in the industrial organization literature. The model of ‘passive learning’ in the evolution of industries (as proposed by Jovanovic, 1982) appears to be supported by our findings, because the growth paths of small firms are quite erratic and noisy whereas those of larger firms are relatively smoothed. Our results also have implications for Gibrat’s law. On the basis of our findings, this ‘law’ would be rejected because, in many cases, growth rates in consecutive years are not independent.

It is, of course, far too early to speak of the possibility of ‘stylized facts’, but since our findings are reasonably robust and also theoretically meaningful, we anticipate that future research will corroborate our results. We also consider that more should be done in way of investigation of the characteristics of extreme high-growth firms (this analysis will be pursued in Chapter 7). These firms are just a small proportion in the number of firms but account for a great proportion of employment growth or market share turbulence. Conventional regression techniques are of limited use in this respect. Quantile regression techniques are far more appropriate, although perhaps future work on high-growth firms could also consider an approach by case studies.

Appendix

In this Appendix we provide further evidence of the robustness of our findings. In particular, we check the robustness of our results by using an alternative technique for sorting firms according to size.

Up until now, we have sorted the firms according to their size in the first time period of our panel dataset, i.e. 1996. However, this could give misleading results. If we sort firms according to size in any one year, there is a danger that the size of some firms in that particular year will not be representative of their size in the other years. For example, suppose a firm experiences a temporary negative shock to its size in one year, but next year it returns to its ‘usual’ size. Such a firm will thus be erroneously classified as a ‘fast-growing small firm’ if it is put into a size class during the year that it is small. Conversely, the year before it would perhaps have been classified as a ‘fast-shrinking medium-sized firm’. If we classify firms according to their size in any one particular year (such as the initial year), we may have a tendency to exaggerate the growth of small firms and underestimate the growth of larger firms. There may also be implications for the relationship between autocorrelation and firm size.

This statistical problem of sorting growing entities according to size is commonly known as the ‘regression fallacy’. In his discussion of this issue, Milton Friedman (1992) suggests that firms should be allocated to size classes according to their average size for the whole period of analysis, rather than attributing them to a size class according to their size in any one year. Therefore, in this Appendix, we classify firms according to their mean size over the whole period (more precisely, the mean number of employees 1996-2002).

We begin by examining whether autocorrelation coefficients do indeed vary with firm size according to this new size-classification scheme. The evidence is shown in Figures 4.10 and 4.11. Again, we see that autocorrelation does vary with firm size.

We also repeat the quantile regression analysis by sorting firms according to their mean size rather than initial size. The plots are shown in Figures 12 and 13, and results are reported in Table 4.9. We conclude that our findings are qualitatively similar to those obtained by

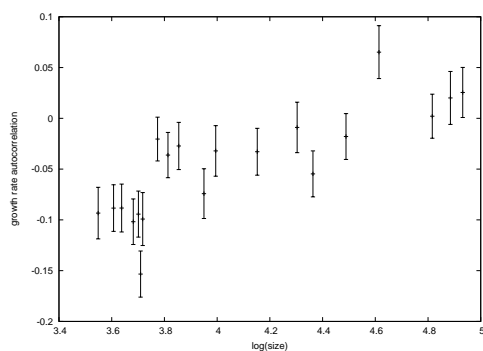


Figure 4.10: Autocorrelation of annual sales growth

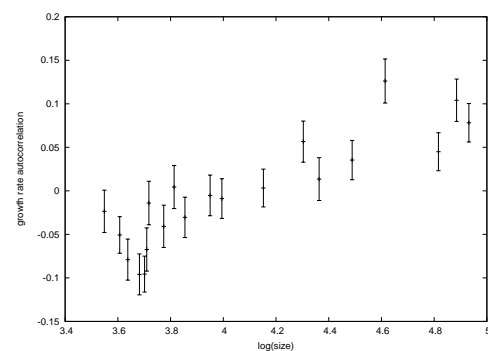


Figure 4.11: Autocorrelation of annual employment growth

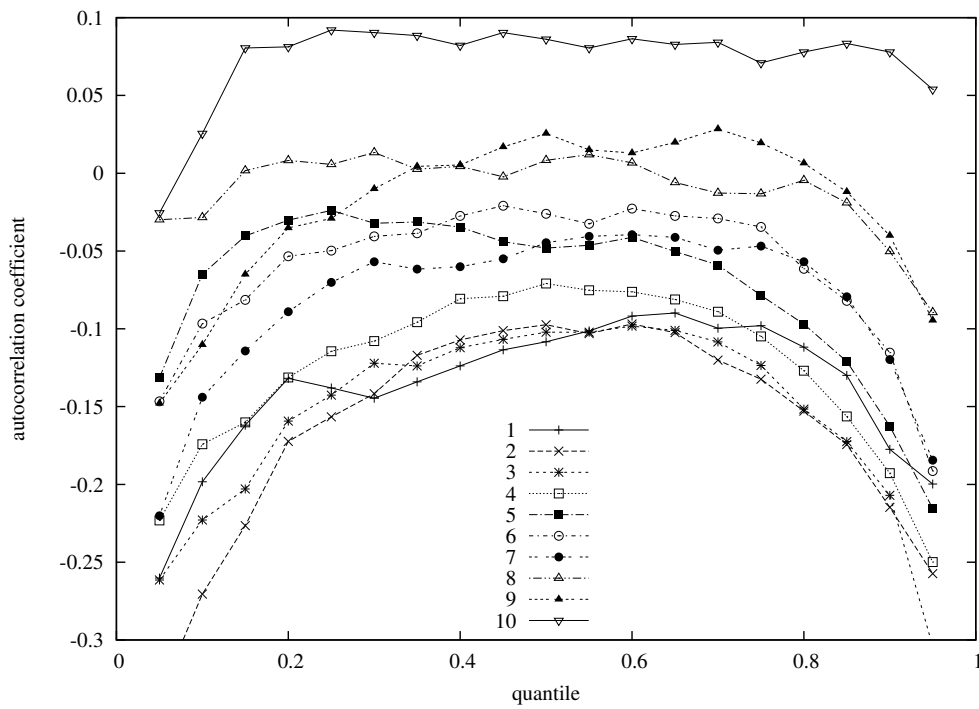


Figure 4.12: regression quantiles for sales growth autocorrelation coefficients across the 10 size groups (group '1' = smallest group)

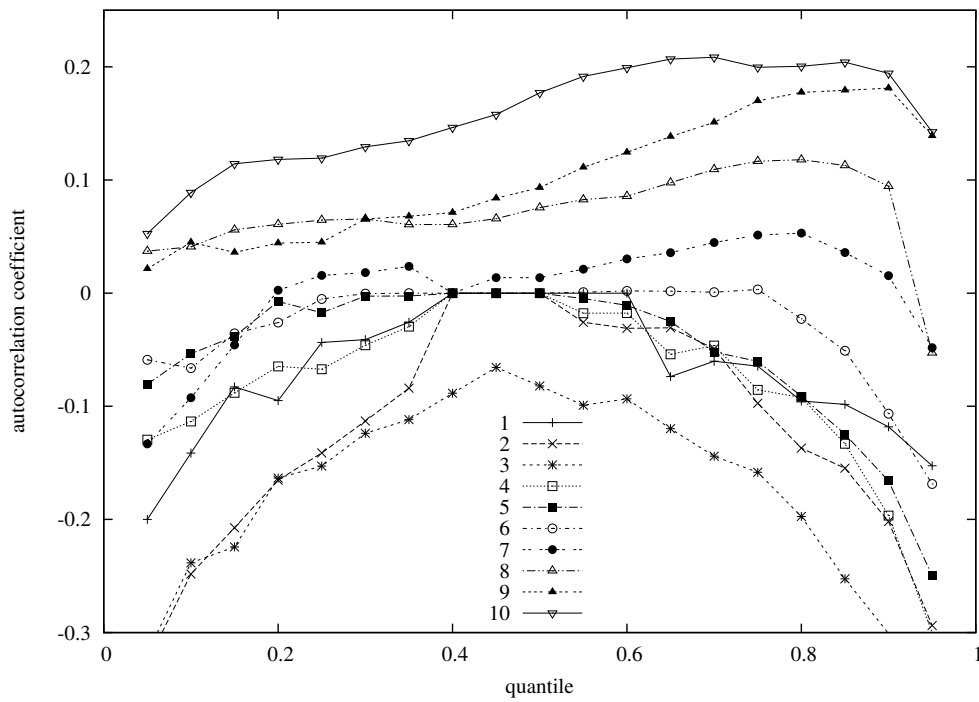


Figure 4.13: regression quantiles for employment growth autocorrelation coefficients across the 10 size groups (group '1' = smallest group)

Table 4.9: Quantile regression estimation of equation (4.7) for the 10%, 25%, 50%, 75% and 90% quantiles for 10 size groups (1 = smallest), allowing for only one lag in serial correlation. The size groups are sorted according to their mean size (employees) 1996-2002. Coefficients significant at the 5% level appear in bold.

	10%	25%	50%	75%	90%
Sales gr.					
1: β_1	-0.1984	-0.1380	-0.1084	-0.0980	-0.1775
(<i>t</i> -stat)	-5.65	-8.57	-10.94	-7.08	-6.36
2: β_1	-0.2706	-0.1566	-0.0974	-0.1324	-0.2147
(<i>t</i> -stat)	-6.63	-12.98	-10.28	-9.54	-5.22
3: β_1	-0.2229	-0.1426	-0.1022	-0.1236	-0.2071
(<i>t</i> -stat)	-5.36	-12.11	-13.68	-8.61	-4.99
4: β_1	-0.1742	-0.1144	-0.0708	-0.1049	-0.1928
(<i>t</i> -stat)	-6.25	-10.33	-8.63	-6.62	-4.71
5: β_1	-0.0650	-0.0239	-0.0482	-0.0785	-0.1626
(<i>t</i> -stat)	-2.01	-2.04	-4.69	-5.88	-4.23
6: β_1	-0.0966	-0.0497	-0.0261	-0.0345	-0.1153
(<i>t</i> -stat)	-3.36	-3.59	-2.45	-2.44	-3.38
7: β_1	-0.1440	-0.0701	-0.0447	-0.0469	-0.1197
(<i>t</i> -stat)	-4.24	-4.98	-5.70	-3.47	-3.28
8: β_1	-0.0285	0.0057	0.0083	-0.0132	-0.0503
(<i>t</i> -stat)	-0.88	0.39	0.83	-0.90	-1.13
9: β_1	-0.1103	-0.0291	0.0255	0.0194	-0.0400
(<i>t</i> -stat)	-2.92	-2.01	2.53	1.43	-1.04
10: β_1	0.0255	0.0920	0.0862	0.0709	0.0779
(<i>t</i> -stat)	0.64	6.93	7.96	3.81	2.11
Empl. gr.					
1: β_1	-0.1414	-0.0436	0.0000	-0.0645	-0.1182
(<i>t</i> -stat)	-3.36	-10.28	0.00	-10.03	-3.47
2: β_1	-0.2482	-0.1412	0.0000	-0.0973	-0.2019
(<i>t</i> -stat)	-6.96	-10.68	0.00	-7.72	-5.14
3: β_1	-0.2384	-0.1528	-0.0820	-0.1584	-0.3008
(<i>t</i> -stat)	-5.60	-9.69	-13.70	-9.85	-6.23
4: β_1	-0.1135	-0.0673	0.0000	-0.0855	-0.1966
(<i>t</i> -stat)	-4.19	-5.28	0.00	-4.43	-3.97
5: β_1	-0.0536	-0.0172	0.0000	-0.0603	-0.1660
(<i>t</i> -stat)	-1.54	-1.90	0.00	-6.92	-3.98
6: β_1	-0.0663	-0.0051	0.0000	0.0032	-0.1066
(<i>t</i> -stat)	-2.52	-1.04	0.00	0.26	-2.81
7: β_1	-0.0924	0.0157	0.0137	0.0514	0.0154
(<i>t</i> -stat)	-2.69	2.59	5.97	3.75	0.40
8: β_1	0.0410	0.0645	0.0755	0.1165	0.0944
(<i>t</i> -stat)	1.60	4.86	9.79	8.41	2.63
9: β_1	0.0450	0.0449	0.0932	0.1700	0.1811
(<i>t</i> -stat)	1.37	3.48	13.01	11.6	4.95
10: β_1	0.0888	0.1194	0.1770	0.1996	0.1943
(<i>t</i> -stat)	1.82	9.60	32.09	18.93	6.92

classifying firms according to their initial size.

Part III

Financial performance and growth

Chapter 5

Neoclassical versus Evolutionary theories of financial constraints: critique and prospectus

Empirical work needs to be guided by a relevant theory. In this chapter I define the theoretical context in which the empirical results in Chapter 6 are to be interpreted.

In this chapter I discuss two different ways of interpreting the relationship between financial performance and growth. According to the mainstream approach, any dependence of firm growth (or investment, to be precise) on financial performance signals financial constraints and market imperfections. According to an alternative theory that has its roots in evolutionary thought, however, it can be argued that any relationship between financial performance and growth is a socially desirable outcome, signalling the efficient allocation of growth opportunities. I argue in favour of this latter approach.

5.1 Introduction

This paper is a critical survey of the “contradictory and inconclusive evidence from almost two decades of cash-flow sensitivity and Euler equation tests” (Whited 2006: 498). I highlight the differences between competing theoretical perspectives on firm growth, and also the rather different policy implications that emerge from them. The three perspectives are the neoclassical q -theory of investment (and the related Euler equation approach – see Chirinko (1993) and Schiantarelli (1996) for surveys), the ‘imperfect capital markets’ theory (following on from Fazzari et al. (1988); see Hubbard (1998) for a survey), and also an evolutionary viewpoint that I develop by considering the contributions of writers such as Nelson and Winter (1982), Metcalfe (1998) and Dosi (2000).

How does firm investment/growth react to current-period financial performance? How

should it? Should investment-cash flow sensitivities be interpreted as evidence of financial constraints? The standard q -theory prescribes that the only significant regressor in investment regressions should be marginal q (proxied by average q). However, for a variety of reasons the empirical results have been disappointing. More recent work on investment highlights the additional explanatory power of current cash-flow, and attributes this to information asymmetries and market imperfections. In contrast, evolutionary theory predicts that it should not be surprising that firm growth responds to current financial performance; in fact, this is what the ‘replicator dynamics’ model of industry evolution would predict.

It is perhaps surprising that the neoclassical and evolutionary approaches have diametrically opposed theoretical predictions. Previously, it had been claimed that the evolutionary attempts to relax the restrictive neoclassical assumptions led in any case to the same neoclassical ‘equilibrium’ solution concepts (Friedman (1953), Rubin (1983)). Whilst neoclassical studies expect that current financial performance (proxied by cash flow) should have no influence on investment, they are puzzled to observe that it does in fact have a significant influence. Evolutionary economists, on the other hand, apply the principle of ‘growth of the fitter’ to the data in the hope that the most profitable firms will grow, but they are nonetheless humbled by their weak results.

This paper also emphasizes that policy recommendations are sensitive to the initial assumptions made by the economist. It is misleading and potentially harmful to derive policy implications from complicated mathematical models, that are constructed from assumptions that are chosen not for their economic relevance but because they ensure mathematical tractability.

In Section 5.2 we review the three theories – q theory, imperfect markets theory, and evolutionary theory. We then discuss these three theories (Section 5.3) and also compare the policy recommendations that emerge from them (Section 5.4). Section 5.5 concludes.

5.2 A review of the three theories

5.2.1 q theory

q -theory states that firm-level investment should be determined by future prospects of return. Assuming that stock prices can accurately summarize future profits, the viability of investment opportunities can be entirely determined by the firm’s value of marginal q (i.e. market value of assets / book value of assets). However, data on marginal q are difficult to obtain, and are usually proxied by average q . Average q has been shown to be a valid proxy for marginal q when four assumptions are met (Hayashi 1982): that firms operate in perfectly competitive product and factor markets, that firms also have linear homogenous production and adjustment cost technologies, that capital is homogenous, and that investment decisions are separable from

Table 5.1: An example of a neoclassical q model: How Blundell, Bond, Devereux and Schiantarelli (1992) derive the regression equation

Equation	Description
(1)	Intertemporal capital market arbitrage condition
(2)	Solving (1) on an infinite horizon
(3)	Defining the discount factor β over an infinite horizon
(4)	Substituting for dividend payments in the firm's stock market value
(5)	Defining the firm's after tax net revenue
(6)	First-order condition for investment
(7)	The evolution of the shadow price of capital
(8)	Rearranging (6) to obtain marginal q
(9)	Rearranging (8) assuming a quadratic functional form for adjustment costs
(10)	Rewriting marginal q assuming linear homogeneity of production and adjustment costs
(11)	Expressing the expected depreciation allowances on an infinite horizon
(12)	Expressing the expected present value of all cash flows associated with debt
(13)	Regression equation

other real and financial decisions. Assuming that firms seek to maximize shareholder value and possess 'rational expectations', it is possible to take the first-order condition of a mathematical model as the basis for a regression model. In this final model, q should be the only predictor for investment (Chirinko, 1993).

As an example of an empirical study based on the neoclassical q model, Table 5.1 shows how Blundell et al. (1992) derive their regression equation. This Table illustrates how the interpretation of the empirical results obtained from regression analysis of their equation (13) is framed by a rather long list of previous assumptions. Empirical analyses such as these could be deemed as 'hyper-parametric' because their results are only open to identification within the straightjacket of a complicated mathematical model. Perhaps unsurprisingly, we observe that "Q models have not been noticeably successful in accounting for the time series variation in aggregate investment" (Blundell et al 1992: 234).

An alternative to the q model is the Euler equation model. The Euler equation describes the optimal path of investment in a parametric adjustment costs model. Although it is derived from the same dynamic optimization problem as the q -theory model, it has the advantage of avoiding the requirement of measuring q . "It states that the value of the marginal product of capital today, net of adjustment costs, must equal the cost of a new machine minus the cost savings due to the fact that the firm can invest less tomorrow and still maintain the capital stock on its optimal path" (Schiantarelli, 1996: 75). As an example of a Euler equation study, Table 5.2 describes how Whited (1992) arrives at her regression equation after a lengthy theoretical introduction. (For other examples of Euler equation studies, see Bond and Meghir (1994), Galeotti et al. (1994) and Bond et al. (2003).) Again, we direct the reader's attention to how the regression results are placed squarely in the context of the preceding mathematical

Table 5.2: An example of a Euler equation model: How Whited (1992) derives the regression equation

Equation	Description
(1)	Equilibrium expression for the value of the firm's shares
(2)	Solving (1) to obtain the firm's time zero market value
(3)	Evolution of the capital stock
(4)	Expression for cash inflows and outflows
(5)	Dividends must be non-negative
(6)	Transversality condition restricting a firm's borrowing
(7)	First order condition for the firm's maximization problem - choice of capital stock
(8)	First order condition for the firm's maximization problem - choice of borrowing
(9)	Borrowing constraints
(10)	Rewriting the first-order condition in (8)
(11)	Substituting (10) into (7)
(12)	Marginal product of capital
(13)	Quadratic form for adjustment costs
(14)	Differentiating (13), inserting into (7), and substituting (12) into (7) to obtain the regression equation

models. Any interpretation of the results as evidence of 'suboptimal' behaviour on the part of firms is thus precluded.

Empirical research into investment decisions based on q models, and the related Euler equation models, have typically produced disappointing results (Barnett and Sakellaris, 1998). The explanatory power is typically rather low (Blundell et al., 1992). Unfortunately, though, the discrepancy between the expected results and the actual results is usually attributed to 'measurement error' instead of 'theoretical error'. Also, contrary to the theory other variables enter significantly into the investment equation, such as lagged q (Chirinko, 1993) cash flow (Fazzari et al., 1988), and output (Blundell et al., 1992). Furthermore, the implied adjustment costs of investment are generally so high that they seem economically implausible (Schaller, 1990). Different versions of the same underlying theory (i.e. q models and Euler equation models) sometimes give quite different results (Whited, 2006). It has also been suggested that tests of the q -theory of investment have been outperformed by simpler 'accelerator' models of investment (Whited, 1992).

We can conclude from the preceding discussion that the q -theory of investment performs unsatisfactorily. However, we don't exactly know why. Estimation of regression equations such as (13) in Table 5.1 is not just a test of a single null hypothesis, but instead it is essentially a joint test of the whole series of previous assumptions. The failure of the model to produce results in line with the theory could be due to the failure of any of these assumptions. One problem is that average q may not be a good indicator of expected future profit (Chirinko, 1993; Erickson and Whited, 2000; Gomes, 2001). This may occur if the stock market is not perfectly efficient at foreseeing a firm's fortunes or allocating resources. Furthermore,

the denominator of q includes only fixed capital, and regrettably it does not include those elements that are truly valued by shareholders and that cannot be easily bought or sold on asset markets, such as management skill, human capital or R&D capital. Furthermore, q may not be a good predictor of investment if managers are boundedly rational, or if they just don't choose to grow on the basis of maximizing shareholder value. q may also fail to predict investment if the other assumptions mentioned above do not hold.

5.2.2 Imperfect markets theory

In the light of the disappointing performance of q -models, Fazzari et al. (1988a; FHP88 hereafter) consider US manufacturing firms that are listed on the stock market,¹ include cash flow into the investment equation and observe that it is significant. They follow up their analysis with a lengthy (if not tedious) robustness check, which reinforces their findings. Why is cash flow a significant determinant of investment? Predictions based on the neoclassical model (which is built on a large number of unreasonable assumptions such as perfect competition, perfect foresight, perfectly efficient financial markets, managers that are selfless and optimizing, linear homogenous production technologies, etc.) do not allow for cash flow to be a predictor of investment. The real reason why cash flow is significant is not really known. For example, in an uncertain environment it could be that combining cash flow and average q may yield a better proxy for marginal q than just average q alone. If firms are unable to predict the future, they may prefer to base their investment decisions on current-period indicators rather than speculative stock-market indices.² Alternatively, it could be because firms are wary of becoming dependent on external finance.³ It could also be because managers are reluctant to distribute dividends and prefer to spend free cash flow on additional investment projects (Jensen, 1986). However, *the interpretation that FHP88 chose to give is that any sensitivity of investment to cash-flow is due to financial constraints*. The authors associated any such sensitivity to catchphrases such as 'market imperfections', 'asymmetric information', and the

¹FHP88 had originally intended to study small firms, as is evident from the following quote: "Conventional representative firm models in which financial structure is irrelevant to the investment decision may well apply to mature companies with well-known prospects. For other firms, however, financial factors appear to matter in the sense that external capital is not a perfect substitute for internal funds, particularly in the short run" (FHP88: 142). However, given the requirement to obtain observations on market value (for calculating q), the final sample contains only listed firms. This may be somewhat ill-appropriate, because these firms have already reached a certain size.

²Note that Whited (2006) uses cash flow as a proxy variable for investment opportunities.

³David Packard, of Hewlett-Packard, relates how he was reluctant to become dependent on external sources of finance: "I often helped my father in looking up the records of those companies that had gone bankrupt. I noted that the banks simply foreclosed on firms that mortgaged their assets and these firms were left with nothing... The firms that did not borrow money had a difficult time, but they ended up with their assets intact and survived... From this experience I decided our company should not incur any long-term debt. For this reason Bill [Hewlett] and I determined we would operate the company on a pay-as-you-go basis, financing our growth primarily out of earnings rather than by borrowing money" (Packard, 1995: 84).

'lemons' problem. In other words, any dependence of investment on cash-flow is seen as a welfare-reducing policy problem, a failure of the capital markets, a source of inefficiency akin to the problems raised in Akerlof (1970) and Stiglitz and Weiss (1981).

One caveat of the FHP88 analysis is their choice of sample of firms. As they introduce the concept of 'financial constraints', they explain that small firms should be subject to such constraints whereas larger firms should not: "only the largest and most mature firms are likely to face a smoothly increasing loan interest rate ... Small and medium-sized firms are less likely to have access to impersonal centralized debt markets. ... during periods of tight credit, small and medium-sized borrowers are often denied loans in favor of better-quality borrowers." (FHP88: 153).⁴ However, it is perhaps ironic that their final sample consists of large firms that are quoted on the stock-market. The authors do this because they require values of Tobin's q for these firms. However, the snag is that these firms can hardly be described as small. In fact, FHP88 acknowledge this, observing that even the smallest firms in their study are "still large relative to US manufacturing corporations in general" (p159). I therefore suggest that problems of asymmetric information, which affect smaller firms much more than larger firms, is not a useful interpretation for investment-cash flow sensitivities in their study of large listed US firms.

Following on from their empirical findings, FHP88 elaborated upon the implications for policy. They underlined the importance of investment opportunities being foregone due to credit market imperfections, and they discussed the possibility of policy interventions to provide finance for liquidity-constrained firms. They also highlighted the influence of average tax rates (and not just marginal tax rates) on investment in financially-constrained firms (see also Fazzari et al., 1988b). However, in the hurry to provide an interpretation for investment-cash flow sensitivities, they seemingly overlooked other relevant dimensions of the issue. In particular, in the panel discussion following the target article, Blinder (1988) remarked that the possibility that 'managerial waste' of resources in unprofitable growth is dismissed quite precociously. Other members of the panel were critical of other aspects of the paper, such as the empirical methodology.

FHP88 has since spawned a large stream of subsequent literature and is nowadays often branded as a 'seminal paper'. The original FHP88 regression strategy has been replicated and extended on a large number of datasets. As one author remarked, "[t]he last two decades have seen a flood of empirical studies of the effects of external finance constraints on corporate investment" (Whited 2006: 467). Among this large body of research, we can mention Hu and Schiantarelli (1992), Oliner and Rudebusch (1992), Whited (1992), Gilchrist and Himmelberg (1995), Hadlock (1998) and Carpenter and Petersen (2002) for US firms, Hoshi et al (1991)

⁴A wealth of evidence on this topic is provided in Beck et al. (2005). In particular, they observe that while financial constraints are significant for small firms in developing countries, they are not important for large firms in developed countries.

for Japanese firms, Schaller (1993) for Canadian firms, Galeotti et al. (1994) and Fagiolo and Luzzi (2006) for Italian firms, Bond et al. (2003) for European firms, Audretsch and Elston (2002) for German firms, Lamont (1997) for US oil companies, and Himmelberg and Petersen (1994) and Bougheas et al. (2003) for sensitivities of R&D investments to cash flow.

A common theme of these studies is that, whenever investment (or firm growth) is associated with changes in cash flow, this is presented as ‘bad news’. It is implicitly assumed that any investment-cash flow sensitivities are signs of financial constraints, that investment opportunities have been foregone, and also that these investment opportunities would have been ‘optimal’. An interpretation based on market imperfection is evoked, and policymakers have frequently been urged to intervene to help constrained firms to grow.

However, the FHP88 approach to investment research has recently met an extensive criticism by Kaplan and Zingales (1997, 2000).⁵ To begin with, Kaplan and Zingales present a theoretical model to show that any sensitivity of investment to cash flow should not be interpreted as evidence of financial constraints. (See also the theoretical model by Alti (2003).) They also re-examine the original FHP88 database in conjunction with a scrutiny of annual company reports of these companies, and observe that the highest investment-cash flow sensitivities actually belong to those firms that seem to be the *least* financially-constrained. Indeed, ‘wrong-way’ differential investment-cash flow sensitivity has also been found by a number of other researchers, such as Gilchrist and Himmelberg (1995), Kadapakkam, Kumar and Riddick (1998), Cleary (1999) and Erickson and Whited (2000). One notable example mentioned by Kaplan and Zingales (2000) is that, in 1997, Microsoft would have been labelled as ‘financially constrained’ according to the classification schemes of Fazzari et al. (1988, 2000) even though it had almost \$9 billion in cash, corresponding to eighteen times its capital expenditures!

5.2.3 Evolutionary theory

The basic evolutionary prediction is that expansion of operations should be the domain of the ‘fitter’ firms (but not necessarily only the ‘fittest’). In contrast, the weakest should decline and exit. Furthermore, evolutionary economics stresses the importance of the Simonian notion of ‘bounded rationality’. A firm’s future is not known, it cannot be ‘rationally anticipated’, and its course can be changed by luck or human will. As a result, a firm cannot make its investment decisions on discounted expected future returns on an infinite horizon. Instead, its investment is determined by the firm’s current financial performance. The existence of any significant explanatory power of market value (reflected in Tobin’s q) over and above that of current financial performance does not undermine the fundamental relationship between growth and current profitability, instead it would probably be welcomed as supplementary

⁵See also Fazzari et al. (2000) for a reply.

information.

The dependence of firm growth on current period financial performance, or in evolutionary terms ‘selection via differential growth’, has its roots in Alchian (1950) and has been formalized in a number of analytical models (see e.g. Winter (1964, 1971) and Metcalfe (1993, 1994, 1998)) and also simulation models (see, among others, Nelson and Winter (1982), Chiaromonte and Dosi (1993), Dosi et al. (1995), Marsili (2001) and Dosi et al. (2006); see also Kwasnicki (2003) for a survey). The ‘backbone’ of these evolutionary models is the mechanism of ‘replicator dynamics’, by which growth is imputed according to some broad measure of ‘fitness’ or ‘viability’ (usually the operating margin). This mechanism can be presented formally by Fisher’s ‘fundamental equation’, which states that:

$$\delta x_i = \alpha x_i (F_i - \bar{F}) \quad (5.1)$$

where δ stands for the variation in the infinitesimal interval $(t, t + \delta t)$, x_i represents the market share of firm i in a population of competing firms, F_i is the level of ‘fitness’ of the considered firm (i.e. operating margin), α is a parameter and \bar{F} is the average fitness in the population, i.e. $\bar{F} = \sum_i x_i F_i$. It is straightforward to see that this equation favours the above-average firms with increasing market share, whilst reducing that of ‘weaker’, less profitable firms.

Empirical investigations of the evolutionary principle of ‘growth of the fitter’ are nonetheless surprisingly scarce. To my knowledge, the only two such studies of evolutionary flavour are Coad (2005) for French manufacturing firms (reproduced here as Chapter 6) and Bottazzi et al. (2007) for Italian firms.⁶ These studies regress growth on operating margin, whilst including controls for other potentially significant factors. It should be noted, however, the regression methodology is slightly different from those studies reviewed above. First of all, firm growth is measured in terms of sales growth rather than investment in fixed assets, because evolutionary theory emphasizes the important role of firm-specific capabilities and intangible capital (rather than fixed tangible assets) in economic change. Furthermore, operating margin is used instead of cash-flow as a measure of current-period financial performance: these two indicators are nonetheless closely related.⁷ Table 5.3 presents the regression equations investigated in the different theoretical approaches.

⁶See also Dosi (2007) for scatterplots of growth vs profitability for Italian manufacturing firms.

⁷Cash flow can be defined simply as “an ambiguous term that usually means cash provided by operations” (Horngren 1984: 776). More specifically, the difference between cash-flow and gross operating income is a question of adding taxes and removing depreciation and amortization. Bougheas et al. (2003) use net profit as a proxy for cash-flow. Other studies (e.g. Bond et al., 2003) build their cash flow variable from an operating margin variable, by subtracting taxes and adding depreciation.

5.3 A comparison of these theoretical perspectives

A major difference between the neoclassical and evolutionary frameworks resides in the use of mathematics. Neoclassical economics has developed a far more impressive mathematical toolkit. For example, in the paper of Blundell et al. (1992) the regression equation is presented as equation number (13) after being derived from a standard model of a perfectly competitive profit-maximizing firm (see Table 5.1). We only arrive at the regression model after making a long list of assumptions, some of which are frankly quite unrealistic.⁸ In my view, a regression strategy of this type is rather ‘over-cooked’ and should be seen as a ‘semi-empirical’ analysis, because the interpretation of the regression results is greatly overshadowed by theoretical prejudices. Instead of ‘letting the data speak’, the data is gagged and bound, the soundtrack is noisy and the main source of interpretation comes from the subtitles. Neoclassical economics may well have gained the comparative advantage in theoretical modelling, but in doing so it has had to sacrifice some of the realism of its basic assumptions – I argue that this places it at a *disadvantage* for empirical work.

Another difference between the aforementioned theoretical standpoints is the choice of relevant time horizon. Neoclassical q theory assumes that agents can accurately foresee the future and that they maximize on an infinite time horizon. Current decisions are neither influenced by past nor present values, but respond only to (rationally anticipated) future developments. It can be argued that the ‘imperfect capital-markets’ literature pioneered by FHP88 only emerged as something of an ‘ex-post rationalization’ of empirical work which showed that, contrary to the theoretical predictions, investment decisions are influenced not exclusively by expectations of the future but also by current financial performance. Evolutionary economics, however, acknowledges bounded rationality and limited plasticity in firm behaviour (i.e. limited plasticity in production, firm-specific capabilities, investment rules, cognition etc.) and prefers to explain current decisions largely in terms of past decisions that are embodied in current production routines.

A further difference concerns the characterization of the firm. In the neoclassical view, firms are assumed to be rational optimizers, with an implicit ‘optimal size’ to which they strive. Once they reach the ‘optimal size’, firms are satisfied and grow no more. In the evolutionary perspective, however, firms struggle against each other for growth opportunities, ‘firms exist to grow’, and their growth is limited only by their ability to finance such growth. (However, we need not assume that all firms have the same propensity to grow.) As a result, whilst a neoclassical might accept the statement: “If the information asymmetries could

⁸These assumptions include: the firm operates in a perfectly competitive industry, maximizes shareholder wealth, faces convex adjustment costs, has a linear homogenous production function, satisfies a capital market arbitrage condition, and optimizes on an infinite horizon (Blundell et al. (1992: 236-9)). I expect that such a combination of many unrealistic assumptions may interact multiplicatively to considerably reduce the validity of the results.

Table 5.3: Types of regression equations associated with the different theoretical perspectives

Theoretical approach	Basic regression equation	Remarks
<i>q</i> -theory (e.g. Blundell et al., 1992)	$(I/K)_{it} = \alpha + \beta_1 q_{it} + \varepsilon_{it}$	If the assumptions hold, investment should be entirely explained by <i>q</i>
Euler equation (e.g. Bond et al., 2003)	$(I/K)_{it} = \beta_1 (I/K)_{i,t-1} - \beta_2 (I/K)_{i,t-1}^2 - \beta_3 (\Pi/K)_{i,t-1} + \beta_4 (Y/K)_{i,t-1} + \varepsilon_{it}$	Investment dynamics should follow the optimal investment path in the context of parametric adjustment costs. Marginal costs of investment in time <i>t</i> are set equal to marginal costs of foregone investment in <i>t</i> + 1. Theory predicts that $\beta_1 \geq 1, \beta_2 \geq 1, \beta_3 > 0$ and $\beta_4 \geq 0$. If the Euler equation regressions perform poorly, one explanation could be that firms are financially constrained.
Fazzari et al. (1988)	$(I/K)_{it} = \beta_1 q_{it} + \beta_2 (CF/K)_{it} + \varepsilon_{it}$	Any explanatory power of cash flow over and above that of <i>q</i> indicates financial constraints
Fagiolo-Luzzi (2006)	$(\Delta S/S) = \beta_2 (CF/S)_{it} + \varepsilon_{it}$	Cash flow taken as a proxy for financial constraints. Any sensitivity of sales growth to cash flow should be interpreted as financial constraints
Evolutionary approach (e.g. Coad (2005))	$(\Delta S/S) = \beta_2 (OM/S)_{it} + \varepsilon_{it}$	Sales growth should be associated with operating margin according to the principle of ‘growth of the fitter’

Notes: *I* is investment for firm *i* at time *t*, *K* is fixed assets, *q* is Tobin’s *q*, *Y* is output, *CF* is cash flow, $(\Delta S/S)$ is the growth rate of sales, *OM* is operating margin, ε is the residual error term. $\Pi_{it} = p_{it}F(K_{it}, L_{it}) - p_{it}G(I_{it}, K_{it}) - w_{it}L_{it}$ (see Bond et al. (2003: 156)).

be eliminated, financing constraints would disappear”,⁹ the evolutionary economist acknowledges that firms would always seek to grow until their financial condition prevents them from growing further. Evolutionary firms are thus eternally financially constrained, irrespective of information asymmetries, simply because they would always prefer to be a little bit bigger than they currently are.

Predictions from evolutionary economics are also in line with those originating in the behavioural finance literature. Consider the empirically-based ‘financial pecking-order’ theory (Myers, 1984), which supposes there is an imperfect substitutability of internal and external sources of finance. In this view, firms are quite willing to spend free cash flow on investment projects but are much less enthusiastic about having to resort to external finance. As a result, changes in cash flow would be positively associated with changes in investment. Furthermore, evolutionary economics is able to accommodate ‘managerial’ theories of firm growth (see e.g. Marris, 1964), which posit that managers attach positive utility to their firm’s size. In this perspective, managers pursue growth even when this is not in the interest of shareholders. Growth is thus maximized subject to certain constraints (i.e. a minimum value for the firm’s shares). Under these circumstances, investment will respond positively to improvements in current financial performance. Relatedly, the ‘agency problem’ of free cash flow (Jensen, 1986) should be mentioned. This theory predicts that managers will be reluctant to distribute available cash flow as dividends but will prefer to spend it on investment projects (even if these are likely to generate low returns).¹⁰ Recently, however, attempts have been made by mainstream economists to introduce these afore-mentioned ‘behavioural finance’ considerations into the FHP88-based financial constraints literature (see the promising work by Goergen and Renneboog (2001) and Degryse and De Jong (2006)).

One of the dangers of the evolutionary approach is the ‘Panglossian’ notion that the evolutionary mechanism of selection transports the economy to an optimum. We should reject the kind of optimality arguments found in Friedman’s (1953) discussion of Alchian (1950), whereby ‘natural selection’ which operates via the weeding out of the weakest firms yields an ‘optimal’ economy consisting only of firms who behave ‘as if’ they maximize. Selection of firms is certainly imperfect and in some cases it is even perverse. The economy is far from optimal, there is considerable room for improvement, and as a consequence there *is* a role for policy intervention. However, the main contribution of evolutionary economics is the acceptance that firm growth will always be constrained by available liquidity, and that the viability of perceived growth opportunities cannot be taken for granted. In many cases, any sensitivity of investment to cash flow will merely reflect the healthy workings of the economy.

⁹Taken from Lerner (1998: 776).

¹⁰One difference between the ‘managerial’ and ‘free cash flow’ perspectives and the evolutionary perspective, however, is that the observed investment-cash flow sensitivities are signs of value-reducing investment in the first case but are more likely to be value-creating in the latter.

The evolutionary view therefore considers that the problem of financial constraints inhibiting investment has been exaggerated by the mainstream literature.

5.4 A comparison of the policy recommendations

In this essay it is argued that the neoclassical assumptions, that also form the basis of the ‘asymmetric information’ models, find their way into the policy conclusions. In particular, I criticize the assumption of perfectly rational, shareholder-wealth-maximizing managers. The motivations behind this choice of assumption are technical in nature and have little to do with the underlying economic reality; this assumption exists mainly to aid tractability of the mathematical construct. However, this assumption has an important role in the framing of the research question. In discussions of the empirical results, questions relating to the quality of manager’s investment projects are no longer posed. Instead, when the q -model is observed to perform poorly and cash-flow is observed to be statistically significant, all too often buzzwords such as ‘asymmetric information’ and the ‘lemons’ problem are automatically applied. In many empirical studies, it appears to be implicitly accepted that firms should have the right to realize their investment opportunities, and that the government should intervene to make sure these firms get the finance they want. To sum up, one caricature of the neoclassical approach could be: “Assume firms are efficient. Financial-market imperfections prevent them from getting enough funding for their expansion plans. Policy should intervene, perhaps by subsidizing firm investment in some way.”

A major caveat of the mainstream neoclassical literature is that it takes as a starting point the assumption that firms are perfectly rational and will invest only if this increases their long-term profits. Evolutionary economics, in contrast, discards assumptions of hyper-rationality and starts from the hypothesis that not all firms deserve to grow. This is in line with recent work (surveyed in Santarelli and Vivarelli (2006)) on the theme of excessive start-up (i.e. entry beyond the ‘socially optimum’ level). Some theoretical contributions have related over-entry to over-optimistic forecasts of entrepreneurs (Dosi and Lovallo (1998), Camerer and Lovallo (1999) and Arabsheibani et al. (2000)). These articles go on to suggest that entry of over-confident low-quality entrepreneurs may even crowd out higher-quality entrepreneurs. Another factor contributing to over-entry is that marginal entrepreneurs can free-ride on the credentials of more able entrepreneurs, thus bringing down the average quality of the credit pool (de Meza and Webb (1987, 1999), de Meza (2002)). Marginal entrants should thus be discouraged from entering. This body of theoretical work also suggests that the use of internal finance to fund start-ups has beneficial effects on start-up survival rates (through ‘incentive effects’) and also plays a role in reducing moral hazard. As a result, it has been suggested that

start-ups should not be subsidized.¹¹ Empirical evidence on excessive start-up should also be taken into consideration (e.g. Dunne et al. (1988), Bartelsman et al. (2005)). These studies highlight the waste associated with entry of new firms, by showing that a large proportion of entrants can be expected to fail only a few years.

It is perhaps unsettling to observe that the recommendations emerging from the neoclassical literature have, to a certain extent, been able to guide policy. In the United States, for example, there have been public initiatives to provide finance to small firms that are suspected of being ‘financially constrained’. According to Lerner (2002: 81-82), these “public venture capital programmes are often characterised by a considerable number of underachieving firms. . . . The end result can be a stream of government funding being awarded to companies that consistently underachieve.” Levenson and Willard (2000) are also critical of schemes such as the provision of guaranteed loans to small firms.¹² They remark that “there is no direct evidence that small firms are, in fact, credit rationed in formal capital markets” (2000: 84). Using data from a national survey in 1988-89, they calculate an upper bound for the share of small businesses that were credit-rationed as 6.36%, and conclude that “the extent of true credit rationing appears quite limited” (p83). Finally, it should be noted that apart from being a waste of funds, government initiatives to alleviate financial constraints also have the drawback of encouraging socially-wasteful rent-seeking behavior (Lerner, 2002).

5.5 Conclusion

In the face of “mounting evidence that cash flow sensitivities are not interesting measures of finance constraints” (Whited 2006: 496), I develop an evolutionary opinion on the issue. As I survey the literature on financial constraints and firm growth, I document the failure of ‘hyper-parametric’ neoclassical models. I consider that perfect rationality has been overemphasized at the expense of more ‘behavioural’ and ‘managerial’ perspectives on growth. I maintain that it is not possible to talk about problems of limited finance for firm investment by starting from the assumption that firms invest only in profit-maximizing projects. The assumption that managers are rational and maximize shareholder wealth is not a good benchmark or reference point. A much more suitable starting point would be the evolutionary position that firms are heterogeneous, do not know how they will perform, and have a lot of discretion in their growth rates. Furthermore, it is meaningful to suppose that profitable firms have higher quality investment projects than less profitable ones. I also point out that, whilst the existence of any sensitivity of investment to cash-flow is interpreted as a problem for policy for

¹¹de Meza and Webb (1999) even go on to suggest that entrepreneurs should be given incentives not to enter, or else that they should be taxed if they do enter.

¹²The Small Business Administration (SBA) provided \$2.8 billion in guaranteed loans to small firms in 1986 alone.

neoclassical economists, for their evolutionary counterparts who do not have such restrictive theoretical lenses it is merely a sign of a well-functioning economy. As a result, I suggest that the problem of asymmetric information leading to financial constraints has been exaggerated by much of the mainstream literature.

Neoclassical theory has the advantage of a developed theoretical apparatus. Evolutionary economics does not have such clear-cut mathematical models because it has preferred not to sacrifice realism for analytical tractability. In this sense, whilst neoclassical modelling may have the upper hand in theoretical modelling, evolutionary economics may have the advantage in empirical work. Indeed, if we try to apply complex neoclassical structural models to empirical analysis, we may quickly assume too much and lose sight of the ‘reality’ that the data is actually trying to tell us.

One caveat in this discussion is that we have not considered the varying importance of financial constraints over the firm’s life-cycle in a satisfactory manner. It is reasonable to suppose, if anything, that young small firms have a need for finance that exceeds their revenue, whereas older and larger firms have a revenue that exceeds their need for finance. In this way, young firms would be financially constrained whereas old firms would be more prone to ‘managerial’ phenomena associated with excess cash flow. However, both the neoclassical and the evolutionary perspectives on financial constraints, as presented here, have not taken this into account in an adequate way. As a result, we may have overlooked the importance of financial constraints for young firms, even if financial constraints are of limited relevance for older firms. Nevertheless, evidence presented by Levenson and Willard (2000) suggests that financial constraints are quite limited even for small firms.

After the frequently negative tone of this confrontation between the neoclassical and evolutionary perspectives, it is nonetheless possible to salvage a handshake. One ‘stylized fact’ that emerges from both mainstream and evolutionary approaches is that firm investment and growth is, to a large extent, idiosyncratic. Firms have a considerable amount of discretion in their investment decisions and growth rates. This is indeed a stumbling-block for both the q theory and evolutionary theory.

Chapter 6

Testing the principle of ‘growth of the fitter’: the relationship between profits and firm growth

“The race is not to the swift or the battle to the strong,
nor does food come to the wise or wealth to the brilliant or favor to the learned;
[nor is expansion of operations to the more profitable firms;]
but time and chance happen to them all.”

Ecclesiastes 9:11, The Holy Bible (NIV).

In this Chapter I look at the relationship between profits and growth, where the interpretation of the coefficients is placed in the context of the discussion in Chapter 5. Despite the bold and largely unsubstantiated assumptions made in a number of theoretical models, we observe that the expected relationship between profits and growth appears to be largely absent.

6.1 Introduction

The modern economy is increasingly characterized by turbulent competition and rapid technical change, and as a consequence a dynamic theory of competitive advantage may well be more relevant to understanding the economics of industrial organization than the more neo-classical concepts of equilibrium and static optimization. Evolutionary economics has thus been able to make a significant impact on IO thinking, because it proposes a *dynamics first!* conceptualization of the economy. Evolutionary theory has its foundations in Schumpeter’s vision of capitalism as a process of ‘creative destruction’, and borrows the notions of diversity creation and selection to account for the dynamics of economic development. Alchian’s (1950)

theoretical paper argues that the evolutionary mechanism of selection sets the economy on the path of progress, as fitter firms survive and grow whilst less viable firms lose market share and exit. The notion of selection via differential growth is also a central theme in Nelson and Winter's (1982) seminal book. These authors present a formal microfounded simulation model in which firms compete against each other in a turbulent market environment. Firms that are more profitable are assumed to grow, whilst firms that are less successful are assumed to lose market share. Agent-based simulation modeling has since remained a dominant tool in the evolutionary literature (see, among others, Chiaromonte and Dosi (1993), Dosi et al. (1995), and Marsili (2001); see also Kwasnicki (2003) for a survey). In addition to computer simulation models, the principle of 'growth of the fitter' has also formed the foundations of analytical evolutionary models (see, for example, Winter (1964, 1971), Metcalfe (1993, 1998)).

The backbone of these evolutionary models is undeniably the mechanism of 'replicator dynamics', by which growth is imputed according to profitability. This mechanism can be presented formally by Fisher's 'fundamental equation', which states that:

$$\delta M_i = \rho M_i (F_i - \bar{F}) \quad (6.1)$$

where δ stands for the variation in the infinitesimal interval $(t, t + \delta t)$, M_i represents the market share of firm i in a population of competing firms, F_i is the level of 'fitness' of the considered firm, ρ is a parameter and \bar{F} is the average fitness in the population, i.e. $\bar{F} = \sum M_i F_i$. It is straightforward to see that this equation favours the 'fitter' firms with increasing market share, whilst reducing that of 'weaker' firms. This 'replicator dynamics' does sound intuitively appealing, because implicit in it is the idea that selective pressures act with accuracy, that financial constraints prevent inefficient firms from growing, and that the economic system adapts so as to efficiently allocate resources amongst firms, such that firms 'get what they deserve'. However, these assumptions may not find empirical validation for a number of reasons. First of all, it cannot be assumed that all firms have the same propensity to grow. Some high-profit firms may not be interested in business opportunities that are instead taken up by less demanding firms. Freeland (2001), for example, describes how GM's shareholders resisted investing in additional business opportunities and sought to restrict growth expenditure even when GM was a highly profitable company. If this is the case, then stricter internal selection will cause high-profit firms to overlook opportunities that are instead taken up by less profitable competitors. In this way, growth may be negatively related to profitability. An extension of this idea is presented by the managerial literature, which identifies a tension between profits and growth – this arises when managers seek to grow at a rate higher than that which would be 'optimal' for the firm as a whole, with the resulting growth rate being limited by shareholder supervision. If shareholders monitor management closely, growth rates

are predicted to be low and profit rates high. Second, high profits may be made by firms that can exercise market power by restricting their production to obtain a higher price per unit sold. In this case, a firm which has sufficiently inelastic demand for its goods would have a higher profit rate if it reduces its capacity. In this case too, increases in profits would be associated with negative growth. Third, if a firm occupies a highly profitable niche market, it may not have opportunities to expand despite its high profits. Fourth, a firm may experience a higher profit rate due to efficiency gains by downsizing and concentrating on its core competence. Here again, we have no reason to suppose a positive association between profits and firm growth.

Some empirical studies have also cast doubt on the validity of the principle of ‘growth of the fitter’. Baily et al. (1996) observe that, among plants with increasing labour productivity between 1977 and 1987, firms that grew in terms of employees were balanced out by firms that decreased employment. They find that about a third of labour productivity growth is attributable to growing firms, about a third to downsizing firms, and the remaining third is attributable to the processes of entry and exit. Foster et al. (1998) also fail to find a robust significant relationship between establishment-level labour productivity or multifactor productivity and growth (see also the review in Bartelsman and Doms (2000: 583-584)). In addition, using a database of Italian manufacturing firms, Bottazzi et al. (2002) fail to find a robust relationship between productivity and growth (see also Dosi (2007)). Furthermore, evidence from UK manufacturing plants reveals a *negative* between-effect in allocation of market share between firms according to productivity, over a time scale of 6 years (Disney et al. (2003: 683)). These studies present some scraps of evidence hinting that the rule of ‘growth of the fitter’ does not necessarily hold when productivity is taken as a proxy for fitness. However, a serious limitation of these studies with regard to our present investigation is that they do not deal with the econometric issues of time lags, inclusion of control variables (such as size, industry effects, and firm-specific fixed effects), or endogeneity.

If profits are taken as the proxy, then the profits and growth series appear to have rather different statistical properties. Empirical studies have shown that relative profit rates are remarkably persistent, experiencing significant positive serial correlation (see, for example, Mueller (1977) and also Dosi (2007) for a review). Firm growth rates, however, are much more random, and it has been suggested that they are best modelled as a random walk (Geroski, 2000).¹ These preliminary observations fuel suspicion that above-average profits are not translated into above-average firm growth. Geroski and Mazzucato (2002) comment on this statistical discrepancy and conclude that profits and growth are ‘deeply incongruent’ (p642). It is also relevant to mention that Sargent-Florence (1957) fails to find the expected correlation between growth in market value and growth in assets, for large listed UK firms –

¹See, however, Chapter 4 for evidence and a discussion of firm growth rate autocorrelation.

“Curiously enough, the two measures pointed in different directions” (p246). In this paper we aim to complement these studies by testing the principle of ‘growth of the fitter’, measuring ‘fitness’ using the profit rate (i.e. operating surplus/Value Added). We prefer this proxy, because Fisher’s fundamental equation is usually applied to evolutionary models by taking profits as the proxy for fitness (e.g. Nelson and Winter, 1982).

As we have seen, very few empirical studies have considered the link between profits and growth.² This is quite surprising given the central position of replicator dynamics (equation (6.1)) in evolutionary modeling. What is perhaps more worrying is that the simplifying assumptions made in evolutionary models have even often been accepted not as simplifications but as fact, and thus adopted by subsequent theory. As Gavetti writes: “[the evolutionary economics] perspective’s need for a stark formal apparatus led to the choice of oversimplified behavioral foundations (Nelson and Winter, 1982), and the effects of this choice remain embedded in current theoretical and empirical work” (Gavetti, 2005: 1). The principle of ‘growth of the fitter’ is frequently not just seen as a modeling simplification, but it seems to be largely accepted in theoretical discourse. We therefore consider it necessary to focus explicitly on testing the theory of ‘growth of the fitter’. Indeed, if evolutionary economics claims to be a *dynamics first!* discipline, it is of paramount importance that it take great care in its conceptualization of economic dynamics.

We perform the analysis using an extensive longitudinal balanced dataset on 8405 French manufacturing firms over the period 1996-2004. We begin by presenting non-parametric plots that allow a visual appreciation of the underlying relationship. We then present a parametric analysis using in particular the ‘system GMM’ panel data estimator, which is of special interest here because of its ability to give consistent coefficient estimates in the presence of endogenous explanatory variables. Whilst the previous studies surveyed above have nourished speculation that the principle of ‘growth of the fitter’ does not hold, they can by no means be considered to provide conclusive evidence. There are several econometric issues that have yet to be taken into account. The originality of this paper is that we focus explicitly on the relationship between profits and growth and tackle econometric difficulties head-on. We control for the effects of other variables (such as size or firm-specific effects) on the relationship between profits and growth, we allow for a time lag, and we face up to the very real problem of endogeneity.

The layout of the paper is as follows. Section 6.2 presents the database. Section 6.3 presents the theoretical motivations for suspecting endogeneity in the relationship between profits and growth, and then presents the ‘system GMM’ panel data estimator which is able

²The work of Bottazzi et al. (2006), which came to the author’s attention rather recently, is also worth mentioning here. Applying non-parametric techniques to Italian manufacturing firms, they fail to find any substantial relationship between either profitability and sales growth, or productivity and sales growth. However, their results emerge mainly from an observation of scatterplots, and as a result their analysis does not take into consideration econometric issues such as time lags, the inclusion of control variables, or endogeneity.

to give unbiased and consistent estimates in the presence of endogeneity. Section 6.4 presents both non-parametric plots and parametric regression results, and section 6.5 concludes.

6.2 Database

This research draws upon the EAE databank collected by SESSI and provided by the French Statistical Office (INSEE). This database contains longitudinal data on a virtually exhaustive panel of French firms with 20 employees or more over the period 1989-2004. We restrict our analysis to the manufacturing sectors.³ For statistical consistency, we only utilize the period 1996-2004 and we consider only continuing firms over this period. Firms that entered midway through 1996 or exited midway through 2004 have been removed. Since we want to focus on internal, ‘organic’ growth rates, we exclude firms that have undergone any kind of modification of structure, such as merger or acquisition. In contrast to some previous studies (e.g. Bottazzi et al., 2001), we do not attempt to construct ‘super-firms’ by treating firms that merge at some stage during the period under study as if they had been merged from the start of the study, because of limited information on restructuring activities. In order to avoid misleading values and the generation of NANs⁴ whilst taking logarithms and ratios, we retain only those firms with strictly positive values for Value Added, total fixed assets and employees in each year. Firms are classified according to their sector of principal activity. To start with we had observations for around 22 000 firms per year for each year of the period.⁵ In the final balanced panel constructed for the period 1996-2004, we have 8405 firms for each year.

The reader may have noticed that our database in this chapter differs from the data used in Chapters 3 and 4 in that it includes supplementary data for 2003 and 2004. This data became available only relatively recently. We consider it to be important to repeat our earlier analysis using this extended database in order to have a larger number of observations, thereby ensuring that our results are as reliable as possible.

The empirical literature on industrial structure and dynamics proposes several different indicators of firm size, although the most common are probably sales and number of employees. We consider three candidate measures of firm size – sales, employment, and Value Added. The correlation coefficients for these three indicators are shown in table 6.1, and the size distributions are shown in figure 6.1. Value Added is shown to be better correlated with the two other variables, and so it would appear to be the preferable size indicator.

³More specifically, we examine firms in the two-digit NAF sectors 17-36, where firms are classified according to their sector of principal activity (the French NAF classification matches with the international NACE and ISIC classifications). We do not include NAF sector 37, which corresponds to recycling industries.

⁴NAN is shorthand for Not a Number, which refers to the result of a numerical operation which cannot return a valid number value. In our case, we may obtain a NAN if we try to take the logarithm of a negative number, or if we try to divide a number by zero.

⁵22 319, 22 231, 22 305, 22 085, 21 966, 22 053, 21 855, 21 347 and 20 723 firms respectively.

Table 6.1: Correlations between size indicators ($N=75645$; p -values in parentheses)

	log_sales	log_empl	log_va
log_sales	1.0000	-	-
log_empl	0.8405 (0.0000)	1.0000	-
log_va	0.8905 (0.0000)	0.8881 (0.0000)	1.0000

Table 6.2: Correlations between growth indicators ($N=67240$; p -values in parentheses)

	gr_sales	gr_empl	gr_va
gr_sales	1.0000	-	-
gr_empl	0.3805 (0.0000)	1.0000	-
gr_va	0.6430 (0.0000)	0.3557 (0.0000)	1.0000

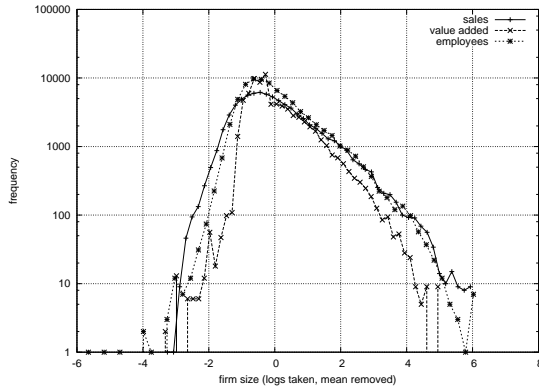


Figure 6.1: Firm size distribution ($N=75645$, log scale on y)

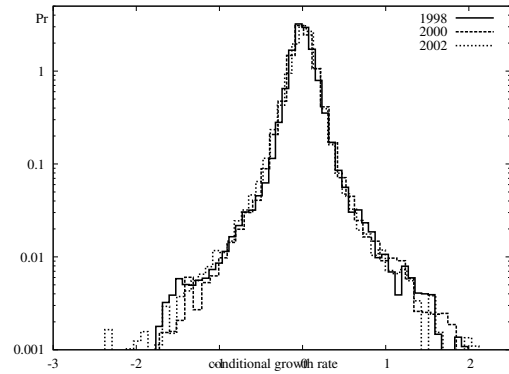


Figure 6.2: Growth rates distribution ($N=67240$, log scale on y)

In keeping with previous studies, our measure of growth rates is calculated by taking the differences of the logarithms of size:

$$GROWTH_{it} = \log(SIZE_{it}) - \log(SIZE_{i,t-1}) \tag{6.2}$$

where $SIZE$ is measured in terms of sales, employees or Value Added, for firm i at time t . The correlations between the growth rate indicators are shown in table 6.2, and the growth rate distributions are shown in figure 6.2. Sales growth is the better correlated with the two other measures. Employment growth is the least strongly correlated with the others, but we consider it to be of interest in its own right – indeed, employment growth is a crucial objective from the point of view of policy-makers.

Care must be taken in constructing our profit rate indicator, because in the past firm profit rates have been criticised as potentially misleading indicators (Fisher and McGowan, 1983). The phenomenon of interest here is the raw commercial viability associated with the production process, without the distortion of such things as taxes or overhead costs. As a result, we construct our profit indicator using a firm’s gross operating surplus (‘excédent brut d’exploitation’ *en français*). This is then scaled down by Value Added in order to obtain a profit ratio.⁶

⁶To be precise, operating surplus at time t is scaled down by Value Added at time $t - 1$ to avoid spurious

One shortcoming of this study is that it considers a balanced panel of surviving firms and does not deal with exit. It is reasonable to expect that firms with poorer financial performance have a higher exit rate. Nonetheless, we maintain that the finding that there is virtually no relationship between profit rate and growth rate, even among surviving firms only, is nonetheless quite powerful in itself. Put differently, selection can be seen to have two components – selection via differential growth (‘growth of the fitter’) and selection via exit (‘survival of the fitter’). Although the extreme form of selection embodied in the principle of ‘survival of the fitter’ is quite likely to be observed, many authors (such as Nelson and Winter, 1982) assume both selection mechanisms to be at work. In this article I am testing the principle of ‘growth of the fitter’ and not that of ‘survival of the fitter’.

6.3 Methodology

In this section we will discuss the problem of endogeneity in the relationship between profits and growth from a theoretical perspective. We then present the ‘system GMM’ estimator, which is able to give consistent regression estimates even if some explanatory variables are not strictly exogenous.

6.3.1 Sources of endogeneity in the regression of profits on growth

In this paper we are interested primarily in the effects of profit rate on firm growth, but we cannot investigate this without considering the (possibly simultaneous) effects of growth on profitability. Several authors have identified ways in which firm growth can be negatively associated with rates of profit. The classical, Ricardian stance is that if a firm is enjoying relatively high profit rates, it will expand to exploit additional business opportunities that are less profit-intensive but that nonetheless generate profit. In neoclassical terms, such a firm grows until its marginal cost of production is equal to the marginal revenue on goods sold. Such a firm begins by exploiting its most profitable business opportunities, and then includes less and less profitable opportunities until the marginal profit on the last opportunity exploited is equal to zero. Thus, a profitable firm that expands in this way maximizes its overall levels of profits, but experiences a decrease in its profit *rate* when profits are divided by scale of production. Edith Penrose (1959) also suggests that growth may lead to a reduction in the profit rate, although for different reasons. Firm growth requires managerial attention, and if managers focus on the expansion of their firm, their attention is diverted from keeping operating costs down. Thus, ‘Penrose effects’ occur when costs inflate as managers focus not on operating efficiency but instead on exploiting new opportunities. On the other hand,

results associated with the ‘regression fallacy’ (for more on this, see Friedman (1992)).

the notion of ‘increasing returns’ predicts that growth will lead to a higher, not lower, profit rate. Static increasing returns may allow a firm to achieve gains from specialization and build up economies of scale in production, thus reducing the unit cost of its products. Dynamic increasing returns, as described by Kaldor and Verdoorn, can also be applied at a firm-level, such that firm growth leads to increases in productivity and thus increases in profit rates. Expanding firms may invest in new technologies and learn about more efficient methods of production. Their growth may also be an anticipation of medium-term demand prospects, which (if correctly anticipated) would allow them to earn large profits in the future. Finally, from the resource-based perspective, growth may lead to increases in profits if it feeds off organizational slack and puts resources that were previously idle or underutilized to good use. An implication of learning-by-doing is that managerial (and other) resources are continually being freed up as time passes and experience accumulates. Large profits can be earned if these newly-liberated resources are used to grow the firm.

In the following quantitative analysis, we will investigate both the effects of profits on growth, and of growth on profits. The quantitative analysis will help us to evaluate the theoretical contributions described above, because we will be able to see if growth has a positive or negative overall effect on the profit rate.

6.3.2 An introduction to system GMM

Ordinary Least Squares (OLS) regression estimation requires that the explanatory variables be orthogonal to the residual error term. This condition is not satisfied if the explanatory variables are endogenous, i.e. if there is a bi-directional causation between the dependent variable and the explanatory variables. In such cases OLS performs poorly, yielding biased and inconsistent estimates.

This problem of endogeneity can be overcome by a judicious choice of instrumental variables. These latter are uncorrelated with the error term but are nonetheless able to give information about the explanatory variable, and so they can be included in the regression calculations where appropriate in place of the problematic explanatory variable. If instrumental variables are poorly correlated with the explanatory variable, however, then the instruments are said to be weak. Weak instruments give regression estimates that are biased and inconsistent.

Arellano and Bond (1991) proposed a GMM estimator for panel data which includes instruments yielding additional information about potentially endogenous explanatory variables. The regression equations are expressed in terms of first differences (thus eliminating the time-invariant firm-specific effects), and endogenous explanatory variables are instrumented with suitable lags of their own levels. Monte Carlo tests reveal that this estimator can give su-

terior results to previously used methods (Arellano and Bond, 1991). However, it also has drawbacks. If the lagged levels are weakly correlated with the differences of the explanatory variables, then the supplementary instruments included by this estimator are not very useful, and so large finite sample bias may still occur. Such a weak correlation can arise if the lagged levels to be used as instruments are a highly persistent series. Indeed, persistence in profit rates has been found in previous studies (e.g. Mueller, 1977).

An improved panel data GMM estimator was outlined by Arellano and Bover (1995) and fully developed by Blundell and Bond (1998). Arellano and Bover (1995) construct a panel data GMM estimator in which the regression equations are in levels, and the additional instruments are expressed in lagged differences. Blundell and Bond (1998) augment the original differences GMM estimator with the level-equation estimator to form a system of equations known as ‘system GMM’. The resulting system of regression equations in differences and also levels has better asymptotic and finite sample properties than the Arellano-Bond (1991) differences GMM estimator.

System GMM is a suitable estimator for panel datasets in which the explanatory variables are not strictly exogenous (see Bond (2002) for an introduction to system GMM and associated estimators). Yasar et al. (2006a), for example, use GMM to investigate the effects of plant-level productivity on exporting behavior, where the phenomenon of learning-by-doing is suspected of introducing a feedback from exporting behavior to productivity. Blundell and Bond (2000) apply their system GMM estimator to the estimation of a Cobb-Douglas production function, where persistence in series reduces the reliability of the Arellano-Bond estimator (i.e. ‘difference GMM’).

In the context of this study, system GMM is able to deal with endogeneity and firm-specific effects, and can give unbiased and consistent estimates even though the dataset only spans a 9-year period (for system GMM, the minimum requirement is that $T \geq 3$ (Blundell and Bond, 1998)). To help overcome difficulties linked to endogenous explanatory variables, system GMM uses a potentially large matrix of available instruments and weights them appropriately. However, the inclusion of extra instruments requires additional moment conditions. Consider the panel-data regression equation:

$$y_{it} = a_{it} + b_{it}x_{it} + u_{it} \quad (6.3)$$

where $u_{it} = \nu_i + e_{it}$. x_{it} is a vector of variables that are not strictly exogenous, ν_i are the unobserved time-invariant firm-specific effects, and e_{it} are the observation-specific error terms. The additional moment conditions can be formalized as follows:

$$E(\Delta e_{it}y_{i,t-r}) = 0; E(\Delta e_{it}x_{i,t-r}) = 0; \text{ where } t = 3, \dots, T \text{ and } r \geq 2 \quad (6.4)$$

$$E(u_{it}\Delta y_{i,t-r}) = 0; E(u_{it}\Delta x_{i,t-r}) = 0; \text{ where } t = 4, \dots, T \text{ and } r \geq 1 \quad (6.5)$$

Equation (6.4) comes from the difference GMM estimator's need for orthogonality between the differences of the errors and the lagged levels of the variables, which are to be used as instruments. Equation (6.5) comes from the levels-equation GMM estimator's need for orthogonality between the firm-specific effects and the lagged differences of the variables, which will be used as instruments. If these two moment conditions are not satisfied, then the additional instruments are not valid. It is therefore of use to check the validity of the instruments using specification tests (i.e. tests of overidentifying restrictions). We report Hansen test statistics⁷ alongside the regression results, and these test statistics indicate that our instruments are in fact valid and that the moment conditions in equations (6.4) and (6.5) are met.⁸ Another requirement of the system GMM estimator is that there is no serial correlation (of order 2) in the error terms. We report the relevant statistics with the regression results. Although first-order autocorrelation is present, we generally do not observe AR(2) correlation.⁹ We therefore consider the system GMM estimator to be suitable for this study.

6.4 Analysis

To start with, we present non-parametric scatterplots of the relationship between profits and growth. These plots offer us a visual appreciation of the underlying qualitative phenomenon before we move on to more technical, and perhaps less transparent, quantitative methods.

6.4.1 Non-parametric analysis

In what follows, we plot the profit rate (at time $t - 1$) on the abscissa, and the growth rate (over the period $t - 1 : t$) on the ordinate.

The clouds of points shown in figures 6.3, 6.4 and 6.5 do not reveal any obvious relationship between profit rate and subsequent growth, whether growth is measured in terms of sales, employment or Value Added. We also verified that changing the number of lags in the relationship between profits and growth does not change the picture greatly.

To ensure that the clouds of points are not merely the result of statistical aggregation, we repeat the analysis at a sectoral level. Figure 6.6 presents plots for six 2-digit ISIC sectors

⁷Tests for over-identifying restrictions usually give the Sargan statistic. However, we prefer the Hansen J statistic, since the Sargan statistic is not robust to heteroskedasticity or autocorrelation (Roodman, 2005). This Hansen J statistic is the (robust) minimized value of the two-step GMM criterion function, whereas the Sargan statistic is the minimized value of the one-step GMM criterion function (Roodman, 2005).

⁸In this study, the Hansen statistics are relatively small, and the corresponding p -values are high, so we cannot reject the null hypothesis that the moment conditions are satisfied.

⁹The null hypothesis of no AR(2) serial autocorrelation is rejected if the z statistics are high and the corresponding p -values are low (lower than 0.05 for the 5% significance level).

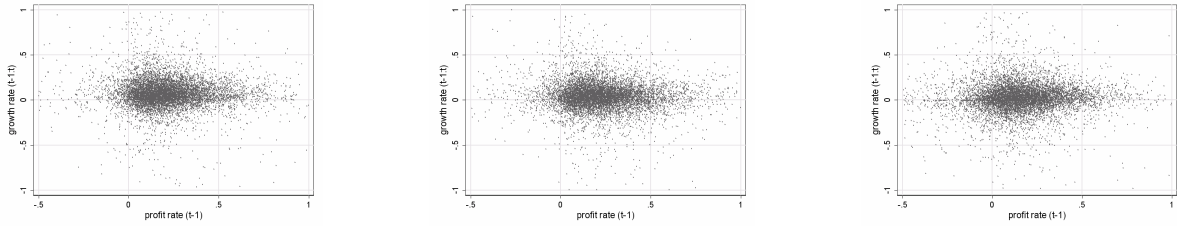


Figure 6.3: The relationship between profit rate ($t - 1$) and sales growth($t - 1 : t$) in 1998 (left), 2001 (centre) and 2004 (right)

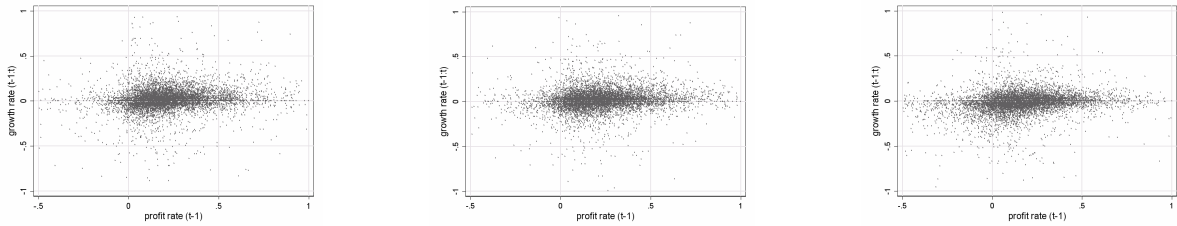


Figure 6.4: The relationship between profit rate ($t - 1$) and employment growth($t - 1 : t$) in 1998 (left), 2001 (centre) and 2004 (right)

that have been selected according to the twin criteria of having diverse production technologies and also containing a reasonable number of observations. Once again, we fail to observe a relationship between profit rate and subsequent growth.

6.4.2 Parametric analysis

The preceding graphs were useful in providing a visual representation of the underlying relationship between profit rate and subsequent growth, but they are admittedly rather crude and were presented merely by way of introduction to the data. In order to rigorously examine the underlying relationship between profit rate and subsequent growth, we need to control for any potentially misleading influence on growth rates of lagged growth, size dependence (i.e. possible departures from Gibrat's law), sectoral growth patterns or unobserved heterogeneity in the form of time-invariant firm-specific effects. Furthermore, graphs can only present associations and are not able to address the direction of causality between the two variables. To face this issue, we will now use panel-data instrumental-variable techniques in an attempt to

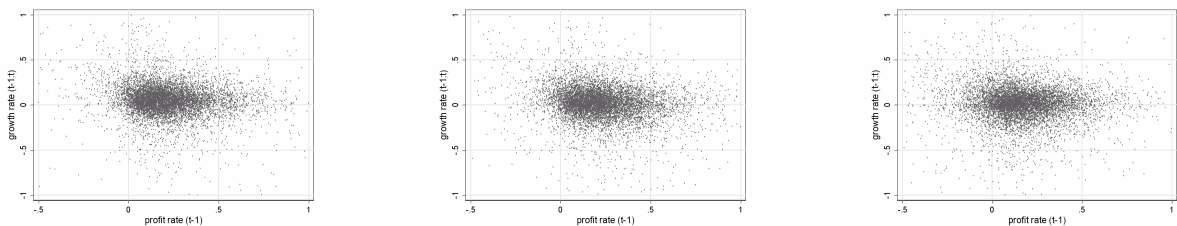


Figure 6.5: The relationship between profit rate ($t - 1$) and Value Added growth($t - 1 : t$) in 1998 (left), 2001 (centre) and 2004 (right)

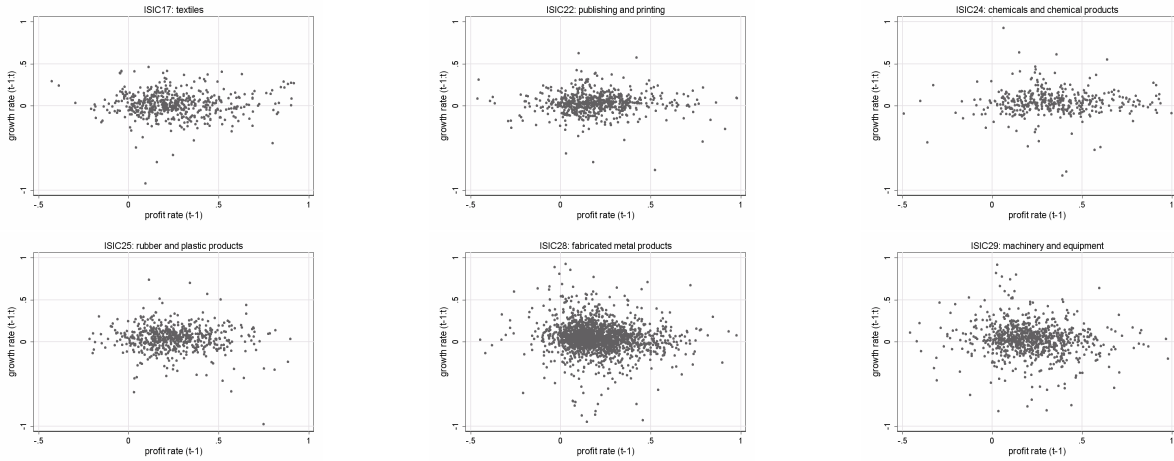


Figure 6.6: The relationship between profit rate ($t-1$) and sales growth($t-1:t$) in 2001 for selected 2-digit sectors

disentangle the bi-directional relationship between profit rate and growth rate.

The effect of profits on growth

To investigate the influence of the profit rate on subsequent growth, we estimate the following regression equation:

$$GROWTH_{it} = \beta + \sum_{k=1}^q \gamma_k PROFIT_{i,t-k} + \zeta CONTROL_{i,t-1} + \varepsilon_{it} \quad (6.6)$$

where β , γ_k , and ζ are parameters to be estimated, and ε_{it} are i.i.d. error terms. $PROFIT_{it}$ represents the profit rate of firm i in year t . We control for macroeconomic fluctuations and industry effects by including dummy variables for each year and for each 2-digit manufacturing sector, and control for lags of the dependent variable. Given that the ‘Gibrat’s law’ literature generally identifies a weak negative relation between firm size and expected growth rate, we also take (lagged) firm size into consideration. These control variables are included in all of our regressions under the variable $CONTROL$, and are often observed to be significant, but for the sake of space they will not be reported in the results tables.

Table 6.3 shows the results for various regression estimators. To begin with, we report pooled OLS and fixed effects estimates, but since these estimators do not address the issue of endogeneity they are likely to perform poorly. Indeed, we observe that they yield results that are not in concordance with each other – the OLS coefficients are all positive whilst the fixed-effects coefficients are all negative. In situations of panel data regressions with endogenous variables, OLS is likely to be biased upwards, whilst fixed-effects estimates are prone to being downward-biased (Blundell and Bond, 2000; Bond, 2002). We also observe that the R^2 statistics for these two estimators are rather low, suggesting that financial performance

Table 6.3: Regression results - finding the right estimator

	Pooled OLS	Fixed effects	Diffs GMM (Arellano-Bond)	Levels GMM (Arellano-Bover)	System GMM (Blundell-Bond)
Dep var:					
Sales gr. ($t-1:t$)	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Op. margin ($t-1$)	0.0052	-0.0094	0.0115	0.0024	0.0033
t -stat	1.58	-1.85	0.24	0.88	1.08
Op. margin ($t-2$)	0.0047	-0.0185	0.0097	0.0031	0.0026
t -stat	2.25	-1.95	0.20	2.34	2.25
Op. margin ($t-3$)	0.0019	-0.0281	0.0097	0.0034	0.0028
t -stat	1.24	-1.71	0.21	2.19	2.56
<hr/>					
R^2 (within)		0.1952			
R^2 (between)		0.1548			
R^2 (overall)	0.0844	0.0384	-	-	-
F -stat	19.24	212.72	89.99	119.01	118.87
DoF	99, 41925	10, 33610	9, 8404	10, 8404	10, 8404
p -value	0.0000	0.0000	0.000	0.000	0.000
AR(1) z -stat	-	-	-9.02	-13.21	-13.80
p -value	-	-	0.000	0.000	0.000
AR(2) z -stat	-	-	0.29	0.06	-0.26
p -value	-	-	0.775	0.948	0.798
No. Instruments			13	16	20
Hansen χ^2	-	-	0.20	3.77	7.24
DoF (p -value)	-	-	3 (0.977)	5 (0.583)	9 (0.612)
Obs.	42025	42025	33620	42025	42025

does not explain a great deal of variation of firm growth.

Turning now to the issue of endogeneity, we begin with the ‘differences GMM’ estimator (Arellano and Bond, 1991). This estimator takes the first-difference of the regression equation (6.6) and uses lagged levels of the endogenous variables as instruments, in accordance with the moment restriction described in equation (6.4). However, given that there is persistence in levels, particularly for the profit rates, this reduces the effectiveness of the instruments (hence the very low t -statistics). To take this into account, we report results from ‘levels GMM’ (Arellano and Bover, 1995), which regresses levels of the variables taking lagged differences as instruments. It appears that the levels GMM estimator is more appropriate in our case. Finally, we report the ‘system GMM’ estimates, which implements a larger instrument matrix by simultaneously exploiting the two moment conditions in equations (6.4) and (6.5).¹⁰ These latter estimates indicate that there is a slight but positive influence of profits on subsequent sales growth. This influence is statistically significant for the second and third lags, although taking longer lags into consideration did not yield significant results.

¹⁰It should be noted, however, that the inclusion of these additional instruments does not decrease the validity of the instrument matrix, since the Hansen statistic indicates that the instruments are exogenous. Given the large values for the Hansen test p -values, we fail to reject the null hypothesis that, collectively, the instruments are exogenous.

Table 6.4: system GMM regression results: profit rate on growth

Dep var: Growth(t)	System GMM					
	sales		empl		VA	
	Coeff.	t -stat.	Coeff.	t -stat.	Coeff.	t -stat.
Profits ($t-1$)	0.0033	1.08	0.0010	0.51	-0.0126	-1.14
Profits ($t-2$)	0.0026	2.25	0.0027	1.41	0.0088	1.25
Profits ($t-3$)	0.0028	2.56	0.0006	0.19	0.0282	2.77
F -stat	118.87		120.35		64.20	
DoF & p -value	10, 8404	0.000	10, 8404	0.000	11, 8404	0.000
AR(1) z -stat & p -value	-13.80	0.000	-4.62	0.000	-14.15	0.000
AR(2) z -stat & p -value	-0.26	0.798	1.55	0.121	-0.53	0.593
No. Instruments	20		20		20	
Hansen	7.24		16.31		8.79	
DoF & p -value	9	0.612	9	0.061	8	0.360
Obs.	42025		42025		42025	

We also applied quantile regression methods to the dataset, because previous research has shown substantial variation in coefficient estimates across the conditional firm growth rate distribution (see Chapters 4 and 7). In this particular case, however, nothing of interest was observed – the coefficient estimates remained roughly constant across the spectrum.

Table 6.4 presents the regression results for both profit indicators and all three growth indicators (results that are significant at the 5% level appear in bold ink). We are able to detect a positive and statistically significant influence of profits on sales growth, when both the second and third lag of profits is taken. Concerning employment growth, none of coefficients on the lagged profit rate are significant at the conventional 5% level. However, the lagged profit rate (at $t - 3$) has a positive and statistically significant effect on Value Added growth 2 years later.

The effect of growth on profits

In light of the discussion in section 6.3.1, we now consider the influence of growth on profits. An introductory inspection of the scatterplots in figure 6.7 reveals that there does not seem to be any clear relationship between firm growth and future profits.

We estimate the following regression equation:

$$PROFIT_{it} = \theta + \sum_{m=0}^p \lambda_m GROWTH_{i,t-m} + \rho CONTROL_{i,t-1} + \xi_{it} \quad (6.7)$$

The control variables are firm size ($t - 1$), 3-digit industry dummies, lagged profit rates and

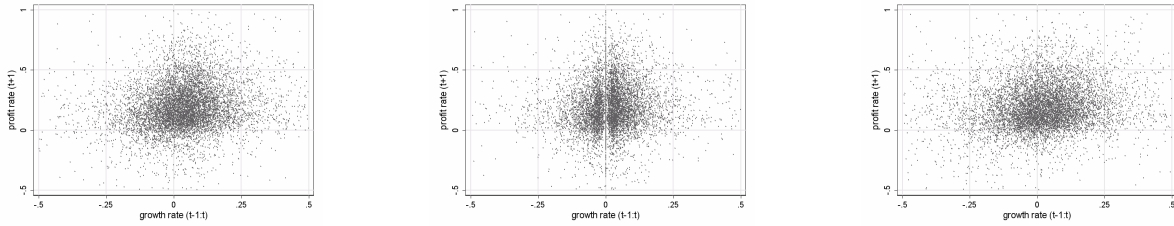


Figure 6.7: The relationship between growth ($t - 1 : t$) and profit rate ($t + 1$), when growth is measured in terms of sales (left), employment (centre) and Value Added (right), for $t = 2001$

year dummies. This time we report only OLS and FE estimates, since these are more or less in agreement with each other, and give estimates that are of the same sign and fairly similar. Moreover, the system GMM estimator is not as appropriate here, because it is particularly difficult to find suitable GMM-style instruments for growth rates given that they are so random.¹¹ The results are presented in Table 6.5.

The regression results indicate that there is a positive and significant influence of growth on profit rates, whether growth is measured in terms of sales, employment or Value Added. This influence is strongest for Value Added growth, where a significant effect is detected till the third lag. In all three cases, however, the R^2 is lower than 17%.

According to our coefficient estimates, an increase in the growth rate of employment of 1% over the period $t-1:t$ leads *ceteris paribus* to an increase in the profit rate at time t of about 0.14% – 0.2%. Thus, the results appear to contradict the theoretical ‘Penrose effects’. Instead, dynamic increasing returns and learning effects seem to be more relevant concepts.

Our results suggest that firm growth has beneficial effects on future profit rates. This leads us to question some prevailing theories in Industrial Organization which predict a negative relationship. The standard approach states that firms begin business with their most profitable opportunity and maximize their total profit by moving to exploit other less profitable opportunities until the marginal profit on the last opportunity exploited is equal to zero. An implication of this is that firm growth would be negatively related to the profit *rate* as the additional activities undertaken are less and less profit intensive. The evidence presented here does not lend support to this idea. It would appear that firms do not start out with their most profitable activities, but instead they learn over time how to produce more efficiently. In particular, periods of growth appear to be important opportunities for learning, whilst a firm that remains the same size lacks such stimuli and would be characterized instead by increasing routinization. In a world of ‘learning-by-doing’, with productivity increasing steadily over time, resources are constantly being freed up. Learning-by-doing implies that, even with a fixed amount of employees and capital inputs, a firm can increase its production over time.

¹¹On this point, Geroski goes so far as to say “The most elementary ‘fact’ about corporate growth thrown up by econometric work on both large and small firms is that firm size follows a random walk” (Geroski, 2000: 169).

Table 6.5: OLS and fixed-effects regression results: growth on profits

	sales growth			empl. growth			VA growth			
	OLS	FE	FE	OLS	FE	FE	OLS	FE	FE	
Dep var: Profits(<i>t</i>)	Coeff.	<i>t</i> -stat.	Coeff.	<i>t</i> -stat.	Coeff.	<i>t</i> -stat.	Coeff.	<i>t</i> -stat.	Coeff.	<i>t</i> -stat.
Growth (<i>t</i>)	0.4529	18.27	0.3872	17.83	0.1994	3.49	0.1397	3.35	0.6872	5.04
Growth (<i>t</i> -1)	0.0442	0.49	0.0734	0.90	-0.0767	-0.97	-0.0781	-1.37	0.1030	0.50
Growth (<i>t</i> -2)	0.0117	0.25	0.0829	1.61	-0.0199	-0.38	-0.0433	-1.38	0.1514	1.40
R^2 (within)			0.0368				0.0232			
R^2 (between)			0.0892				0.0016			
R^2 (overall)	0.1306		0.0417		0.1148		0.0133		0.1667	
<i>F</i> -stat	62.72		94.71		41.45				90.80	
DoF & <i>p</i> -value	100, 50329	0.000	11, 42014	0.000	100, 50329	0.000	11, 42014	0.000	100, 50329	0.000
Obs.	50430		50430		50430		50430		50430	

In such circumstances, staying at the same size would be akin to stagnation. If firm-level learning does not lead to growth, then the resources liberated by efficiency gains are merely absorbed as organizational slack. Successful firms, however, can apply what they have learned to grow and obtain higher profits.

6.5 Conclusion

Why do the richest countries face a decline in population, whereas the poorest countries are experiencing a much higher population growth? For an evolutionary theorist, this is a puzzling question.¹² Indeed, the evolutionary principle of ‘growth of the fitter’ is not always observed. In this study, we applied this principle at the level of surviving manufacturing firms, by examining the effect of profit rate on growth. Many theoretical contributions have assumed a direct positive influence of profit rate on growth, but this relationship has received insufficient empirical attention. In this study, non-parametric plots failed to show any clear relationship between profit rate and growth, at both an aggregated and disaggregated level of analysis. Whilst standard regression techniques (i.e. OLS and fixed-effects) gave opposing results, we applied state-of-the-art panel-data techniques to observe a relationship that is small yet positive. Practically speaking, however, it may be more useful to consider a firm’s profit rate and its subsequent growth rate as entirely independent.

Evolutionary models, and also theoretical discourse, suppose that profitability is the main driver of firm growth. This proposition is rejected by our data, and this rejection has certain consequences. First of all, we are led to reject theoretical contributions (e.g. Alchian, 1950) that have suggested that the mechanism of selection via differential growth acts effectively in favour of the ‘fittest’ and against the weakest to improve the overall efficiency of the allocation of the economy’s resources. If indeed the economy does improve over time, our results suggest that this is due to learning effects within firms and phenomena of entry and exit, rather than any kind of providential ‘natural selection’ which may influence the allocation of growth opportunities between incumbents. We argue that evolutionary models in the future would do better to abandon the assumption of a direct linear relationship between profit rates and growth rates, and replace it with an assumption of total independence between the two (see van Dijk and Nomaler (2000) for a pioneering example of such a simulation model). Second, an important policy implication concerns the issue of taxation of firm profits.¹³ The evidence

¹²The reader may question the validity of the demographic analogy. It may be argued that, in poor countries, large families occur because social status is attached to having many children. Also, given the higher mortality rate, and the role of children as ‘insurance policies’ or ‘pension plans’, large families may confer stability. Nevertheless, the analogy is able to reply to these arguments because there is also a certain prestige in having a large firm, and also it may be that firms grow (e.g. by diversification) to enjoy greater stability and to guarantee their longer-term survival.

¹³This was first pointed out to me by Giovanni Dosi.

presented here suggests that there is a separation between a firm's profit rate and its growth rate. Our results allude that the policy-maker should not be overly afraid that raising taxes on corporate profits would stifle subsequent investment and growth. However, it should be recognized that our present analysis is only able to provide indirect evidence on this issue.

Another finding is that, if anything, past growth is observed to have a slightly *positive* influence on the subsequent profit rate. This goes against the common wisdom and suggests that what are commonly known as 'Penrose effects' are not a dominant characteristic of industrial dynamics. Instead, growth seems to generate dynamic increasing returns and important learning opportunities.

Part IV

Innovation and growth

Chapter 7

Innovation and firm growth in high-tech sectors: a quantile regression approach

“Executives overwhelmingly say that innovation is what their companies need most for growth.”

McKinsey Global Survey of Business Executives (Carden, 2005:25).

In the literature review in Chapter 2, we remarked that empirical work had not really accounted for the influence of innovation on sales growth in a satisfactory manner. This is despite the central role for firm growth that both theoretical contributions and questionnaire evidence have ascribed to innovation. In this chapter we address this issue.

Our main results come from a semi-parametric quantile regression analysis. The chief advantage of this technique is that we can account for heterogeneous behavior across firms. More specifically we observe that whilst most firms don't grow very much, there is nonetheless a handful of firms that grow very fast, and it is the growth of these firms that is largely due to innovation. By taking such an econometric approach, we can reconcile the bold theoretical predictions with empirical evidence.

The analysis in the following two chapters separates itself from the preceding empirical analyses because we use a second database consisting of large American firms. We need to introduce a second database at this stage because we were unable to obtain the desired information relating to innovation (i.e. data on R&D expenditures and patents) for firms in the French database.

7.1 Innovation and Sales Growth – What do we know?

A major difficulty in observing the effect of innovation on growth is that it may take a firm a long time to convert increases in economically valuable knowledge (i.e. innovation) into economic performance. Even after an important discovery has been made, a firm will typically have to invest heavily in product development. In addition, converting a product idea into a set of successful manufacturing procedures and routines may also prove costly and difficult. Furthermore, even after an important discovery has been patented, a firm in an uncertain market environment may prefer to treat the patent as a ‘real option’ and delay associated investment and development costs (Bloom and Van Reenen, 2002). There may therefore be considerable lags between the time of discovery of a valuable innovation and its conversion into commercial success. Another feature of the innovation process is that there is uncertainty at every stage, and that the overall outcome requires success at each step of the process. In a pioneering empirical study, Mansfield et al. (1977) identify three different stages of innovation that correspond to three different conditional probabilities of success: the probability that a project’s technical goals will be met (x); the probability that, given technical success, the resulting product or process will be commercialized (y); and finally the probability that, given commercialization, the project yields a satisfactory return on investment (z). The overall success of the innovative activities will be the product of these three conditional probabilities ($x \times y \times z$). If a firm fails at any of these stages, it will have incurred costs without reaping benefits. We therefore expect that firms differ greatly both in terms of the returns to R&D (measured here in terms of post-innovation sales growth) and also in terms of the time required to convert an innovation into commercial success. However, it is anticipated that innovations will indeed pay off on average and in the long term, otherwise commercial businesses would obviously have no incentive to perform R&D in the first place.

How do firms translate innovative activity into competitive advantage?¹ Our gleaning of this literature of the influence of innovative activity on sales growth yields a sparse and rather motley harvest. (This may be due to difficulties in linking firm-level innovation data to other firm characteristics.) Mansfield (1962) considers the steel and petroleum sectors over a 40-year period, and finds that successful innovators grew quicker, especially if they were initially small. Moreover, he asserts that the higher growth rate cannot be attributed to their pre-innovation behavior. Another early study by Scherer (1965) looks at 365 of the largest US corporations and observes that inventions (measured by patents) have a positive effect on company profits via sales growth. Of particular interest to this study is his observation that

¹This is not the place to consider how innovative activity affects other aspects of firm performance apart from sales growth. For a survey of the literature on innovation and market value appreciation, see the introduction in Chapter 8, and for a survey on the relationship between innovation and employment growth (i.e. the ‘technological unemployment’ literature) see Section 2.2.3 in Chapter 2.

innovations typically do not increase profit margins but instead increase corporate profits via increased sales at constant profit margins. This suggests that sales growth is a particularly meaningful indicator of post-innovation performance. Mowery (1983) focuses on the dynamics of US manufacturing over the period 1921-1946 and observes that R&D employment only has a significantly positive impact on firm growth (in terms of assets) for the period 1933-46. Furthermore, using two different samples, he observes that R&D has a similar effect on growth for both large and small firms. Geroski and Machin (1992) look at 539 large quoted UK firms over the period 1972-83, of which 98 produced an innovation during the period considered. They observe that innovating firms (i.e. firms that produced at least one ‘major’ innovation) are both more profitable and grow faster than non-innovators. The influence of specific innovations on sales growth are nonetheless short-lived (p. 81) - “the full effects of innovation on corporate growth are realized very soon after an innovation is introduced, generating a short, sharp one-off increase in sales turnover.” In addition, and contrary to Scherer’s findings, they observe that innovativeness has a more noticeable influence on profit margins than on sales growth. Geroski and Toker (1996) look at 209 leading UK firms and observe that innovation has a significant positive effect on sales growth, when included in an OLS regression model amongst many other explanatory variables. Roper (1997) uses survey data on 2721 small businesses in the U.K., Ireland and Germany to show that innovative products introduced by firms made a positive contribution to sales growth. Freel (2000) considers 228 small UK manufacturing businesses and, interestingly enough, observes that although it is not necessarily true that ‘innovators are more likely to grow’, nevertheless ‘innovators are likely to grow more’ (i.e. they are more likely to experience particularly rapid growth). Finally, Bottazzi et al. (2001) study the dynamics of the worldwide pharmaceutical sector and do not find any significant contribution of a firm’s ‘technological ID’ or innovative position² to sales growth.

A critical examination of these studies reveals that the proxies that they use to quantify ‘innovativeness’ are rather noisy. Figure 7.1 shows that the variable of interest (i.e. ΔK – additions to economically valuable knowledge) is measured with noise if one takes patent statistics P as a measure of innovative output. In order to remove this noise, we collect information on both innovative input (R&D) and output (patents), and extract the common variance whilst discarding the idiosyncratic variance of each individual proxy that includes noise, measurement error, and specific variation. In this way, we believe we have obtained useful data on a firm’s innovativeness by considering both R&D expenditure and patent statistics simultaneously in a synthetic variable.³ Another criticism is that previous studies have lumped together firms from

²They measure a firm’s innovativeness by either the discovery of NCE’s (new chemical entities) or by the proportion of patented products in a firm’s product portfolio

³Griliches (1990) considers that patent counts can be used as a measure of innovative *output*, although this is not entirely uncontroversial. Patents have a highly skew value distribution and many patents are practically

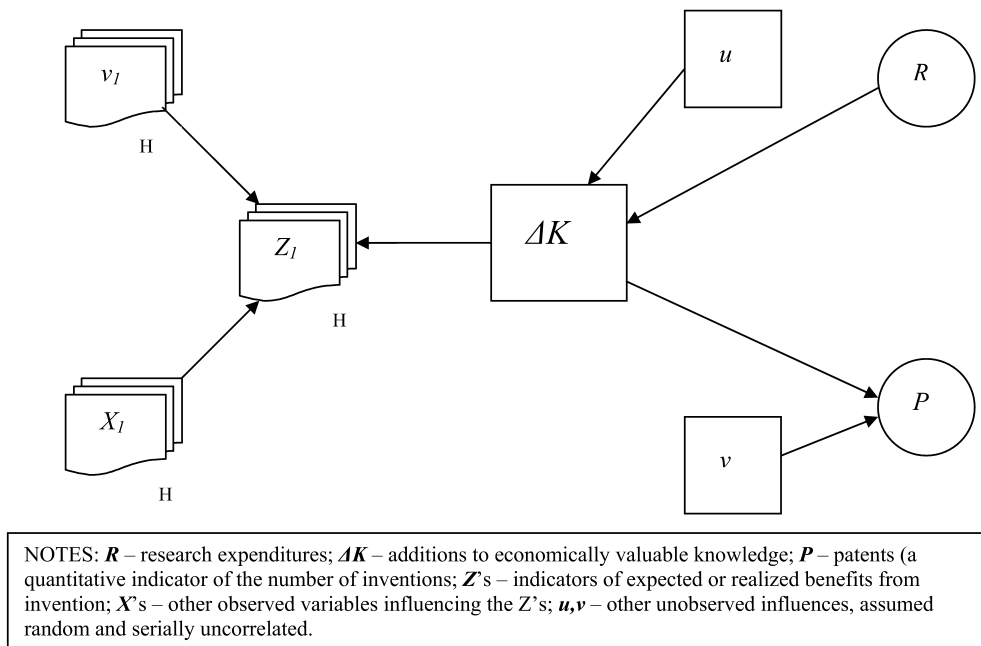


Figure 7.1: The Knowledge ‘Production Function’: A Simplified Path Analysis Diagram (based on Griliches 1990: 1671)

all manufacturing sectors – even though innovation regimes vary dramatically across industries. In this study, we focus on specific 2-digit and 3-digit sectors that have been hand-picked according to their intensive patenting and R&D activity. However, even within these sectors, there is significant heterogeneity between firms, and using standard regression techniques to make inferences about ‘the firm on average’ may mask important phenomena. Using quantile regression techniques, we investigate the relationship between innovativeness and growth at a range of points of the conditional growth rate distribution. We observe that, whilst for the ‘average firm’ innovativeness may not be so important for sales growth, innovativeness appears to be of crucial importance for the ‘superstar’ high-growth firms.

“Linking more explicitly the evidence on the patterns of innovation with what is known about firms growth and other aspects of corporate performance - both at the empirical and at the theoretical level - is a hard but urgent challenge for future research” (Cefis and Orsenigo, 2001:1157). We are now in a position to rise to this challenge. In Section 7.2 we discuss the methodology, focusing in particular on the shortcomings of using either patent counts or R&D figures individually as proxies for innovativeness. We describe how we use Principal Component Analysis to extract a synthetic ‘innovativeness’ index from patent and R&D data. Section 7.3 describes how we matched the Compustat database to the NBER innovation

worthless. As a result, patent numbers have limitations as a measure of innovative output – some authors would even prefer to consider raw patent counts to be indicators of innovative *input*. We take an intermediary stance and consider patents as being partway between an input and an output.

database, and we present the synthetic ‘innovativeness’ index. Section 7.4 contains the quantile regression results, and Section 7.5 contains implications for policy and some concluding thoughts.

7.2 Methodology - How can we measure innovativeness?

Activities related to innovation within a company can include research and development; acquisition of machinery, equipment and other external technology; industrial design; and training and marketing linked to technological advances. These are not necessarily identified as such in company accounts, so quantification of related costs is one of the main difficulties encountered in innovation studies. Each of the above mentioned activities has some effect on the growth of the firm, but the singular and cumulative effect of each of these activities is hard to quantify. Data on innovation *per se* has thus been hard to find (Van Reenen, 1997). Also, some sectors innovative extensively, some don’t innovate in a tractable manner, and the same is the case with organizational innovations, which are hard to quantify in terms of impact on the overall growth of the firms. However, we believe that no firm can survive without at least some degree of innovation.

We use two indicators for innovation in a firm: first, the patents applied for by a firm and second, the amount of R&D undertaken. Cohen et al. (2000) suggest that no industry relies exclusively on patents, yet the authors go on to suggest that the patents may add sufficient value at the margin when used with other appropriation mechanisms. Although patent data has drawbacks, patent statistics provide unique information for the analysis of the process of technical change (Griliches, 1990). We can use patent data to access the patterns of innovation activity across fields (or sectors) and nations. The number of patents can be used as an indicator of inventive as well as innovative activity, but it has its limitations. One of the major disadvantage of patents as an indicator is that not all inventions and innovations are patented (or indeed ‘patentable’). Some companies – including a number of smaller firms – tend to find the process of patenting expensive or too slow and implement alternative measures such as secrecy or copyright to protect their innovations (Archibugi, 1992; Arundel and Kabla, 1998). Another bias in the study using patenting can arise from the fact that not all patented inventions become innovations. The actual economic value of patents is highly skewed, and most of the value is concentrated in a very small percentage of the total (OECD, 1994). Furthermore, another caveat of using patent data is that we may underestimate innovation occurring in large firms, because these typically have a lower propensity to patent (Dosi, 1988). The reason we use patent data in our study is that, despite the problems

mentioned above, patents would reflect the continuous developments within technology. We complement the patent data with R&D data. R&D can be considered as an input into the production of inventions, and patents as outputs of the inventive process. R&D data may lead us to systematically underestimate the amount of innovation in smaller firms, however, because these often innovate on a more informal basis outside of the R&D lab (Dosi, 1988). For some of the analysis we consider the R&D stock and also the patent stock, since the past investments in R&D as well as the past applications of patents have an impact not only on the future values of R&D and patents, but also on firm growth. Hall (2004) suggests that the past history of R&D spending is a good indicator of a firm's technological position.

Taken individually, each of these indicators for firm-level innovation has its drawbacks. Each indicator on its own provides useful information on a firm's innovative activity, but also idiosyncratic variance that may be unrelated to a firm's innovative activity. One particular feature pointed out by Griliches (1990) is that, although patent data and R&D data are often chosen to individually represent the same phenomenon, there exists a major statistical discrepancy in that there is typically a great randomness in patent series, whereas R&D values are much more smoothed. Principal Component Analysis (PCA) is appropriate here as it allows us here to summarize the information provided by several indicators of innovativeness into a composite index, by extracting the common variance from correlated variables whilst separating it from the specific and error variance associated with each individual variable (Hair et al., 1998). We are not the only ones to apply PCA to studies into firm-level innovation however – this technique has also been used by Lanjouw and Schankerman (2004) to develop a composite index of 'patent quality' using multiple characteristics of patents (such as the number of citations, patent family size and patent claims).

We only consider certain specific sectors, and not the whole of manufacturing. This way we are not affected by aggregation effects; we are grouping together firms that can plausibly be compared to each other. We are particularly interested in looking at the growth of firms in highly innovative industries. To this end, we base our analysis on firms in 'complex' technology industries (although we also examine pharmaceutical firms). We base our classification of such firms on the typology put forward by Hall (2004) and Cohen et al. (2000). The authors define 'complex product'⁴ industries as those industries where each product relies on many patents held by a number of other firms and the 'discrete product' industries as those industries where each product relies on only a few patents and where the importance of patents for appropriability has traditionally been higher.⁵ We chose four sectors that can be classified under the 'complex products' class. The two digit SIC codes that match the 'complex technology'

⁴During our discussion, we will use the terms 'products' and 'technology' interchangeably to indicate generally the same idea.

⁵It would have been interesting to include 'discrete technology' sectors in our study, but unfortunately we did not have a comparable number of observations for these sectors. This remains a challenge for future work.

sectors are SIC 35 (industrial and commercial machinery and computer equipment), SIC 36 (electronic and other electrical equipment and components, except computer equipment), SIC 37 (transportation equipment) and SIC 38 (measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks). Our analysis also includes pharmaceutical firms (SIC 283), because of their intensive patenting activity. To summarize, then, our dataset can be said to include high-tech ‘complex technology’ industries (SIC’s 35, 36 and 38), a ‘complex technology’ sector that is, technologically speaking, more mature (SIC 37 – Transportation) and a high-tech sector that nonetheless cannot be classified as a ‘complex technology’ industry (SIC 283 – Drugs). By choosing these sectors that are characterised by high patenting and high R&D expenditure, we hope that we will be able to get the best possible quantitative observations for firm-level innovation.

7.3 Database description

7.3.1 Database

We create an original database by matching the NBER patent database with the Compustat file database, and this section is devoted to describing the creation of the sample which we will use in our analysis.

The patent data has been obtained from the NBER Database (Hall et al., 2001b). The NBER database comprises detailed information on almost 3 416 957 U.S. utility patents in the USPTO’s TAF database granted during the period 1963 to December 2002 and all citations made to these patents between 1975 and 2002. The initial sample of firms was obtained from the Compustat⁶ database for the aforementioned sectors comprising ‘complex product’ sectors. These firms were then matched with the firm data files from the NBER patent database and we found all the firms⁷ that have patents. The final sample thus contains both patenters and

⁶Compustat has the largest set of fundamental and market data representing 90% of the world’s market capitalization. Use of this database could indicate that we have oversampled the Fortune 500 firms. Being included in the Compustat database means that the number of shareholders in the firm was large enough for the firm to command sufficient investor interest to be followed by Standard and Poor’s Compustat, which basically means that the firm is required to file 10-Ks to the Securities and Exchange Commission on a regular basis. It does not necessarily mean that the firm has gone through an IPO. Most of them are listed on NASDAQ or the NYSE.

⁷The patent ownership information (obtained from the above mentioned sources) reflects ownership at the time of patent grant and does not include subsequent changes in ownership. Also attempts have been made to combine data based on subsidiary relationships. However, where possible, spelling variations and variations based on name changes have been merged into a single name. While every effort is made to accurately identify all organizational entities and report data by a single organizational name, achievement of a totally clean record is not expected, particularly in view of the many variations which may occur in corporate identifications. Also, the NBER database does not cumulatively assign the patents obtained by the subsidiaries to the parents, and we have taken this limitation into account and have subsequently tried to cumulate the patents obtained by the subsidiaries towards the patent count of the parent. Thus we have attempted to create an original database that gives complete firm-level patent information.

Table 7.1: Summary statistics before and after data-cleaning (SIC's 35-38 only)

	sample before cleaning <i>n</i> =4395 firms		sample used <i>n</i> =2113 firms	
	mean	std. dev.	mean	std. dev.
Total Sales	1007	6809	1164	7145
Patent applications	5.55	42.06	8.67	54.61
R&D expenditure	59.05	372.94	55.88	355.08

non-patenters.

The NBER database has patent data for over 60 years and the Compustat database has firms' financial data for over 50 years, giving us a rather rich information set. As Van Reenen (1997) mentions, the development of longitudinal databases of technologies and firms is a major task for those seriously concerned with the dynamic effect of innovation on firm growth. Hence, having developed this longitudinal dataset, we feel that we will be able to thoroughly investigate whether innovation drives sales growth at the firm-level.

Table 7.1 shows some descriptive statistics of the sample before and after cleaning. Initially using the Compustat database, we obtain a total of 4395 firms which belong to the SICs 35-38 and this sample consists of both innovating and non-innovating firms. These firms were then matched to the NBER database. After this initial match, we further matched the year-wise firm data to the year-wise patents applied by the respective firms (in the case of innovating firms) and finally, we excluded firms that had less than 7 consecutive years of good data. Thus, we have an unbalanced panel of 2113 firms belonging to 4 different sectors. Since we intend to take into account sectoral effects of innovation, we will proceed on a sector by sector basis, to have (ideally) 4 comparable results for 4 different sectors.

We also show results for four 3-digit sectors as further evidence that our results are not driven by mere statistical aggregation. These 3-digit sectors were chosen because they have featured in numerous industry case studies into the dynamics of high-tech sectors. We also felt that the peculiarities of the dynamics of these industries may not be as visible when they are 'lumped' together with their 2-digit 'classmates' that are sometimes quite dissimilar.⁸ The 3-digit sectors that we study are SIC 357 (Computers and office equipment), SIC 367 (Electronics); SIC 384 (Medical Instruments) and SIC 283 (Drugs).⁹

⁸We are indebted to Giovanni Dosi for advice on this point.

⁹The reader may have noticed that SIC 283 (Drugs) does not lie in the SIC 35-38 range for which the database creation procedure is described above. It was necessary to create a new dataset, using an analogous procedure to that described above for SIC's 35-38, to collect data for this 3-digit sector.

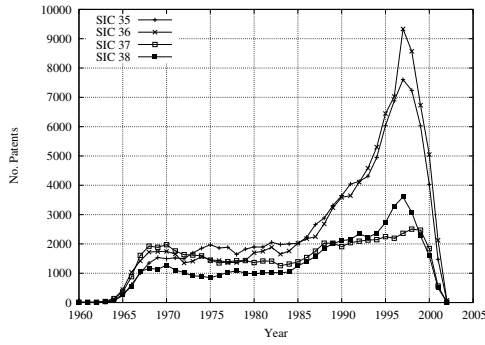


Figure 7.2: Number of patents per year. SIC 35: Machinery & Computer Equipment, SIC 36: Electric/Electronic Equipment, SIC 37: Transportation Equipment, SIC 38: Measuring Instruments.

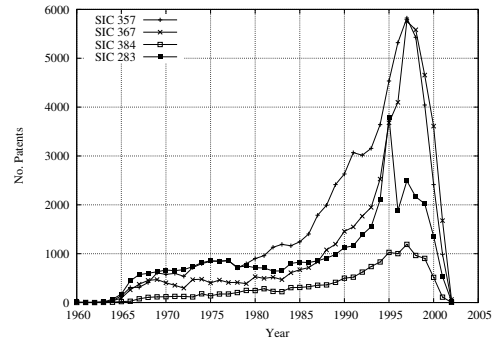


Figure 7.3: Number of patents per year. SIC 357: Computers and office equipment, SIC 367: Electronics, SIC 384: Medical Instruments, and SIC 283: Drugs.

Table 7.2: The Distribution of Firms by Total Patents, 1963-1999 (SIC's 35-38 only)

	0 or more	1 or more	10 or more	25 or more	100 or more	250 or more	1000 or more
Firms	2113	1122	733	511	222	128	56

7.3.2 Summary statistics and the ‘innovativeness’ index

Figures 7.2 and 7.3 show the number of patents per year in our final database. For some of the sectors there appears to be a structural break at the beginning of the 1980s which may well be due to changes in patent regulations (see Hall (2004) for a discussion). Table 7.2 presents the firm-wise distribution of patents, which is noticeably right-skewed. We find that 47% of the firms in our sample have no patents. Thus the intersection of the two datasets gave us 1122 patenting firms who had taken out at least one patent between 1963 and 1999, and 991 firms that had no patents during this period. The total number of patents taken out by this group over the entire period was 332 888, where the entire period for the NBER database represented years 1963 to 2002, and we have used 269 102 of these patents in our analysis i.e. representing about 81% of the total patents ever taken out at the US Patent Office by the firms in our sample. Though the NBER database provides the data on patents applied for from 1963 till 2002, it contains information only on the granted patents and hence we might see some bias towards the firms that have applied in the end period covered by the database due the lags faced between application and the grant of the patents. Hence to avoid this truncation bias (on the right) we consider the patents only till 1999 so as to allow for a 3-year gap between application and grant of the patent.¹⁰ Concerning R&D, 2100 of the 2113 firms report positive R&D expenditure, and 2078 of these report R&D for more than seven years.

¹⁰This average gap has been referred to by many authors, among others Bloom and Van Reenen (2002) who mention a lag of two years between application and grant, and Hall et al. (2001a) who state that 95% of the patents that are eventually granted are granted within 3 years of application.

Table 7.3: Contemporaneous correlations between Patents and R&D expenditure

	SIC 35	SIC 36	SIC 37	SIC 38	SIC357	SIC 367	SIC 384	SIC 283
<i>CORRELATIONS</i>								
ρ	0.5402	0.3410	0.4983	0.6720	0.5406	0.6287	0.6924	0.4672
p -value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
<i>RANK CORRELATIONS</i>								
ρ	0.4305	0.4557	0.4322	0.4651	0.5075	0.5692	0.4619	0.5172
p -value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	9911	10158	3054	8853	4163	3498	3522	6067

Table 7.4: Contemporaneous correlations between ‘patent intensity’ (patents/sales) and ‘R&D intensity’ (R&D/sales)

	SIC 35	SIC 36	SIC 37	SIC 38	SIC357	SIC 367	SIC 384	SIC 283
<i>CORRELATIONS</i>								
ρ	0.0262	0.7516	0.0290	0.1173	0.0263	0.5999	0.0715	0.3504
p -value	0.0118	0.0000	0.1191	0.0000	0.1032	0.0000	0.0000	0.0000
<i>RANK CORRELATIONS</i>								
ρ	0.1207	0.2134	0.2076	0.1801	0.0726	0.3868	0.1799	0.3443
p -value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	9233	9462	2880	8260	3853	3271	3263	4751

Table 7.3 shows that patent numbers are well correlated with (deflated) R&D expenditure, albeit without controlling for firm size. To take this into account, Table 7.4 reports the correlations between firm-level patent intensity and R&D intensity. We prefer the rank correlations here, because they are more robust to outliers. For each of the sectors we observe positive and highly significant rank correlations, which nonetheless take values of 0.4 or lower. These results would thus appear to be consistent with the idea that, even within industries, patent and R&D statistics do contain large amounts of idiosyncratic variance and that either of these variables taken individually would be a rather noisy proxy for ‘innovativeness’.¹¹ Indeed, as discussed in Section 7.2, these two variables are quite different not only in terms of statistical properties (patent statistics are much more skewed and less persistent than R&D statistics) but also in terms of economic significance. However, they both yield valuable information on firm-level innovativeness.

Our synthetic ‘innovativeness’ index is created by extracting the common variance from a series of related variables: both patent intensity and R&D intensity at time t , and also the actualized stocks of patents and R&D. These stock variables are calculated using the conventional amortization rate of 15%, and also at the rate of 30% since we suspect that the

¹¹Further evidence of the discrepancies between patent statistics and R&D statistics is presented in the regression results in Tables 5 and 6 of Coad and Rao (2006a).

Table 7.5: Extracting the ‘innovativeness’ index used for the quantile regressions - Principal Component Analysis results (first component only, unrotated)

	SIC 35	SIC 36	SIC 37	SIC 38	SIC357	SIC 367	SIC 384	SIC 283
R&D / Sales	0.4321	0.3889	0.4567	0.4126	0.4342	0.4232	0.4214	0.4159
Patents / Sales	0.3946	0.3340	0.3400	0.4069	0.3975	0.2966	0.3950	0.3702
R&D stock / Sales ($\delta=15\%$)	0.4005	0.4364	0.4566	0.4078	0.3986	0.4384	0.4204	0.4239
Pat. stock / Sales ($\delta=15\%$)	0.4100	0.4264	0.3579	0.4069	0.4093	0.4168	0.3955	0.4040
R&D stock / Sales ($\delta=30\%$)	0.4001	0.4328	0.4583	0.4085	0.3981	0.4383	0.4205	0.4249
Pat. stock / Sales ($\delta=30\%$)	0.4112	0.4214	0.3595	0.4069	0.4105	0.4182	0.3955	0.4081
Prop ⁿ Variance explained	0.6509	0.7820	0.5142	0.5522	0.6576	0.7513	0.5164	0.6908
No. Obs.	8500	8738	2653	7638	3527	3025	3004	4254

15% rate may be too low (following Hall and Oriani, 2006). Information on the factor loadings is shown in Table 7.5. We consider the summary ‘innovativeness’ variable to be a satisfactory indicator of firm-level innovativeness because it loads well with each of the variables and explains between 51% to 78% of the total variance.

An advantage of this composite index is that a lot of information on a firm’s innovative activity can be summarized into one variable (this will be especially useful in the following graphs). A disadvantage is that the units have no ready interpretation (unlike ‘one patent’ or ‘\$1 million of R&D expenditure’). In this study, however, we are less concerned with the quantitative point estimates than with the qualitative variation in the importance of innovation over the conditional growth rates distribution (i.e. the ‘shape’ of the graphs).

Figure 7.4 presents some scatterplots of innovativeness on sales growth, for the four 2-digit sectors. (Bear in mind that the innovativeness indicator has been normalized to having a mean 0.0000, and that it is truncated at the left, which reflects the fact that patenting and R&D activity are limited to taking non-negative values only.) The innovativeness variable is calculated at time $t - 1$ but, by construction, it contains information on innovative activity over the period $t - 3 : t - 1$. The relationships presented in the plots are admittedly very noisy, with the expected positive relationship being quite difficult to see. Similar plots are also obtained for the 3-digit sectors, although naturally we have fewer observations.

These scatterplots give us an opportunity to visualize the underlying nature of the data, to ‘have a look at the meat before we cook it’, so to speak, but it would be improper to base conclusions on them. In particular, such plots don’t take into account the need to control for any potentially misleading influence on growth rates of lagged growth, size dependence (i.e. possible departures from Gibrat’s law) and sectoral growth patterns. We therefore continue our analysis with regression techniques.

7.4 Quantile regression results

We now estimate the following linear regression model:

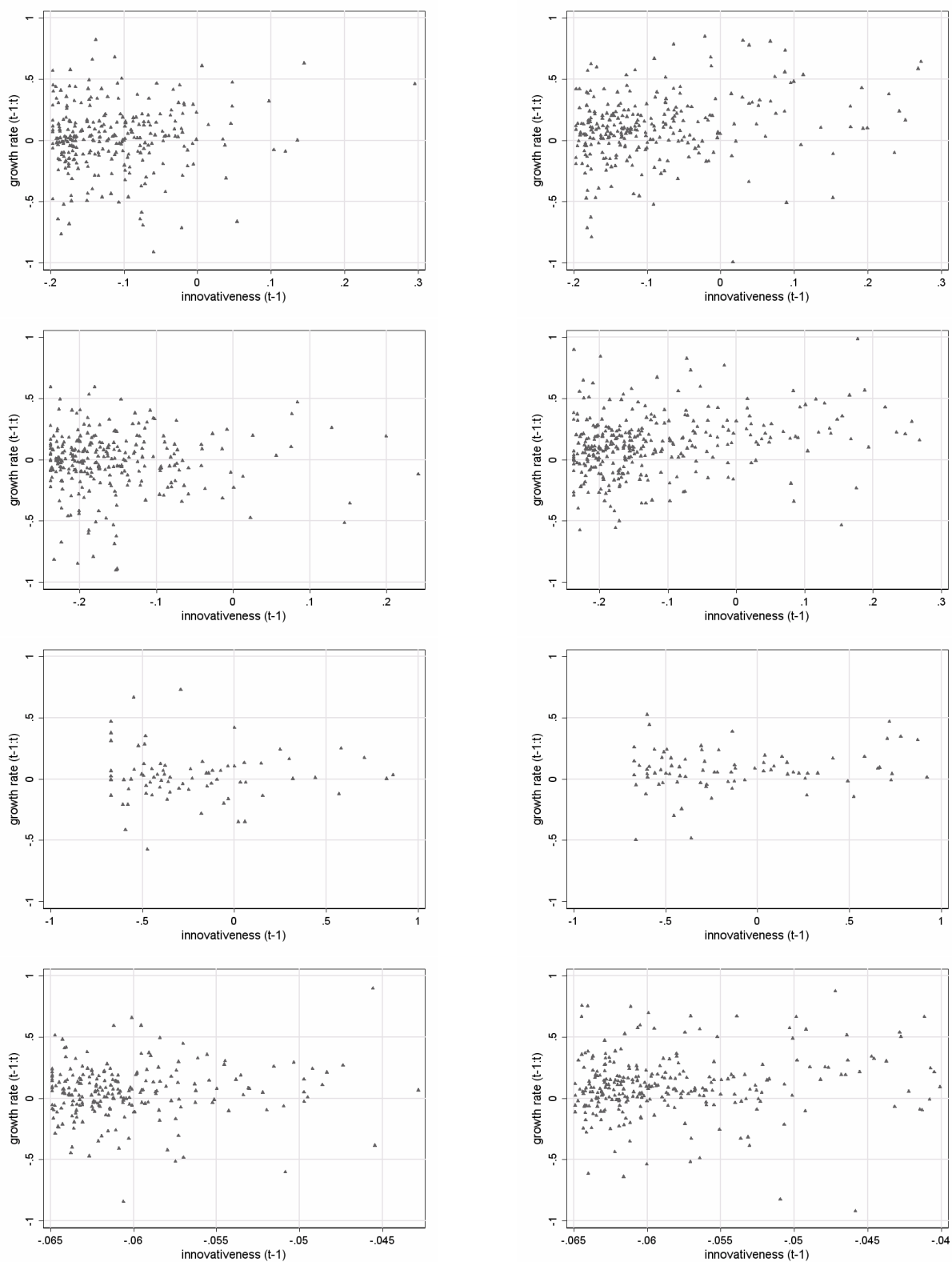


Figure 7.4: Scatterplots of innovation ($t - 1$) on growth ($t - 1 : t$). Top row: SIC 35; 2nd row: SIC 36; 3rd row: SIC 37; bottom row: SIC 38. $t=1985$ on the left and $t=1995$ on the right.

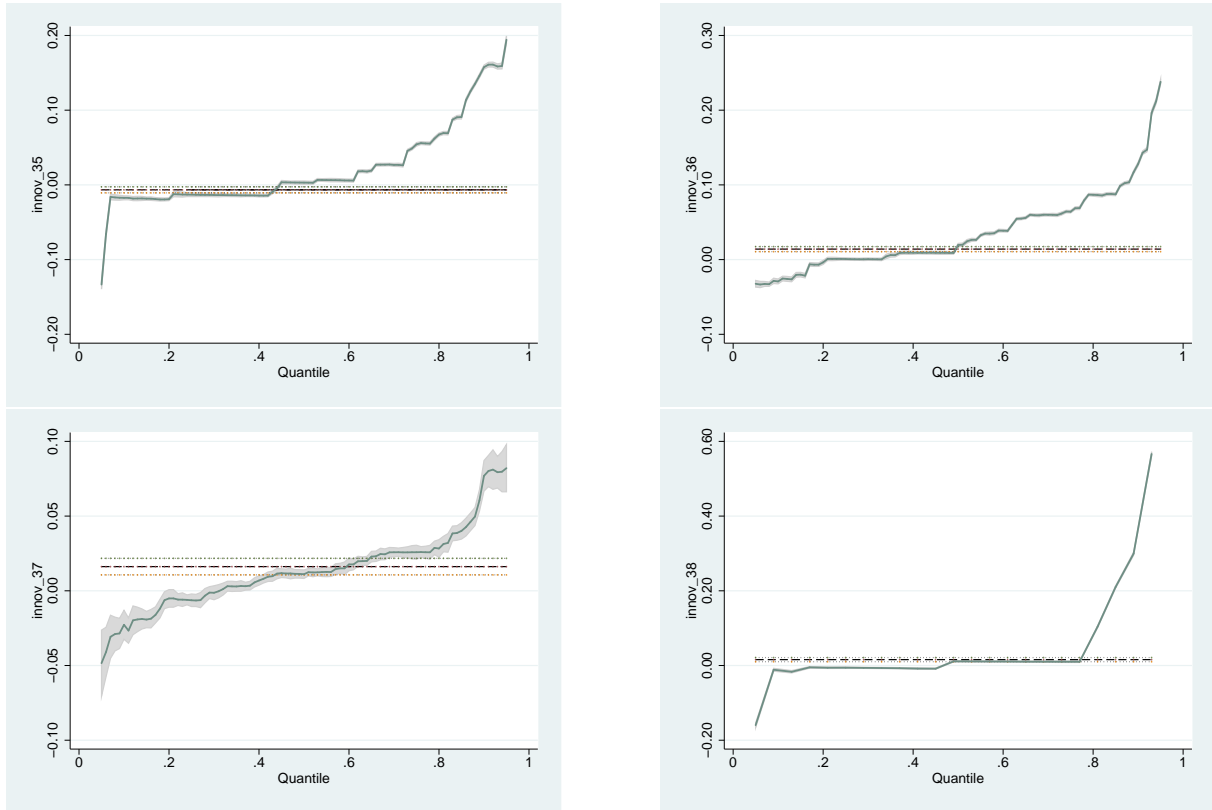


Figure 7.5: Variation in the coefficient on ‘innovativeness’ (i.e. β_1 in Equation (7.1)) over the conditional quantiles. Confidence intervals extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & Computer Equipment (top-left), SIC 36: Electric/Electronic Equipment (top-right), SIC 37: Transportation Equipment (bottom-left), SIC 38: Measuring Instruments (bottom-right). Graphs made using the ‘grqreg’ Stata module (Azevedo, 2004).

$$GROWTH_{i,t} = \alpha + \beta_1 INN_{i,t-1} + \beta_2 GROWTH_{i,t-1} + \beta_3 SIZE_{i,t-1} + \beta_4 IND_{i,t} + y_t + \epsilon_{i,t} \quad (7.1)$$

where $INN_{i,t-1}$ is the ‘innovativeness’ variable for firm i at time $t - 1$. The control variables are lagged growth, lagged size (measured in sales) and 3-digit industry dummies. We also control for common macroeconomic shocks by including year dummies (y_t).

Quantile regression results for the 2-digit sectors are presented in Figure 7.5. The OLS estimates are presented as horizontal lines, together with their confidence intervals. It is clear that the OLS estimates do not tell the whole story. The quantile regression curves show that the value of the estimated coefficient on innovativeness varies over the conditional growth rate distribution. When the quantile regression solution is evaluated at the median firm (i.e. at the 50% quantile), innovativeness only appears to have a small influence on firm growth. However, for those fast-growth firms at the upper quantiles, the coefficient on innovation rises sharply.

The numerical results for OLS, fixed-effects and quantile regression estimation are reported

in Table 7.6. The coefficients can be interpreted as the partial derivative of the conditional quantile of y with respect to particular regressors, $\delta Q_\theta(y_{it}|x_{it})/\delta x$. Put differently, the derivative is interpreted as the marginal change in y at the θ^{th} conditional quantile due to marginal change in a particular regressor (Yasar et al., 2006b). For each of the four sectors, the coefficient on innovativeness is much larger at the higher quantiles. At the 90% quantile, for example, the coefficient of innovativeness on growth is about 40 times larger than at the median, for two of the four 2-digit sectors. The evidence here suggests therefore that, when we consider the high-growth firms, investments in innovative activity make an important contribution to their superior growth performance. This is reinforced by the fact that the pseudo- R^2 's, although always rather modest in regressions of this type, do tend to rise at the upper extremes of the conditional distribution.

We checked the robustness of our results by reestimating the regressions using shorter time periods of ten years. It would appear that our findings on the relationship between innovation and sales growth are robust across sub-periods of the database.

If they ‘win big’, innovative firms can grow rapidly. Conversely, there are many firms that invest a lot in both R&D and patents that nonetheless perform poorly and experience disappointing growth. Indeed, at the lowest quantiles, innovativeness is even observed to have a *negative* effect on firm growth. Admittedly, this result may appear counterintuitive at first but it does in fact have a tentative interpretation. As Freel comments: “firms whose efforts at innovation fail are more likely to perform poorly than those that make no attempt to innovate. To restate, it may be more appropriate to consider three innovation derived sub-classifications – i.e. ‘tried and succeeded’, ‘tried and failed’, and ‘not tried’” (Freel, 2000: 208). Indeed, unless a firm strikes it lucky and discovers a commercially viable innovation, its innovative efforts will be no more than a waste of resources.¹²

Similar results are obtained for the 3-digit industries, and these are shown in the lower panel of Table 7.6 and in Figure 7.6. Once again, the OLS and fixed-effects estimates are seen to do a poor job of summarizing the relationship between innovativeness and growth. Quantile regression results indicate that, for most firms, growth is only weakly related to innovativeness. However, fast-growth firms owe a lot of their success to their innovative efforts.

¹²In further exercises (not shown here) we tested this hypothesis by *i*) considering only those firms with strictly positive patent intensities in each of the last three years (i.e. the ‘lucky ones’), and *ii*) considering only those firms with above-median R&D intensities and yet no patents in the last three years (i.e. the ‘losers’). In the case of *i*), we should expect that β_1 , the coefficient on innovativeness, is more positive than for the unrestricted sample, being positive even at the lower quantiles. In the case of *ii*), we should expect that the coefficient is more negative. It was encouraging to observe that the results did lean in the expected directions.

Table 7.6: Quantile regression estimation of Equation (7.1): the coefficient and t -statistic on ‘innovativeness’ reported for the 10%, 25%, 50%, 75% and 90% quantiles. Coefficients significant at the 5% level appear in bold.

			Quantile regression				
	OLS	FE	10%	25%	50%	75%	90%
SIC 35	-0.0066	-0.0023	-0.0173	-0.0132	0.0030	0.0543	0.1576
(7867 obs.)	-1.33	-0.32	-12.69	-10.20	2.68	44.52	111.38
[Pseudo-] R^2	0.0551	0.0217	0.0719	0.0614	0.0602	0.0710	0.0909
SIC 36	0.0141	0.0147	-0.0292	0.0008	0.0195	0.0641	0.1280
(8110 obs.)	1.94	2.35	-17.44	0.93	17.45	74.04	95.74
[Pseudo-] R^2	0.0535	0.0233	0.0461	0.0440	0.0543	0.0762	0.0980
SIC 37	0.0162	0.0232	-0.0227	-0.0063	0.0111	0.0258	0.0769
(2484 obs.)	2.22	2.37	-4.59	-2.94	7.62	10.81	14.70
[Pseudo-] R^2	0.0979	0.0813	0.0855	0.0815	0.0848	0.0823	0.0984
SIC 38	0.0158	0.0213	-0.0107	-0.0058	0.0112	0.0102	0.3759
(7076 obs.)	3.02	3.62	-5.48	-5.82	12.55	10.05	131.96
[Pseudo-] R^2	0.0256	0.0102	0.0359	0.0310	0.0350	0.0441	0.0609
SIC 357	-0.0154	-0.0097	-0.293	-0.0235	-0.0159	0.0149	0.0950
(3228 obs.)	-2.46	-0.98	-11.47	-8.50	-7.33	7.22	31.02
[Pseudo-] R^2	0.0577	0.0163	0.0806	0.0711	0.0682	0.0647	0.0630
SIC 367	0.0239	0.0372	-0.0328	-0.0091	0.0313	0.0547	0.0858
(2813 obs.)	2.44	2.76	-9.91	-3.49	16.21	29.78	32.19
[Pseudo-] R^2	0.1178	0.0918	0.0790	0.0744	0.0874	0.1200	0.1649
SIC 384	0.0322	0.0415	-0.0584	-0.0117	-0.0143	0.1472	0.7036
(2763 obs.)	2.05	3.46	-11.70	-5.70	-8.54	37.12	93.70
[Pseudo-] R^2	0.0343	0.0246	0.0458	0.0310	0.0277	0.0315	0.0627
SIC 283	0.0527	0.0800	-0.0446	-0.0208	0.0383	0.0887	0.5133
(3502 obs.)	4.48	4.06	-11.60	-11.29	22.78	31.56	78.48
[Pseudo-] R^2	0.0498	0.0439	0.0712	0.0212	0.0132	0.0570	0.1441

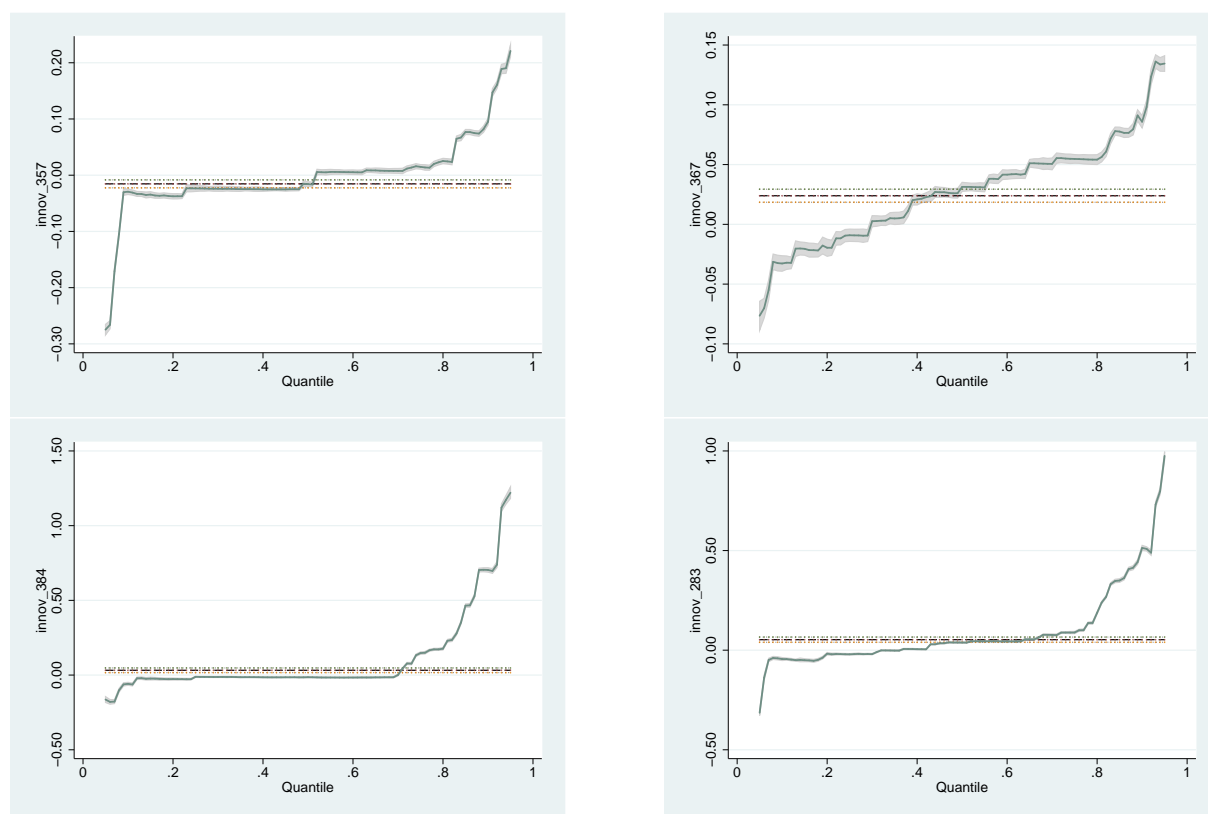


Figure 7.6: Variation in the coefficient on ‘innovativeness’ (i.e. β_1 in Equation (7.1)) over the conditional quantiles. Confidence intervals extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 357: Computers and office equipment (top-left), SIC 367: Electronics (top-right); SIC 384: Medical Instruments (bottom-left) and SIC 283: Drugs (bottom-right).

7.5 Conclusions and Implications for Policy

In modern economic thinking, innovation is ascribed a central role in the evolution of industries. In a turbulent environment characterized by powerful forces of ‘creative destruction’, firms can nonetheless increase their chances of success by being more innovative than their competitors. Investing in R&D is a risky activity, however, and even if an important discovery is made it may be difficult to appropriate the returns. Firms must then combine the invention with manufacturing and marketing know-how in order to convert the basic ‘idea’ into a successful product - only then will innovation lead to superior performance. The processes of creating competitive advantage from firm-level innovation strategies are thus rather complex and were the focus of this paper.

Nevertheless, and perhaps surprisingly, the bold conjectures on the important role of innovation have largely gone unquestioned. This is no doubt due to difficulties in actually measuring innovation. Whilst variables such as patent counts or R&D expenditures do shed light on the phenomenon of firm-level innovation, they also contain a lot of irrelevant, idiosyncratic variance. In this study, innovation was measured by using Principal Component Analysis to create a synthetic ‘innovativeness’ variable for each firm in each year. This allows us to use information on both R&D expenditure and patent statistics to extract information on the unobserved variable of interest, i.e. ‘increases in commercially useful knowledge’, whilst discarding the idiosyncratic variance of each variable taken individually. We observe that a firm, on average, experiences only modest growth and may grow for a number of reasons that may or may not be related to ‘innovativeness’. However, while standard regression analyses focus on the growth of the mean firm, such techniques may be inappropriate given that growth rate distributions are highly skewed and that high-growth firms should not be treated as outliers but instead are objects of particular interest. Quantile regressions allows us to parsimoniously describe the importance of innovativeness over the entire conditional growth rate distribution, and we observed that, compared to the average firm, innovation is of great importance for the fastest-growing firms.

In the sectors studied here, there is a great deal of technological opportunity. Competition in such sectors is organized according to the principle that a successful (and fortunate) innovator may suddenly come up with a winning innovation and rapidly gain market share. The reverse side of the coin, of course, is that a firm that invests in R&D but does not make a discovery (either through missed opportunities or just plain bad luck) may rapidly forfeit its market share to its rivals. As a result, firms in turbulent, highly innovative sectors can never be certain how they will perform in future. Innovative firms may either succeed spectacularly or (if they don’t happen to discover a commercially valuable innovation) they may waste a large amount of resources, whilst their market share is threatened by more successful rivals.

This may be because they have inferior R&D capabilities or it may just be because they were unlucky. Innovative activity is highly uncertain and although it may increase the probability of superior performance, it cannot guarantee it. We are thus wary of innovation policies of narrow scope that put ‘all the money on one horse’ and focus on just one or a few firms. Instead, our results favour broad-based innovation policies that offer support to many firms engaged in multiple directions of search, because it may not be possible to pick out *ex ante* the winners from the losers.

We have seen that, on average, firms have a lot of discretion in their growth rates. Innovation is uncertain and generally lacks persistence (Geroski, 2000; Cefis and Orsenigo, 2001); similarly, firm growth is highly idiosyncratic and lacks persistence – in spite of this circumstantial evidence, however, we should resist the temptation to overplay the relationship between innovative activity and firm growth. On the whole, firm growth is perhaps best modelled as a random walk (Geroski, 2000). Only a small group of highly-innovative firms are identified and rewarded by selection pressures. Although the virtues of selective pressures operating on heterogeneous firms have been extolled in theoretical contributions (e.g. Alchian, 1950), it appears here that selection only wields influence over the outliers (this is in line with a conjecture in Bottazzi et al. (2002)). Most firms, it seems, are quite oblivious to selection. We should thus avoid the Panglossian view that unseen market forces reward the fittest and eliminate the weakest to take the economic system to an ‘optimum’. The evidence presented here suggests that selection is not particularly efficient. However, can selection be stimulated or reinforced by intervention? This is a policy question we leave open. We simply note here that if the ‘viability’ of firms is open to manipulation or observed with error, the results of such intervention could be counterproductive.

Many years ago, Keynes wrote: “If human nature felt no temptation to take a chance, no satisfaction (profit apart) in constructing a factory, a railway, a mine or a farm, there might not be much investment merely as a result of cold calculation” (1936: 150) – the same is certainly true for R&D. Need it be reminded, an innovation strategy is even more uncertain than playing a lottery, because it is a ‘game of chance’ in which neither the probability of winning nor the prize can be known for sure in advance. In the face of such radical uncertainty, some firms may well be overoptimistic (or indeed risk-averse) about what they will actually gain. For other firms, there may be over-investment in R&D because of the ‘managerial prestige’ attached to having an over-sized R&D department.¹³ As a result, we cannot rule out the possibility that many firms invest in R&D far from something which could correspond to the ‘profit-

¹³In analogy to the principles of managerial economics, we advance that if the size of the R&D lab enters into the R&D manager’s utility function, then investment in R&D may be far above the ‘profit-maximizing’ level. Consider here the examples of the prestigious Bell Laboratories or Xerox’s renowned Palo Alto Research Centre, which came up with many great inventions and generated several Nobel prizes, but were unable to make any money from these ideas (Roberts, 2004).

maximizing' level (whatever 'profit-maximizing' may mean). In fact, we remain pessimistic that R&D will ever enter into the domain of 'rational' decision-making (i.e. a 'cost-benefit analysis'). Successful innovation, and the 'super-star' growth performance that may result, require risk-taking and perhaps just a little bit of craziness.

Chapter 8

Innovation and market value: a quantile regression analysis

This Chapter provides additional insights into the relationship between innovation and firm performance. Indeed there may be difficulties in relating innovation to firm growth because of the time lags for innovations to come into effect (see the discussion in Section 7.1 in the preceding chapter). In this chapter, we take market value as an indicator of firm performance, because this indicator has the property of taking future growth prospects into account as soon as they can be anticipated rather than at the time that they actually physically materialize. However, this choice of performance indicator leaves us with a smaller database than that used in the preceding chapter.

Our results support those obtained previously. Again, the uncertain nature of innovation is clearly demonstrated. In some cases innovative firms can experience spectacular increases in market value on the basis of their innovative activity. In other cases, however, less fortunate firms may find that their efforts at innovation are hardly noticed on the stock market.

8.1 Introduction

The impact of firm-level innovative activity on firm performance has received much attention over the last 25 years. One strand of the literature, beginning with Griliches (1981), has measured post-innovation performance by considering Tobin's q (i.e. market value divided by book value of assets). Given that it may take a long time for a successful innovation to be transformed into a profitable finished product, Tobin's q is a useful proxy for firm performance because the (expected) future profit stream is already taken into account. Indeed, there is evidence that the market can evaluate firm-level innovative activity reasonably well (Chan et al. 2001).

The regression methodology of this literature has typically been based on standard least-

squares estimators. However, given that the distribution of Tobin's q is highly skewed, the usual assumption of normally distributed error terms is not warranted and could lead to unreliable estimates. Indeed, the variability in Tobin's q is even higher for high-tech firms than for other firms. Furthermore, firms are fundamentally heterogeneous and it may make little sense to use regression estimators that implicitly focus on the 'average effect for the average firm' by giving summary point estimates for coefficients. Instead, we apply quantile regression techniques that are robust to outliers and are able to describe the influence of the regressors over the entire conditional distribution of Tobin's q . Results obtained from conventional regressions do not show the whole picture. Quantile regression analysis is much more informative and shows that, while low- q firms' efforts at innovation are virtually ignored by financial markets, those few 'super-star' firms with exceptionally high market valuation owe a lot of their success to innovative activity.

A major challenge facing research into firm-level innovative activity is the construction of suitable databases. In particular, it has proved difficult to gather meaningful quantitative indicators of innovation. While R&D expenditures and patent statistics both shed light on the processes of innovation, they also contain a lot of specific variation (for surveys, see Dosi (1988) and Griliches (1990)). For example, one statistical discrepancy is that patent series are typically more erratic and more skewed than R&D expenditures. In this study, we use Principal Component Analysis to create a summary 'innovativeness' variable that extracts the common variance from both R&D and patent statistics (levels and stocks) while discarding the irrelevant variance that includes measurement error and idiosyncratic variation. In addition, we restrict our analysis to four 'complex technology' sectors (Cohen et al. 2000) that are known for their intense R&D and patenting activity. By concentrating on these sectors we attempt to get the best possible observations on firm-level innovation.

8.2 Database Description and Summary Statistics

This paper uses an original database that we created by matching the NBER patent database with the Compustat file database.¹ The patent data has been obtained from the NBER Database (Hall et al. 2001b). The NBER database comprises detailed information on almost 3 416 957 U.S. utility patents in the USPTOs TAF database granted during the period 1963 to December 2002.

The initial sample of firms was obtained from the well-known Compustat database for the 'complex technology' sectors. These firms were then matched with the firm data files from the NBER patent database and we found all the firms² that have patents. The final sample thus

¹We would like to thank Bronwyn Hall for providing us with her calculations of Tobin's q for the Compustat data used in this paper.

²The patent ownership information reflects ownership at the time of patent grant and does not include

Table 8.1: Summary statistics before and after data-cleaning, SIC's 35-38

	sample before cleaning <i>n</i> =1852 firms			sample used <i>n</i> =1331 firms		
	mean	median	std. dev.	mean	median	std. dev.
Total Sales	846.61	61.78	4334	983.05	71.81	4747
Patent applications	9.31	0	54.94	11.22	0	61.89
R&D expenditure	46.18	2.21	254.59	50.38	2.50	264.65
Tobin's <i>q</i>	3.77	1.52	19.35	3.31	1.46	14.04

Table 8.2: The Distribution of Firms by Total Patents, 1963-1999 (SIC's 35-38)

	0 or more	1 or more	10 or more	25 or more	100 or more	250 or more	1000 or more
Firms	1331	877	614	457	229	131	57

contains both patenters and non-patenters.

Descriptive statistics of the sample before and after cleaning is shown in Table 8.1. Initially using the Compustat database, we obtain a total of 1852 firms which belong to the SICs 35-38 and this sample consists of both patenting and non-patenting firms. These firms were then matched to the NBER database. After this initial match, we further matched the year-wise firm data to the year-wise patents applied by the respective firms (in the case of patenting firms) and finally, we excluded firms that had less than 7 consecutive years of good data. Thus, we have an unbalanced panel of 1331 firms belonging to 4 different sectors. Since we intend to take into account sectoral effects of innovation, we will proceed on a sector by sector basis, to have (ideally) 4 comparable results for 4 different sectors.

We find that 34% of the firms in our sample have no patents. Thus the intersection of the two datasets gave us 877 patenting firms who had taken out at least one patent between 1963 and 1999, and 454 firms that had no patents during this period. (See Table 8.2 for more details on the distribution of firms by total patents.) The total number of patents taken out by this group over the entire period was 291,555, where the entire period for the NBER database represented years 1963 to 2000, and we have used 217,770 of these patents in our analysis i.e. representing about 75% of the total patents ever taken out at the US Patent Office by the

subsequent changes in ownership. Also attempts have been made to combine data based on subsidiary relationships. However, where possible, spelling variations and variations based on name changes have been merged into a single name. While every effort is made to accurately identify all organizational entities and report data by a single organizational name, achievement of a totally clean record is not expected, particularly in view of the many variations which may occur in corporate identifications. Also, the NBER database does not cumulatively assign the patents obtained by the subsidiaries to the parents, and we have taken this limitation into account and have subsequently tried to cumulate the patents obtained by the subsidiaries towards the patent count of the parent. Thus we have attempted to create an original database that gives complete firm-level patent information.

Table 8.3: Contemporaneous correlations between Patents and R&D expenditure

	SIC 35	SIC 36	SIC 37	SIC 38
<i>CORRELATIONS</i>				
ρ	0.5281	0.3834	0.4475	0.7766
p -value	0.0000	0.0000	0.0000	0.0000
<i>RANK CORRELATIONS</i>				
ρ	0.4227	0.4672	0.4574	0.4587
p -value	0.0000	0.0000	0.0000	0.0000
Obs.	5986	6219	1972	5241

Table 8.4: Contemporaneous correlations between patents/sales and R&D/sales

	SIC 35	SIC 36	SIC 37	SIC 38
<i>CORRELATIONS</i>				
ρ	0.3446	0.3297	0.0900	0.3230
p -value	0.0000	0.0000	0.0001	0.0000
<i>RANK CORRELATIONS</i>				
ρ	0.0851	0.2153	0.2322	0.1336
p -value	0.0000	0.0000	0.0000	0.0000
Obs.	5986	6219	1972	5241

firms in our sample.

Though the NBER database provides the data on patents applied for from 1963 till 2000, it contains information only on the granted patents and hence we might see some bias towards the firms that have applied in the end period covered by the database due the lags faced between application and the grant of the patents. Hence to avoid this truncation bias (on the right) we consider the patents only till 1999 so as to allow for a 3-year gap between application and grant of the patent.³

Table 8.3 shows that patent numbers are well correlated with (deflated) R&D expenditure, albeit without controlling for firm size. To take this into account, Table 8.4 reports the correlations between firm-level patent intensity and R&D intensity (conventional correlations and also rank correlations that are more robust to extreme observations). For each of the sectors we observe positive and highly significant rank correlations, which nonetheless take values of 0.23 or lower. These results would thus appear to be consistent with the idea that, even within industries, patent and R&D statistics do contain large amounts of idiosyncratic variance and that either of these variables taken individually would be a rather noisy proxy for innovativeness. Indeed, these two variables are quite different not only in terms of statistical properties (patent statistics are much more skewed and less persistent than R&D statistics) but also in terms of economic significance. However, they both yield valuable information on firm-level innovativeness.

As a result, we use Principal Component Analysis to create a composite summary index of firm-level innovative activity. Our synthetic innovativeness index is created by extracting the common variance from a series of related variables: both patent intensity and R&D intensity at time t , and also the actualized 3-year stocks of patents and R&D. These stock variables are calculated using the conventional amortization rate of 15%, and also at the rate of 30% since we suspect that the 15% rate may be too low (Hall and Oriani, 2006). Information on the factor loadings is shown in Table 8.5. We consider the summary innovativeness variable

³This average gap has been referred to by many authors, among others Bloom and Van Reenen (2002) who mention a lag of two years between application and grant, and Hall et al. (2001a) who state that 95% of the patents that are eventually granted are granted within 3 years of application.

Table 8.5: Extracting the ‘innovativeness’ index used for the quantile regressions - Principal Component Analysis results (first component only, unrotated)

	SIC 35	SIC 36	SIC 37	SIC 38
R&D / Sales	0.4097	0.4127	0.4208	0.4408
Patents / Sales	0.4060	0.3740	0.3898	0.3607
R&D stock / Sales ($\delta = 15\%$)	0.4121	0.4307	0.3921	0.4397
Patent stock / Sales ($\delta = 15\%$)	0.4029	0.4002	0.4249	0.3787
R&D stock / Sales ($\delta = 30\%$)	0.4133	0.4280	0.3951	0.4401
Patent stock / Sales ($\delta = 30\%$)	0.4055	0.4012	0.4250	0.3810
Prop ⁿ Variance explained	0.6270	0.5865	0.5588	0.5404
No. Obs.	5094	5305	1702	4467

to be a satisfactory indicator of firm-level innovativeness because it loads well with each of the variables and explains between 54% to 63% of the total variance. An advantage of this composite index is that a lot of information on a firm’s innovative activity can be summarized into one variable (this will be especially useful in the following graphs). A disadvantage is that the units have no ready interpretation (unlike ‘one patent’ or ‘\$1 million of R&D expenditure’). In this study, however, we are less concerned with the quantitative point estimates than with the qualitative variation in the importance of innovation over the conditional distribution of Tobin’s q (i.e. the ‘shape’ of the graphs).

8.3 Quantile regression results

In keeping with the literature,⁴ we estimate the following linear regression model:

$$q_{i,t} = \alpha + \beta_1 INN_{i,t-1} + \beta_3 SIZE_{i,t-1} + \beta_4 IND_{i,t} + y_t + \epsilon_{i,t} \quad (8.1)$$

where $q_{i,t}$, the dependent variable, is the value of Tobin’s q for firm i at time t . INN represents the ‘innovativeness’ index, and the control variables are lagged size (measured in sales (deflated dollars)) and 3-digit industry dummies. We also control for common macroeconomic shocks by including year dummies (y_t).

To assist the inference based on the quantile regression coefficients, we calculate standard errors using bootstrap resampling techniques (for an introduction to bootstrapping techniques, see Efron and Gong (1983); and for an application to quantile regression see Lotti et al., 2003). We consider this to be a particularly important statistical tool in this present case since we have only a relatively small number of observations in this database. Furthermore, the small number

⁴See, among others, Griliches (1981), Pakes (1985), Jaffe (1986), Cockburn and Griliches (1988), Hall (1993a, 1993b), Hall et al. (2005) and Hall and Oriani (2006).

Table 8.6: Quantile regression estimation of equation (8.1): the coefficient and t -statistic on ‘innovativeness’ reported for the 10%, 25%, 50%, 75% and 90% quantiles. t -statistics are computed using bootstrapped standard errors (500 replications). Coefficients significant at the 5% level appear in bold.

			Quantile regression				
	OLS	FE	10%	25%	50%	75%	90%
SIC 35	1.2919	-0.1965	0.0271	0.0942	0.2307	0.6873	1.2807
(4648 obs.)	3.36	-0.34	1.76	3.36	5.14	6.65	5.07
[Pseudo-] R^2	0.0290	0.0145	0.0381	0.0519	0.0727	0.1111	0.1742
SIC 36	0.7277	-0.1736	0.1537	0.2946	0.4590	1.1032	2.2329
(4848 obs.)	3.30	-1.10	4.02	8.75	4.66	5.87	6.68
[Pseudo-] R^2	0.1430	0.0498	0.0406	0.0560	0.0880	0.1470	0.2351
SIC 37	0.0593	-0.0281	0.0013	0.0079	0.0384	0.0364	0.0453
(1567 obs.)	2.72	-1.44	0.19	0.58	3.02	2.18	1.46
[Pseudo-] R^2	0.1938	0.1588	0.1231	0.1394	0.1784	0.2113	0.2634
SIC 38	0.9341	0.4715	0.0309	0.2281	0.6619	1.4918	3.5843
(4080 obs.)	3.67	2.50	0.75	2.03	4.20	5.34	5.36
[Pseudo-] R^2	0.1283	0.0674	0.0336	0.0430	0.0760	0.1353	0.2037

of observations makes bootstrapping techniques more feasible here (i.e. less computationally intensive). For the regression results reported in Table 8.6 we use 500 bootstrap replications, and for the quantile regression graphs reported in Figure 8.1, we use the Stata 9 default value of 20 bootstrap replications. Increasing the number of replications did not appear to alter the accuracy of the estimated standard errors, although it did increase the computational burden considerably.

The numerical results for OLS, fixed-effects and quantile regression estimation are reported in Table 8.6. OLS regressions estimate a positive and significant influence of innovative activity on Tobin’s q , for each of the four sectors. Fixed-effects regressions, on the other hand, only detect a significant (positive) influence for SIC 38.⁵ Median (50%) quantile regression results, which correspond to the Minimum Absolute Deviation (MAD) estimator, are significantly lower than the OLS estimates for each of the four sectors. This suggests that the OLS estimates, which are not robust to extreme observations or non-gaussian distributions of residuals, may be biased upwards.

Quantile regression results are always positive and mostly statistically significant. The quantile regression coefficients can be interpreted as the partial derivative of the conditional quantile of y with respect to particular regressors, $\Delta Q_\theta(y_{it}|x_{it})/\Delta x$. Put differently, the derivative is interpreted as the marginal change in y at the θ^{th} conditional quantile due to marginal change in a particular regressor. For each of the four sectors, the coefficient on innovativeness

⁵See Hall et al. (2005: 26) for a discussion of the poor performance of the fixed-effect estimator in this particular case.

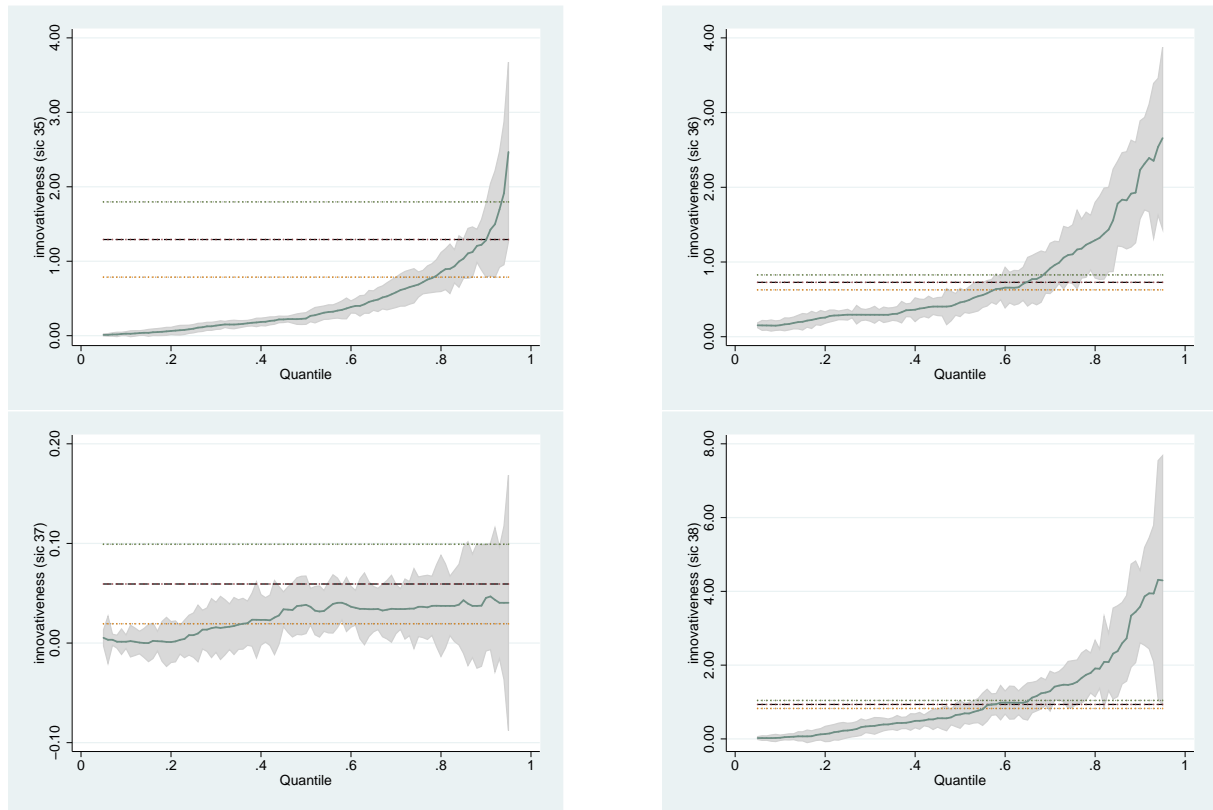


Figure 8.1: Variation in the ‘innovativeness’ coefficient (β_1 from Equation (8.1)) over the conditional quantiles. Confidence intervals extend to 95% confidence intervals in either direction (for computational manageability, we use the Stata default setting of 20 replications for the bootstrapped standard errors). Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & Computer Equipment (top left), SIC 36: Electric/Electronic Equipment (top right), SIC 37: Transportation Equipment (bottom left), SIC 38: Measuring Instruments (bottom right). Graphs made using the ‘grqreg’ Stata module (Azevedo 2004).

is much larger at the higher quantiles. The coefficient estimates at the 75% quantiles are over three times bigger than those at the 25% quantiles, for each of the four sectors. Values for the pseudo- R^2 also rise as we move to the upper quantiles.

Figure 8.1 allows a visual appreciation of the quantile regression results. All four of the sectors show a common pattern, although the plot for SIC 37 is much less elegant than for the other sectors (this is in part due to the smaller number of observations, and perhaps also due to the peculiarities of this sector⁶). At the lowest quantiles of the conditional Tobin's q distribution, the coefficients on innovativeness are very low, close to zero, which suggests that these firms' efforts at innovation are barely recognized by the stock market. As we move up the conditional distribution, however, the coefficient rises significantly, especially at the extreme upper quantiles. For those firms with the highest values of Tobin's q , additional efforts at innovation result in relatively large gains in market value. It is plain to see that the OLS point estimates, shown here as horizontal lines with 95% confidence intervals, provide limited information on the relationship between innovation and market value.

Our results appear to be quite robust, not only across the four 'complex technology' sectors, but also using different data. We repeated the analysis using either 3-year R&D stocks or 3-year patent stocks (instead of combining them in a composite index) and we obtained qualitatively similar results. Furthermore, we repeated the analysis using the Hall et al. (2005) database,⁷ and obtained similar results (although with fewer observations).

To sum up, previous research using conventional regression estimators shows that the stock market does recognize innovative activity undertaken by firms. However, quantile regression analysis adds a new dimension to the literature and suggests that the influence of innovation on market value varies dramatically across the market value distribution. For firms with a low value of Tobin's q , the stock market will barely recognize their attempts to innovate. For firms with the highest values of Tobin's q , however, their market value is particularly sensitive to innovative activity.

⁶SIC 37 (Transportation Equipment) contains manufacturing sectors as diverse as ship-building, bicycles, and guided missiles. Furthermore, while the other 3 sectors are bona fide 'high-tech' sectors, many subclasses of SIC 37 have rather more mature technological bases. For an amusing anecdote on the diversity of industries grouped together in the 'Transportation Equipment' class, see Griliches (1990: 1667).

⁷This database is publicly available (subject to conditions) from Bronwyn Hall's website: <http://elsa.berkeley.edu/~bhhall/bhdata.html>

Part V

Conclusion

Chapter 9

Conclusion

What have we learned about firm growth? To conclude this thesis, we begin by reviewing the main conclusions of the chapters before closing with a general discussion.

A summary of the chapters We opened the thesis with a survey of the literature (Chapter 2). Although it is hardly uncommon to begin a thesis in such fashion, our introductory survey was far more than a perfunctory preamble to the empirical analyses because it helped to identify the aspects of firm growth which would benefit the most from additional research. The main message that seemed to emerge from the survey, however, was that growth rates appeared to be remarkably random by nature, reflecting the existence of a strong idiosyncratic component in the statistical series. The challenge we faced was to make an original contribution to this literature, and our response was built around investigations organized according to three main research themes.

The main lacunae that we identified in the literature review were thus as follows. First, the analysis of an autocorrelation structure appeared to us to promise useful insights into the analysis of firm growth patterns. However, we observed that the previous literature on autocorrelation has mainly contented itself with conflicting results regarding the sign and magnitude of the autocorrelation coefficient. Furthermore, it would appear as if researchers were uninterested in attempting to uncover the source of this disunity, instead preferring to perform growth rate regressions in which any autocorrelation structure is treated as ‘noise’ to be routinely ‘controlled away’ and subsequently forgotten about. The second breach in the literature concerned the relationship between a firm’s financial performance and its growth. Whilst some mainstream studies had considered the relationship between firm-level investment and cash-flow, there had been very few empirical studies into the relationship between financial performance and more conventional measures of firm growth. This was a surprising observation given that theoretical modelling (models of an evolutionary flavour in particular) had often assumed a direct positive relationship between financial performance and growth. Third, we

were taken aback at the rudimentary state of knowledge concerning the influence of innovation on firm growth. A number of theoretical models, especially in recent years, have attributed a central role to innovation in explaining the growth of firms. Furthermore, survey evidence suggested that firms considered innovation to play a crucial role in shaping their firm's growth prospects. Empirical work, however, had been disappointing in that it could not ascribe more than a minor role to innovation in determining a firm's growth rate. Indeed, in some cases, it was observed that innovation had no significant influence on a firm's growth.

Chapter 3 began our empirical analyses, starting off by describing our dataset with some well-known indicators of firm growth and industrial dynamics (such as size distributions and Gibrat's law). These preliminary analyses are, in themselves, meaningful complements to the existing body of literature, because they provide statistical descriptions of a large database on French manufacturing firms that we felt had not been sufficiently exploited in previous work. The later analyses in this chapter, which deal with the scaling of growth rate variance with firm size, and with the distribution of growth rates, yield particularly interesting results given that previous analyses on other datasets gave conflicting findings. Of especial interest is the observation that the distribution of firm growth rates is even fatter tailed than the comparable distributions available for US and Italian datasets. This latter feature was seen to be quite robust to sectoral disaggregation.

Chapter 4 builds on the foundations laid in the previous chapter in an attempt to uncover some statistical regularities in the growth patterns of firms. We began by arguing that previous attempts to find any autocorrelation structure had not had much success, with autocorrelation coefficients taking values that were either positive, negative, or insignificantly different from zero. We interpreted this confusion as a sign that there was no 'one-size-fits-all' autocorrelation structure, and instead we suspected that the contentious results emerging from previous work were in fact signalling the presence of a rather more complex structure. As a result, we were able to discover regularities in growth rate autocorrelation by accounting for heterogeneity along two dimensions – a firm's size and its growth rate. We observed that smaller firms are likely to experience a negative autocorrelation in their annual growth rates, whereas the growth of larger firms displays a mild positive autocorrelation. Furthermore, a strong negative autocorrelation at the extreme quantiles of the growth rate distribution implies that firms that experience either extremely fast positive or negative growth are quite unlikely to repeat their growth performance in the following year. This latter tendency is particularly strong for small firms.

Chapters 5 and 6 contain our analysis of the relationship between financial performance and firm growth. There are in fact two questions to be dealt with here. First, is there any relationship between a firm's financial performance and its growth rate? Second, how should we interpret such a dependence? We begin in Chapter 5 by observing that the mainstream

literature (which bases itself on notions of rational optimizing firms with some sort of an ‘optimal size’) interprets any dependence of firm-level investment on financial performance (i.e. cash flow) in terms of catchphrases such as ‘financial constraints’, the ‘lemons problem’, ‘information asymmetries’ and other instances of market imperfection. However, we show that this interpretation, although widely accepted, does not stand up very well in the light of a more rigorous examination. In contrast to this, we develop what could be called an ‘evolutionary’ interpretation of the relationship between financial performance and growth, in line with the principle of ‘growth of the fitter’. In this context, we should expect that financial performance should have a role in determining a firm’s growth rate, such that this relationship merely signals the healthy workings of an economy. We then test this principle of ‘growth of the fitter’ in Chapter 6, using our database on French manufacturing firms. After controlling for endogeneity in the relationship between financial performance and growth, we find that a firm’s financial performance has essentially no role in explaining its subsequent growth. (In contrast, it appears that growing firms, on average, seem to have higher profit rates.) These results are interpreted as suggesting that firms have a large amount of discretion in their growth rates, and that selection mechanisms do not discriminate very well between firms (as far as the attribution of growth opportunities is concerned).

Chapters 7 and 8 relate innovation to firm performance. For the purposes of these chapters, we introduce a second database that contains information on firm-level innovation. In order to get the best possible quantitative measures of firm-level innovative activity, we focus on four 2-digit sectors that have high propensities for both patenting and R&D expenditure. Another key feature of the analysis is our choice of quantile regressions, which enables us to describe the influence of innovation on growth at various quantiles of the conditional growth rates distribution. In Chapter 7 we observe that most firms do not grow very much, and that innovation makes but a small contribution to their overall growth rate. For the firms that experience the fastest growth, though, a much larger share of their growth appears to be linked to their previous attempts at innovation. Given the long time-lag that may be required in order to convert new knowledge into a final commercial product, however, we reconsider the relationship between innovation and firm performance by measuring this latter via a firm’s market value (Chapter 8). It can be supposed that a firm’s market value can evolve in anticipation of future gains from innovation in a way that a firm’s sales cannot. Here too we observe a remarkable heterogeneity in the outcome of firm-level innovation. For those firms with the highest relative market valuations, their valuations are very sensitive to their previous investments in innovation. At the bottom of the spectrum, however, are those firms with the lowest market valuations for whom any investment in innovation is barely recognised by the stock market. For this latter group, it would appear that their attempts at innovation are merely a waste of resources. We also note that conventional regression estimators, which

give a summary point estimate corresponding to ‘the average effect for the average firm’, are unable to detect these heterogeneous effects.

Concluding discussion One of the more useful theories of firm growth was formulated by Edith Penrose in her celebrated book in 1959. The essence of Penrose’s vision was that firms will always have internal resources for growth because of learning-by-doing effects and, more specifically, the freeing up of managerial attention as managers become increasingly accustomed to their tasks. Unless the firm decides to grow, however, unless it chooses to make use of these spare resources, it appears to us that these newly-liberated managerial resources will be absorbed as organizational slack. Firms need to decide upon the direction into which they can channel these excess resources.

Growth can be considered to be a dissatisfaction with the present scale of operation. Growing firms must have a vision that extends beyond their present situation, and look outward for new opportunities, thereby embarking upon a venture into the unknown. Indeed, growth requires a certain audacity. While low-profit firms may be able to improve their circumstances through growth, their poor past performance offers little credibility to their projects. High-profit firms, if they desire to grow, must look beyond their satisfactory performance and take a chance, without holding back out of fear of compromising their past success. As a result, high-profit firms may not be willing to take this risk. This may be why we observe no net effect of profits on firm growth in Chapter 6.

In contrast, we observed that the influence of growth on profits tended to be more important than the influence of profits on growth. This is consistent with what Starbuck (1971: 74) calls the ‘will-o’-the-wisp’ models of growth. According to these models, there are temporary gains that lure firms to grow. For instance, it has been noted that there is a considerable time lag between increases in productive capacity and the commensurate additions to managerial resources (Starbuck, 1971: 54) or administrative overhead (Dixon, 1953). Relatedly, Penrose speaks of these short-lived gains in terms of her ‘economies of growth’. Firms may choose to expand to a considerable size, even in the absence of economies of scale, simply because there may be short-term gains from marginal growth opportunities that may be present at every step of a firm’s growth. (Clearly, we are far from a static equilibrium optimal-size framework here.)

Although growth opportunities may well be available to every imaginative and enterprising manager, not everyone will take them up. It may be relevant to endorse such a motto as ‘who dares grows’. Some managers may not be willing to take the risks associated with expansion. At the other extreme, it appears from our studies of autocorrelation dynamics in Chapter 4 that firms that attempt to grow too fast will not succeed. Furthermore, we observe that in the majority of cases, success in past growth does not in any way guarantee success in future

growth.¹ It appears to us that future growth concerns the taking up of opportunities that are, in some sense, new; growth involves challenges that have not been faced by the firm previously in this particular form. This is just as true for the small firm that ventures into new local markets as it is for the diversified multinational that launches a new product in a new country. This conception of growth is particularly evident in the ‘stages of growth’ models surveyed in Section 2.5.2, where growth occurs by resolving one organizational crisis by introducing reforms that will, in turn, lead to the arrival of a new crisis. In still other cases, a fortunate firm may, through investment in innovation, happen upon a valuable discovery which propels it into the fast-growth category (as described in Chapter 7). The common theme here is that firm growth is an uncertain undertaking, and perhaps in some sense it is the antithesis to the organizational routine.

Where do we go from here? We wrap up this thesis by, once again, arguing in favour of Herbert Simon’s (1968) research strategy, which emphasizes the need for solid empirical work to first produce the ‘stylized facts’ that theory can then attempt to explain. At this stage, we consider that research into the growth of firms could benefit most from gathering of statistical regularities and ‘stylised facts’. We consider that theory without any solid empirical basis – what we might call ‘armchair axiomatics’ (Dosi, 2004) – will be of little use in furthering our knowledge of the growth of firms and the evolution of industries.

We began the thesis with a quote from William Starbuck: “The subject of organizational growth has progressed beyond abysmal darkness. It is ready for – and badly needs – solid, systematic empirical research directed toward explicit hypotheses and utilizing sophisticated statistical methods” (Starbuck, 1971: 126). We believe we have gone some way in facing up to this challenge. We have presented relatively sophisticated techniques that are capable of dealing with heterogeneity (quantile regression), and also techniques that deal with endogeneity (System GMM). These techniques have been able to meet the econometric difficulties that beset the relationships on which we have focused.

Future work into the growth of firms could benefit from insights gained from other statistical techniques. One promising avenue of research seems to us to be the application of short-panel vector auto-regression (VARs) which have recently been developed in the theoretical econometrics literature (Binder, Hsiao and Pesaran, 2005). This econometric tool will hopefully enable us to better observe the coevolution of series such as employment growth, value added growth, and the growth of profits and productivity. I am currently working on such a project.² Techniques such as Principal Components Analysis and Cluster Analysis

¹Instead, it may well be the case that past success can count against the firm, which risks becoming complacent or having its cognition dulled by illusions of repetition (for more on this point, see Halebian and Finkelstein’s (1999) analysis of growth by acquisition).

²I intend to present some preliminary results along these lines at the EMAEE 2007 conference in Manchester

may also provide helpful insights into taxonomies of firms that are grouped according to their growth behaviour (see Delmar et al. (2003) and de Jong and Marsili (2006) for examples of such work).

Datasets are also continually improving. Although the measurement of innovation has been problematic in the past, enhanced measures of innovation have recently been developed that include a wider range of information, including patent citations (both backward and forward) or even other indicators such as patent claims or patent family size (see Lanjouw and Schankerman, 2004). Furthermore, improvements in databases concerning the decomposition of a firm's business according to its segments of activity can be expected to shed further light on a firm's diversification behavior. Empirical work investigating the growth of firms via diversification is still at a rather primitive stage (see, however, the pioneering study by Teece, Rumelt, Dosi and Winter (1994)). Datasets such as the Compustat Industry Segment (CIS) database (which has been used in the financial economics literature on diversification) are welcome developments along these lines.

These, we anticipate, will be some of the valuable sources of further progress in our understanding of how firms grow.

(an abstract of this research has been accepted by the conference committee). Furthermore, Professor Binder has already kindly provided me with the Matlab code for the short-panel VAR estimator. One drawback of the Binder-Hsiao-Pesaran estimator, however, is that it assumes that the error terms are normally distributed, which as we have seen is not the case for firm growth rates.

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Empirical Investigations into the Characteristics and

Determinants of the Growth of Firms:

RÉSUMÉ EN FRANÇAIS

Remarques générales Le but de cette traduction est de fournir des renseignements aux lecteurs qui ne comprennent pas l'anglais ou qui ne se sentent pas à l'aise en lisant la thèse en anglais. Ce résumé permet de donner une idée au lecteur sur le contenu de la thèse, mais il n'est certainement pas une traduction de la thèse en entier. Alors que ce résumé permet de survoler les principales thèmes abordées, nous conseillons fortement au lecteur qui s'intéresse sérieusement à la croissance des firmes de lire la thèse en anglais afin de saisir toutes les subtilités des résultats.

Introduction générale L'ambition de cette thèse est de mieux comprendre le phénomène de la croissance des entreprises. Plus précisément, nous essayons d'améliorer nos connaissances en ce qui concerne la croissance des firmes en nous appuyant sur des analyses économétriques de données longitudinales. Nous cherchons ainsi à fournir une description statistique de la phénomène de croissance, plutôt que de tenter de construire une nouvelle théorie.

La thèse est structurée en neuf chapitres qui se regroupent en cinq parties. Dans la première partie, nous introduisons le sujet avec, dans un premier temps, une introduction générale, et dans un second temps, avec une revue de la littérature. Cette revue de la littérature permet notamment de développer deux points importants. Premièrement, nous insistons sur l'importance d'une compréhension plus large du phénomène de croissance des firmes. Effectivement, dans les analyses statistiques qui suivent, nous prenons comme indicateur de croissance une mesure purement quantitative (c'est-à-dire un taux de croissance pour une entreprise i pour l'année t) ce qui est bien entendu une énorme simplification. Nous cherchons alors à souligner les aspects qualitatifs de la croissance qui risquent d'être négligés dans l'analyse statistique qui suit. Deuxièmement, la revue de la littérature nous permet d'identifier ce que nous percevons comme les lacunes dans nos connaissances actuelles concernant le phénomène de croissance de firmes.

Dans la deuxième partie, nous commençons nos analyses empiriques en étudiant quelques indicateurs de la structure et la dynamique des industries. Ces analyses se basent sur des données d'entreprises françaises issues d'une enquête nationale menée par l'INSEE, pour la période 1996-2002. Nous regardons d'abord la distribution des firmes selon la taille, et nous retrouvons la distribution habituelle qui ressemble à la distribution de Pareto. Toutefois, il apparaît que cette distribution ne se retrouve pas à un niveau moins agrégé, car lorsque l'on se limite à une analyse au niveau sectoriel nous observons des distributions moins régulières.

Nous considérons ensuite la loi de Gibrat, selon laquelle les moments de l'espérance du taux de croissance sont indépendants de la taille d'une firme. Nous ne pouvons pas rejeter l'hypothèse d'indépendance des taux de croissance de la taille, mais néanmoins nous rejetons la loi de Gibrat parce que nous constatons que la variance des taux de croissance diminue avec la taille. Effectivement, nous observons que les petites firmes ont une variance qui est plus grande que pour les grandes firmes (ceci pourrait s'expliquer en partie par le phénomène de diversification chez les grandes firmes). Ensuite nous présentons la distribution des taux de croissance. Les travaux antérieurs ont montré que cette distribution se ressemble à une distribution de Laplace (on parle alors de 'fat-tailed distributions' en anglais). Dans notre cas, par contre, nous observons que la distribution se distingue de ces travaux car la densité empirique a encore plus de poids dans les extrémités de la distribution que dans le cas Laplacien. Dans le quatrième chapitre, nous nous concentrons sur l'analyse de la structure d'autocorrélation dans les taux de croissance. Nous cherchons des régularités selon deux axes d'analyse – l'autocorrélation en fonction de la taille d'une firme et de son taux de croissance dans la période précédente. Nous trouvons des résultats originaux qui peuvent se résumer ainsi: les expériences de croissance des petites firmes sont beaucoup plus erratiques que celles des grandes firmes. La croissance des petites firmes peut être décrite par une dynamique d'autocorrélation négative, ce qui est particulièrement accentué pour les petites firmes qui ont crû rapidement.

La troisième partie se concentre sur la relation entre la performance financière d'une firme et sa croissance. Nous critiquons la théorie standard des contraintes financières et nous plaidons en faveur d'une interprétation que l'on pourrait qualifier d'évolutionniste (chapitre 5). Cette interprétation évolutionniste de la relation entre performance financière et croissance repose sur le principe de 'la croissance du plus fort'. Nos résultats empiriques, qui se trouvent dans le chapitre 6, sont alors interprétés dans le contexte de cette discussion théorique. Nous utilisons

les mêmes données françaises, mais cette fois pour la période 1996-2004. Nous utilisons une large gamme de techniques statistiques et économétriques, et nous pouvons identifier un effet positive et statistiquement significatif de la profitabilité sur la croissance. Néanmoins, nous reconnaissons que cet effet est assez petit, si bien qu'il serait plus simple de considérer que la profitabilité n'est pas un facteur important pour la croissance. Nous interprétons ce résultat en faisant référence au concept évolutionniste de sélection, et nous concluons que les pressions de sélection ne sont pas très efficaces.

Dans la quatrième partie, nous regardons la relation entre l'innovation des firmes et leur performance. Dans le chapitre 7, nous mesurons la performance en termes de croissance, alors que dans le chapitre 8 nous la mesurons en nous référant à la valeur boursière d'une firme. Nos analyses sont effectuées en créant une nouvelle base de données sur les entreprises américaines. En ce qui concerne le chiffre d'affaires et les dépenses en R et D des firmes, nous nous référons à la base de données 'Compustat'. Nous complétons ces informations avec des données sur les brevets provenant d'une base de données NBER, qui sont des données au niveau de la firme, année par année. De plus, nous nous limitons aux entreprises dans les secteurs d'activité de haute technologie, afin d'obtenir des observations quantitatives fiables pour les dépenses en R et D et le nombre de brevets par firme. Nous observons effectivement que l'innovation a des effets très hétérogènes sur les firmes. Pour la grande partie des entreprises, la croissance prend un caractère idiosyncratique, si bien que l'influence de l'innovation pour la croissance (ou bien pour la valeur boursière) est relativement modeste. Néanmoins, il existe une minorité de firmes qui se distinguent par une croissance particulièrement rapide (ou par une valeur boursière particulièrement élevée). Pour ce dernier groupe de firms, nous observons que les efforts liés à l'innovation jouent un rôle nettement plus important. Ces résultats peuvent être interprétés de la manière suivante: l'innovation est une activité très incertaine, et les

résultats de l'innovation sont distribués d'une façon très inégale. Dans la majorité des cas, la performance des firmes innovantes n'est que faiblement supérieur à celle des firmes qui sont moins innovantes. Dans une minorité des cas, néanmoins, l'innovation permet aux entreprises d'avoir une performance exceptionnelle. Nous soulignons que l'utilisation de la technique de la régression par quantile fait apparaître des résultats qui ne peuvent être détectés par des techniques de regression plus standards qui se basent sur des hypothèses implicites de homogénéité des unités d'observation.

La cinquième partie est une conclusion brève et synthétique de la thèse.

Chapitre 1: Introduction Dans ce chapitre introductif se trouve une discussion générale de la croissance des firmes dans l'économie moderne. Nous commençons par évoquer des aspects historiques qui risquent d'être mis de côté lors des analyses statistiques. Dans le passé, les grandes firmes avaient de nombreux avantages liés à leur grande taille, tels que la stabilité financière, l'organisation de l'activité économique selon le principe de production en masse, et la popularité de la grande firme diversifié et multidivisionnelle. Toutefois, il semblerait qu'aujourd'hui c'est plutôt les petites firmes qui reçoivent les louanges, car celles-ci bénéficient d'une flexibilité supérieure et ont moins besoin de stabilité car les marchés financiers sont plus efficaces de nos jours.

Dans la suite de cette introduction nous soulevons quelques points qui, il nous semble, n'ont pas été suffisamment développés dans la littérature existante sur la croissance des firmes. Nous nous éloignons d'emblée de la notion d'une 'taille optimale', car cette vision théorique n'est pas utile pour comprendre la croissance des firmes. Nous soulignons, par contre, la nécessité de tenir en compte l'hétérogénéité des firmes. En effet, nos analyses statistiques basées sur la régression par quantile (dans les chapitres 4, 7 et 8) se basent sur une reconnaissance de l'hétérogénéité des modes de croissance des firmes, et les résultats que nous obtenons font apparaître des dimensions qui ne peuvent pas être repérées par des techniques économétriques plus standards.

Nous indiquons aussi, à la fin de ce chapitre, que une partie de la recherche à été écrit en collaboration avec des autres auteurs, et qu'une partie de la recherche a été publié ou est en voie de publication.

Chapitre 2: Revue de la littérature Cette revue de la littérature constitue effectivement une large partie de la thèse. Le but de cette revue, ce qui est certes ambitieux, est de fournir une discussion synthétique des aspects empiriques et théoriques les plus importants dans la recherche actuelle sur la croissance des firmes. Ce travail de synthèse permet alors de mentionner les aspects qui ne seront pas traités dans la suite de la thèse, ainsi que d'expliquer au lecteur lesquelles sont ce que nous estimons être les lacunes dans nos connaissances actuelles les plus urgentes.

La revue de la littérature commence par un survol des résultats empiriques et une discussion de leurs implications. Les contributions théoriques seront discutées plus tard, et il apparaît que ces derniers ne sont pas en accord avec les faits stylisés empiriques.

Nous commençons avec un regard sur les distributions de taille des entreprises manufacturières. Cette distribution prend une forme lisse et régulier au niveau agrégé, qui ressemble à la distribution lognormale, ou bien à la loi de Pareto. Nous regardons ensuite la distribution des taux de croissance, et nous constatons que des études empiriques sur données américaines ou italiennes suggèrent que cette distribution ressemble à une distribution de Laplace. Ceci implique que la plupart des entreprises ne croissent pas beaucoup dans une année donnée (autrement dit, ils ont un taux de croissance qui est proche de zéro), alors qu'il existe en chaque période une minorité d'entreprises qui croissent relativement rapidement.

Nous arrivons ensuite à notre discussion de la loi de Gibrat. Selon la version la plus simplistique du modèle de Gibrat, cette loi prévoit que le taux de croissance d'une entreprise est *ceteris paribus* indépendant de sa taille. Nous observons qu'une très large littérature a tenté de vérifier ou de rejeter la loi de Gibrat. Alors que les résultats ne sont pas entièrement convergents, nous arrivons à la conclusion suivante. La loi de Gibrat semble fournir une description satisfaisante de la croissance de 'grandes firmes', alors que parmi les petites firmes

nous observons que le taux de croissance espéré diminue avec la taille. De plus, il semblerait que la variance des taux de croissance a une tendance à diminuer avec la taille des entreprises.

Ensuite nous regardons la littérature traitant le phénomène d'autocorrélation dans les taux de croissance. Cette littérature ne permet pas de converger vers un consensus. Effectivement, un grand nombre d'études empiriques ont fait apparaître des résultats très différents. Alors que dans certains cas des auteurs ont trouvé une autocorrélation positive, dans des autres cas on observe une autocorrélation négative. Dans d'autres cas encore, nous trouvons aucune autocorrélation. Nous nous étonnons face à ces résultats conflictuels et nous tentons de justifier l'analyse des processus d'autocorrélation qui se situe dans le quatrième chapitre.

Quels sont les autres déterminants des taux de croissance des firmes? Cette question est le but de la section suivante. Nous regardons alors les travaux empiriques qui se sont intéressés aux facteurs qui peuvent exercer une influence sur la croissance des firmes. Cette liste de déterminants contient des facteurs tels que l'âge, les efforts liés à l'innovation, la performance financière, ou bien la forme juridique de l'entreprise.

La relation entre l'âge d'une firme et son taux de croissance est une relation qui a reçu beaucoup d'attention. Nous pouvons mentionner ici le résultat générale (mais pas unanime) que le taux de croissance semblerait diminuer avec l'âge d'une entreprise.

En ce qui concerne la relation entre innovation et croissance, il est utile de faire la distinction entre les différentes dimensions de la croissance d'une firme – notamment la croissance en termes de chiffre d'affaires et la croissance en termes du nombre d'employés. Nous commençons en constatant que la théorie économique ainsi que les résultats de questionnaires indiquent, sans ambiguïté, que l'innovation est un des facteurs les plus importants pour la croissance du chiffre d'affaires des entreprises. Nous observons, néanmoins, que les études empiriques qui ont essayé de trouver le lien entre l'innovation d'une entreprise et sa croissance du chiffre

d'affaires n'ont pas eu des résultats concordants. Les études empiriques n'ont pas su attribuer à l'innovation plus qu'un rôle mineur (et dans plusieurs cas, les études empiriques n'ont même pas trouvé de relation entre ces variables). Il nous semblerait utile d'essayer de concilier les prédictions théoriques et les résultats empiriques, et nous justifions ainsi la quatrième partie de la thèse, qui se concentre sur la relation entre l'innovation et la performance des firmes.

Nous regardons aussi la littérature sur la relation entre les activités d'innovation des firmes et leur croissance en termes du nombre d'employés. En fait, il est tout à fait possible que les entreprises innovatrices choisissent de tirer profit de leurs innovations en remplaçant la main d'oeuvre avec des machines – dans ce cas il y aurait peut-être une relation négative entre innovation et croissance en termes d'emploi. Toutefois nous expliquons qu'il existe de nombreux effets de substitution (comme, par exemple, l'hypothèse que les entreprises innovatrices peuvent accroître leur part de marché et ainsi augmenter le nombre total d'employés). Ainsi, il apparaît que le signe de la corrélation entre innovation et nombre d'employés n'est pas bien défini a priori et que nous devons étudier cette relation avec des études empiriques. Nous regardons alors la littérature qui traite de ce sujet, et nous concluons toutefois que l'innovation a, dans de nombreux cas, des effets positifs sur le nombre d'emplois. Toutefois, les innovations de procédé (à l'encontre des innovations de produits) peuvent être associées à des réductions d'emploi.

Nous regardons aussi la relation entre la performance financière des entreprises et leur croissance. L'interprétation habituelle néoclassique consiste à dire que la relation entre la performance financière d'une entreprise et sa croissance (ou plus précisément, ses dépenses d'investissement) témoigne du phénomène des contraintes financières qui restreignent la croissance des entreprises. Cette interprétation néoclassique repose sur une vision de la firme comme un agent infiniment rationnel et optimisateur. Toutefois, nous considérons qu'il est

utile de mentionner une interprétation évolutionniste de la relation entre performance financière et croissance. Cette interprétation fait référence à la ‘loi du plus fort’ et aux effets de sélection pour suggérer qu’une relation positive entre performance financière et croissance témoigne du bon fonctionnement de l’économie. Toutefois, nous concluons cette section sur la relation entre performance financière et croissance en constatant que la performance financière n’en joue qu’un rôle mineur. Ceci signale, nous avançons, un manque de compétition dans l’économie et suggère que les effets de sélection ne sont pas très importants.

Nous nous intéressons aussi à la relation entre la productivité d’une entreprise et sa croissance. Cette relation ressemble à la relation entre performance financière et croissance, quand même, parce que les profits et la productivité sont corrélés entre eux. Nous observons que la productivité relative d’une entreprise n’est pas un facteur majeur de la croissance des entreprises. Ceci indique que les pressions de sélection sont faibles et qu’il pourrait avoir un manque de compétition dans l’économie.

Un certain nombre d’études empiriques ont tenté de trouver des autres déterminants des taux de croissance. Il apparaît que les entreprises multidivisionnelles ont, en moyenne, des taux de croissance plus élevés que ceux des entreprises n’ayant qu’un seul établissement productif. Les entreprises ayant une forme juridique qui ressemble à la forme de la ‘société anonyme’ ont *ceteris paribus* des taux de croissance plus élevés que les entreprises pour lesquelles le propriétaire est personnellement responsable des dettes. Il y a aussi quelques études qui montrent qu’une séparation entre le management et le (ou les) propriétaire (s) a l’effet d’augmenter le taux de croissance espéré, peut-être parce que le management cherchera un taux de croissance plus élevé que celui souhaité par le propriétaire. De plus, il semblerait que les entreprises appartenant au gouvernement ont des taux de croissance moins élevés que les entreprises dans le secteur privé. Par contre, les entreprises appartenant aux compagnies provenant de l’étranger

auront normalement des taux de croissance supérieurs. Toutefois, il paraît que l'incertitude est un facteur qui sert à réduire le taux de croissance (et surtout les dépenses en investissement).

Certains facteurs macro-economiques ont aussi une influence sur le taux de croissance des firmes. Alors que la corruption semble avoir un impact négatif sur le taux de croissance, par exemple, la qualité des institutions financières et légales semble avoir un effet positif. De plus, il est possible que la conjoncture économique ait des effets différents sur la croissance des petites et grandes firmes.

Nous concluons cette revue de la littérature empirique en constatant que ces régressions qui cherchent à trouver les déterminants des taux de croissance ont néanmoins des coefficients R^2 assez faibles, souvent moins que 10%. Ceci signifie que les taux de croissance sont particulièrement aléatoires et que nous sommes loin d'expliquer pourquoi une entreprise a un taux de croissance donné dans une période donnée.

Nous passons ensuite à la revue des contributions théoriques concernant la croissance des firmes, en commençant avec la théorie néoclassique, en passant par la théorie d'Edith Penrose de la croissance des entreprises, la théorie de Marris (c'est-à-dire, la théorie managérialiste), la théorie évolutionniste, et présentant finalement la théorie du 'population ecology' qui provient de la littérature de la sociologie. La théorie néoclassique se base dans un contexte plutôt statique et semble prédire que les firmes croissent uniquement dans le but d'atteindre une taille optimale. Il nous semble que cette théorie n'est pas très pertinente car elle n'est pas en accord avec les résultats empiriques. La théorie de Penrose, par contre, nous paraît beaucoup plus intéressante. Penrose considère que les entreprises cherchent souvent à croître pour tirer profit d'opportunités marginales. De plus, Penrose décrit comment les entreprises ont les moyens ou les 'ressources' nécessaires pour croître qui proviennent du fait qu'ils accumulent progressivement de l'expérience dans leurs opérations. La théorie de Marris nous paraît aussi

intéressant, même si sa portée est peut-être un peu limitée. La théorie de Marris explique comment les managers cherchent à augmenter la taille de l'entreprise au-delà de la taille qui serait souhaitable pour les propriétaires. En ce qui concerne la théorie évolutionniste, nous pouvons mentionner ici le principe de la 'croissance du plus fort' selon laquelle nous pouvons nous attendre à ce que les entreprises les plus profitables aient un taux de croissance plus élevé. Néanmoins ce principe ne semble pas trouver de soutien de la part des études empiriques, ce qui nous amène à nous méfier de ce principe. Nous terminons cette section avec une description de la théorie du 'population ecology', mais cette théorie nous paraît limitée car elle met l'accent sur le rôle des facteurs qui décrivent les secteurs d'activité et qui touchent la population d'entreprises de façon égale (alors que ces facteurs n'ont qu'un rôle mineur selon les études empiriques). Nous concluons cette partie théorique avec le sentiment que la théorie de la croissance des firmes fournit souvent des prédictions fausses et est un peu décevant. La théorie de Penrose est celle qui nous a paru le plus intéressant.

Dans la prochaine section de cette revue de la littérature nous nous concentrons sur les différentes stratégies de croissance. Nous faisons la distinction entre demande d'opportunités de croissance (c'est-à-dire si une entreprise souhaite aggrandir ou pas) et l'offre d'opportunités de croissance (c'est-à-dire si les opportunités de croissance se présentent aux firmes ou pas). Du côté de la demande d'opportunités de croissance, nous abordons la littérature qui traite des attitudes des entreprises envers la croissance. Si les entreprises familiales traditionnelles, par exemple, sont réticents face aux opportunités de croissance, néanmoins il apparaît que les grandes corporations multinationales ont un regard beaucoup plus favorable envers la croissance. Nous discutons des cas dans lesquelles la croissance des entreprises présente des avantages ou des désavantages. De plus, nous nous intéressons à la question de l'intentionnalité de la croissance, et il nous semblerait que la croissance des entreprises requiert néanmoins

une certaine délibération (autrement dit, que la croissance des entreprises n'est pas uniquement un phénomène inconscient ou semi-automatique). Lors de notre discussion de l'offre des opportunités de croissance, il apparaît qu'une entreprise a plusieurs façons de mener à bien ses projets de croissance. Une entreprise peut choisir de croître en suivant une stratégie de croissance par répllication, ou de croissance par diversification. De plus, une firme doit décider entre une stratégie de croissance interne et une stratégie de croissance par acquisition (aussi appelé 'croissance externe'). Nous remarquons aussi que les modes de croissance par diversification et par croissance externe ont souvent été critiqués car elles sont souvent des stratégies de croissance qui sont utilisés par des managers qui cherchent un taux de croissance plus élevé que celui qui serait préférable pour l'actionnaire.

Dans la section suivante, nous nous concentrons finalement sur les différences de croissance entre les petites firmes et les grandes firmes. D'abord nous nous limitons au cas binaire, où l'on fait la distinction entre petites et grandes firmes. Il apparaît que les expériences de croissance des petites firmes sont particulièrement effrénées. Effectivement, les petites entreprises se trouvent face à une situation selon laquelle elles doivent 'croître ou mourrir'; ou autrement dit que leur probabilité de survie est liée à leur taille. Les grandes entreprises, par contre, sont plutôt caractérisées par une croissance plus lissée. Ces grandes firmes ont déjà atteint une taille qui leur confère une certaine stabilité, ce qui signifie qu'alors que la croissance est une prérogative pour les petites firmes, elle est moins importante pour les grandes firmes.

Nous poursuivons notre discussion des différences entre les petites entreprises et les grandes entreprises en passant en revue les modèles des 'stades de la croissance (appelé les 'stages of growth models' en anglais). Un exemple d'un modèle de stade de croissance est le modèle de Greiner, qui est représenté dans la Figure 1. Ces modèles de stades de croissance permettent d'identifier des différentes étapes dans la croissance des entreprises, depuis la jeunesse

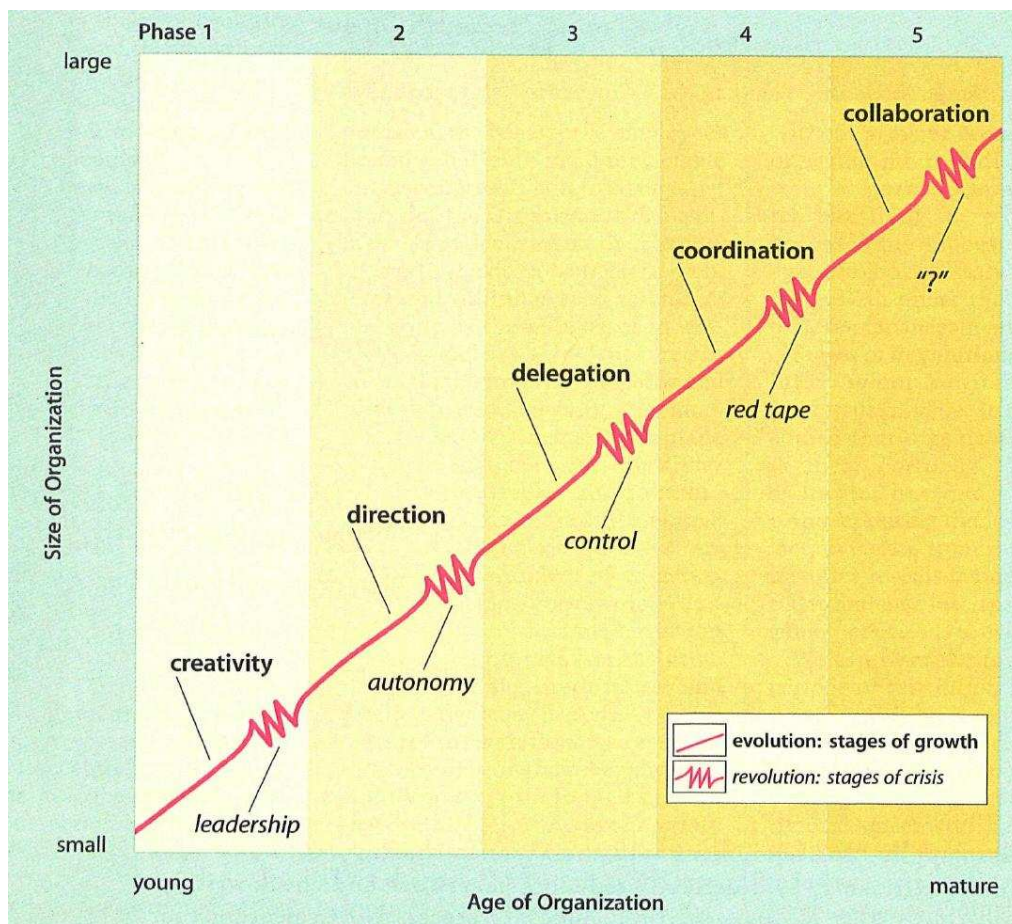


Figure 1: Un exemple d'un modèle de stades de croissance (Source: Greiner (1998:58))

d'une entreprise jusqu'à sa maturité. Un des thèmes récurrents dans ces modèles est que le gouvernance d'une entreprise varie beaucoup en fonction de son étape de développement. Alors que les petites entreprises peuvent être caractérisées par un fondateur énergétique et une structure organisationnelle relativement informelle, les grandes entreprises doivent faire face à des difficultés de coordination (ces difficultés sont bien entendu liées à la grande taille de ces derniers). Ainsi, les entreprises ayant atteint une certaine maturité tendent à devenir relativement formalisés, bureaucratiques et peut-être un peu rigides.

Cette revue de la littérature a donc permis de traiter deux aspects importants.

Premièrement, nous insistons sur l'importance d'une compréhension plus large du phénomène de croissance des firmes. Effectivement, dans les analyses statistiques qui suivent, nous prenons comme indicateur de croissance une mesure purement quantitative (c'est-à-dire un taux de croissance pour une entreprise i pour l'année t) ce qui est bien entendu une énorme simplification. Nous cherchons alors à souligner les aspects qualitatifs de la croissance qui risquent d'être négligés dans l'analyse statistique qui suit.

Deuxièmement, la revue de la littérature nous permet d'identifier ce que nous percevons comme les lacunes dans nos connaissances actuelles concernant le phénomène de croissance de firmes. Nous avons essentiellement identifié trois lacunes. Premièrement, alors que les études préalables sur l'autocorrélation des taux de croissance n'ont donné que des résultats amenant à la confusion, nous chercherons à trouver une structure autorégressive dans les taux de croissance (chapitre 4). Deuxièmement, il nous semble que la relation entre la performance financière d'une firme et sa croissance n'a pas été suffisamment exploré dans la littérature, surtout lorsque l'on tient compte des implications qui en découlent de cette relation. Troisièmement, il nous semble que la relation entre innovation et croissance n'a pas été décrit de façon satisfaisante par les études empiriques préalables, si bien que nous nous

consacrons à cette problématique dans la quatrième partie de la thèse.

Chapitre 3: Analyses préliminaires de la croissance des firmes Dans ce chapitre nous présentons nos premiers résultats originaux. Nous commençons avec une graphique qui montre la distribution des firmes selon leur taille, et nous procédons ensuite à une analyse des données selon la loi de Gibrat. Ensuite, nous présentons ce qui est probablement le résultat le plus intéressant de ce chapitre, notamment la distribution des taux de croissance. Nous observons que, dans le cas des entreprises françaises, cette distribution est particulièrement ‘fat-tailed’ – c’est-à-dire qu’il y a un grand poids de la distribution dans les extrémités.

Nous commençons alors en présentant la distribution des firmes selon leur taille. En fait, un grand nombre d’études préalables se sont intéressés à la distribution des tailles des entreprises. Pour le cas des entreprises françaises, nous obtenons la distribution qui se trouve dans la Figure 2. Cette graphique montre que la distribution est tirée vers la droite (c’est-à-dire que la distribution présente un skewness positif). La forme de cette distribution montre que la plupart des entreprises françaises sont relativement petites, alors qu’il existe un nombre non-négligeable de firmes qui sont extrêmement grandes en termes relatifs. Nous constatons toutefois, dans les analyses vers la fin de ce chapitre, que la forme régulier et lisse de la distribution des tailles des entreprises au niveau agrégé n’est plus visible lorsque l’on s’intéresse aux entreprises qui sont dans des secteurs qui sont plus étroitement définies.

Ensuite nous cherchons à tester la loi de Gibrat pour le cas de notre base de données des entreprises françaises. Afin d’estimer l’équation de régression qui correspond à la loi de Gibrat, nous tenons compte d’une possible autocorrélation dans les taux de croissance (même si ces tentatives de contrôler pour une structure autoregressive sont relativement simplistes). De plus, nous utilisons un estimateur de la classe des estimateurs ‘Minimum Absolute Deviation’ pour tenir compte du fait que les résidus ne sont pas normalement distribués. Les résultats que nous obtenons ne nous permettent pas de rejeter la loi de Gibrat, parce que il semblerait

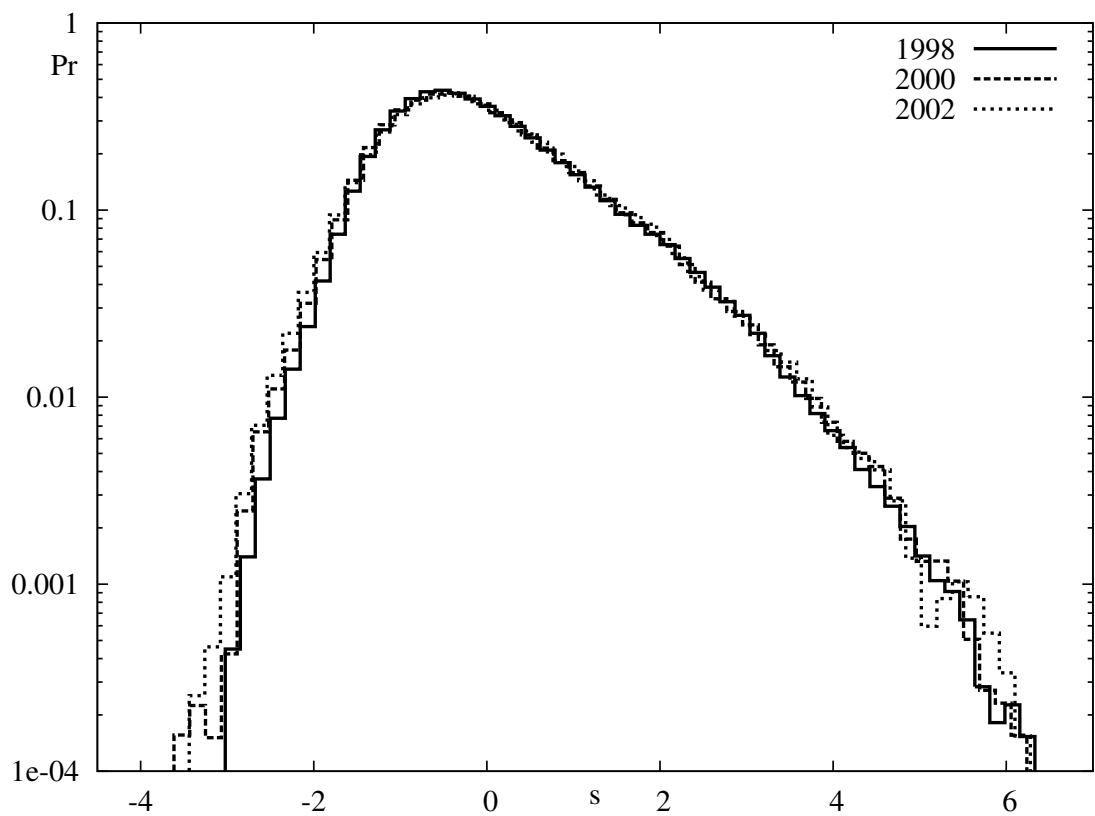


Figure 2: Kernel estimates of the density of firm size in 1998, 2000 and 2002. Densities are computed in 64 equispaced points using an Epanenchnikov kernel. Note the logarithmic scale on the y-axis.

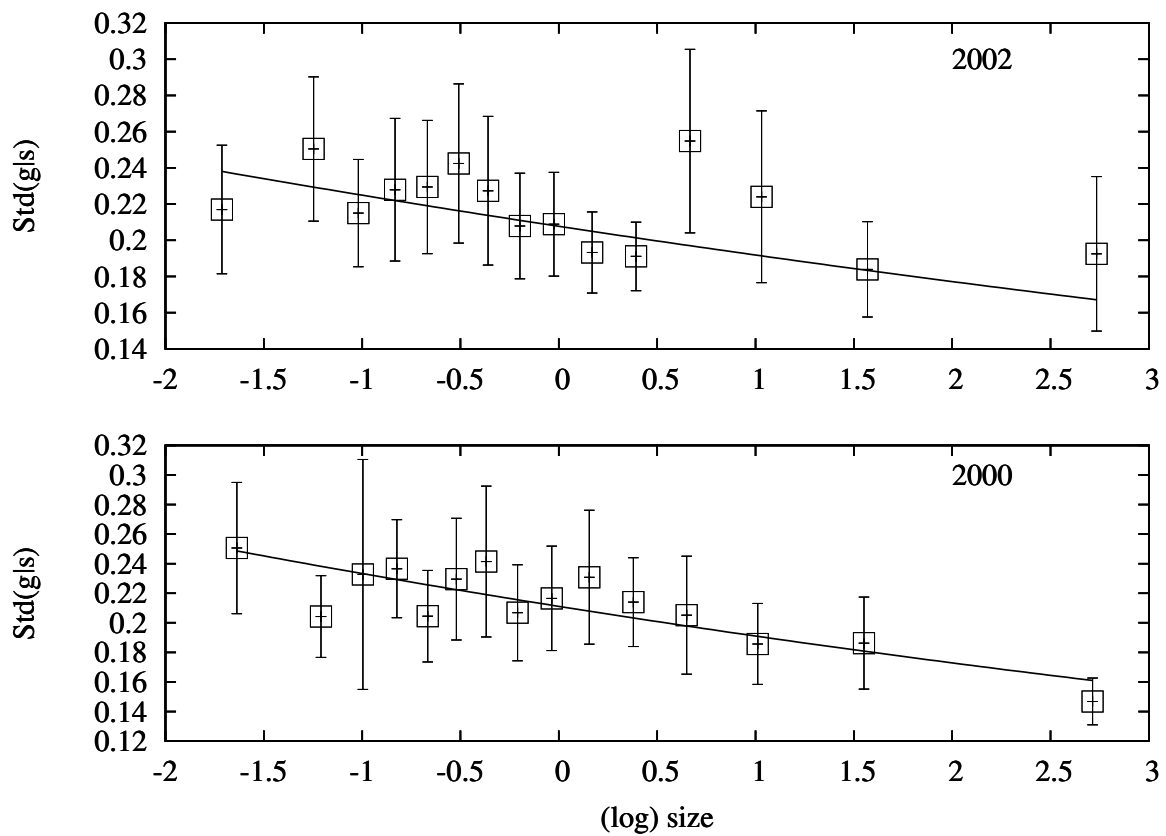


Figure 3: Relation entre l'écart-type conditionnel du taux de croissance par rapport à la taille (logarithmique) d'une entreprise, calculé en utilisant 15 groupes équipopulés pour les années 2000 et 2002. Les intervalles de confiance sont indiquées en montrant deux écarts-types.

que les taux de croissance des entreprises françaises sont plus ou moins indépendants de la taille des entreprises. Effectivement, il paraît que la loi de Gibrat fournit, approximativement, une description pertinente de la croissance des firmes, au moins dans notre cas. (Toutefois, nous reconnaissons que des autres travaux sur la loi de Gibrat qui analysent des autres bases de données ont trouvé des résultats différents.)

Ayant constaté que l'espérance du taux de croissance des entreprises est approximativement indépendant de leur taille, nous nous intéressons par la suite à la relation entre la taille d'une entreprise et la variance des taux de croissance. Les résultats de notre analyse sont présentés alors dans la Figure 3. Ce graphique met en évidence une relation négative entre la taille d'une entreprise et la variance des taux de croissance. Toutefois, lorsque l'on fait la comparaison avec les résultats pour les entreprises américaines, il apparaît que la variance des taux de croissance pour les entreprises françaises diminue moins rapidement. Par contre, nous rappelons aussi les résultats provenant d'analyses sur données italiennes qui indiquent que la variance des taux de croissance des entreprises italiennes semble être indépendante de la taille de ces dernières.

Dans la partie suivante du Chapitre 3, nous nous intéressons à la forme de la distribution des taux de croissance pour le cas des entreprises françaises. Cette distribution apparaît dans la Figure 4. En regardant cette distribution, nous pouvons observer qu'il y a un grand poids de la distribution qui est proche de la moyenne. Toutefois, nous observons qu'un poids non-négligeable de la distribution se situe aux extrémités de la distribution. Cette forme de la distribution des taux de croissance ressemble aux distributions qui correspondent aux entreprises américaines et italiennes, sauf que dans le cas français il y a plus de poids dans les extrémités de la distribution. Ceci signifie que les événements de croissance rapide arrivent relativement souvent pour les entreprises françaises. Nous procédons à une analyse approfondie des différences entre le cas français et le cas des autres pays, en nous appuyant sur des

analyses des distributions de croissance selon les distributions de la classe de Subbotin. Les différences entre la distribution des taux de croissance pour les entreprises françaises s'avèrent statistiquement significativement différents des cas italiens et américains.

Finalement, nous terminons ce chapitre en regardant comment les caractéristiques statistiques que nous retrouvons au niveau agrégé peuvent être retrouvés lors d'une désagrégation par secteur d'activité. Il apparaît que la forme de la distribution des taux de croissance est robuste à la désagrégation sectoriel, alors que la forme de la distribution des tailles des entreprises n'est pas robuste.

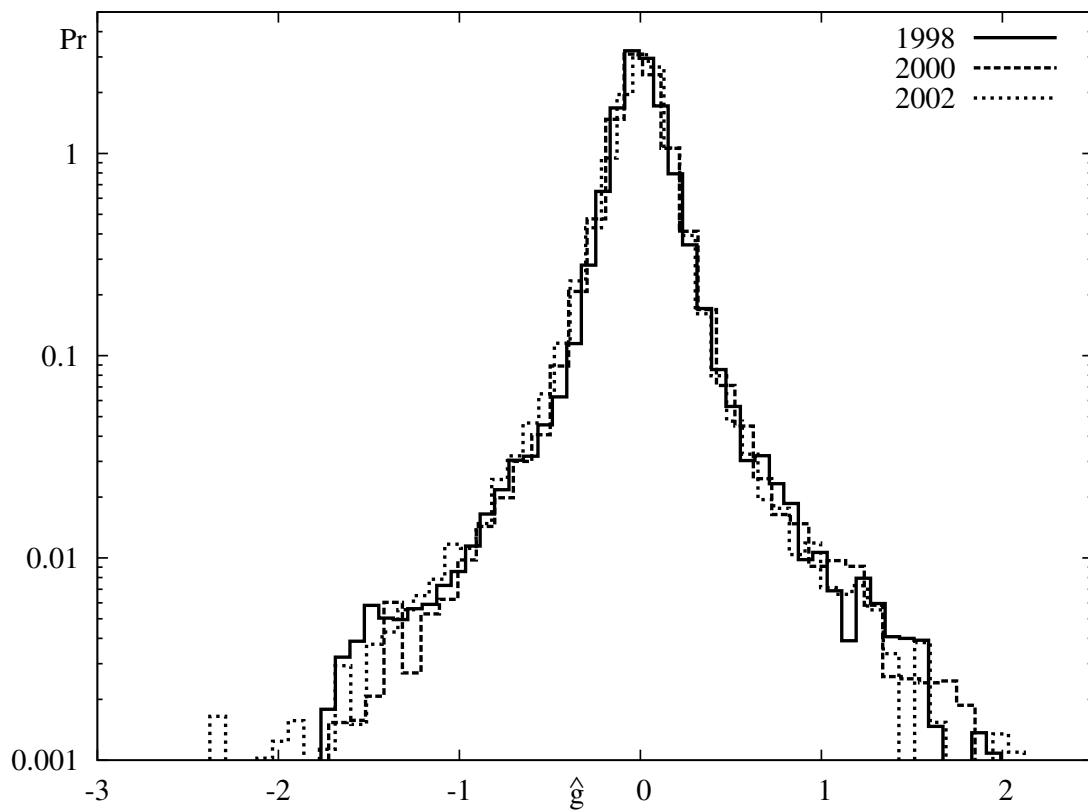


Figure 4: Estimation par la technique de ‘kernel’ de la distribution des taux de croissance pour les années 1998, 2000 et 2002. Les distributions sont calculées pour 64 points en utilisant un kernel de type ‘Epanenchnikov’.

Chapitre 4: Analyse de l'autocorrélation dans les taux de croissance Alors que dans le chapitre précédent nous avons trouvé une structure autoregressive simple (d'ordre 1), dans ce chapitre nous allons approfondir nos analyses de l'autocorrélation du processus de croissance.

Dans ce chapitre, nous nous concentrons sur l'analyse de la structure d'autocorrélation dans les taux de croissance. Nous commençons avec une revue de la littérature sur l'existence d'une structure autoregressive dans le processus de croissance des firmes, et il apparaît que les travaux scientifiques ne fournissent pas d'explication cohérente concernant ce sujet. Alors que quelques études ont trouvé une autocorrélation positive, des autres ont trouvé une autocorrélation négative, et d'autres études encore n'ont même pas trouvé d'autocorrélation. Toutefois, nous nous étonnons du fait que ces études n'ont pas cherché à expliquer ces divergences, mais se sont contentés avec ces résultats conflictuels. Toutefois, il nous semble que le sujet d'autocorrélation est un sujet relativement important et nous essayerons de trouver des régularités dans le cadre d'une analyse approfondie des processus de croissance.

Nous cherchons des régularités selon deux axes d'analyse – l'autocorrélation en fonction de la taille d'une firme et de son taux de croissance dans la période précédente. Nous trouvons des résultats originaux qui peuvent se résumer ainsi: les expériences de croissance des petites firmes sont beaucoup plus erratiques que celles des grandes firmes. La croissance des petites firmes peut être décrite par une dynamique d'autocorrélation négative, ce qui est particulièrement accentué pour les petites firmes qui ont crû rapidement.

La Figure 6 permet de voir comment l'autocorrélation dans les taux de croissance varie selon la taille de l'entreprise. Ces graphiques montrent la taille sur l'axe horizontal et le coefficient d'autocorrélation sur l'axe vertical. Il semblerait que les petites firmes ont tendance à avoir une autocorrélation négative dans leurs taux de croissance, alors que les grandes firmes

sembleraient avoir une autocorrélation positive dans leurs taux de croissance. Ce résultat peut être observé lorsque l'on considère la croissance du chiffre d'affaires ou bien la croissance en termes d'emploi.

Nous avons ainsi trouver une relation entre le coefficient d'autocorrélation et la taille de l'entreprise. Ceci nous aide a comprendre pourquoi les travaux antérieurs ont obtenu des résultats divergents – ceci pourrait s'expliquer par le fait que ces travaux ont utilisé des différentes bases de données comprenant des entreprises de différentes tailles.

Dans la Figure 7 nous pouvons observer les résultats d'une approche par la régression par quantile. Dans ces graphiques nous pouvons observer que l'autocorrélation ne semble pas avoir de très grande influence sur les firmes qui se trouvent près de la moyenne. Toutefois, lorsque nous regardons les quantiles les plus extremes, nous observons que le coefficient d'autocorrélation diminue rapidement. Il parait que, selon cette première analyse avec les données agrégées, que l'autocorrélation touche plutôt les firmes ayant les taux de croissance les plus hautes ou les plus basses. Notons aussi que nous retrouvons la même relation entre le coefficient d'autocorrélation et le taux de croissance lorsque l'on considère la croissance en termes du chiffre d'affaires ou en termes de la croissance du nombre d'emplois.

Dans les Figures 8 et 9 nous mettons ensemble ces deux dimensions d'analyse. La Figure 8 présente le cas de l'autocorrélation dans le croissance du chiffre d'affaires alors que la Figure 9 présente les résultats pour le cas de l'autocorrélation dans la croissance d'emploi.

Nous étudions alors la variation dans le coefficient d'autocorrélation selon la taille des entreprises et selon leur taux de croissance actuelle. Notre base de données des entreprises françaises est divisé en dix groupes selon la taill de l'entreprise. Nous faisons ensuite des régressions par quantile pour chacun de ces dix groupes d'entreprises, et les résultats sont présentés dans le graphique. Ce graphique montre d'abord que la croissance des petites

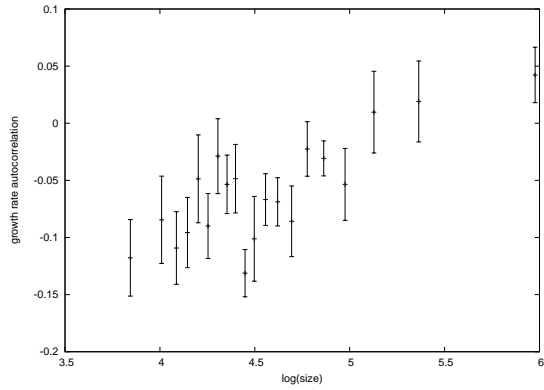


Figure 5: Autocorrélation de la croissance du chiffre d'affaires

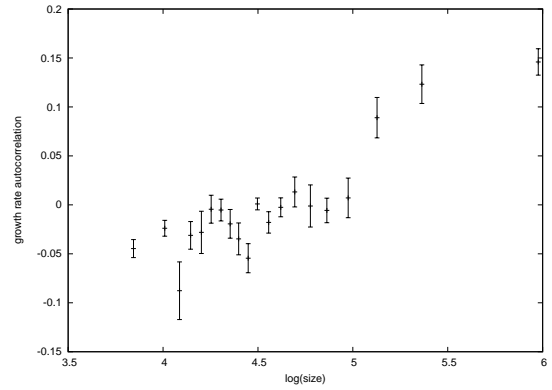


Figure 6: Autocorrélation de la croissance du nombre d'employés

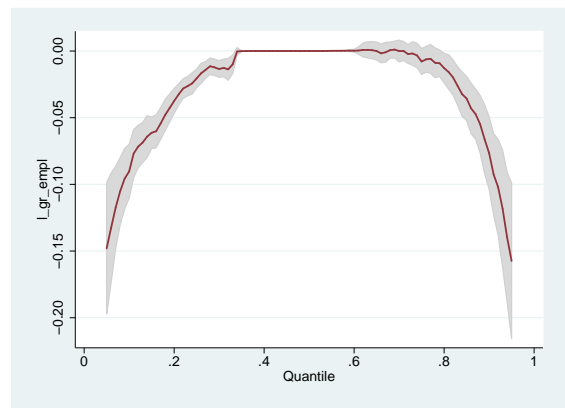
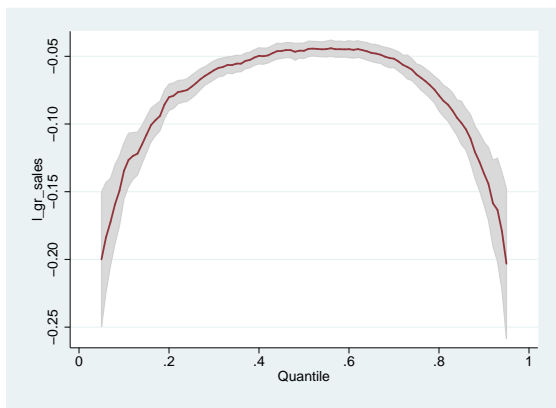


Figure 7: Résultats des régressions par quantile pour la croissance du chiffre d'affaires (à gauche) et la croissance en termes d'emploi (à droite), avec des intervalles de confiance de 95%.

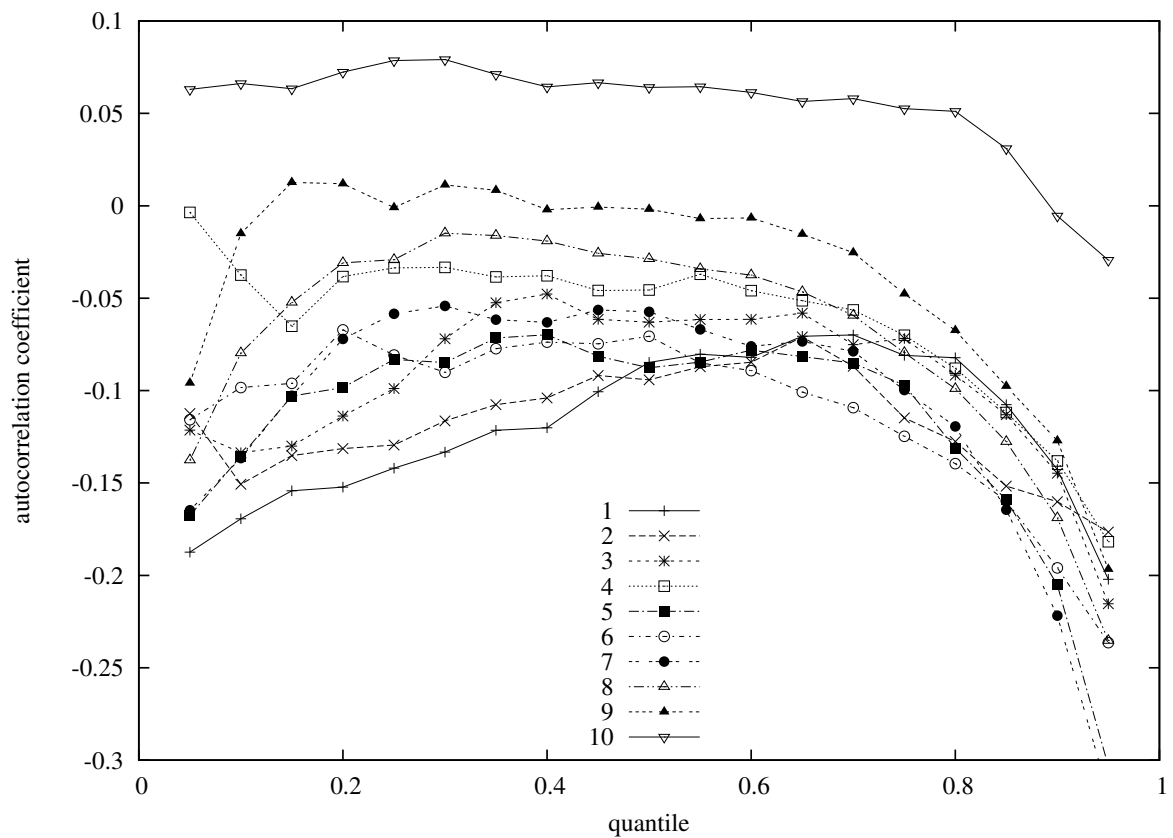


Figure 8: Résultats des régressions par quantile pour les coefficients d'autocorrélation selon les 10 groupes des entreprises groupés par taille. Groupe '1' contient les entreprises les plus petites. Ce graphique correspond au cas d'autocorrélation dans la croissance du chiffre d'affaires.

entreprises est touché par une autocorrélation négative qui est particulièrement accentuée pour les firmes qui ont des taux de croissance assez extrêmes. Autrement dit, les petites entreprises qui ont des taux de croissance particulièrement élevés, ou bien particulièrement négatifs, subissent généralement une forte autocorrélation négative. Pour les plus grandes entreprises, par contre, leur croissance semble être assez stable pour toutes les quantiles du taux de croissance. Les grandes entreprises bénéficient d'une légère autocorrélation positive dans leur dynamique de croissance.

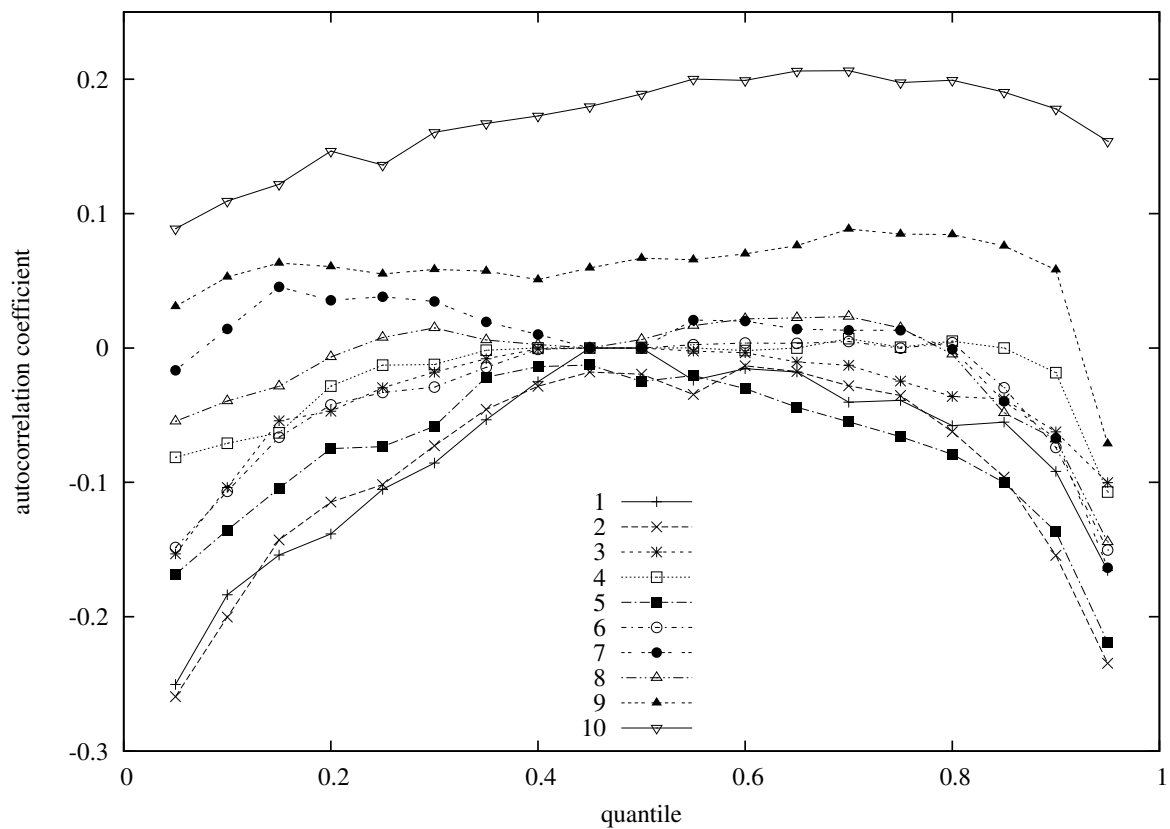


Figure 9: Résultats des régressions par quantile pour les coefficients d'autocorrélation selon les 10 groupes des entreprises groupés par taille. Groupe '1' contient les entreprises les plus petites. Ce graphique correspond au cas d'autocorrélation dans la croissance du nombre d'emplois.

Chapitre 5: Une comparaison des théories néoclassiques et évolutionnistes des contraintes de liquidité Dans ce chapitre nous présentons une discussion théorique sur les différences entre les théories néoclassiques et évolutionnistes des contraintes financières. Nous critiquons la théorie standard des contraintes financières et nous précisons pourquoi la théorie évolutionniste nous semble plus pertinent dans ce cas que la théorie standard qui se base sur des fondations néoclassiques. Ce chapitre peut ainsi être vu comme le chapitre le plus controversiel de la thèse, parce qu'elle critique une assez grande littérature qui traite de l'investissement et les contraintes financières.

Nous commençons en présentant la théorie néoclassique des contraintes financières. Plus précisément, nous commençons en décrivant la théorie qui est connu sous le nom de '*q theory*'. Cette théorie prévoit que, dans un contexte néoclassique d'entreprises rationnelles et maximisatrices, le seul facteur explicative de l'investissement devrait être la valeur boursière. Toutefois, les test empiriques de la '*q theory*' n'ont pas obtenu de résultats favorables car le pouvoir explicative de la valeur boursière est généralement assez bas. De plus, il apparaît que des autres facteurs ont un effet significatif sur l'investissement, alors que selon la théorie ceci ne devrait pas être le cas.

Etant donné la performance insatisfaisante de la '*q theory*', Fazzari, Hubbard et Peterson ont offert une autre explication dans leur papier publié en 1988 dans la série des 'Brookings Papers on Economic Activity'. Ces auteurs constatent que l'investissement répond à des fluctuations dans la performance financière de l'entreprise (plus précisément, la capacité d'autofinancement de l'entreprise), et ces auteurs expliquent ce résultat en parlant du concept de 'contraintes financières' qui limitent l'investissement des entreprises. Cet article de Fazzari, Hubbard et Peterson a eu un grand impact sur la littérature, si bien que de nos jours une corrélation entre investissement (ou croissance) et performance financière est le plus souvent

interprété dans ce contexte de contraintes financières.

Toutefois, cette interprétation d'une éventuelle corrélation entre investissement et performance financière ne nous séduit pas. Nous préférons une interprétation évolutionniste qui repose sur le principe évolutionniste de 'la croissance du plus fort'. Selon cette interprétation, nous reconnaissons que les entreprises ne sont pas parfaitement rationnelles et qu'elles font souvent des fautes. On ne peut pas exclure *a priori* le fait que les entreprises se trompent dans leurs projets d'expansion ou leurs projets d'investissement. Ainsi, nous préférons une interprétation qui repose sur la notion simonienne de rationalité limitée et de l'hétérogénéité des entreprises. Le principe évolutionniste de 'la croissance du plus fort' offre un cadre interprétatif qui est capable de répondre à ces soucis.

Chapitre 6: Une étude de la relation entre performance financière et croissance

Nous nous intéressons maintenant à la relation entre la performance financière des entreprises et leur croissance, d'un point de vue empirique. Dans ce chapitre nous présentons donc nos résultats empiriques, qui seront alors dans le contexte de la discussion théorique de chapitre 5. Nous testons le principe de la 'croissance du plus fort', ce qui correspond au modèle des 'replicator dynamics' qui sert comme fondement pour un certain nombre de modèles évolutionnistes. Nous reconnaissons toutefois que le test de ce principe n'équivaut pas du tout un test de la théorie évolutionniste pris dans son ensemble.

Nous utilisons les mêmes données françaises que lors de nos analyses dans les troisième et quatrième chapitres, mais cette fois nous avons aussi des données pour la période 2002-2004, ce qui signifie que notre base de données recouvre la période 1996-2004.

Nous utilisons une large gamme de techniques statistiques et économétriques, et nous pouvons identifier un effet positive et statistiquement significatif de la profitabilité sur la croissance. Néanmoins, nous reconnaissons que cet effet est assez petit, si bien qu'il serait plus simple de considérer que la profitabilité n'est pas un facteur important pour la croissance. Nous interprétons ce résultat en faisant référence au concept évolutionniste de sélection, et nous concluons que les pressions de sélection ne sont pas très efficaces.

Pour commencer les analyses, nous regardons des graphiques avec le profits d'une entreprise (ou plus précisément, l'excédent brut d'exploitation) sur l'axe horizontal et la croissance de l'entreprise sur l'axe vertical. Un exemple d'un tel graphique est fourni dans le Figure 10 qui montre le cas de la croissance du chiffre d'affaires pour l'année $t = 2001$. Nous observons effectivement que le nuage de points ne semble pas indiquer la relation positive que laisse supposer le principe de la 'croissance du plus fort'. Au contraire, ce graphique semblerait indiquer que les deux séries sont plus ou moins indépendents. Toutefois, nous ne pouvons pas nous

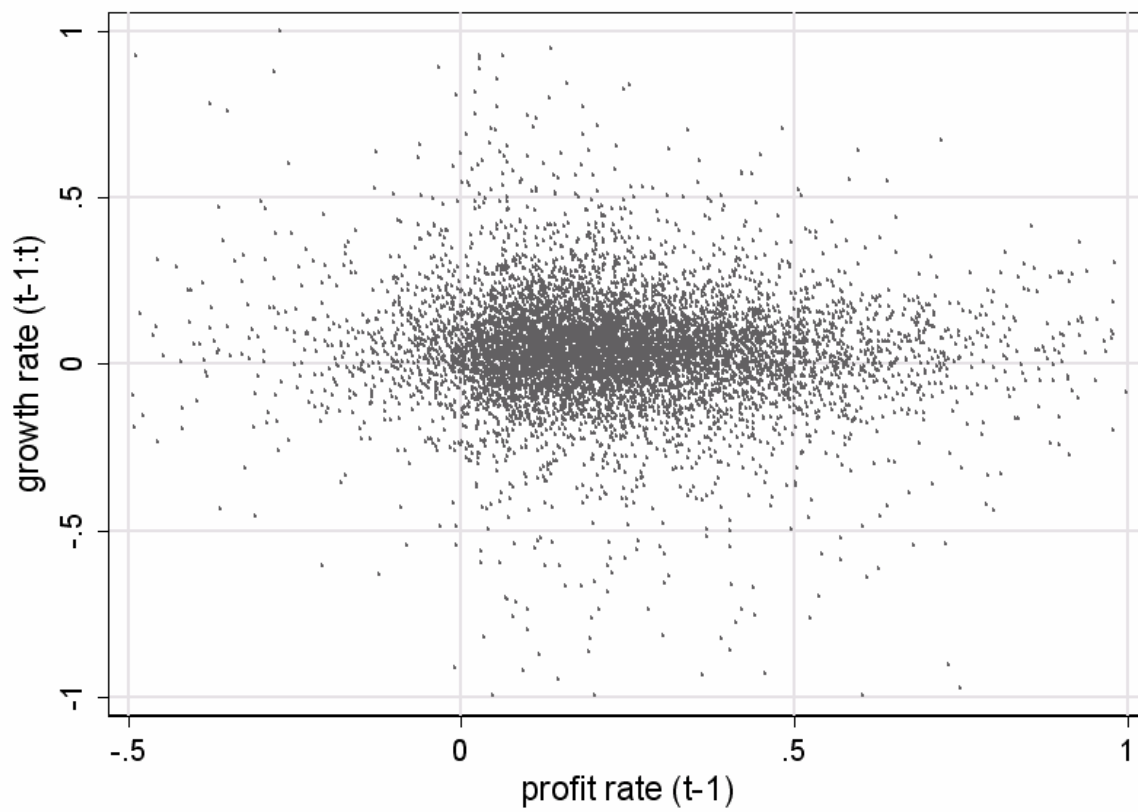


Figure 10: Relation entre profits et croissance

contenter d'une analyse avec des telles graphiques. Ce type de graphique ne peut pas répondre aux difficultés économétriques liés aux délais temporels, n'inclut pas de variables de contrôle, et ne prend pas en compte l'endogénéité dans la relation entre profits et croissance. (Effectivement nous discutons ici des motivations théoriques qui nous amènent à soupçonner l'existence de l'endogénéité dans la relation entre profits et croissance.) Nous montrons aussi les résultats des régressions des estimateurs des moindres carrés ordinaires et de l'estimateur dit 'Fixed Effects', mais nous rappelons le lecteur que ces estimateurs ne sont pas entièrement appropriés non plus parce qu'elles ne peuvent pas prendre en compte les difficultés économétriques liés à la présence d'endogénéité. Pour faire face à ce problème d'endogénéité, nous utilisons l'estimateur connu sous le nom de 'System GMM'. Les résultats que nous obtenons en appliquant cet estimateur à notre base de données des entreprises françaises sont néanmoins relativement modestes. Nous observons un effet positif et statistiquement significatif, mais la magnitude du coefficient est tellement basse que nous concluons qu'il serait plus simple de concevoir que les profits n'ont pratiquement aucune influence sur la croissance dans les périodes suivantes.

Nous interprétons ce résultat en suggérant que les effets de sélection ne sont pas très importants. Ceci pourrait également témoigner d'une manque de concurrence dans l'économie. Effectivement, il paraît que les opportunités de croissance se présentent aux entreprises sans discriminer entre celles-ci selon des critères de performance financière.

Nous nous intéressons aussi à l'influence de la croissance sur les profits. Ici aussi, nous obtenons un coefficient qui est positif et statistiquement significatif, mais cette fois le coefficient est relativement grand. Ceci nous amène à suggérer que l'influence de la croissance sur le profit est plus important que l'influence du profit sur la croissance. Nous pouvons alors mentionner ici la notion de rendements croissants dynamiques et l'idée des 'économies de croissance'

développé dans le livre d'Edith Penrose.

Chapitre 7: Innovation et croissance des firmes – une application de la régression

par quantile Dans le chapitre 7 et le chapitre 8, nous nous intéressons à la relation entre innovation et la performance des entreprises, car il nous semble que la littérature n'a pas assez creusé cette relation. Nous analysons une nouvelle base de données en appliquant des méthodes statistiques nouvelles, et nous obtenons des résultats originaux qui mettent en évidence l'hétérogénéité de la performance des entreprises innovatrices.

Dans le chapitre 7, nous mesurons la performance en termes de croissance du chiffre d'affaires. Nos analyses sont effectuées en créant une nouvelle base de données sur les entreprises américaines. En ce qui concerne le chiffre d'affaires et les dépenses en R et D des firmes, nous nous référons à la base de données 'Compustat'. Nous complétons ces informations avec des données sur les brevets provenant d'une base de données NBER, qui sont des données au niveau de la firme, année par année.

Il nous semble important d'utiliser des données non seulement sur les dépenses en recherche et développement, mais aussi sur les brevets, car ces deux indicateurs fournissent des informations complémentaires sur la performance innovatrice des entreprises. En fait, nous créons une variable synthétique à partir de ces deux variables. Cette variable synthétique est créée en utilisant la méthode de l'analyse par composants principaux, ce qui nous permet de trouver la variance commune entre les dépenses en R et D et le nombre de brevets, tout en éliminant la partie idiosyncratique de la variance dans chacun de ces variables lorsque celles-ci sont prises individuellement. Ainsi nous obtenons ce qui semble être un indicateur de l'activité innovatrice qui est assez fiable.

De plus, nous nous limitons aux entreprises dans les secteurs d'activité de haute technologie, afin d'obtenir des observations quantitatives fiables pour les dépenses en R et D et le nombre de brevets par firme. Nous observons effectivement que l'innovation a des effets

très hétérogènes sur les firmes. Pour la grande partie des entreprises, la croissance prend un caractère idiosyncratique, si bien que l'influence de l'innovation pour la croissance (ou bien pour la valeur boursière) est relativement modeste. Néanmoins, il existe une minorité de firmes qui se distinguent par une croissance particulièrement rapide (ou par une valeur boursière particulièrement élevée). Pour ce dernier groupe de firms, nous observons que les efforts liés à l'innovation jouent un rôle nettement plus important. Ces résultats peuvent être interprétés de la manière suivante: l'innovation est une activité très incertaine, et les résultats de l'innovation sont distribués d'une façon très inégale. Dans la majorité des cas, la performance des firmes innovantes n'est que faiblement supérieur à celle des firmes qui sont moins innovantes. Dans une minorité des cas, néanmoins, l'innovation permet aux entreprises d'avoir une performance vraiment spectaculaire. Nous soulignons que l'utilisation de la technique de la régression par quantile fait apparaître des résultats qui ne peuvent être détectés par des techniques de régression plus standards qui se basent sur des hypothèses implicites de homogénéité des unités d'observation.

Figure 11 permet de visualiser les résultats des régressions par quantile. Ce graphique montre la relation entre innovation et croissance pour quatre secteurs d'activité, qui sont: SIC 35 – le secteur de l'équipement industriel et commercial (y compris l'équipement informatique); SIC 36 – équipement électrique et électronique; SIC 37 – équipement de transport; et SIC 38, qui regroupe les industries des instruments. Ce graphique montre que le coefficient sur l'activité innovatrice varie selon les quantiles de la distribution (conditionnelle) des taux de croissance. Pour les firmes qui ont les taux de croissance proche de la moyenne, il paraît que les efforts liés à l'innovation n'ont pas beaucoup d'importance dans l'explication des taux de croissance. Pour les entreprises qui croissent extrêmement rapidement, par contre, nos résultats peuvent suggérer que la croissance de ces firmes est relativement fortement influencé

par leurs efforts liés à l'innovation.

Figure 11 permet de visualiser les résultats des régressions par quantile. Ce graphique montre la relation entre innovation et croissance pour quatre secteurs d'activité, qui sont: SIC 35 – le secteur de l'équipement industriel et commercial (y compris l'équipement informatique); SIC 36 – équipement électrique et électronique; SIC 37 – équipement de transport; et SIC 38, qui regroupe les industries des instruments. Ce graphique montre que le coefficient sur l'activité innovatrice varie selon les quantiles de la distribution (conditionnelle) des taux de croissance. Pour les firmes qui ont les taux de croissance proche de la moyenne, il paraît que les efforts liés à l'innovation n'ont pas beaucoup d'importance dans l'explication des taux de croissance. Pour les entreprises qui croissent extrêmement rapidement, par contre, nos résultats peuvent suggérer que la croissance de ces firmes est relativement fortement influencé par leurs efforts liés à l'innovation.

Figure 12 permet de visualiser les résultats des régressions par quantile lorsque l'on s'intéresse à un niveau d'aggrégation plus fine.

Chapitre 8: Innovation et valeur boursière – une application de la régression par quantile

Alors que dans le chapitre 7, nous avons mesuré la performance en termes de croissance du chiffre d'affaires, dans le chapitre 8 nous la mesurons en nous référant à la valeur boursière d'une firme. Ceci nous paraît intéressant car on peut supposer qu'il y aurait ainsi un délai moins long entre l'innovation et une performance supérieure.

Nos analyses sont effectuées en la base de données sur les entreprises américaines. En ce qui concerne le chiffre d'affaires, les dépenses en Recherche et Développement des entreprises, et la valeur boursière des entreprises, nous nous référons à la base de données 'Compustat'. Nous complétons ces informations avec des données sur les brevets provenant d'une base de données NBER, qui sont des données au niveau de la firme, année par année. Toutefois, nous n'utilisons pas exactement la même base de données que dans le chapitre précédent car nous avons moins d'observations sur la valeur boursière des entreprises.

Il nous semble important d'utiliser des données non seulement sur les dépenses en recherche et développement, mais aussi sur les brevets, car ces deux indicateurs fournissent des informations complémentaires sur la performance innovatrice des entreprises. En fait, nous créons une variable synthétique à partir de ces deux variables. Cette variable synthétique est créée en utilisant la méthode de l'analyse par composants principaux, ce qui nous permet de trouver la variance commune entre les dépenses et R et D et le nombre de brevets, tout en éliminant la partie idiosyncratique de la variance dans chacun de ces variables lorsque celles-ci sont pris individuellement. Ainsi nous obtenons ce qui semble être un indicateur de l'activité innovatrice qui est assez fiable.

De plus, nous nous limitons aux entreprises dans les secteurs d'activité de haute technologie, afin d'obtenir des observations quantitatives fiables pour les dépenses en R et D et le nombre de brevets par firme. Nous observons effectivement que l'innovation a des effets très

hétérogènes sur les firmes. Pour la grande partie des entreprises, la valeur boursière prend un caractère idiosyncratique, si bien que l'influence de l'innovation pour la valeur boursière est relativement modeste. Néanmoins, il existe une minorité de firmes qui se distinguent par une valeur boursière particulièrement élevée. Pour ce dernier groupe de firmes, nous observons que les efforts liés à l'innovation jouent un rôle nettement plus important sur la performance des entreprises. Ces résultats peuvent être interprétés de la manière suivante: l'innovation est une activité très incertaine, et les résultats de l'innovation sont distribués d'une façon très inégale. Dans la majorité des cas, la performance des firmes innovantes n'est que faiblement supérieur à celle des firmes qui sont moins innovantes. Dans une minorité des cas, néanmoins, l'innovation permet aux entreprises d'avoir une performance vraiment spectaculaire. Nous soulignons que l'utilisation de la technique de la régression par quantile fait apparaître des résultats qui ne peuvent être détectés par des techniques de régression plus standards qui se basent sur des hypothèses implicites de homogénéité des unités d'observation.

Figure 13 permet de visualiser les résultats des régressions par quantile. Ce graphique montre la relation entre innovation et la valeur boursière des entreprises pour quatre secteurs d'activité, qui sont: SIC 35 – le secteur de l'équipement industriel et commercial (y compris l'équipement informatique); SIC 36 – équipement électrique et électronique; SIC 37 – équipement de transport; et SIC 38, qui regroupe les industries des instruments. Ce graphique montre d'une façon assez claire que le coefficient sur l'activité innovatrice varie selon les quantiles de la distribution (conditionnelle) des valeurs boursières des entreprises. Pour les firmes qui ont les taux de croissance proche de la moyenne, il paraît que les efforts liés à l'innovation n'ont pas beaucoup d'importance dans l'explication des taux de croissance. Pour les entreprises qui croissent extrêmement rapidement, par contre, nos résultats peuvent suggérer que la croissance de ces firmes est relativement fortement influencé par leurs efforts liés à

l'innovation.

Chapitre 9: Conclusion générale * Ch 9: Conclusion

Ce chapitre constitue la conclusion de la thèse. Elle commence par un résumé de la thèse, chapitre par chapitre, avant de passer à une discussion synthétique de ce que nous avons appris sur le phénomène de croissance des firmes. Ce chapitre esquisse aussi quelques directions dans lesquelles nous pensons que des travaux futurs seraient particulièrement fructueux.

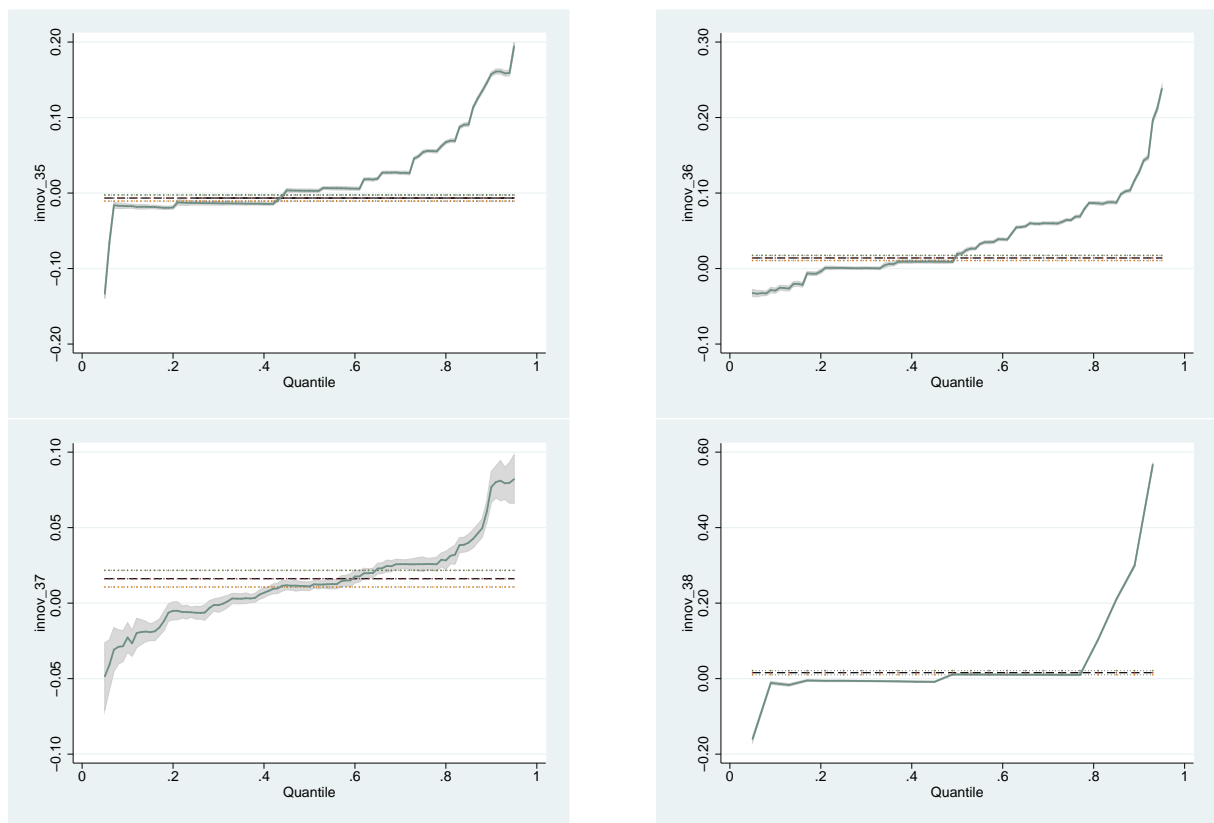


Figure 11: Variation de l'influence de l'innovation sur la croissance en utilisant la méthode de la régression par quantile.

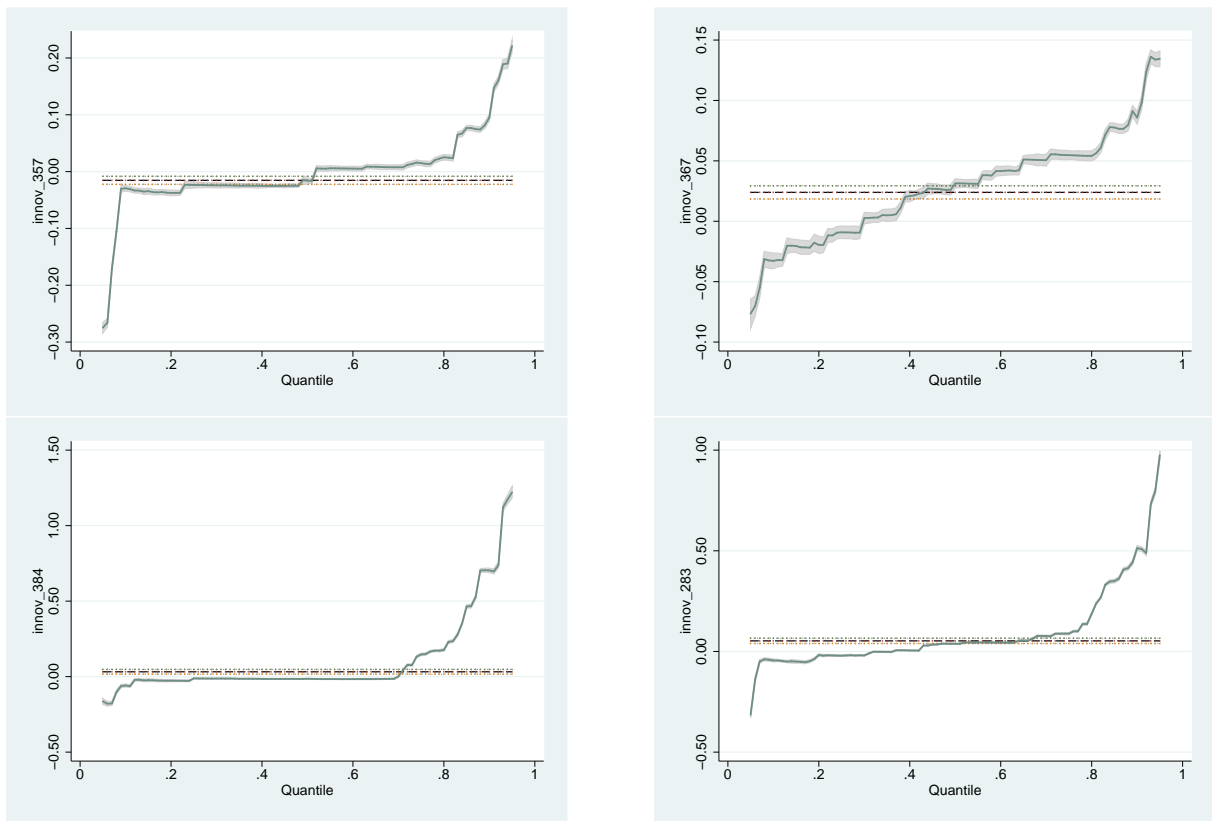


Figure 12: Variation de l'influence de l'innovation sur la croissance en utilisant la méthode de la régression par quantile.

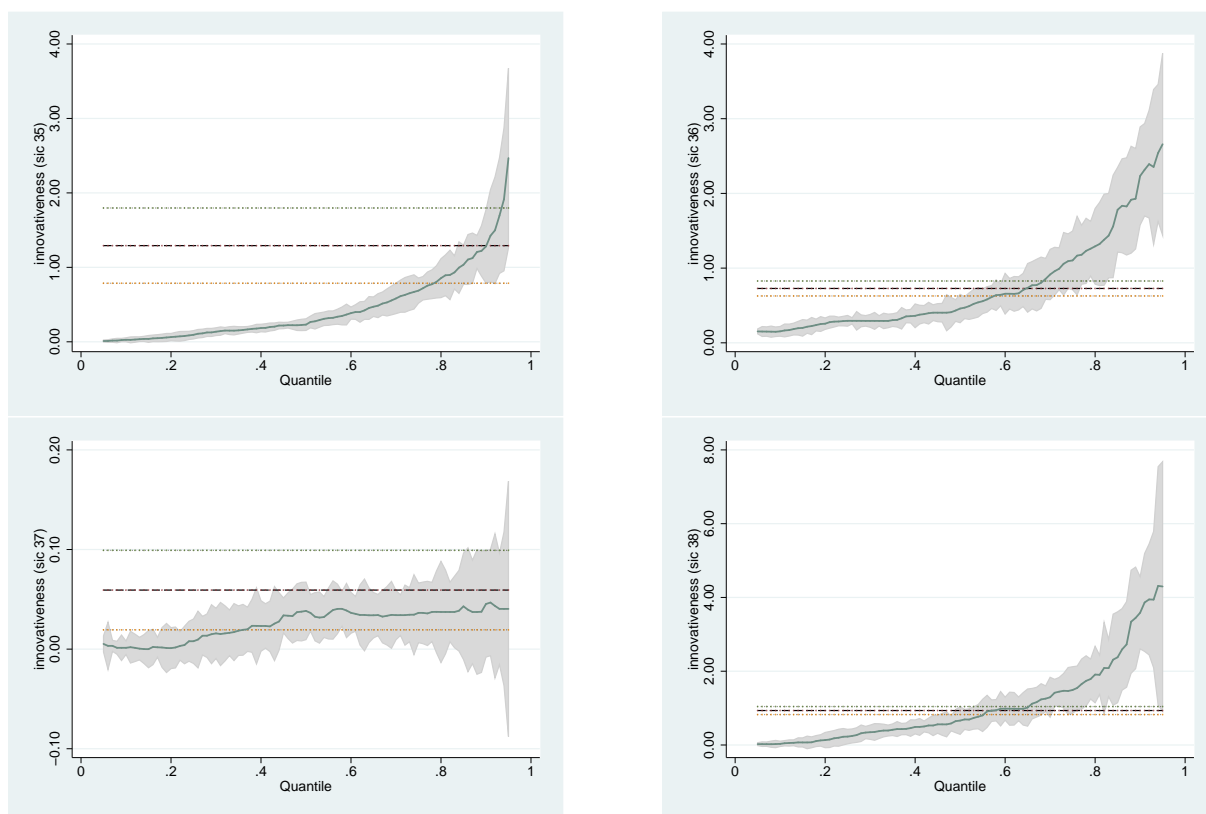


Figure 13: Variation de l'influence de l'innovation sur la croissance en utilisant la méthode de la régression par quantile.

Thèse rédigée en anglais suivi d'un résumé en français

Abstract :

This thesis presents empirical investigations into the growth of firms, using datasets on French and US manufacturing firms. We begin with a lengthy literature review to clearly identify the gaps in the existing literature. We then investigate Gibrat's law and examine the distribution of growth rates. We investigate serial correlation patterns in growth rates and observe that small firms have negative autocorrelation whilst larger firms have positive autocorrelation. In a theoretical discussion we contrast the mainstream 'financial constraints' theory with evolutionary theory, and conclude that neoclassical work may have exaggerated the extent of financial constraints. In our dataset, firm growth is more or less independent from financial performance and we conclude that selection pressures are weak. In the final part we consider the relationship between innovation and firm performance. Quantile regression techniques reveal that innovation leads to remarkably superior performance in a minority of cases (the 'superstar firms') but has little effect for the 'average firm'.

Résumé :

Cette thèse se concentre sur les investigations empiriques de la croissance des firmes, en utilisant des bases de données des firmes manufacturières françaises et américaines. Nous commençons avec une revue de la littérature afin d'identifier les lacunes dans la littérature actuelle. Nous regardons ensuite la loi de Gibrat et la distribution des taux de croissance. Puis nous observons des effets d'autocorrélation dans la croissance des firmes. Dans un discussion théorique nous contrastons la théorie des 'contraintes financières' à la théorie évolutionniste, et nous concluons que la recherche néoclassique a peut-être exagéré le problème des contraintes financières. Dans notre base de données, nous observons que la croissance est plus ou moins indépendante de la performance financière, et nous concluons que la sélection est assez faible. Dans la dernière partie nous étudions la relation entre l'innovation et la performance des firmes. Des régressions par quantile indiquent que l'innovation a des effets spectaculaires dans une minorité des cas, mais pour 'la firme moyenne' elle n'a que peu d'influence.

Discipline : Sciences Economiques

Mots-clés :

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