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Does Market Selection Reward Innovators? R&D, patents, and growth in the US Pharmaceutical Industry

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Pelin Demirel* and Mariana Mazzucato*

Abstract

If market 'selection' works, and if innovation leads to greater efficiency (higher quality and/or lower costs), then one should expect to find a relationship between innovation and firm growth. Yet the empirical evidence for the impact of innovation on firm growth is rather mixed.

The paper looks at the relationship between innovation and firm growth, and the effects of this relationship on market structure for the pharmaceutical industry (firms quoted on the US stock market between 1950-2003 and sub-periods). We find that innovation (proxied via R&D spending, patents and citations) affects growth rates only for firms with particular characteristics. These are firms that are persistent innovators, have biotechnology alliances, and are small. This suggests that market selection operates on a *mix* of firm characteristics. Furthermore, it is precisely firms with these characteristics which shape the 'complex' patterns in industry structure which have recently caused many industrial economists to puzzle over the non-gaussian properties of firm size and growth (e.g. *bimodality* of firm size distributions and *fat tails* in the growth distributions).

Key words: market selection, innovation, firm growth, size distributions, pharmaceutical industry.

JEL: L1 Market Structure, Firm Strategy, and Market Performance, **O3** Technological Change.

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1. Introduction

Both evolutionary and neoclassical approaches to market selection assume that more efficient firms grow more, and since innovation is aimed at achieving higher efficiency, this translates to an assumption that on average more innovative firms (firms with lower costs and/or better products) should grow more than less innovative ones (Friedman, 1953; Nelson and Winter, 1982). Yet the literature linking innovation to firm growth is inconclusive. In some cases it even appears that innovation has a negative effect on firm growth (Brouwer et al., 1993). Furthermore, the finding that firm innovation (patents) and firm profits exhibit more 'persistence' than firm growth rates has also caused confusion amongst industrial economists on how market selection dynamics translate into the time series properties of firm performance (Geroski and Machin, 1992). And studies using non-parametric techniques, which allow growth and size distributions to be studied without strong imposing theoretical assumptions, have found these to exhibit properties that do not coincide with assumptions of 'normality' in the neoclassical theory of the firm (Bottazzi and Secchi, 2006).

The paper is motivated by these findings, asking firstly, whether market selection fails to reward innovators or whether it rewards only certain types of innovative firms. If so, which? And secondly, whether the answer to this question helps us to better understand the 'complex' properties behind firm size and growth distributions alluded to above.

The focus is on pharmaceutical firms quoted on the US stock market from 1950-2003, with innovation proxied by both innovation inputs and outputs: R&D spending, patent numbers and citations to patents[1]. The pharmaceutical industry is a particularly interesting industry to study in this context due to the exponential increase in both R&D spending and patents since the 1980's[2]. Has this increase in innovative effort led to higher growth rates? If not, why not? Recent alarms raised over the low efficiency of innovation in the industry, a sort of 'innovation paradox'[3](i.e. the low amount of drugs that have resulted notwithstanding exponential rises in R&D spending), make it an even more interesting industry in which to study market selection dynamics (Drews and Ryser, 1996, Harris, 2002; Hopkins et al., 2007; Grabowski, 2004). It is also an industry which has undergone fundamental changes in the way that large and small firms interact around innovation. Much has been written about the new division of innovative labor between large and small firms whereby the large firms

[1] As discussed in Section 3 below, an innovation in this industry is not a patent but a new drug, hence both R&D and patents are just 'proxies' for the innovation 'effort' that a firm undertakes.
[2] This is due both to (1) institutional factors like the 1980 Bayh-Dole Act which allowed publicly funded research to be patented (Mowery and Ziedonis, 2002)—and to (2) competitive factors, such as the need for firms in this industry to constantly produce blockbuster drugs and/or to extend the patent life of existing drugs
[3] Provocatively we call this an 'innovation paradox' recalling the debates in the late 1990s on the 'productivity paradox' or the 'computer paradox' which asked why spending on IT technology did not appear to result in higher productivity or growth in the economy ("We see computers everywhere except in the productivity statistics." (Solow, 1987).

focus more the marketing and distribution efforts around new drugs, while small dedicated firms, often biotech related, focus on the more uncertain process of innovation around niche drugs (Angell 2005; Arora and Gambardella, 1994; Gambardella 1995). Figure 1 and 2 illustrate that as the number of small firms in this industry has increased so has their ability to innovate. How have these changes affected, if at all, the relationship between innovation and firm growth? And what impact has this had on industry market structure and the properties of firm size and firm growth rate distributions?

The first part of the study uses econometric techniques to study the relationship between growth and innovation for firms with different innovation characteristics. The second part of the study uses non-parametric techniques to study the distributions of firm size and firm growth rates by dividing the sample using these same characteristics so to understand whether the relationship between innovation and growth is the key to better understanding the 'complex' properties in market structure that have been highlighted in recent papers.

Our first main result is that innovation (proxied by R&D, patents and citations) appears to affect growth rates only for firms with particular characteristics. These are small firms that are persistent innovators and/or have biotech alliances. This suggests that it is not that market selection doesn't work properly but that it works on a mix of characteristics. And understanding this mix in the context of new forms of competition between large and small firms might shed some light on the dynamics of market selection as well as the fall in R&D efficiency which continues to puzzle and worry analysts of this sector.

Our second main result is that it is firms with precisely these innovation characteristics (i.e. innovative persistence and participants of biotech alliances) which shape the 'complex' patterns in industry structure (Axtell, 2001). That is, we find that *bimodal* size distributions, as well as *fat tails* in growth rate distributions —both examples of non-gaussian behavior which cause problems for economics models which assume normality in these variables--arise, at least in part, due to the presence of firms with these structural characteristics. This is very important since up to now the presence of such complex patterns was assumed to be 'good news' for evolutionary economists, without actually any real evidence that they were related to structural characteristics of innovation. By making this link we think we indeed bring some 'good news'.

The paper is organized as follows. Section 2 reviews some of the growth literature that considers the impact of innovation on firm growth, as well as more general literature that considers the impact of inter-firm differences on growth. Section 3 reviews the data and methodology used in the study. Section 4 presents a simple innovation-growth model and its

results. Section 5 looks at how these results allow us to better understand some 'complex' patterns in firm size and growth rate distributions. Section 6 concludes.

2. Heterogeneity and Growth

Before presenting our model of growth and innovation in the pharmaceutical industry, we briefly review here some of the empirical literature that has considered how innovation affects the growth of different types of firms. We focus on the role of innovative 'persistence' (innovation breeds new innovation), size, and alliances on firm growth since these three variables are found to be important factors affecting the impact of innovation on firm growth in Sections 4 and 5.

2.1. Testing for Structure

Industrial economists have over the last decades continued to puzzle over the sources and patterns of firm growth. The work of Gibrat (1931) set off a stream of works that studied whether firm growth follows a more 'random walk' type behavior or a more structured pattern due to different types of dynamic increasing returns (Ijiri and Simon, 1977; for a review see Marsili 2001). Models interested in looking at the effect of innovation on the firm growth process often use the Gibrat assumption that firms grow independently of their initial size and with small uncorrelated stochastic shocks as a null hypothesis of a lack of structural characteristics (Geroski and Mazzucato, 2002). Results in this empirical literature are inconclusive. Some studies have found a *positive* impact of innovation on growth (Coad and Rao, 2008; Del Monte and Papagni, 2003; Geroski and Machin, 1992; Geroski and Toker 1996). Others *no significant impact* (Almus ,1999). And still others even a *negative* impact (Brouwer et al., 1993). The most interesting work in this line, and the one that our work builds on most closely,, is the literature which acknowledges that the impact of innovation on growth is indeed different for different types of firms, i.e. slow growing/fast growing; above-average R&D intensity/below-average R&D intensity, low tech/high tech (Coad and Rao, 2008; Brouwer et al., 1993, and Del Monte and Papagni, 2003). Most studies, however, tackle the innovation-firm growth question at a more general level with little reference to differences in firm characteristics.

2.2. Innovation, Growth and Heterogeneity

Given the heterogeneity of firms' innovative activities within an industry and within size classes, it is important to understand how differences between firms affect the influence of innovation on firm growth. For example, do persistent innovators grow as fast as the non-persistent ones? Does the degree of openness to technology collaborations determine how

innovation affects firm growth? What role does firm size play in the innovation-growth relationship? We review here some of the literature that looks at the effects of these differences since they will prove to be important for understanding the results in Sections 4 and 5.

(a)Firm Size

The innovative characteristics of firms differ by size. Small and large firms are known to conduct different types of innovative activities that vary in scale, scope, and efficiency levels. Small firms tend to explore more the novel technologies and concentrate on product innovations while large firms excel in process innovations and incremental changes to established technologies (Baldwin and Gellatly, 2003). Small firms also differ from large firms by conducting innovations on a less *persistent* basis (Cefis, 2003;Geroski and Walters, 1997) and undertaking mostly informal R&D distributed among various operational units (Santarelli and Sterlacchini, 1990). Small firms appear to score higher on R&D productivity figures, measured by number of patents per unit of R&D expenditure (Acs and Audretsch, 1988) which is attributed to the advantages of small firms in innovation and the informal organisation of R&D in small firms which cannot be captured by official R&D figures (Rothwell, 1989).

The innovative activities of firms are not only different across size classes but also within size classes. Among firms of the same size, there exists a wide range of differences in R&D capabilities, sources of innovation (e.g. suppliers/customers/scientific developments), degrees of innovativeness and innovative persistence (Baldwin and Gellatly, 2003; Utterback and Suarez, 1993). Managerial attitudes towards innovation also vary in terms of planning and external orientation (i.e. the degree of openness in search for innovation) (De Jong and Marsili, 2006).

(b) Persistence

Many studies have found that most innovating firms tend to innovate occasionally rather than persistently (Geroski et al.,1997). The few persistent innovators, however, are the source of the majority of innovations in each industry (Cefis and Orsenigo, 2001; Cefis, 2003). The degree of persistence in innovative activities in an industry determines the characteristics of innovating firms (i.e. small/large/young/established), the degree to which innovations build on existing knowledge and capabilities, and the degree to which the identity of innovators persists over time (i.e. the probability of established innovators being replaced by new ones). Hence, despite their small numbers, persistent innovators have a significant role in shaping (a) the direction of technological change and (b) the industry structure by defining

the composition and characteristics of innovators as well as the specific entry and exit features in the industry.

(c)Alliances

Small firms often use alliances for improving their access to financial resources and markets as well as gaining recognition and scale-scope advantages in the market place (Havnes and Senneseth, 2001; Stuart, 2000) while large firms benefit from the technological expertise of small firms (Powell et al., 1996). Small-large firm alliances are especially common in industries such as pharmaceuticals where the knowledge base is complex, diverse and expanding (Powell et al., 1996).

How does involvement in the technology based alliances affect firm growth? Do those firms involved in such alliances grow faster than those not involved? And if there is a growth premium associated with involvement in technology based alliances, is that similar for small and large firms which have very distinct roles in the alliance?

Powell et al. (1996), Link and Bauer (1987) and Baum et al. (2000) find that small firms in 'hi-tech' industries grow as a result of being involved in a network. Stuart's (2000) results suggest that only alliances with large innovative firms boost firm growth because affiliation to a large and innovative firm brings recognition and social status alongside other benefits alliances deliver. On the other hand, Havnes and Senneseth (2001) do not identify any short term effects of alliances on firm growth but they find being involved in an alliance is important for the long term benefits of the small firms.

Even though there is evidence that these alliances deliver innovative products the growth benefits of such alliances for large firms is less clear. For instance, Stuart (2000) finds partnering with small firms does not deliver growth for large firms. Similarly, in a study based on the IT industry, Mortehan and De La Potterie (2007) find that alliances solely based on R&D have very weak or even negative effects on the sales of large and incumbent firms while benefiting their small partners. More broad and informal alliances based on a mix of activities such as sales, marketing and R&D seems to deliver positive growth for large firms.

Given the heterogeneity of firms' innovative activities within an industry and within size classes, it is important to understand how each of the factors individually influences firm growth. For example, do persistent innovators grow as fast as the non-persistent ones? Does the degree of openness to technology collaborations determine how innovation affects firm growth? What role does firm size play in the innovation-firm growth relationship?

3. Data

The above studies suggest that there is still much to learn about the innovation-growth relationship—and hence for our understanding of market selection. We approach the problem by building a simple growth model where growth rate is dependent on firm size, past growth as well as different innovation measures (R&D intensity, number of patents, and citation weighted patents), and test the model for different types of firms (sources of heterogeneity) in terms of their size, their innovative persistence, and their alliances. The reason we choose to focus on these sources of heterogeneity is due to important issues raised by the literature reviewed in 2.2 above. We first review how the various variables are constructed.

The model we develop in in Section 4 explores the impact of innovation on firm growth rates using simple panel regression analysis. **Firm size** is measured in terms of (logarithm) revenues and **firm growth rate** is the change in firm size from year t-1 to t. Three proxies for **innovation** are used: *R&D intensity* of firms (between 1950 and 2003), *patent counts* (between 1965 and 1998) and *citation weighted patent counts* (between 1975 and 1998)[4].

Annual revenues and R&D expenditures of firms are extracted from the S&P 500 Pharmaceutical industry database (GICS Code 352020). These figures are then deflated by the US Medical Care Inflation Index to adjust for inflationary effects[5]. All revenues and R&D data is presented in 1982-84 real terms.

R&D expenditures signal a firm's commitment to innovation. Different studies have found R&D to be positively correlated with different performance measures such as market value (Hall et al., 2001). Yet because R&D is an *input* to innovation, it does not reveal much information about the quality and effectiveness of the research undertaken by firms. As a complement to this input variable, two *output* variables are used as proxies for innovation: patent counts and citation weighted patent counts. Patent counts reflect the number of patents a firm has applied for (and eventually received a grant for) in a given year. The application year is used as the year patents are assigned to firms (Hall et al. 2001). Both patent counts and citation counts are extracted from the NBER patent database (http://elsa.berkeley.edu/~bhhall/bhdata.html) that covers patents granted to firms by the US

[4] Note that pharmaceutical industry patents do not have a one-to-one relationship with a certain product (i.e. drug). . Firms take several patents for a single drug often to fight off competition. In this study, all innovation variables are used as a "signal" of innovative activity rather than proof of an innovative product.

[5] Grabowski and Vernon (1990) find evidence that drug prices have not always correlated with economy-wide prices. In the 1970s, drug prices lagged behind overall economy prices while in the 1980s, drug prices far exceeded economy-wide prices. The Medical Care Inflation Index makes it possible to capture the real impacts on drug pricing over time.

Patent Office between 1963 and 2002 and citations made to these patents between 1975 and 2002. These patents and citations are matched to the pharmaceutical firms in the S&P 500 database. After cleaning the database for firms that have less than 7 years of consecutive data, 256 pharmaceutical firms comprise the final sample. Approximately one-third of the firms in the database do not have any patents. Table 1 reports the mean and standard deviation of the key variables in the final sample.

Table 1

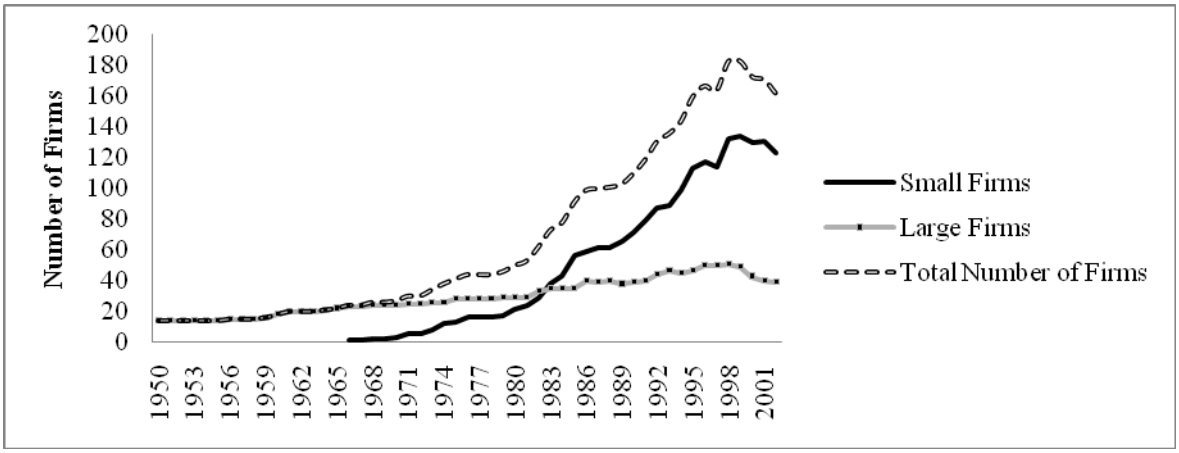
A third database that is used in this database is the BioAbility database that presents an exhaustive list of biotechnology related external actions between firms in the 1978-1999 period (http://www.bioability.com/). The 256 firms in the final sample were screened for a wide range of external actions in the Bioability Database namely: *Equity/ Legal/Joint Venture/ Licensing Agreement/ Marketing Agreement/ Production Agreement/ Partial Acquisition/ Research Contract/ Supply Agreement and New Venture*. Those firms involved in any one of these actions within the period 1978-1999 were classified as 'involved in biotechnology related external actions' while those that never participated were classified as 'not involved'. The participation of a pharmaceutical firm in any of the biotechnology related external actions listed above signals its involvement and commitment to biotechnology related alliances which may potentially affect firm growth as discussed in Section 2.2.

A major challenge in using patent and citations data is correcting for the two types of truncations in this database: patents (as the database only contains data on patents that are eventually granted, those still pending at the end of the sample are not included) and citations (i.e. future citations to patents towards the end of the database are not known). Hall et al. (2001) suggest two ways for dealing with the truncation in patents and citations: the *fixed effects* and the *quasi-structural* approach. The fixed effects approach scales the patents/citations with the average number of patent/citation counts in a given year for a group of patents/citations. The quasi-structural approach, on the other hand, uses econometric estimation techniques to distinguish the multiple effects on citations and corrects for them.

We have chosen to correct for truncation using the fixed effects method. Following Mazzucato and Tancioni (2007), we use a slightly modified version of the fixed effects correction. To correct for patent and citation truncation, we divide these by yearly industry averages instead of the total. The main reason for using this method is the unbalanced nature of the data. As is clear in Figure 1 below, the number of firms increases over time; therefore, the total number of patents and citations increases proportionally. Dividing by the total would introduce a downward bias in the corrected patent counts especially in the post-

1980 period when more firms entered the industry (See Mazzucato and Tancioni, 2007 p.13). The last 4 years of data are cut off as the truncation problem for both the patents and citations becomes so severe that a truncation correction would not provide satisfactory results. In the final version of the regressions, we use patent data between 1965 and 1998 and citations data between 1975 and 1998.

Figure 1: Total Number of Firms in the Pharmaceutical Industry



Note: Small firms have less than 500 employees and large firms have at least 500 employees.

To look into the impact of innovations on firm growth rates and other performance variables, the innovation variable can be included in either flow or stock form, i.e. the depreciated cumulative values of the flow variables over time (Hall, 1993). We prefer to specify the innovation variables in stock form as this is more standard in the literature (e.g. Niefert, 2005), specifically because using the flow forms of innovation variables poses a model specification challenge due to the unbalanced structure of our panel[6].

Appendix 1 explains how the innovation stocks are calculated. Note that the stock innovation variables are divided by the lagged firm revenues (rev_{it-1}) in the model discussed in Section 4 to avoid potential problems that could result from the correlation between firm size and the right hand side innovation variables (Hall and Marisse, 1995).

[6] The major difficulty occurs when determining the right lags at which innovation variables enter into the regressions to impact firm growth. The most commonly used method to determine the lags of the right hand side variables is looking at the Akaike Information Criterion (AIC) (or the Schwarz Bayesian Criterion (SBC) if the sample size is small)) and choosing the model that minimizes this criterion. Neither of these criteria is adjusted to the sample size which means that samples in the models being compared must be the same size (Greene, 2003). Unfortunately, this is not possible for our data as firms enter and exit the panel at various times causing the sample size to vary. We have not considered balancing our panel to allow for a constant sample size as we value the information provided by the entry and exit of the firms.

4. The innovation-growth model

To inspect the impact of innovation on firm growth, equations 1, 2 and 3 are used in which the innovation variables are defined in *stock* form. Firm size for firm i in year t is defined as the logarithm of firm revenues in that year ($y_{i,t} = \ln(rev)_{i,t}$)[7]. Firm growth is defined as the change in firm size (i.e., revenues) between year t and t-1 (i.e. $gr = ln(rev)_{i,t} - ln(rev)_{i,t-1}$). In the following equations RDS refers to the ($R\&Dstock_{i,t}/rev_{i,t-1}$), $PatS$ to the ($Patent\ stock_{i,t}/rev_{i,t-1}$) and $WpatS$ to the ($Citation\ weighted\ patent\ stock_{i,t}/rev_{i,t-1}$) Subscripts i and t respectively refer to the i[th] firm and year t. The Hausman specification tests reveal that the fixed effects specification is a better fit for our data in all of the equations and samples we have worked with. This specification allows for the unobserved firm specific effects to be correlated with the right hand side variables. Note that alongside with the fixed firm effects, we also introduce fixed time effects (ρ_t) in our equations[8].

The growth model we use is a nested model whose null hypothesis is that firm growth is a random walk as in Gibrat's Law, i.e. no structural dynamic. Gibrat's Law (or the Law of Proportionate Effect) states that firms grow independently of initial firm size and with small and uncorrelated stochastic shocks (Gibrat, 1931; Kalecki, 1945; Ijiri and Simon, 1977). In other words, one expects Gibrat's Law to hold in cases where $\beta_1 = 0$ (firm growth is independent of firm size), $\beta_2 = 0$ (i.e. firm growth does not persist over time) and $\gamma = 0$ (i.e. innovation is not a systematic determinant of growth rates).

In the following equations RDS , $PatS$ *and* $WpatS$ refer to the R&D, patent and citation weighted patent stocks divided by the lagged revenues variable($rev_{i,t-1}$) Subscripts i and t respectively refer to firm i and time t and the (ρ_t) is the time effects in our equations

$$gr_{i,t} = \alpha_{i,t} + \rho_t + \beta_1 y_{i,t-1} + \beta_2 gr_{i,t-1} + \gamma(RDS)_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

$$gr_{i,t} = \alpha_{i,t} + \rho_t + \beta_1 y_{i,t-1} + \beta_2 gr_{i,t-1} + \gamma(PatS)_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

$$gr_{i,t} = \alpha_{i,t} + \rho_t + \beta_1 y_{i,t-1} + \beta_2 gr_{i,t-1} + \gamma(WpatS)_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

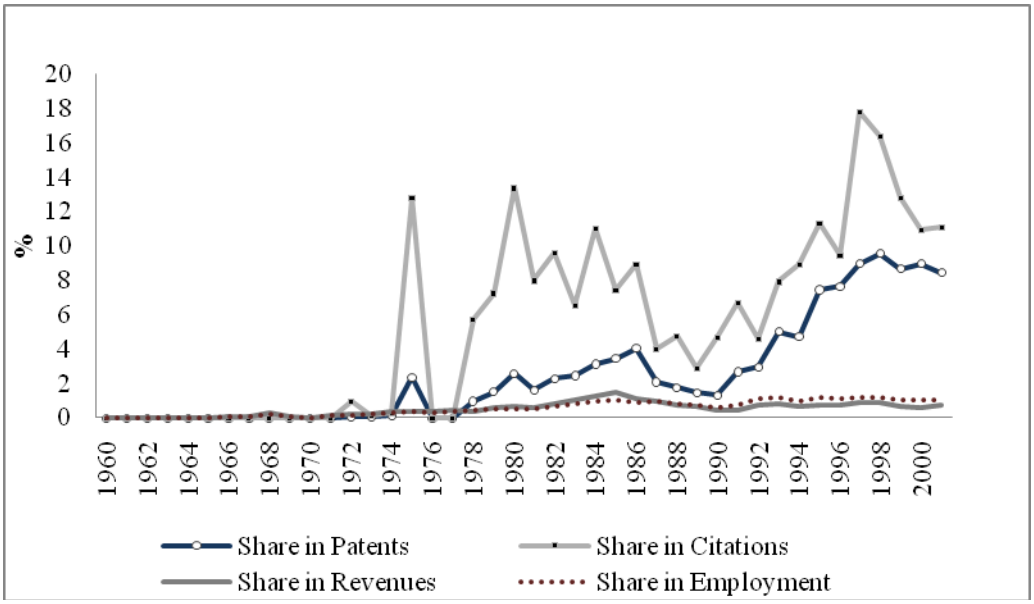
[7] To avoid the problem of missing values that result with firm exit when the firm size falls to zero, we augment the firm revenues series by 0.1 as in Audretsch et al. (1999).

[8] Note that there is a possibility of endogeneity problem in our equations as firm growth and innovation may be determined endogeneously and the causality could be running in either way. As is the case for most innovation studies, we cannot find good exogenous instruments for the innovation variables as the lagged values of the 'stock' innovation variables are also correlated with firm growth. Our tests of causality reveal that firm growth results from innovation in most cases and not the other way round. Hence, we believe that endogeneity is not a serious problem in our case. If the endogeneity problem is present, our estimates of the coefficients for innovation variables would be upwardly biased, but they still remain as the best "predictors".

The pharmaceutical firms in the sample are classified into several categories based on the characteristics reviewed in Section 2.2: size, persistence and alliances (in this case biotech related alliances). We run each regression for the whole pharmaceutical sample as well as 3 sub-categories to investigate whether the impact of innovation on firm growth rates varies across different types of firms. The different categories are:

1. The first firm category is **firm size.** Following Acs and Audretsch (1988), we define small firms as those with fewer than 500 employees and large firms as those with a minimum of 500 employees. We take the average number of employees throughout the life of a firm to determine its classification as a small or a large firm[9]. Fewer than 500 employees seems like a reasonably good definition for a small pharmaceutical company since the average number of employees per firm has always been more than 5000 employees for this industry. Figure 1 shows that the number of small firms increased in the pharmaceutical industry especially in the post 1980 period. Moreover, as Figure 2 shows, small firms started playing an increased role in their share of innovative activities (measured by patents and citation weighted patents), which far exceed their share in industry revenues and employment.

Figure 2: Share of Small firms in Industry Revenues, Employment and Innovative Activities



2. The second way that firms are divided is by their patenting behavior: whether they are a patenter or not and whether this patenting is persistent. ***Patentee firms*** are those firms which have applied for and were granted at least one patent between 1965 and 2002. A firm

[9] Employee numbers are not as consistently reported as firm revenues that we use as the proxy for firm size. Hence, there are missing values especially at the beginning and the end of the data series. Averaging the reported employee numbers over time for a given firm addresses the database's missing values problem.

is classified as a ***persistent patentee*** if it is granted at least one patent each year for any 3 consecutive years between 1965 and 2002. The average length of patent spells in our sample of patenting firms is 2.97 years and hence, 3 years of consecutive patenting is a reasonable definition for "innovative persistence"[10].

3. The third way that firms are divided is according to whether they are involved or not in **alliances with the biotech industry**. We assume that the participation of a pharmaceutical firm in any of the biotech related external actions listed in the Bioability Database in the 1978-1999 period signals its involvement and commitment to biotech related activities. Hence, firms are classified as either 'involved in biotech' or 'not involved in biotech' depending on their participation in at least one of the biotechnology related external actions listed above. Although we are aware that different types of alliances (e.g. marketing agreement, acquisition, R&D cooperation) have very different implications, rather than apriori discriminating between types, we allow all the different alliances to define our 'proxy' for the connection of the firm with the biotech industry[11].

Table 2 reports the number of firms in each firm category as well as the key descriptive statistics according to the firm categories.

Table 2

4.1. Results

(a) The Impact of R&D Stock on Firm Growth Rates

The results from regressions (1), (2) and (3) are reported in Tables 3 and 5. We first look at the impact of *R&D stock* on firm growth rates. The overall impact on the whole sample of pharmaceutical firms is positive. However, the results vary when we consider the firm subcategories in Table 2.

Table 3 reports the impact of R&D stock on the growth rates of different categories of pharmaceutical firms and Table 4 summarizes these results.

Table 3

Small Pharmaceutical Firms: For small pharmaceutical firms, the impact of R&D on firm growth rates is positive for patentee firms. Yet, among the small patentee firms, R&D has a positive impact only for the persistent patentees.

[10] Defining persistence as 5 years of consecutive patenting does not dramatically alter the results in Section 4 and 5.

[11] To investigate the impact of alliances further, it would be necessary to test whether different types of alliances have a different impact on firm growth. This is not the object of the present paper but an excellent avenue for further research (Mortehan and De la Potterie 2007).

When small pharmaceutical firms are divided into two groups based on their participation in biotech related external actions (referred as "involved in biotech" in the tables), we find that only the small firms involved in biotech related external activities grow faster as a result of their R&D activities.

Large Pharmaceutical firms: Similar to small firms, while large patentee firms grow faster as a result of their R&D activities, the R&D activities of large non-patentees have no significant impact on firm growth rates.

Among the large patentees, only the persistent ones grow faster due to their R&D efforts. As in the case of small pharmaceutical firms, large pharmaceutical firms that participate in biotech related external activities grow faster as a result of their R&D. Yet, those large firms that do not participate in biotech related external activities experience negative growth as a result of their R&D.

Table 4: The Impact of R&D Stock on Firm Growth Rates (1950-2003)

	Small Firms	**Large Firms**	**All Firms**
Patentee	+	+	+
Non-patentee	0	0	0
Persistent Patentees	+	+	+
Non-persistent Patentees	0	0	0
Involved in Biotech	+	+	+
Not involved in Biotech	0	-	0

(b) The Impact of Citation-weighted Patent Stock on Firm Growth Rates

In the next stage of our investigation, we limit our sample to patentee firms only, to investigate the impact of firms' patent and citation-weighted patent stocks on their growth rates. Our results from the raw-patent stock model clearly reveal the noise associated with raw patent counts and hence, in Table 5, we only report the results from the model with citation-weighted patent counts.

Table 5

Small Pharmaceutical Firms: Similar to the results when using R&D stock, we find that only the small firms that patent persistently grow faster as a result of their innovative

activities when citation-weighted patent stock is used as the innovation proxy. Likewise, among the small patentee firms, only those that participate in biotech related external actions grow faster as a result of the innovative activities they undertake.

Large Pharmaceutical Firms: Firm growth does not seem to respond to innovation activities for any type of patentee firms when citation weighted patent stock is used as a proxy for their innovative activities. There is no evidence that large persistent patentees, or large patentees that participate in biotech related research grow faster due to innovative activities.

Table 6: The Impact of Citation-Weighted Patent Stock on Firm Growth Rates (1975-1998)

	Small Patentees	**Large Patentees**	**All Patentee Firms**
Persistent Patentees	+	0	+
Non-persistent Patentees	0	0	0
Involved in Biotech	+	0	+
Not involved in Biotech	0	NA	0

Notes*: The sample is limited to patentee firms only. The sample size for large patentees not involved in biotech is too small and hence, we do not report the regression results in the table.*

The different impacts of R&D stock and citation weighted patent stock on the growth rates of large firms may result due to a combination of two factors: (1) R&D expenditures is an input measure of innovation while the citation weighted patent stock is an output measure. As documented by various sources (NIHCM, 2002; Tufts CSDD, 2007), large pharmaceutical firms suffer from declining R&D productivity problems in which the innovative output of large firms are low despite the growing levels of R&D expenditures. Hence, the output measures of innovation are better indicators of the actual innovation undertaken by firms. (2) The R&D figures of large pharmaceutical firms often include the marketing and sales related expenditures and this makes the R&D data a less precise measure of innovation (Angell, 2005).Hence, we believe the citation-weighted patent stock presents a better proxy for innovation in our equations.These finding suggest that innovation leads to an increase in growth only for firms that have a mix of particular characteristics. We find that innovation positively affects the growth of firms under at least one of the two firm categories: persistent patentees and firms involved in biotech alliances. Yet, when these two firm categories are further divided by firm size, we find that only small firms that patent persistently and/or participate in biotechnology. alliances grow faster as a result of their innovative activities.

Since firm growth dynamics have an impact on industry market structure, we now ask whether these growth dynamics are responsible for some of the interesting properties on market structure and firm size/growth distributions that have been recently highlighted by the industry dynamics literature.

5. Innovation, Growth and 'Complex' Patterns in Market Structure

Puzzles concerning the growth-innovation relationship have also emerged recently from studies that have used non-parametric techniques to study the distributions of growth and size. These studies have found that firm growth rates exhibit much fatter tails than the normal distribution (Axtell, 2001). Bottazzi and Secchi (2006) have hypothesized that the underlying structure of fat tails is due to firms' persistence (autocorrelations) in capturing opportunities for growth (e.g. innovations), but it remains only a hypothesis since they don't use any innovation data in the analysis. Dosi (2005) interprets fat tails to mean that there is some underlying 'structural dynamic' which is 'good news' for evolutionary economists. Yet this may be an overly optimistic conclusion unless one can show that the degree of fat tails co-evolves with changing structural dynamics, such as the changing characteristics of innovation. If not, it is hard to interpret the existence of non-gaussain behaviour as evidence of structure. Our goal in this section is to explore for this evidence.

Demirel and Mazzucato (2007) show that bimodality emerges at a specific period in the life-cycle of the pharma industry, i.e. the post 1980's after the biotech revolution and the advent of a new division of labor between large and small firms. In this section of the paper we ask whether the complex properties around size and growth rate distributions, such as bimodality and fat tails, emerge due to the structural characteristics of the firms studied in Section 4, for example whether fat tails are due to in fact to the inclusion of persistent innovators in the sample.

We use a Normal Kernel function with an automatic Silverman bandwidth to look at the shape of the FSD and analyse the kurtosis values of the FGD to identify the degree to which fat tails exist. Others pursuing this line of research have fitted Subbotin distributions to the data to identify the departures from normality (Bottazzi and Secchi, 2006).

As identified by Reichstein and Jensen (2005) and Demirel and Mazzucato (2007) the FSD of the pharmaceutical industry has a *bimodal* distribution while the FGD has significantly fatter tails compared to the Gaussian distribution. Our contribution here is to see whether the bimodality and the fat tails is related in any way to the innovation dynamics. For example, do fat tails disappear if we look only at non-persistent innovation (one-off success that would be more similar to an iid type explanation)? To do so, we compare the kernel

density estimates of the FSD for different types of pharmaceutical firms (i.e. patentees/non-patentees/persistent patentees/firms involved in biotech/not involved in biotech etc.) to identify whether the peculiar bimodal shape of the FSD can be traced back to certain types of firms. The (log) firm size distributions are plotted for different time periods and different types of pharmaceutical firms. Similar to Bottazzi and Secchi (2004), here, the firm size observations are grouped for a range of years instead of presenting a snapshot of a given year. The evolution of FSD is rather slow and FSDs of different years display a large degree of overlap. Hence, grouping observations from different years should not lead to any serious problems especially because the way that innovation and firm growth evolve over the industry life-cycle and over time (as the knowledge regimes are changing (Gambardella, 1995)) is taken into account in the following analysis as we consider the breaks in the data (e.g. the year when many small firms enter and change the shape of the FSD).

Similarly growth rate observations are grouped together over years while taking special care to mark different time periods when firm growth dynamics are significantly different (i.e pre/post 1960, pre/post 1980 etc.). As in Reichstein and Jensen (2005), 5% of the growth rate observations that deviate most from the mean growth rate are eliminated so that the results are not sensitive to outliers. The kurtosis values of the FGD for different types of firms are compared to identify whether the fat tails emerge due to the activities of certain types of firms such as persistent patentees.

5.1. Firm Size Distribution (FSD)

Bottazzi et al. (2003) note the high degree of diversity in the FSDs across the manufacturing sector with different degrees of skewness, and different kurtosis values as well as major differences in how the distributions look. In their work, the pharmaceutical industry also stands out as a unique industry with the peculiar bimodal shape of its FSD. Bimodal size distributions are interpreted as **a)** the disappearance of the moderate/middle size classes **b)** evidence of two separate centers of attraction for firm size **c)** co-existence of an oligopolistic core and a fringe and **(d)** sub-populations with different size distributions aggregated under one industry classification .The emphasis in these studies is on the statistical properties of the FSD since the suggested economic reasoning behind the bimodality remains mostly untested. The following results make a contribution to this specific literature by testing whether the bimodality is related to the innovation dynamics (i.e. patenting and persistence in patenting) and the biotech related external actions among small and large innovative firms in the pharmaceutical industry.

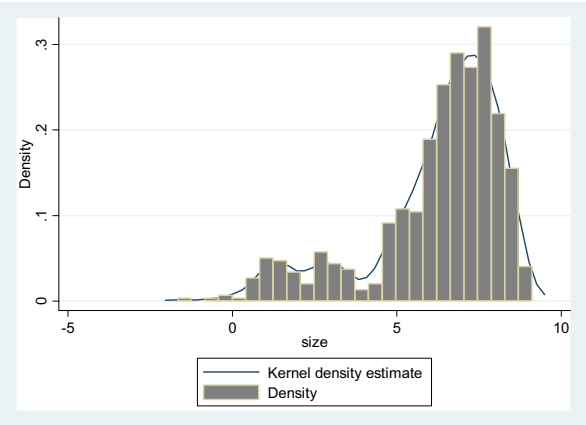
The following plots include a histogram and a kernel density estimate for FSD. Kernel plots are produced as described using the STATA module “kdensity”. The total number of observations used in each plot is indicated.

Demirel and Mazzucato (2007) indicate that the bimodality of the FSD emerges in the 1970s and becomes a stable characteristic of the FSD in the following decades. Notably, the second mode (the left hand side mode) that emerges in 1970s keeps growing over time and eventually far exceeds the size of the initial mode (the right hand side). However, the initial mode that consists of large firms shows a large degree of persistence in the identity of firms: 80% of the firms in this mode (e.g. Abbot Labs, Johnson & Johnson etc.) in 1970 are still in in the same mode in the late 1990s. This suggests that the innovative and fast growing small firms in BIMODE II are not able to replace the large firms in the industry’s core, i.e., a low probability that a firm will move from one mode to the other.

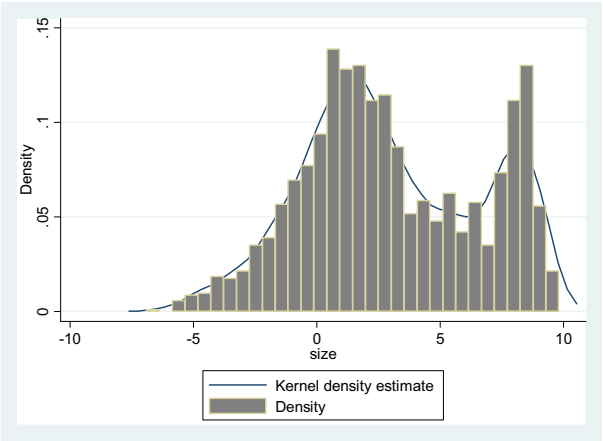
Next, in Figures 3 and 4, we examine the FSD for different firm types to uncover the underlying dynamics of the bimodality. The plots in Figure 3 reveal the bimodality feature only holds for persistent patentees.

Note that the number of non-patentees and non-persistent patentees are very small for the pre-1980 period when the industry consisted of mainly large firms that innovated persistently. Hence, the FSD representations in Figures 3.(c) and 3.(g) are not as robust as the post- 1980 representations (3.(d) and 3.(h)). Yet, we include these in Figure 3. for the reader’s information.

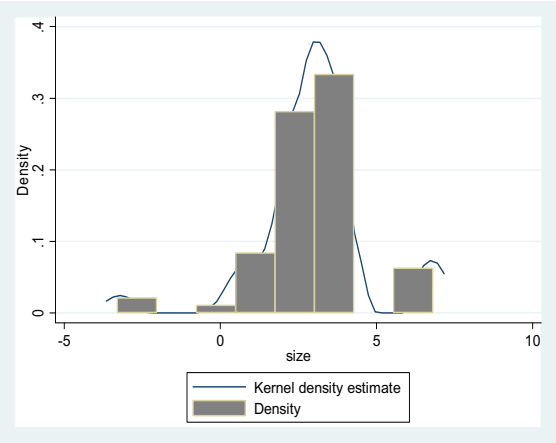
Figure 3: FSD for Different Types of Firms



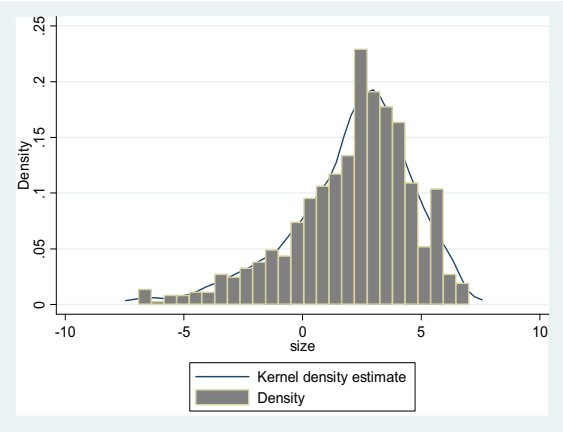
3 (a): *Pre-1980 Patentee firms: 715 observations*



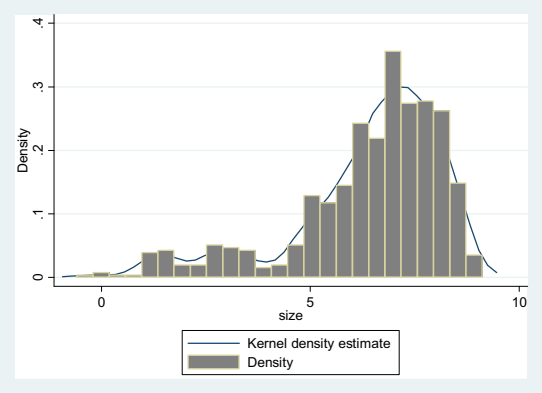
3 (b): *Post 1980 Patentee firms: 1956 observations*



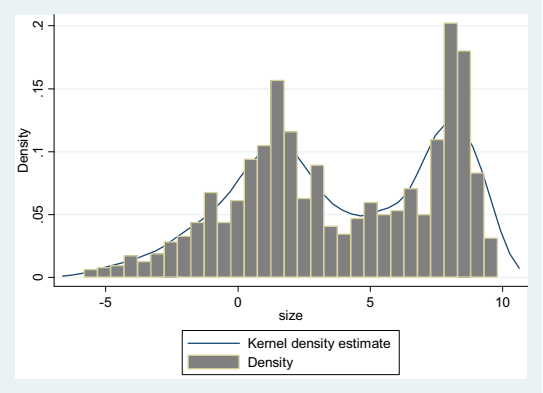
3 (c): *Pre-1980 Non-patentee Firms: 76 obs*



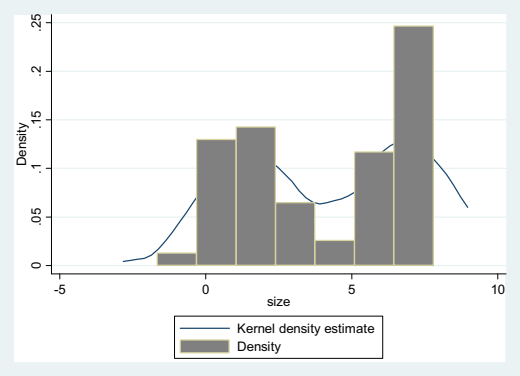
3 (d): *Post-1980 Non-Patentee Firms: 685 obs*

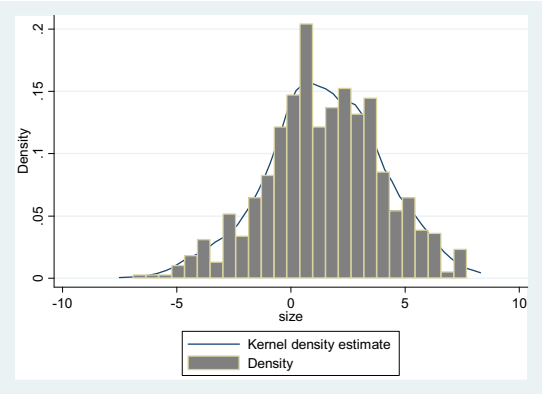


3 (e) *Pre-1980 Persistent Patentees 658 obs*



3 (f) *Post-1980 Persistent Patentees: 1267 obs*





3 (g) *<u>Pre-1980 Non-persistent Patentees:</u> 57 obs*

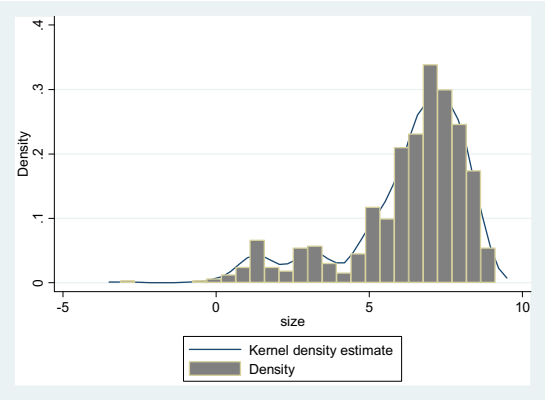
3 (h):*<u>Post-1980 Non-Persistent Patentees:</u> 689 obs*

Clearly, the bimodality feature is closely related to innovations in this industry. When the non-patentee firms or the non-persistent patentees are considered, FSD shows less divergence from the Gaussian distribution. Bimodal FSD only emerges among persistent patentees.

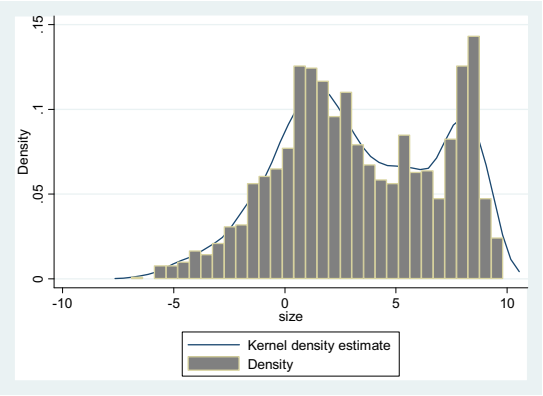
Finally, Figure 4, illustrates whether “being involved in biotech related external actions” relates to FSD bimodality. The results suggest that bimodality only holds for small and large firms involved in biotech related external actions. Fifty two percent of small pharmaceutical firms and 72% of large pharmaceutical firms are involved in biotech related external actions. The significance of these biotech related collaborations should be considered in the context of the biotechnology industry’s post-1980 rise and the concurrent emergence of innovative divisions of labour among small and large firms (Gambardella, 1995).

Finally, to summarise the findings of this section, Figure 5 shows that bimodal FSD is evident in persistentlypatenting firms involved in biotech related external actions. Conversely, FSD shows little divergence from the Gaussian distribution among non-patentee firms and non-persistent patentees not involved in biotech related research.

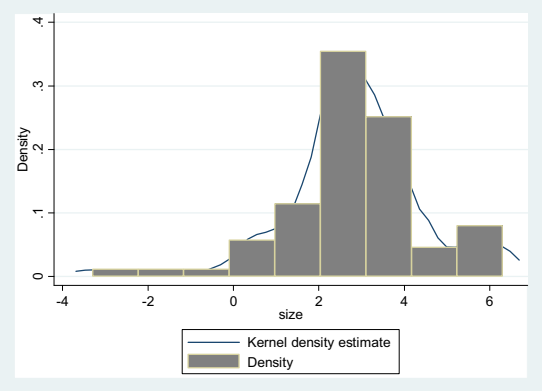
Figure 4: FSD for Firms Involved/Not Involved in Biotech Related External Actions



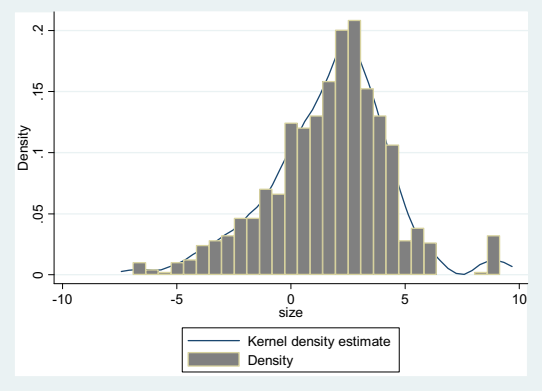
4 (a)*Pre-1980-Firms involved in Biotech related external actions: 709 obs*



4 (b) *Post-1980: Firms involved in Biotech related external actions: 1739 obs*



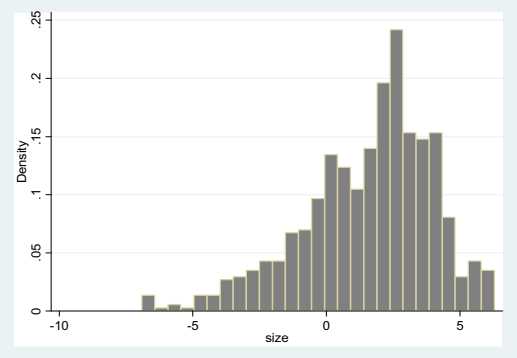
4 (c) *Pre-1980 Firms not involved in Biotech related external actions: 82 obs*

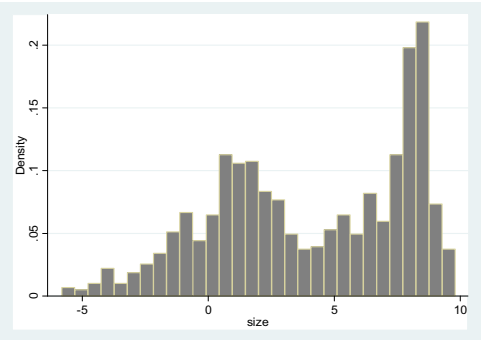


4 (d) *Post-1980 Firms not involved in Biotech Related external actions: 902 obs*

Note: *Again, the number of firms not involved in biotech related external actions in the pre-1980 period is very small. The representation of FSD in Figure 4.3.c is less robust than the post-1980 period representation of FSD for similar firms in 4.3.d.*

Figure 5: Post-1980 (a) Non-patentees and Non-persistent Patentees not involved in biotech related research vs. 5(b) Persistent Patentees Involved in Biotech Related Research





5.2 Firm Growth Rate Distributions (FGD)

Firm growth rate distributions (FGD) show a large degree of similarity across different sectors with their tent-like, fat tailed shapes that resemble exponential (Laplace) distributions (or an even fatter tailed distribution like the Subbotin family of distributions) instead of Gaussian distribution. The FGD for the pharmaceutical industry is no exception to this with its tent-shaped, fat tailed distribution.

Bottazzi and Secchi (2005) interpret fat tails as evidence of dynamic increasing returns to scale, such as economies of scale and scope, network externalities and increasing returns to knowledge accumulation (p.18). Dosi (2005) argues that fat tails imply much richer structure in the growth dynamics than that assumed by Gibrat's law. Bottazzi et al.'s (2008) work finds that the extreme growth rates (both positive and negative) at the tails of the FGD result from firms less likely to default financially. However, neither Bottazzi's work nor other subsequently related studies (e.g. Reichstein and Jensen, 2005, Coad and Rao, 2008) directly explore what constitutes the "structure" underlying fat tails in the FGD. Our work contributes to this literature by empirically testing whether fat tails are related to the dynamic increasing returns from innovations. The results confirm that fat tails are closely related to the characteristics of innovative pharmaceutical firms.

In Table 7, the kurtosis values are shown for different time periods and different types of firms. Kurtosis value of a distribution indicates the degree to which it has fat tails. Gaussian distribution has a kurtosis value of 3. Distributions with kurtosis values higher than 3 are known to have fatter tails compared to Gaussian distribution.

Important findings from Table 7 include[12]:

a) The FGD has fat tails for all firm categories, yet the degree of "fatness" is different for different types of firms.

b) The FGD of patentees displays fatter tails than that of non-patentees. Note the higher kurtosis values in Table 7.

c) The FGD for persistent patentees displays fatter tails than that of the non-persistent patentees.

d) The FGD for firms involved in biotech related external actions has fatter tails compared to that of firms which do not participate in biotech related external actions.

[12] We have checked the robustness of these results by taking out random sets of firms (e.g. first 100 firms or last 100 firms in alphabetical order) from the sample to see whether the tails of the FGD become thicker in all cases when one limits the sample size. We found that in some cases the tails were thicker yet in others, they were slimmer. This suggests that what affects the thickness of the tails is not solely affected by taking out a number of firms but the "type" of firms we take out.

Fat tails indicate that firm growth events are indeed *"lumpy"* instead of being *normally distributed, small and independent* (Dosi, 2005,p.11). This is much in line with Schumpeter's view in which he argued that *"innovations are not at any time distributed randomly… but they are by nature lopsided and disharmonious…[G]rowth based on technical innovation [is] more like a series of explosions than a gentle and incessant transformation"* (Freeman, 1995). The majority of firms in an industry experience *very close to average* growth rates while only a few experience big spurts of growth due to higher levels of available opportunities (Bottazzi and Secchi, 2005). The results from Table 7 show that patentee firms (and especially persistent patentees) and firms involved in biotech related external actions) experience more extreme growth compared to other firms in the industry. Hence, fat tails of the FGD in the pharmaceutical industry possibly result more so from the growth activities of innovating (i.e. patentee/ persistent patentee) firms and firms that participate in biotech related actions. As already shown in Sections 4, these are exactly the types of firms that have the innovative characteristics favoured by market selection forces. However, for other firms less involved in innovations, biotech related activities and cooperation (non-patentees/ non-persistent patentees/ not involved in biotech related external actions), the FGD's tails are not as fat, which suggests firm growth is more normally distributed for these types of firms.

Is this good news for evolutionary economists? Dosi (2005) argues that fat tails might be signals that innovations in the form of new products lead to lumpy growth. The empirical tests in this section provide evidence (the first that we know of) for this view by showing that in fact fat tails emerge especially for firms that are persistent innovators with particular alliances. That is, firms with particular structure behind their innovation experience even more lumpy growth.

6. Conclusions

The paper has shown that the impact of innovation on firm growth is far from being a simple causal relationship where innovation leads to growth. Innovating alone does not boost firm growth unless the firm is of a *certain type*.

The results suggest that the fitness criteria upon which market selection processes operate is a mix between firm size and the different aspects of the firms' innovative activities such as patenting, persistence in patenting and involvement in biotech related external actions. Small firms grow faster as a result of innovative efforts while large firm growth is not necessarily related to innovative activities. Whether a firm is a *persistent* patentee affects its subsequent growth resulting from innovative activities. Innovation-growth dynamics also depend on whether firms participate in biotech related external actions, such as research agreements.

While small firms that participate in biotech related external actions grow faster as a result of their innovative activities, large firms display a more mixed result.

Most importantly, the paper reveals how market selection plays a key role in determining some 'complex' properties of industry structure, such as the bimodality and fat tails found in firm size and firm growth distributions (Axtell, 2001; Bottazzi and Secchi, 2006) Firms able to grow through innovative activities are those that shape these peculiar aspects of industry structure which are not consistent with the Gaussian behavior assumed by Neoclassical theory. This is good news for evolutionary economists for several reasons: Not only does firm growth not behave as it would in a world of representative agents where innovation is an iid random variable, but even more importantly, the structure behind growth appears to react directly to the innovative characteristics of firms. More persistent innovators have fatter tails.

Do these results help us better understand the falling efficiency of R&D (the 'innovation paradox') recently highlighted in the financial pages? To investigate this further it would be essential to study whether the low R&D efficiency in this sector is due to the wrong mix of firm activities, and if so, which mix of characteristics. This study suggests to start looking at the variables around persistence of innovation, size and alliances. For example, does the fact that the small dedicated biotech firms in this sector are often later acquired by the large firms, hinder the efficiency of the division of labor between them and impact on the strength of the initial alliance[13]? What factors prevent first time innovators to become 'persistent' innovators? Does State funding of the knowledge base have an impact on persistence?

These questions are interesting to consider in light of the Lisbon Agenda (2005) which has set a target of 3% R&D spending in Europe in order to achieve higher growth. Industrial policy can be informed by these results lwhich suggest that increases in R&D spending should be done in the context of specific mixes of innovative abilities needed by the firms doing the R&D. Future research might focus on the different mix of characteristics needed by firms for their R&D spending to translate into growth, and how this mix differs (or not) between sectors and between phases of the industry life-cycle.

[13] The fact that the core firms in the right hand side mode are very stable (as discussed in Demirel and Mazzucato (2007)) implies some inertia. Hence one might also investigate whether the degree to which small firms, grow, replacing the large firms in the 'core', with a new cohort of small firms entering to form the left hand side mode, would also affect the R&D efficiency in the industry.

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Table 1: Descriptive Statistics for Key Variables in the Final Sample

	Mean	Standard Deviation
Revenues ($mil.)	823.22	1866.76
Patent Applications	249.21	908.34
R&D Expenditures ($ mil.)	78.63	207.41
Employees	9170	18490

Table 2: Key Descriptive Statistics for Firm Categories

	Mean R&D ($mil)	Mean Revenues ($mil)	Mean Employee Numbers	Mean Patent Applications per firm	Average R&D Intensity
Small Patentees (120 firms)	3.34	9.36	1014	17.97	0.36
Small Non-Patentees (50 firms)	2.22	17.68	1900	0	0.12
Small Persistent Patentees (60 firms)	4.27	9.97	1099	33.65	0.43
Small Non-Persistent Patentees (60 firms)	2.29	8.75	931	3.13	0.26
Small Firms Involved in Biotechnology (89 firms)	3.76	9.034	1303	19.65	0.41
Small Firms Not Involved in Biotechnology (81 firms)	1.94	10.05	1286	3.81	0.19
Large Patentees (66 firms)	196.23	2070.63	218929	824.79	0.09
Large Non-Patentees (20 firms)	15.38	193.47	31769	0	0.08
Large Persistent Patentees (44 firms)	215.94	2237.96	235955	1039	0.096
Large Non-Persistent Patentees (22 firms)	28.26	519.83	62346	2.66	0.05
Large Firms Involved in Biotechnology (62 firms)	187.76	1977.37	207985	774.34	0.09
Large Firms Not Involved in Biotechnology (24 firms)	87.45	914.54	121271	10.18	0.09

Table 3: Regression results: The Impact of R&D Stock on Firm Growth Rates (Dependent Variable: Firm Growth Rate)

Firm Categories	$(s)_{t-1}$	$(s^2)_{t-1}$	$(RDS)_{t-1}$	Number of Cross Sections and Total Observations	R^2
Small Patentees	-0.44* (0.048)	-0.024 (0.049)	0.0004* (0.00018)	120/858	0.365
Small Non-Patentees	-0.31* (0.077)	0.073 (0.081)	0.0018[t] (0.0009)	50/392	0.373
Small Persistent Patentees	-0.35* (0.063)	-0.05 (0.058)	0.00043* (0.00016)	60/462	0.38
Small Non-Persistent Patentees	-0.61* (0.075)	0.034 (0.09)	0.00008 (0.0008)	60/396	0.41
Small Firms Involved in Biotech	-0.38* (0.05)	0.005 (0.05)	0.0004* (0.00016)	89/746	0.36
Small Firms Not-Involved In Biotech	-0.40* (0.074)	-0.016 (0.083)	0.0006 (0.0006)	81/504	0.356
Small Firms	-0.39* (0.04)	0.0006 (0.04)	0.00042* (0.0001)	170/1250	0.35
Large Patentees	-0.08* (0.017)	-0.07 (0.056)	0.013* (0.005)	66/1165	0.287
Large Non-Patentees	-0.22* (0.08)	0.007 (0.09)	-0.04 (0.029)	20/117	0.46
Large Persistent Patentees	-0.068* (0.017)	-0.13 (0.08)	0.014* (0.005)	44/1058	0.27
Large Non-Persistent Patentees	-0.33* (0.059)	-0.055 (0.103)	0.016 (0.029)	22/107	0.69
Large Firms Involved in Biotech	-0.08* (0.018)	-0.08 (0.05)	0.013* (0.005)	62/1168	0.26
Large Firms Not Involved in Biotech	-0.22* (0.04)	0.13 (0.09)	-0.07* (0.026)	24/114	0.70
Large Firms	-0.10* (0.017)	-0.07 (0.045)	0.012* (0.0056)	69/1282	0.30
Patentees	-0.34* (0.03)	-0.06 (0.04)	0.00053* (0.0001)	186/2023	0.32
Persistent Patentees	-0.24* (0.038)	-0.08[t] (0.05)	0.00055* (0.0001)	104/1520	0.32
Involved in Biotech	-0.30* (0.038)	-0.025 (0.04)	0.00051* (0.00016)	151/1914	0.31
Non-Patentees	-0.30* (0.07)	0.05 (0.07)	0.001 (0.009)	70/509	0.36
Non-Persistent Patentees	-0.58* (0.069)	0.017 (0.082)	0.000 (0.0007)	82/503	0.40
Not Involved in Biotech	-0.39* (0.069)	-0.02 (0.08)	0.0007 (0.0006)	105/618	0.35
All Firms	-0.333* (0.033)	-0.022 (0.038)	0.00052* (0.0001)	239/2532	0.32

Data Source: **S&P 500 Pharmaceutical Industry Database and the NBER patent and citations Database**
Notes**: Heteroskedasticity robust White Errors reported in parentheses. * significant at 5% and [t] significant at 10%.**

Table 5: Regression results: The Impact of Patent Citation Stock on Firm Growth Rates (Dependent Variable: Firm Growth Rate)

Firm Categories	$(r)_{it-1}$	$(gr)_{it-1}$	$(CitsF)_{it-1}$	Number of Cross Sections and Total Observations	R^2
Small Persistent Patentees	-0.29* (0.077)	-0.18* (0.09)	0.004* (0.0019)	51/310	0.38
Small Non-Persistent Patentees	-0.55* (0.09)	0.08 (0.09)	-0.07 (0.14)	48/308	0.40
Small Patentees Involved in Biotech	-0.35* (0.066)	-0.10 (0.08)	0.003* (0.001)	68/473	0.36
Small Patentees not Involved in Biotech	-0.49* (0.17)	0.06 (0.13)	0.043 (0.11)	31/165	0.47
Small Patentees	-0.38* (0.06)	-0.06 (0.07)	0.003[t] (0.0017)	99/618	0.36
Large Persistent Patentees	-0.13* (0.047)	-0.02 (0.117)	-0.019 (0.064)	43/634	0.22
Large Non-Persistent Patentees	-0.36* (0.12)	-0.09 (0.13)	0.07 (0.105)	22/125	0.66
Large Patentees Involved in Biotech	-0.14* (0.04)	0.004 (0.07)	-0.03 (0.05)	47/663	0.24
Large Patentees not Involved in Biotech[a]					
Large Patentee Firms	-0.145* (0.04)	0.003 (0.07)	-0.03 (0.05)	65/759	0.26
Persistent Patentees	-0.22* (0.05)	-0.16* (0.07)	0.004* (0.0018)	94/944	0.33
Non-Persistent Patentees	-0.54* (0.09)	0.07 (0.08)	-0.065 (0.13)	70/433	0.40
Patentees Involved in Biotech	-0.31* (0.05)	-0.098 (0.065)	0.003* (0.001)	115/1136	0.32
Patentees Not Involved in Biotech	-0.49* (0.15)	0.068 (0.11)	0.04 (0.1)	49/241	0.46
All Patentee Firms	-0.329* (0.047)	-0.068 (0.05)	0.003* (0.001)	164/1377	0.33

Data Source: **S&P 500 Pharmaceutical Industry Database and the NBER patent and citations Database**
Notes**: Heteroskedasticity robust White Errors reported in parenthesis. * significant at 5% and [t] significant at 10%.**
[a] The results are not reported due to small sample size.

Table 7: FGD Kurtosis Values for Different Types of Firms

	Kurtosis Values	Number of Observations
Pre-1960	16.57	145
Post-1960	6.44	2783
Pre-1980	17.80	740
Post-1980	5.51	2218
1960-1980	16.45	595
Pre-1980 Patentees	20.96	676
Pre-1980 Non-Patentees	3.91	64
Post-1980 Patentees	5.72	1658
Post-1980 Non-Patentees	4.86	560
Post -1980 Persistent Patentees	6.37	1111
Post-1980 Non-Persistent Patentees	4.75	547
Post-1980 Involved in Biotech Related External Actions	6.13	1504
Post-1980 Not Involved in Biotech Related External Actions	4.57	714

APPENDIX :

Calculation of the Stock Innovation Variables:

When calculating the innovation stock (R&D, patent and citation-weighted patent stocks), the perpetual inventory method is used in which a 15% depreciation rate and a 5% annual growth rate is assumed for the stock (Hall and Marisse, 1995). In what follows, we demonstrate the calculation of the R&D stock.

δ represents the depreciation rate which is assumed to be 15% in this case, $RDSTOCK_{i,t}$ is the R&D stock for firm i in year t, $RD_{i,t}$ is the R&D expenditures of firm i in year t (in flow form).

$$RDSTOCK_{i,t} = RD_{i,t} + (1-\delta)RD_{i,t-1} + (1-\delta)^2 RD_{i,t-2} + ... + (1-\delta)^t RD_{i,o} \quad \text{(A1)}$$

Equation (A1) can be reduced to (A2) as in Lach (1995)

$$\mathrm{RDSTOCK}_{i,t} = (1-\delta)\mathrm{RDSTOCK}_{i,t-1} + \mathrm{RD}_{i,t} \quad \text{(A2)}$$

For (A2) to make sense, we need to know the firm's R&D stock value in year zero, the year a firm first enters the market (in our case, the year it gets quoted on the American Stock Exchange). To calculate this, we assume that the innovation stock grows at an annual rate of 5%. According to (A3), Lach (1995, p.102-103) shows that the R&D stock is roughly equal to 5 times the R&D expenditures the firm makes in the first year it enters the database (assuming that δ=0.15 and g=0.05).

$$RDSTOCK_{i,o} = RD_{i,o}/(\delta + g) \quad \text{(A3)}$$

The same method above is used to calculate the stock of patents and citation weighted patents. The truncation in patents and citations is corrected first, then the stock calculation operations are undertaken.