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# Innovation and Firm Growth in High-Tech Sectors: A Quantile Regression Approach [*]

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## Abstract

We relate innovation to sales growth for incumbent firms in four high-tech sectors. 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, given that firms are heterogeneous and that growth rates distributions are heavy-tailed, it may be misleading to use regression techniques that focus on the 'average firm'. Using a quantile regression approach, we observe that innovativeness is of crucial importance for a handful of 'superstar' fast-growth firms. We also discuss policy implications of our results.

**JEL codes:** O31, L25
**Keywords:** Innovation, Firm Growth, Quantile Regression, Innovation Policy, Patents

"Executives overwhelmingly say that innovation is what their companies need most for growth."
*McKinsey Global Survey of Business Executives (Carden, 2005:25).*

# 1 Introduction

## 1.1 In Search of the Determinants of Firm Growth

Early contributions on firm growth focused on the empirical validation of Gibrat's Law, also known as the Law of Proportionate Effect. Taken in its simplest form, this 'law' predicts that expected growth rates are independent of firm size. Regressions have found, in general, that growth patterns in modern economies are characterized by a weak negative dependence of growth rates on size (i.e. a slight reversion to the mean), leading us to reject Gibrat's Law (among a large number of studies see for example Mansfield (1962), Hall (1987), Evans (1987), Hart and Oulton (1996), Bottazzi et al. (2005), Bottazzi et al. (2006); see also Sutton (1997) for a review). Mean-reversion is typically observed in samples of small firms, but is much weaker or even nonexistent for larger firms (Mowery (1983), Hart and Oulton (1996), Lotti et al. (2003)). Although strictly speaking we are led to reject Gibrat's Law, it does appear to be useful as a rough first approximation. Size does not appear to be a major determinant of the rate of growth – indeed, the explanatory power of Gibrat-type regressions is often found to be rather low, and the coefficient estimates, though significant, are often quite small.

Attention has also been placed on the influence of other factors on firm growth, using a variety of different databases. One classic research topic has been to investigate the influence of age on firm growth. Indeed, it has even been suggested that the correct causality runs from age to size to growth, such that size has no effect on the expected growth rates if age is taken into account (Fizaine, 1968; Evans, 1987). In any case, age is observed to have a negative influence on firm growth. Legal status seems to have an influence, with public firms and firms with limited liability having significantly higher growth rates in comparison with other companies (Harhoff et al., 1998). Proprietary structure also appears to affect growth, when this latter is taken at the plant-level. Evidence suggests that the expected growth rate of a plant declines with size for plants owned by single-plant firms but increases with size for plants owned by multiplant firms (Dunne et al., 1989). Looking at data on industry leaders, Geroski and Toker (1996) identify other variables that are observed to influence growth. Advertising expenditure, the demand growth of an industry, and also the industry concentration are observed to have a positive influence on firm growth rates.

However, even though such explorations into the determinants of firm growth rates may obtain coefficient estimates that are statistically significant, the explanatory power is remarkably weak (Geroski, 2000). As Marsili (2001) points out, the $R^2$ coefficient in such studies is generally lower than 30%. "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..." (Marsili, 2001:18). "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). It seems that there is little more that we can say about firm growth rates apart from that they are largely unpredictable, stochastic, and idiosyncratic. However, as Geroski (2000) concludes, these characteristics of growth rates may be due to the unpredictable and stochastic nature of innovation success; i.e. that looking at firm-level innovations could be the key to understanding firm-level growth. We

believe that this idea deserves further investigation.

## 1.2 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 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

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[1]This 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 Hall and Oriani (2006), and for a survey on the relationship between innovation and employment growth (i.e. the 'technological unemployment' literature) see Niefert (2005).

NOTES: **R** – research expenditures; **ΔK** – additions to economically valuable knowledge; **P** – patents (a quantitative indicator of the number of inventions; **Z**'s – indicators of expected or realized benefits from invention; **X**'s – other observed variables influencing the Z's; **u,v** – other unobserved influences, assumed random and serially uncorrelated.
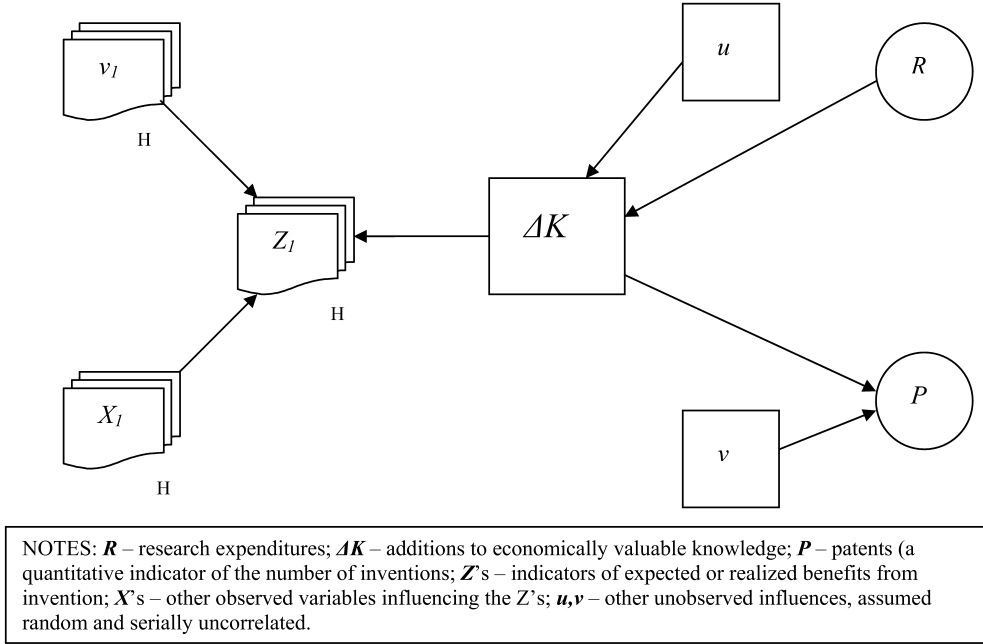
Figure 1: The Knowledge 'Production Function': A Simplified Path Analysis Diagram (based on Griliches 1990:1671)

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 position[2] to sales growth.

A critical examination of these studies reveals that the proxies that they use to quantify 'innovativeness' are rather noisy. Figure 1 shows that the variable of interest (i.e. $\Delta K$ – 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

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[2]They 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

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 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 average firm 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 is 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 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 3 describes how we matched the Compustat database to the NBER innovation database, and we present the synthetic 'innovativeness' index. Section 4 contains the quantile regression analysis, beginning with a brief introduction to quantile regression (Section 4.1) before we present the results (Section 4.2). Section 5 contains implications for policy and some concluding thoughts.

# 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 during the 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 innovative 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

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[3]Griliches (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 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.

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 occuring 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 (Engelsman and van Raan, 1990). 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 the firms 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

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

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' 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.

# 3    Database description

## 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 Compustat[6] 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 firms[7] that have patents. The final sample thus contains both patenters and non-patenters.

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[5]It 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.

[6]Compustat 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.

[7]The 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 1: Summary statistics before and after data-cleaning (SIC's 35-38 only)

|  | sample before cleaning $n$=4395 firms | | sample used $n$=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 |

Table 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 |

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 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]

## 3.2 Summary statistics and the 'innovativeness' index

Figures 2 and 3 show the number of patents per year in our final database. For some of the sectors there appears to be a strong structural break at the beginning of the 1980s which

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

[9]The 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.
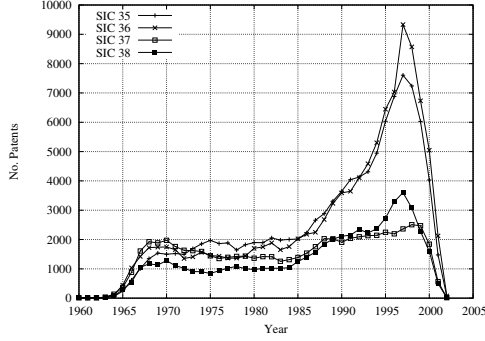
Figure 2: Number of patents per year. SIC 35: Machinery & Computer Equipment, SIC 36: Electric/Electronic Equipment, SIC 37: Transportation Equipment, SIC 38: Measuring Instruments.
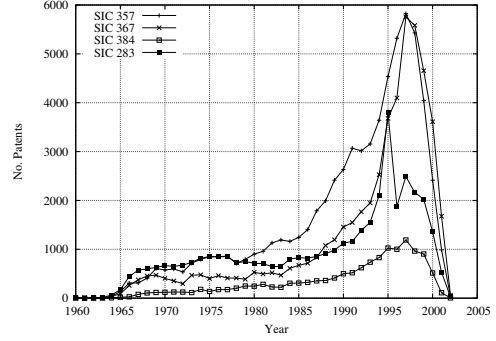
Figure 3: Number of patents per year. SIC 357: Computers and office equipment, SIC 367: Electronics, SIC 384: Medical Instruments, and SIC 283: Drugs.

may well be due to changes in patent regulations (see Hall (2004) for a discussion). Table 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 account for the average 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.

Table 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 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 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

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[10]This 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.

[11]Further 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 3: Contemporaneous correlations between Patents and R&D expenditure

|  | SIC 35 | SIC 36 | SIC 37 | SIC 38 | SIC357 | SIC 367 | SIC 384 | SIC 283 |
|---|---|---|---|---|---|---|---|---|
| *CORRELATIONS* | | | | | | | | |
| $\rho$ | 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 |
| *RANK CORRELATIONS* | | | | | | | | |
| $\rho$ | 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 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 |
|---|---|---|---|---|---|---|---|---|
| *CORRELATIONS* | | | | | | | | |
| $\rho$ | 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 |
| *RANK CORRELATIONS* | | | | | | | | |
| $\rho$ | 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 |

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 amortizement 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 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.

Figure 4 presents some scatterplots of innovativeness on sales growth, for the four 2-digit

Table 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 |
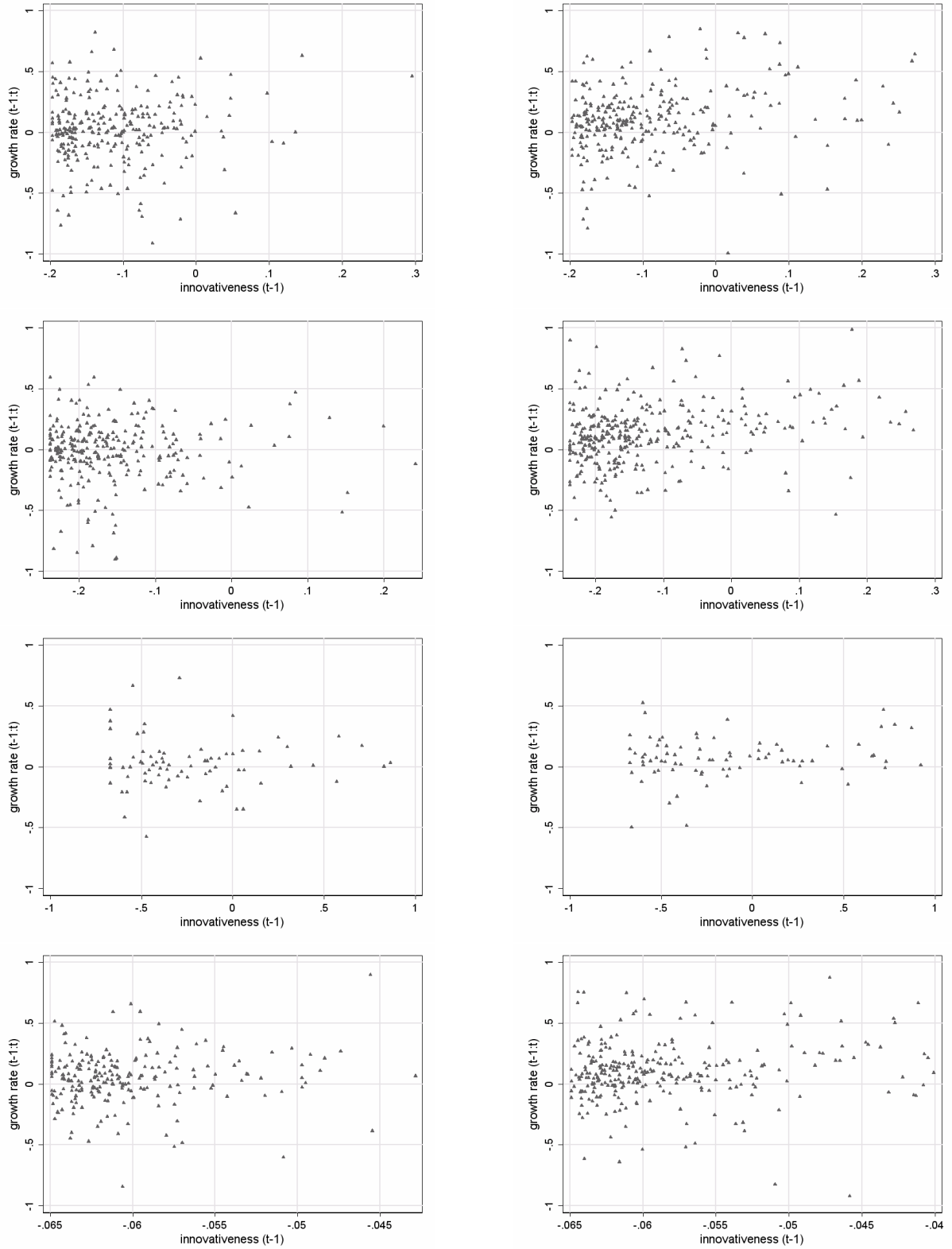
Figure 4: Scatterplots of innovation $(t-1)$ on growth $(t-1:t)$. Top row: SIC 35; 2nd row: SIC 36; 3rd row: SIC 37; bottom row: SIC 38. $t=1985$ on the left and $t=1995$ on the right.

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.

# 4  Quantile Regression

We begin this section with a brief introduction to quantile regression, and then apply it to our dataset.

## 4.1  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 firm may hide important features of the underlying relationship. 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 relationship between innovation and firm growth.

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 (see Stanley et al. (1996) and Bottazzi and Secchi (2003) for the growth rates distribution of Compustat firms). 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 $\check{\beta}_\theta$ is invariant to outliers of 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 ap-

proach 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 in Koenker and Bassett's (1978) seminal contribution, can be written as:

$$y_{it} = x'_{it}\beta_\theta + u_{\theta it} \qquad \text{with} \qquad \text{Quant}_\theta(y_{it}|x_{it}) = x'_{it}\beta_\theta \tag{1}$$

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

$$\min_\beta \frac{1}{n} \left\{ \sum_{i,t:y_{it} \geq x'_{it}\beta} \theta|y_{it} - x'_{it}\beta| + \sum_{i,t:y_{it} < x'_{it}\beta} (1-\theta)|y_{it} - x'_{it}\beta| \right\} = \min_\beta \frac{1}{n} \sum_{i=1}^{n} \rho_\theta u_{\theta it} \tag{2}$$

where $\rho_\theta(.)$, which is known as the 'check function', is defined as:

$$\rho_\theta(u_{\theta it}) = \left\{ \begin{array}{ll} \theta u_{\theta it} & \text{if } u_{\theta it} \geq 0 \\ (\theta - 1)u_{\theta it} & \text{if } u_{\theta it} < 0 \end{array} \right\} \tag{3}$$

Equation (2) is then solved by linear programming methods. As one increases $\theta$ 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 Coad (2006) and also the special issue of *Empirical Economics* (Vol. 26 (3), 2001). For a quantile regression analysis of the relationship between innovation and market value (i.e. Tobin's $q$), see Coad and Rao (2006b).

## 4.2   Quantile regression results

We now estimate the following linear regression model:

$$GROWTH_{i,t} = \alpha + \beta_1 INN_{i,t-1} + \beta_2 GROWTH_{i,t-1} + \beta_3 SIZE_{i,t-1} + \beta_4 IND_{i,t} + y_t + \epsilon_{i,t} \tag{4}$$

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 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. We also note that the 95% confidence intervals on the quantile regression curves are rather 'tight'.
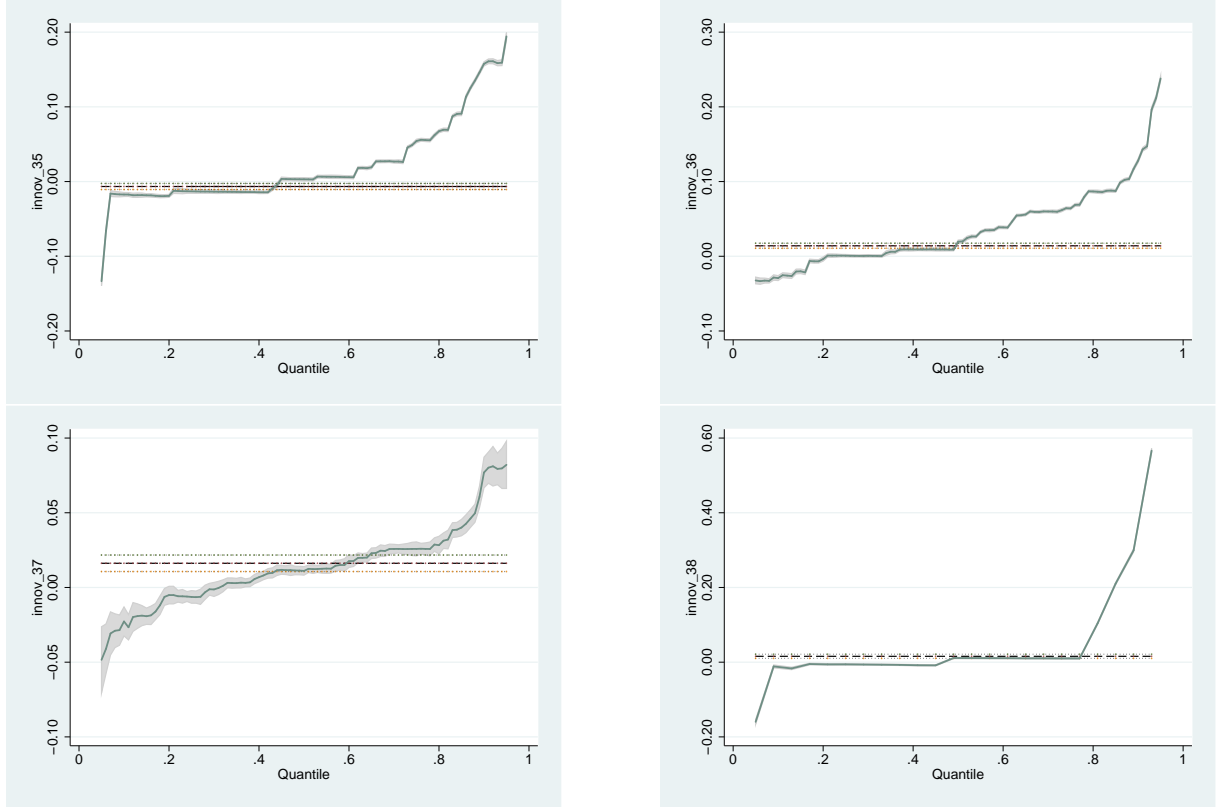
Figure 5: Variation in the coefficient on 'innovativeness' (i.e. $\beta_1$ in Equation (4)) over the conditional quantiles. Confidence intervals extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 35: Machinery & Computer Equipment (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).

The numerical results for OLS, fixed-effects and quantile regression estimation are reported in Table 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 $\theta^{th}$ conditional quantile due to marginal change in a particular regressor (Yasar et al., 2006). 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.

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 6 and in Figure 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.

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[12]In 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 $\beta_1$, 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 6: Quantile regression estimation of Equation (4): 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.

| | OLS | FE | Quantile regression | | | | |
| | | | 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 |
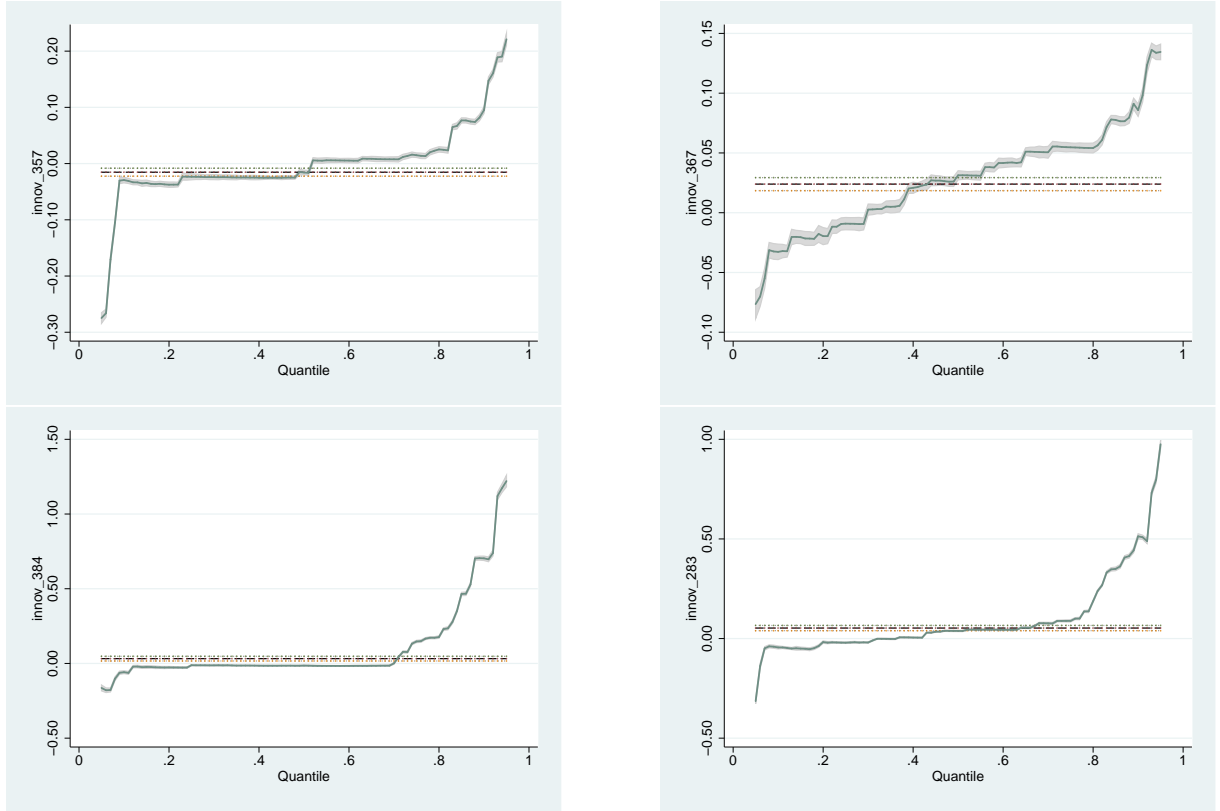
Figure 6: Variation in the coefficient on 'innovativeness' (i.e. $\beta_1$ in Equation (4)) over the conditional quantiles. Confidence intervals extend to 2 standard errors in either direction. Horizontal lines represent OLS estimates with 95% confidence intervals. SIC 357: Computers and office equipment (top-left), SIC 367: Electronics (top-right); SIC 384: Medical Instruments (bottom-left) and SIC 283: Drugs (bottom-right).

# 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 – inspite of this circumstantial evidence, however, we should resist the temptation to overplay the relationship between

innovativeness 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 (see also Coad, 2005). 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-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.

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[13]In 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).

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