Stock Price Volatility and Patent Citation Dynamics: the case of the pharmaceutical industry

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Abstract

Recent finance literature highlights the role of technological change in increasing firm specific and aggregate stock price volatility (Campbell et al. 2001, Shiller 2000, Pastor and Veronesi 2005). Yet innovation data is not used in these analyses, leaving the direct relationship between innovation and volatility untested. Our aim is to investigate more closely the relationship between stock price volatility and innovation using firm level patent citation data. The analysis builds on the empirical work by Mazzucato (2002; 2003) where it is found that stock price volatility is highest during periods in the industry life-cycle when innovation is the most 'competence-destroying'. Here we ask whether firms which invest more in innovation (more R&D and more patents) and/or which have 'more important' innovations (patents with more citations) experience more volatility. We focus the analysis on firms in the pharmaceutical and biotechnology industries between 1974 and 1999. Results suggest that there is a positive and significant relationship between idiosyncratic risk, R&D intensity and the various patent related measures. Preliminary support is also found for the 'rational bubble' hypothesis linking both the level and volatility of stock prices to innovation.

Key words: Idiosyncratic Risk; Volatility; Technological Change; Industry Life-Cycle.

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1. Introduction

In recent years there has been increased attention, by both the economics profession and the popular press, on the topic of stock price volatility. Interest peaked after the 'New Economy' period when many high-tech stocks that were considered overvalued experienced a large drop in their share price. But still now there persists the idea that the 'knowledge economy' (less unfashionable a term than the New Economy), has resulted in greater volatility, especially of small innovative firms which tend to go public earlier in their life-cycle than in previous times.

Yet, in reality, there has been no trend increase of aggregate stock price volatility (Schwert 1989; 2002). Particular periods have been characterized by high volatility, such as the 1970's and the 1990's, but the increase has not persisted. Firm specific volatility has, on the other hand, experienced a trend increase over the last 40 years (Campbell et al. 2001). Various works have highlighted technological change as one of the key factors responsible for this increase in firm specific risk, as well as the periodic increases of aggregate stock price volatility. For example, Shiller's work (2000) has shown that 'excess volatility', i.e. the degree to which stock prices are more volatile than underlying fundamentals, is highest in periods of technological revolutions when uncertainty is greatest. Campbell et al. (2001) find that firm level idiosyncratic risk, i.e. firm specific volatility (as opposed to industry specific or market level), has risen since the 1960's and claim that this might be due to the effect of new technologies, especially those related to the 'IT' revolution, as well as the fact that small firms tend now to go public earlier in their life-cycle when their future prospects are more uncertain. And Pastor and Veronesi (2004) claim that the reason that high tech firms have prices that appear unjustifiably high (at the beginning of a 'bubble') is not due to irrationality, but due to the effect that new technology has on the uncertainty about a firm's average future profits. The basic idea behind all these works (reviewed further below) is that innovation, especially when 'radical', leads to high uncertainty hence more volatility.

Yet none of these studies actually use innovation data. Innovation is alluded to (e.g. the 'IT revolution', the New Economy, radical change) but not measured, especially not at the firm or industry level[1]. The aim of our paper is to better understand the dynamics of stock price volatility by seeing whether we can in fact find evidence that stock price volatility is related to firm level innovation. That is, we do not *assume* that volatility is a sign of greater uncertainty due to underlying innovation but instead empirically test for this very relationship.

[1] Of the above cited authors, Shiller (2000) comes closest to considering the impact of technology by looking at excess volatility during the course of technological revolutions.

The paper builds on our previous work (Mazzucato and Semmler 1999; Mazzucato 2002; 2003) where it is found that excess volatility and idiosyncratic risk are highest in periods of the industry life-cycle when innovation is the most 'radical'. However, while there we measured innovation at the industry level (e.g. through a quality index derived from hedonic prices), in the current paper we go a step further in linking innovation to volatility by using *firm level* patent data. The productivity literature on market value and innovation has already established a positive relationship between a firm's market value, its R&D intensity and its citation weighted patents (Griliches 1981; Pakes 1985; Hall 1993, Hall, Jaffe and Trajtenberg 2005). Here we see whether this type of data can also help us better understand volatility dynamics which, as argued above, have not been studied in light of firm specific innovation dynamics.

Both Frank Knight (1921) and John Maynard Keynes (1973), who distinguished 'risk' from 'uncertainty', used technological innovation as an example of *true uncertainty* which cannot be calculated via probabilities like risk[2]. We start from the assumption that patents that are "more important" are those that are the most uncertain due to the way they challenge the status quo, more so at least than incremental innovations (Tushman and Anderson 1986). We use citation weighted patents as a proxy for the 'importance' of an innovation and see whether firms with more 'important' innovations experience more volatility. Specifically, we test for the relationship between firm level idiosyncratic risk and the following innovation variables: R&D intensity, patent counts, and patents weighted by their citations. We also look at the impact of these variables on the level of price-earnings as this relationship lies at the core of the 'rational bubble' hypothesis where both the level and volatility of stock prices are related to the uncertainty regarding a firm's average future profits (Pastor and Veronesi 2004; 2005).

As in our previous work, we focus our study on one particular sector so that we can better relate stock price dynamics to the changing character and intensity of innovation over the industry life-cycle (Gort and Klepper 1982). The biotechnology and pharmaceutical industries (from now on biotech and pharma) are particularly interesting to study in this regard due to their high rates of patenting and R&D intensity (providing us with ample innovation data to study), and due to the way that the search process for innovations has changed over the last half century (as documented in Gambardella [1995], Henderson et al.

[2] *"The practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either from calculation a priori or from statistics of past experience). While in the case of uncertainty that is not true, the reason being in general that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique…"* (Knight, 1921, p. 232-233)

[1999]) — motivating us to also ask whether the relationship between innovation and volatility has co-evolved with such transformations.

Our analysis is carried out in 3 stages. We first see whether we can replicate the results found in the market value (Tobin's q) and innovation literature (Griliches, 1981; Hall, Jaffe and Trajtenberg 2005 from now on HJT) using flow rather than stock variables (cumulative and depreciated), since in the case of volatility it is the latest 'news' that is relevant. Second, we test for a statistical relationship between idiosyncratic risk and these innovation variables in order to explore the hypothesis that technology is the source of the increase in firm specific risk (as suggested but not tested in Campbell et al. [2001], and Shiller [2000]). Third, we test the 'rational bubble' hypothesis in Pastor and Veronesi (2004) by exploring the relationship between the level of price-earnings (P/E) and the innovation variables, as well as the direct relationship between idiosyncratic risk and P/E.

Our results provide preliminary evidence that there is indeed a positive and significant relationship between firm specific volatility and firm level innovation. We find that both idiosyncratic risk and the level of price earnings are significantly related to R&D intensity, and to the various patent related measures used in the analysis. We also find a positive relationship between these innovation measures and the level of price-earnings, as is predicted by the 'rational bubble' hypothesis. We pay particular attention to the lag structure of the independent variables as this provides information on the speed at which the market reacts to news regarding innovation. In this regard it appears that the lag on innovation outputs (patents) is lower than that on inputs (R&D), and also that the lags for biotech are lower than those in pharma, suggesting that the market reacts more quickly to innovation in newer segments of the sector.

The rest of the paper is organized as follows. Section 2 reviews the literature on innovation and stock prices; Section 3 discusses the data used and the variables constructed; Section 4 provides descriptive statistics and a discussion of the model selection criteria; Section 5 presents the results and Section 6 concludes.

2. Innovation and Stock Prices (level vs. volatility): a quick review

Uncertainty in finance models refers to how *expectations* about a firm's future growth affects its market valuation (Campbell, Lo and McKinley 1997[3]). Both Knight (1921) and

[3] *"The starting point for any financial model is the uncertainty facing investors, and the substance of every financial model involves the impact of uncertainty on the behaviour of investors, and ultimately, on market prices."* (Campbell, Lo and MacKinlay, 1997)

Keynes (1973) highlighted the way that technological innovation is an example of true uncertainty, which cannot be calculated via probabilities like risk. Yet, even though a firm's investment in technological change is a major determinant of its (potential) future growth, few finance models link stock price dynamics to innovation variables at the level of the firm and industry. The few studies that do relate stock price dynamics to innovation, do so mainly by linking changes in the stock price *level* to innovation, rather than linking changes in *volatility* of stock prices to innovation. This is ironic given that it is especially the *volatility* of stock prices, more than their *level*, which should be related to 'news' on changes in technology. In this section we review the literature that relates stock price dynamics to innovation, dividing it between those contributions that focus on the *level* of stock returns (2.1), and those that focus on the *volatility* of stock returns (2.2)—neither one using innovation data—and then our own contributions which have studied volatility dynamics using industry innovation data (2.3). The rest of the paper is then dedicated to studying volatility dynamics using firm level innovation data.

2.1 Innovation and stock prices (level)

Studies that link the level of stock prices to innovation come principally from the applied industrial economics literature which studies innovation and stock prices during the industry life-cycle (e.g. Jovanovic and MacDonald 1994; Jovanovic and Greenwood 1999; Mazzucato and Semmler 1999) and the productivity literature on market value (Tobin's q) and patents (e.g. Griliches 1981; Hall, Jaffe and Trajtenberg 2005 from now on HJT).

Jovanovic and MacDonald (1994) make predictions concerning the evolution of the average industry stock price level around the "shakeout" period of the industry life-cycle. They predict that just before the shakeout occurs the average stock price will fall because the new innovation precipitates a fall in product price which is bad news for incumbents. Building on this work, Jovanovic and Greenwood (1999) develop a model in which innovation causes new capital to destroy old capital (with a lag) and since it is primarily incumbents who are (initially) quoted on the stock market, innovations by new start-ups cause the stock market to decline immediately since rational investors with perfect foresight foresee the future damage to old capital. In a study of the US auto industry (1899-1998), Mazzucato and Semmler (1999) also relate the dynamics of the average industry stock price to the dynamics of the industry 'shakeout'.

Another body of literature that connects stock prices to innovation is that on the relationship between a firm's market value, its stock of R&D, and its stock of patents (Griliches 1981; Griliches, Hall and Pakes 1991; HJT 2005). Using a Tobin's q equation, this literature tries to evaluate whether the market positively values the investment of a firm in technological change: if patent statistics contain information about *shifts in technological opportunities,* then they should be correlated with current changes in market value since market values are driven by the expectations about future growth. Given the skewed nature of the value of patents, Griliches, Hall and Pakes (2001) make use of patent citation data to distinguish important patents from less important ones. Using a Tobin-q equation, they find a significant relationship between citation-weighted patent stocks and the market value of firms where market value increases with citation intensity, at an increasing rate. They find that while a reasonable fraction of the variance of market value can be explained by R&D spending and/or the stock of R&D, patents are informative above and beyond R&D only when weighted by citations (unweighted patent applications are far less significant). The market premium associated with citations is found to be due mostly to the high valuation of the upper tail of cited patents (as opposed to a smoother increase in value as citation intensity increases)[4]. A more recent study (HJT, 2005) finds further support for the relationship between knowledge assets and market value, highlighting differences between sectors: elasticity tests find that the marginal effect of additional citations per patent on market value is especially high in knowledge intensive industries such as the pharmaceutical industry. R&D stocks are more tightly correlated with market value than patents and patent citations stock is more significant than patents stock.

2.2 Innovation and stock price volatility (with no innovation data)

The few works that have looked at the relationship between innovation and the *volatility* of stock prices have done so mainly at the aggregate level, and without using innovation data. Shiller's work has shown that excess volatility is higher during periods of technological revolutions (Shiller 2000). He claims that the efficient market model greatly underestimates stock price volatility due to the fact that it does not incorporate the social mechanism by which expectations are formed (i.e. animal spirits, herd behavior, bandwagon effects). In periods of technological revolutions, such effects are strongest due to the increased uncertainty regarding both technology and demand (causing investors to be less confident about their own judgments).

[4] That is, after controlling for R&D and the unweighted stock of patents, they find no difference in value between firms whose patents have no citations, and those firms whose patent portfolio has approximately the median number of citations per patent. There is, however, a significant increase in value associated with having above-median citation intensity, and a substantial value premium associated with having a citation intensity in the upper quartile of the distribution (HJT 2001).

Campbell et al. (2001) study the idiosyncratic versus systematic nature of volatility by decomposing the return of a typical stock into three components: the market wide return, the industry specific residual and a firm specific residual. They use variance decomposition analysis to study the volatility of these components over time. The firm specific residual is the *idiosyncratic* component of risk, while the market wide return captures the *systematic* component of risk. They find that while aggregate market and industry variances have been stable (updating and confirming Schwert's 1989 finding that market volatility did not increase in the period 1926-1997), firm level variance displays a large and significant positive trend, actually doubling between 1962 and1997. They claim that this increase is related to the impact of the IT revolution on various factors including the speed of information flows.

Finally the work of Pastor and Veronesi (2005) provides interesting insights on the relationship between innovation, uncertainty and both the level and volatility of stock prices. They claim that if one includes the effect of uncertainty about a firm's average future profitability into market valuation models, then bubbles can be understood as emerging from *rational*, not irrational, behavior about future expected growth. Building on the result in Pastor and Veronesi (2004) that uncertainty about average productivity increases market value (because market value is convex in average productivity), they extend the model to explain why technological revolutions cause the stock prices of innovative firms to be more volatile and experience bubble like patterns. The basic idea is that when a firm introduces a new technology, its stock price rises due to the expectations regarding the positive impact of the new technology on its productivity. Volatility also rises because risk is idiosyncratic when technology is used on a small scale. But if/once the new technology gets adopted throughout the economy, then risk becomes systematic causing the stock price to fall and volatility to decrease. This bubble like behavior is strongest for those technologies that are the most uncertain (and the most 'radical').

2.3 Firm level innovation and stock price volatility (with innovation data)

As none of the studies cited above (2.2) use innovation data, the relationship between innovation and volatility remains only a hypothesis. Our earlier work tests this hypothesis using firm and industry level innovation data. The fact that most shocks are idiosyncratic to the firm or plant makes this imperative (Davis and Haltiwanger, 1992). In a comparative study on the auto and computer industries, Mazzucato (2002) finds that idiosyncratic risk and

excess volatility (as measured in Shiller [1981][5]) are highest precisely during the decades in the industry life-cycle in which innovation is the most radical[6] and market shares the most unstable—the latter due to the 'competence destroying' effect of radical innovations on industry market structure (Tushman and Anderson 1986). For this reason Mazzucato and Tancioni (2006) argue that both market share instability and stock price volatility are indices of competition that 'capture' well the dynamics of creative destruction (in the PC industry better than entry/exit rates).

Mazzucato and Tancioni (2005) attempt to generalize the above finding by studying whether idiosyncratic risk is higher for those firms and industries that are more R&D intensive (and in general more innovative according to sectoral taxonomies of innovation found in Pavitt 1984, and Marsili 2001). The study is first performed on 34 different industries using data on industry level stock prices and R&D intensity, and then on firm level panel data for 5 specific industries that span the highly innovative to low innovative horizon (biotech, pharma, computers, textiles and agriculture). In the latter, firm-level idiosyncratic risk is regressed on firm level R&D intensity, for 822 firms between 1974-2003. It is found that while it is not true that more innovative industries are on average more volatile than less innovative ones (echoing to some extent the finding in Campbell et al. 2001 that industry level risk has not increased), at the firm level a positive and significant relationship is found between idiosyncratic risk and R&D intensity. Interestingly, the relationship is stronger for the biotech industry and the textile industry than for pharma and computers. This may be because investors react strongly to news on innovation by firms in uncertain new industries, such as biotech or nanotechnology (with high potential growth), as well as to innovative firms in relatively static non innovative industries (such as textiles) since the latter 'stick out' from the crowd. Firms in innovative but mature industries, like pharma or computers, tend instead to provoke less of a reaction since innovation is common (with high average R&D intensity) but less radical and uncertain due to the particular stage of the industry in its life-cycle.

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[5] In Mazzucato and Semmler (1999) and Mazzucato (2002), "excess volatility" is measured as in Shiller (1981), i.e. the difference between the standard deviation of actual stock prices (vt) and efficient market prices (v*t): $v_t = E_t v_t^*$ and $v_t^* = \sum_{k=0}^{\infty} D_{t+k} \prod_{j=0}^{k} \gamma_{t+j}$ where v_t^* is the ex-post rational or perfect-foresight price, D_{t+k} is the dividend stream, γ_{t+j} is a real discount factor equal to $1/(1+r_{t+j})$, and r_{t+j} is the short (one-period) rate of discount at time *t+j.*

[6] Innovation is measured here using quality change data derived, as in Filson (2001), by dividing hedonic prices by actual BEA prices. Hedonic prices are from Raff and Trajtenberg (1997, for autos), and Berndt and Rappaport (2000, for computers). In the case of autos, the analysis is supported by the use of an innovation survey by Abernathy et al. (1983) which ranks all innovations in the auto industry between 1890 and 1982 in terms of the degree to which the innovations altered products and processes.

In the remaining sections of the paper, rather than using indirect or input measures of innovation, we use firm level patent citation data (as in the studies reviewed above by Pakes 1985 and HJT 2001;2005). Our aim is to see whether the degree of excess volatility of returns and thus the dynamics of idiosyncratic risk are indeed positively correlated with more "important" innovations as is implied in the works cited above. We also explore the relationship between radical innovation and the level of stock returns, as is implied (but not tested) in the work by Pastor and Veronesi (2004; 2005). Before discussing the details of the models we review the data, and in particular various issues related to patent citation data.

3. Data and constructed variables

3.1 Data

We study the pharma and biotech industries from 1975 to 1999. Our sample of firms is constructed by merging financial data from S&P (purchased from S&P Custom data dept) and USPTO patent data (extracted from the NBER patent citation database included in the book/CD by Jaffe and Trajtenberg 2002). The NBER patent citations database provides detailed patent related information on 3 million US patents granted between January 1963 and December 1999, and all citations made to these patents between 1975 and 1999 (over 16 million). For each patent, information on the citations it *received* (a forward looking measure, which captures the relationship between a patent and subsequent technological developments that build up on it, i.e. its descendants), and the citations *made* (a backward looking measure which captures the relationship between a patent and the body of knowledge that preceded it, i.e. its antecedents). Weighting patents by citations is important since studies have found that the distribution of the value of patents is highly skewed, with few patents of very high value, and many of low value (a large fraction of the value of the stream of innovations is associated with a small number of very important innovations, Scherer, 1965). There is also information on the number of *claims*, which is often recognized as an indicator of the wideness of the patent. Although in our future work we plan to take into account various indices constructed using citations (e.g. the level of generality or originality of an innovation)[7], in the current work we use only the number of patents for each firm and the number of citations received per patent.

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[7] For example, the degree to which an innovation is 'general' or 'original' can be measured using indices which use citations *received* and citations *made* data along with data on particular technological fields. A patent which is very general is one which has received citations from other patents in a wide variety of fields. A patent which is instead highly original is one which makes citations to other patents in a limited set of technological fields. Inserting this information in our future work will allow us to see whether the market places more/less value on certain types of innovations than others.

We have S&P financial data for 323 pharma firms and 563 biotech firms quoted on the stock market between 1950 and 2003. We use the firm CUSIP code to match firms in the two data bases. Only firms pertaining to the GIC codes (which in 2000 replaced the SIC codes), 352010 for biotech and 352020 for pharma are included in the analysis. To merge the two databases, we use the patent *application date* rather than the patent *granted date* since the latter is subject to idiosyncratic changes in the speed of the patent review process (however it is only patents granted that are in the database). The merging of the two databases results in a restricted sample: out of a total of 323 pharmaceutical firms and 563 biotech firms in the S&P database, the merged sample contains 126 pharma firms and 177 biotech firms. In order to avoid dealing with highly volatile stock price data, we have omitted firms present in sample for less than eight years. Since we consider a three-year maximum lag in our estimates, this guarantees that data is available for at least five years. We thus end up with 63 firms in the pharma industry and 71 firms in the biotech industry[8]. When we work with the larger number of firms (126 and 177 firms in pharma and biotech) the results are not qualitatively different, but less significant. Details on the number of observations employed in the estimates and on the sectional dimension are reported in the tables.

Figure 1 indicates that the number of firms rose steadily in both industries, slowing down in the early 90s for pharma, and in the late 90s for biotech. A look at the herfindahl index shows that in both industries, the rise in firms was accompanied by a fall in concentration. To deal with unbalanced sample panel estimations, we employ standard correction techniques to control for the presence of missing data in some periods.

We use the following firm level variables from the S&P database: stock price (P), dividends (D), revenues (Rev), price-earnings ratio (P/E), market value (MKTV), and R&D. We also use the average S&P500 value for all these financial variables[9]. The following innovation variables are used from the patent database: the annual number of patent applications (PAT); patents weighted by citations *received* (PATW); and patents per R&D, or the patent yield which captures the efficiency of R&D (PATY). We also explore the use of citations *made* (i.e. backward citations) but find this measure to be less significant than citations received so use only the latter in the final analysis.

[8] Other sample selection criteria have been used in the literature. For example, in a related study on spill-overs and market value, Deng (2005) omits firms with less than 3 years in the Compustat database.

[9] On average, nearly 95% and 97% of the merged sample is available when financial variables are matched with, respectively, R&D intensity and patents weighted by citations received.

The financial variables are monthly; R&D is quarterly; and patents are annual[10]. Following Schwert (1989), the monthly S&P data is used to calculate the volatility of annual returns (the standard deviation is calculated over 12 month observations on returns). We use monthly financial data, rather than daily data, since it would be exaggerated to expect that quarterly R&D figures and annual patent data have an impact on daily stock prices. Furthermore, Campbell et al (2001) analyze volatility using both daily and monthly data and do not find qualitative differences (in trends).

To measure idiosyncratic risk we do not use the variance decomposition method used in Campbell et al. (2001) which isolates firm, industry and market level volatility through a variance decomposition analysis. Rather, we use a proxy for idiosyncratic risk (IR) which captures the degree to which firm specific returns are more volatile than market level returns: the log ratio between the standard deviation of a firm's return[11] and the standard deviation of the average industry return (the standard deviation of the S&P500 return for the specific industry to which the firm belongs). When considering the whole sample of 134 firms in our analysis, we also control for (fixed) industry effects with an industry dummy (for biotech).

The R&D and patent variables are entered in terms of flows rather than stocks. This lies in contrast to the market value and innovation literature (HJT 2005), which instead uses stocks (defined applying a Permanent Inventory approach with a 15% depreciation assumption). We use flow variables because while it makes sense to think that it is the stock of intangible assets that affects the level of market value, changes in stock prices (hence their volatility) are affected mainly by recent 'news' that the market did not previously take into account (flows not stocks). Since we are mainly concerned with the determinants of IR (which is stationary in mean over time), the use of cumulative and thus trended variables such as stocks would render the estimations unbalanced (from the point of view of the statistical properties of the data) and thus potentially distorted. Furthermore, in a study by Hall (1993), where R&D is entered both as a stock and as a flow in the market value equation, it is found that the flow variable has more explanatory power than the stock *"…which implies a higher valuation on recent R&D than on the history of R&D spending."* (Hall 1993, p. 261)[12].

[10] The patent application date is listed by year, while patent grant date is listed by month.

[11] The return of a firm's stock is defined as: $\frac{(P_t - P_{t-1}) + D_t}{P_{t-1}}$.

[12] Hall (1993) notes that the significance of the R&D flow is reduced when cash flow is included as a regressor suggesting that at least part of the R&D flow effect arises from its correlation with cash flow. In contrast, the R&D stock variable is not sensitive to the inclusion of the cash flow variable. We test for this below and find that the cash flow variable is less significant than it is in Hall (1993).

3.2 Truncation and other data issues

Patents citation data are naturally susceptible to two types of truncation problems. One has to do with the patent counts and the other one with the citation counts[13]. The former arises from the fact that as the end date is approached, only a percentage of the patents that have been applied for (and are later granted) are available in the data. The second truncation problem regards citation counts. As the NBER data ends in 1999, we have no information on the citations *received* by patents in the database beyond this period. Although this affects all the patents in the database (patents keep receiving citations over long periods, even beyond 50 years), it is especially serious for patents close to the end date. Since every year suffers a different degree of this problem (with the later years suffering more), it makes comparison between years difficult.

There are two main ways to deal with both these truncation problems The first is the *fixed effects* approach, the second is the *structural* approach (both reviewed in detail in Jaffe and Trajtenberg 2002, Ch. 13). The fixed effects approach involves *scaling* citation counts by dividing them by the total citation count for a group of patents to which the patent of interest belongs (e.g. by period, or by field). In essence, this means calculating the firm's *share* of total industry patents[14]. The quasi structural approach is a more involved approach based on estimating the shape of the citation lag distribution, i.e. the fraction of lifetime citations (defined as 30 years after the grant date) that are received in each year after the patent is granted (HJT 2005)[15]. Unlike the fixed effects approach it allows one to distinguish real from artefactual differences between years and fields. For example, one can see whether the patents issued in the late 1990's made fewer citations, after controlling for the size and fertility of the stock of patents to be cited, than those before. By doing this, one can get the "real" 1975 patents, just as with CPI adjustments.

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[13] Another problem regarding citations is that since the propensity to cite is not constant, it is important to distinguish when an increase in the number of citations (e.g. technological impact of the patent) is "real" as opposed to "artefactual". The latter includes the possibility that in some periods there was "citation inflation", e.g. due to institutional factors (e.g. USPTO practices) and/or differences across fields.

[14] To remove year and/or field effects, the number of citations received by a given patent are divided by the corresponding year-field mean, or only by yearly means to remove only year effects. The justification for the correction is to remove factors of time variability that are not related to substantial innovation, as in the case of legislative interventions which affect number of patents and citations (e.g. the Bayh-Dole act), or by the truncation issue. The problem with this method is that it does not distinguish between differences that are real and those that are artefactual (e.g. if patents in the 1990's really did have more technological impact, removing the year effects ignores this real factor.).

[15] Given the distribution, which is assumed stationary and independent of the overall citation intensity, the authors estimate the total citations of any patent for which a portion of its citation life is observed. This is done by dividing the observed citations by the fraction of the population that lies in the time interval for which citations are observed (HJT, 2005, p. 13)

We follow a slightly modified version of the fixed effects approach. We divide the firm-level data by the *average* industry citations not the *total*, since the latter varies with the changing number of firms in our unbalanced sample. That is, since the number of firms that are present in the sample increases over time[16] (as evident in Figure 1), while the innovative activity at the firm-level remains relatively stable, the standard fixed effects correction would bias downward the measure of innovation[17]. Dividing by the yearly *average* (as opposed to the yearly total), means that the correction is not affected by the changing number of firms in the sample[18].

Lastly, another way we confront the truncation problem is to test our results on two samples. One sample which ends in 1999, i.e. the last year included in the NBER patent citation database, and another sample which ends in 1995, before the truncation problem becomes serious. This strategy, which is also followed in HJT (2005), is a crude way of getting rid of the most problematic (later) years referred to above and an admission that all the truncation adjustments don't totally solve the problem.

3.3 The pharma-biotech sector

As in our previous work on stock price volatility (Mazzucato and Semmler 1999; Mazzucato 2002; 2003), we focus on a single sector so to better take into account the possible effect of qualitative and quantitative changes in innovation over the industry life-cycle (not possible in more static cross-section industry studies). We focus on the pharma and biotech industries due to the fact that the high R&D and patenting intensity of these industries provides us with ample innovation data, and also because much has been written about changes in innovation dynamics in this sector, allowing us to test whether the relationships we study have evolved alongside such transformations. For example, Henderson et al. (1999) describe the changes that have taken place since the mid 1980's in the innovative division of labor between large pharma firms and small (dedicated) biotech

[16]The number of firms that are contemporaneously present in the whole sample goes from 31 in 1980 to 187 in 2003, while the average number of patent applications per firm is (only) doubled in the same period.

[17] Furthermore, the FE approach suggested in Jaffe and Trajtenberg (2002) removes the time series variability, since the evolution of innovative intensity over time is substantially extracted by the correction.

[18] An example: in 1970, Abbot Technologies has 7 patents, that receive a total of 40 citations, and in the entire pharmaceutical industry there are 20 firms, with 107 patents which have 792 citations. This means that we need to first divide 40 by 7 to get the numerator. However, since we don't want to eliminate the data on patents that receive no citations (to distinguish them from those firms that have no patents at all) we add 1 to each citation figure so that it is 41 divided by 7, equal to 5.85. Then to adjust for the two types of truncation problems we divide 5.85 by the total number of citations in the industry (+1), divided by the average number of patents in the industry which is 793/107, divided then by the number of firms, 20 = .370. So the figure in 1970 for Abbot Technologies is 15.81.

firms. Similarly, Gambardella (1995) describes how advances in science (enzymology, genetics and computational ability) since the 1980's caused a change in the way that firms search for new innovations: a pre 1980 period of "random screening", and a post-1980 period of "guided screening" characterized by more scale economies and path-dependency[19]. An important institutional event which affected patenting behavior in this period was the 1980 Bayh-Dole act which allowed universities and small businesses to patent discoveries emanating from publicly sponsored research (e.g. by the NIH), prompting many biotech spin-offs from academia.

As many patents in the pharma industry do not result in new drugs (Harris, 2002; Pisano 2006) [20], we do not assume that patents represent actual innovations (e.g. a new drug), but rather *signals* that the market receives regarding the potential 'innovativeness' of a firm. The more patents a firm has the stronger the signal regarding its potential innovativeness, and the more citations per patent, the more important (trustworthy) the signal. This lies in contrast with the usual interpretation of R&D as an *input* and patents as an *output* of the innovation process. In fact, it might be that because there are so many patents in this industry (inflated especially after the 1980 Bayh-Dole act), the market treats them as more noisy signals than in other industries, and hence citations take on an even more important role as a filtering device. The biotech part of the sector is in an earlier phase of its life-cycle than pharma, and in some respects more innovative (since biotech firms are more focused on research, and less on marketing and distribution, than pharma firms), hence it is interesting to see whether in biotech, patents are treated as stronger signals of potential innovations than in pharma. It is also interesting to see whether the fact that biotech firms are more focused on single research projects, hence less diversified in their research portfolio, produces more volatility. In general, the role of biotech in the innovative division of labor (Henderson et al. 1999), affects the degree to which patents act as signals in the sector, the speed of the market's reaction to such 'news', and the perceived risk.

To understand the uncertainty around patents as signals of innovativeness it is important to remember that we merged the databases using the patent *application date* (rather than the patent granted date) when there is the highest uncertainty: uncertainty whether the patent will be granted, uncertainty whether, even if it is granted, the patent will be successful, etc. And as the approximate lag between the application date and the granted

[19] Gambardella (1995) documents that although the guided regime did not increase the number of new molecules discovered, it did decrease the failure rate of those tested (hence making the process more efficient).

[20] Pisano (2006) reports that it takes an average of 10-12 years for a company to get a drug out on the market. Only 10%-20% of drug candidates beginning clinical trials have been approved by the FDA.

date is 3 years, when considering the lag structure of the models below, a lag of t-1 on patent applications is like a forward lag of t+2 for patents granted.

4. Descriptive statistics and model selection

4.1. Descriptive statistics

Table 1 contains descriptive statistics on the different variables used in the study for the (a) full sample, (b) for pharma only, and (c) for biotech only[21]. The Table contains first the information for the three financial variables (market value, price-earnings, idiosyncratic risk) and then for the innovation variables, including the productivity of R&D, i.e. the patent yield' (PAT/R&D) used in HJT (2005).

The average number of patent applications (PAT) per firm is 8.3 (9.5 for pharma and nearly 4 for biotech), with large variability in both industries (standard deviations are 17.5 and 18.4 respectively). Employing a standardized measure of variability (coefficient of variation), we observe that patenting activity is more heterogeneous amongst the biotech firms than the pharma firms. In the case of weighted patents (PATW), both the sample mean and the standard deviation are much higher for the biotech industry—indicating that although there are more patents in pharma, they are on average more 'important' in biotech. Sample means and standard deviations of R&D intensity are much higher in pharma than biotech (though as is well known, what is counted as R&D in pharma, sometimes also includes marketing type activities). The skewness measure indicates a high degree of asymmetry (long right tails) for all the innovation variables, with R&D more skewed in pharma than biotech, but patenting more skewed in biotech than pharma. The Kurtosis measure indicates that the distributions (in both samples) are also leptokurtic compared to the normal.

With regards to the financial variables, the *level* of market value and the level of price earnings (MKTVAL and P/E) exhibit a large amount of variation, while idiosyncratic risk (IR) appears more concentrated around a normal distribution. They result all positively skewed and leptokurtic, with the distribution of IR being closer to the normal. The average P/E for biotech is three times that in pharma, as would be expected given the smaller average size of biotech firms, the fact that they often have low earnings (Pisano 2006), and their higher innovativeness (evidenced by their higher patent yield) hence higher expected growth.

[21] For descriptive purposes, we do not impose the minimum presence condition at this stage. This because our aim is to give a more comprehensive summary of the data structure.

Contemporaneous correlations between the variables don't show much significance. This evidence is supported by the regression results (below) which show that the relationships hold mostly dynamically and, in particular, that patents are correlated with lagged R&D intensity. Even if we do not perform dynamic correlations, we can obtain a visual appreciation of the relationships by plotting different variables together over time. From Figure 2a and 2b, idiosyncratic risk appears remarkably correlated with both R&D intensity and, to a lesser extent in the biotech industry, to citation weighted patents. These figures provide a first, albeit simplistic, indication of the co-evolution of idiosyncratic risk and innovation—investigated more rigorously below.

It is interesting to see that in Figure 3 the rise in citation weighted patents is accompanied in both pharma and biotech (but more so for biotech) by a rise in market share instability[22]. This is precisely what would be expected by the literature on 'competence-destroying' innovations (Tushman and Anderson 1986) and gives us a preliminary reason to expect that citation weighted patents also affect the volatility of stock prices (as these are affected by the expected future market share of a firm). This result in fact confirms that found in Mazzucato (2002): market share instability is highest in periods of the industry life-cycle when innovation is the most 'radical' or competence destroying (discussed in 2.3).

4.2 Model selection

In the remaining sections, we test the relationship between the innovation variables discussed above and the level and volatility of stock returns (all the variables are entered in logs). We first try to replicate the results found in HJT (2005) regarding the relationship between market value, R&D, and patents (Model 1). Second, we regress idiosyncratic risk on the innovation variables to test whether firm specific risk is related to innovation, as hypothesized (but not tested) in Campbell et al. (2001) (Model 2). Third, we test the relationship between innovation and the level and volatility of stock prices found in the "rational bubble" hypothesis (Pastor and Veronesi, 2004), by regressing the P/E ratio on idiosyncratic risk (IR) (Model 3) and then directly on the innovation variables (Model 4).

[22] The market share instability index is defined in Hymer and Pashigian (1962): $I = \sum_{i=1}^{n} [| s_{it} - s_{i,t-1} |]$, where s=market share of firm i, and n=number of firms.

Specifically, the relationships we estimate are:

Model 1

$$\log\left(MKTVAL_{i,t}\right)=\alpha_{(i)}+\boldsymbol{\beta}\mathbf{x}_{i,t-l}+\left(u_i\right)+\varepsilon_{i,t}$$

Model 2

$$\log\left(IDRISK_{i,t}\right)=\alpha_{(i)}+\boldsymbol{\beta}\mathbf{x}_{i,t-l}+\left(u_i\right)+\varepsilon_{i,t}$$

Model 3

$$\log\left(P/E_{i,t}\right)=\alpha_{(i)}+\beta\log\left(IDRISK_{i,t-l}\right)+\left(u_i\right)+\varepsilon_{i,t}$$

Model 4

4a. $\log\left(P/E_{i,t}\right)=\alpha_{(i)}+\boldsymbol{\beta}\mathbf{x}_{i,t-l}+\left(u_i\right)+\varepsilon_{i,t}$

where $\mathbf{x}_{i,t}$ is a vector of contemporaneous and lagged regressors representing different innovation variables. Specifically, $\mathbf{x}'_{i,t-l}=\log\left(\frac{RD_{i,t-l}}{REV_{i,t-l}}\right)$ (a scalar) in Models 1a, 2a and 4a, $\mathbf{x}'_{i,t-l}=\left[\log\left(\frac{RD_{i,t-l}}{REV_{i,t-l}}\right)\ \log\left(PAT_{i,t-l}\right)\right]$ in 1b, 2b and 4b and $\mathbf{x}'_{i,t-l}=\left[\log\left(\frac{RD_{i,t-l}}{REV_{i,t-l}}\right)\ \log\left(PATW_{i,t-l}\right)\right]$ in Models 1c, 2c and 4c.

The lag structure is chosen on the basis of likelihood ratio tests. The alpha subscript *i* in brackets and the $\left(u_i\right)$ error factor are entered as we allow, alternatively, for fixed and random effects. In the pooled panel model case such sectional controls are removed.

In each estimation we include a control for firm size: a firm's market share (firm revenues divided by industry revenues) or, alternatively, the share of a firm's capitalization compared to the industry capitalization. As the former is found to be more significant than the latter, we report results in the tables only with market share as the firm size control. Controlling for firm size is important due to the fact that small firms tend to be more volatile than large firms (in both growth rates and stock prices). Two dummies are also used to control for various aspects of the innovation dynamics discussed in 3.2: a period dummy to test whether the relationships are stronger/weaker in one of the two innovation regimes (pre/post 1985); and, when employing the whole sample, an industry dummy to see whether the dynamics differ in biotech, the relatively newer segment of the industry[23].

[23] In each model, we also test a version of equation (c) that includes the patent yield variable (PATY), but we don't report on the results for this variable as it emerges as not significant in all the estimates.

The panel structure of the data-set suggests to employ as natural model alternatives the pooled, the Fixed Effects (FE) and the Random Effects (RE) specifications. With the FE model (alpha subscript *i* in equations above) firm level factors systematically enter the relationships, while in the RE model (the error component (u_i) in equations above) these factors are distributed randomly, i.e. they are an error component which is constant over time. The FE model thus presumes that there are omitted variables that have section-specific effects, such as tacit knowledge and related managerial capabilities. HJT (2005) adopt a pooled model with period and industry dummies. Aside from the fact that their significant results (between market value and innovation) disappear when FE are used (as also in the related literature), they do not include FE for two reasons. First on the grounds that since R&D *stocks* change slowly over time (by construction), the inclusion of FEs would capture those systematic components that are deemed related to firm specific R&D strategies, i.e. to the independent variable. Second, on the grounds that since firms change their strategies over time in response to market signals, the FE model is inappropriate as it presumes permanent firm specific effects.

In our case, the first point is irrelevant since we are dealing with volatile flow data and not with slowly-changing stocks, hence FEs are not likely to be excessively correlated with the independent variable and thus to capture the sample correlation between the dependent and independent variables. Concerning the second point, we believe that even if firm strategies vary in response to time-varying market signals, the presence of publicly available information on fundamentals (that are likely to be relatively firm-specific) may result in systematic cross-sectional factors, reflecting relatively permanent aspects of the firm's fundamentals that are not explicitly taken into account in the model specification[24].

For these reasons, unlike HJT (2005), we do not impose any particular model specification and base our choices on statistical information only. The model selection procedure is implemented in two steps, first evaluating the statistical relevance of the individual (firm) effects and then whether they are correlated with the regressors. This is done by testing, via the Breusch-Pagan LM test, for the presence of individual effects against the common constant model (pooled estimator), and then testing the null of orthogonality of the

[24] We don't think there is an objective reason to believe that firm specific effects are fixed over time and randomly distributed over the sample, as implied in the RE specification. Moreover, the RE model presumes that the section specific effects and the explanatory variables are uncorrelated. This assumption is questionable, since it is likely that the omitted factors that are relevant for the dependent variable are also relevant in determining the explanatory variable (Mundlack, 1978). As regards our specific analysis, the omitted factors no doubt include tacit knowledge and managerial capabilities, factors that have relevant effects on both innovative activity and the market performance of a given firm.

individual effects, i.e. the RE specification, assuming a FE as alternative hypothesis. In this second step the reference evaluation tool is the Hausman test.

The Breusch-Pagan test rejects the null hypothesis of the pooled model (common constant) for nearly the entire set of specifications. A pooled model is selected only for Models 2a, 2b and 2c when employing the biotech sample. In all the other cases, the Breusch-Pagan test indicates a RE specification. According to the Hausman test, a RE model is selected for Models 2 (a, b, c) and 4 (a, b, c) when employing the whole sample and Models 4 (a, b, c) when employing the pharma sample. In all the other cases a FE specification is selected. The model selection results are presented in detail in tables 2a, 2b and 2c (respectively for the whole, pharma and biotech samples) and summarized in column 1 of Tables 3-4-5.

5. Results

The results of the preferred models are summarized in Table 3 for the whole sample and Tables 4-5 for the pharma and biotech samples. Concerning robustness, our estimates are substantially unchanged when employing the reduced sample with end date fixed at 1995 in the place of 1999 (as done also in HJT 2005). This suggests that our correction for the truncation problem, using the modified fixed effects approach discussed above, was efficient. Moreover, the estimation results are qualitatively robust to different calibrations of the minimum presence criterion[25].

According to the F tests (Pooled and FE model specifications) and Wald tests (RE model specifications), the models are all globally significant with the unique exception of Model 2a and, marginally, of Model 2b, when employing the biotech sample. The regression is thus statistically insignificant when only a standard measure of innovation input is entered R&D), while it turns out significant when augmented with patents and in particular weighted patents.

Adjusted R-sq (Pooled model) and overall R-sq statistics (FE and RE specifications) signal an acceptable measure of fit for Model 1[26] and, with the exception of the biotech

[25] We have repeated the estimates by selecting a minimum presence condition spanning from three to ten years, obtaining qualitatively constant estimates. Even employing no selection at all, the estimates remain relatively significant in nearly all models. The main differences are, in this case, a moderate loss of statistical significance, in particular for Models 3 and 4 in the case of the biotech sample.

[26] In Model 1, the average measure of fit, spans from nearly 24% for the whole sample estimates, to 40% for the pharma sample and 37% for the biotech sample.

sector, for Models 3 and 4[27]. The measure of fit is instead weak for Model 2, particularly when employing the biotech sample[28]. It is interesting to note that, when employing the whole and the pharma samples the measure of fit improves moving from Model 3 to Model 4. This happens irrespective of the specific version of Model 4 (a, b or c), signaling that direct measures of innovation outperform our measure of uncertainty (IDRISK) in explaining the variability of the P/E ratio.

Concerning the dynamic specification of the models, best estimates are obtained with lagged regressors in all the models. Moreover, by nesting the selected dynamic structures of Models 2 to 4, we can infer that innovation precedes idiosyncratic risk in the dynamic correlations with the P/E ratio. If we consider the whole sample, from Model 3 we obtain a lag 1 for IDRISK, while for Model 4 we select a lag 3 for RD/REV and a lag 2 for PAT-PATW. This result is consistent with the selection of a lag 2 and 1 (respectively for RD/REV and PAT-PATW in Model 2, and it is an indication of the validity of our theoretical hypothesis. In this respect, consistent result are obtained also for the pharma and biotech estimates, i.e. the dynamics of the P/E ratio depends on lagged uncertainty, which in turn depends on lagged measures of innovation, with innovation preceding idiosyncratic risk.

When the estimations are done employing the FE model, the introduction of the biotech industry dummy (in the case of the whole sample) does not make sense. Hence, in the case of FE model estimates the industry dummy estimates are not present. Yet, by imposing a RE model specification irrespective of the indications of the Hausman test and maintaining the industry control, we find that the sign and significance of the biotech dummy is always significant, with a negative sign in model 1 (i.e. biotech firms have on average 10% less market value than the sample mean), a positive sign in Model 2 (biotech firms experience on average 30-35% more idiosyncratic risk than the sample mean), and a positive effect in Models 3 and 4 (biotech firms have on average 35% higher P/E than the sample mean). Considering the final estimates reported in Table 3, for RE Models 2 and 4, the dimension of the industry specificity can be derived by comparing the estimated value of the biotech dummy with that of the constant term. The biotech industry dummy is always positive and significant.

[27] For Model 3 the average fit spans respectively nearly 11%, 18% and 4%. For Model 4 they are, respectively, nearly 25%, 22% and 2%.

[28] The fit in this case is, on average, nearly 5% for the whole and pharma samples and 1% for the biotech sample.

The inclusion of the post 1985 period dummy resulted statistically significant for Models 2, 3 and 4 (spec. a, b and c) in the whole sample, in Models 2a, 1, 3 and 4 (all specs) in the pharma sample and in Model 1 (all specs) signaling the possibility of a structural break in the dynamics of volatility after 1985, i.e. that there is more firm specific volatility in the second period, a result confirmed in the work of Campbell et al. (2001). We plan to study this phenomenon more in our future work, trying to link it to changes in the search (innovation) regimes discussed in Gambardella (1995) and elsewhere.

Column 5 in Tables 3 and 4 shows that the sign for the control of firm size (market share) is as expected: firm size has a positive effect on the level of market value, but a negative effect on volatility and the price-earnings ratio. That small firms experience more volatility, in both growth and stock prices, is a well known phenomenon. The fact that small firms also have high price-earnings is easier to interpret for highly innovative firms who have low earnings but high potential growth. It is less easy to interpret for those small firms that are not particularly innovative, but we cannot look into this unless we put their innovativeness as the dependent variable (something we may explore in our future work). The use of the firm's capitalization share as the control for firm size instead results statistically insignificant in Models 3-4 for the whole sample, in Models 2-3 for the pharma sample and in Model 4 for the biotech sample. It is interesting to highlight that, with the exception of Model 3 for the biotech sample, the control for firm size is never significant when employing the FE estimator, signaling that this effect is relatively stable over time and captured by the firm specific dummies (its presence does not alter the qualitative and quantitative results of the estimates).

In what follows we review the results from Models 1-4, commenting only on the effect that the various innovation variables have on market share, idiosyncratic risk and price-earnings.

Model 1: Market value and innovation

Whole sample estimation results for Model 1 illustrate that R&D intensity, patent counts, and weighted patents have a positive and significant effect (each at the 1% level) on the level of market value. It is interesting that positive results arise even when using flow data, instead of the usual stock measures used in the market value and innovation literature (HJT 2005). Furthermore, the introduction of the simple patent count does not lead to a statistically insignificant R&D intensity coefficient, as it does when using stock measures.

When the patent count variable is entered in 1b, the R&D intensity coefficient is slightly reduced in size, signaling that there is a certain degree of correlation between R&D

intensity lagged 2 years and patent applications lagged 1 year. When we run the pharma and biotech samples separately, PAT and PATW remain significant at the 1% level, while the reduction in the size of the coefficient for R&D intensity is stronger. In particular, in Models 1b and 1c estimated over the biotech sample the R&D intensity coefficient turns out insignificant, signaling the presence of a higher correlation between PAT and R&D intensity in this part of the industry (not surprising given the higher mean patent yield in biotech). The preferred lag for R&D intensity is 3 in the pharma and 2 in the biotech sample, while the preferred lag for patents is 1 in the pharma sample and 2 in the biotech sample[29]. These results suggest that the market reacts quicker to news on patents than to news on R&D, most probably due to its understanding of the lengthy process of research in this industry (Pisano 2006).

When patents are weighted by citations *received* (1c) the estimated coefficients are smaller in size (due to the augmented average dimension induced by the weights) while their statistical significance is maintained, irrespective of the specific sample being considered. When employing patents weighted by citations *made*, rather than received, the R&D intensity coefficient resulted weaker in both size and statistical terms. In sum, the fit for Model 1 is consistent with the result of HJT [2005], even if it does not improve when patents are weighted by citations received (as it does in that study). The introduction of the patent yield variable proved insignificant.

Model 2: Idiosyncratic risk and innovation

In Model 2 we evaluate the hypothesis that idiosyncratic risk is related to firm level innovation, as proxied by R&D intensity, patents and weighted patents. Considering the whole sample estimates, we find that the innovation variables are significant, but less so here than in Model 1. R&D intensity is always significant at the 5% level, even when patent measures are included as well. Patent counts are significant at the 5% level, while weighted patents are significant at the 1% level. Thus unlike market value in Model 1, it appears that volatility reacts more strongly to citation weighted patents (i.e. more important patents) than simple patent counts.

As in Model 1 the lag on R&D is higher than that on patents (2 and 1 years respectively), in line with the results from Model 1. The lags we find seem reasonable as

[29] To better investigate this dynamic relationship, we have regressed patent applications on different lags of R&D intensity. The best fit is obtained when the explanatory variable is entered with 2 lags in the whole and in the pharma samples and contemporaneously in the biotech sample.

they suggest that R&D investment takes more time than patents to have an effect on volatility. As in Model 1, the patent yield is insignificant.

When we ran the pharma and biotech samples separately, we found that in the case of pharma the significance of R&D intensity rose (to the 1% level), while the significance of patents and weighted patents remained unchanged (respectively, at the 5% and 1% levels). The patent yield resulted insignificant again. The lag on R&D intensity for pharma is lower (1 lag) than that obtained in the combined sample (2 lags), suggesting that the market takes less time to react in this older segment of the industry (perhaps because it observes it less intensely through specialized market analysts who are more focused on new emerging sectors, like biotech and nanotechnology). The fact that we select the same lag structure for innovation input and output measures might signal that the market foresees the patent application given the spending on R&D that has already occurred (a hypothesis we are currently investigating further). In the case of the biotech sample, R&D intensity is insignificant irrespective of the specification being considered, while PAT and PATW remain significant, respectively at the 5 and 1% levels.

Model 3: Price-earnings ratios and idiosyncratic risk (rational bubble)

Pastor and Veronesi (2004) claim that if one includes the uncertainty about a firm's average future profitability into market valuation models, then bubbles can be understood as emerging from rational behavior about expected future profitability[30]. As discussed above, this model predicts a positive relationship between the level and volatility of stock returns, both increasing when new technologies first emerge, then falling when the uncertainty around the technologies decreases. With Models 3 and 4 we evaluate these hypotheses empirically: we first regress price-earnings on idiosyncratic risk (Model 3), and then price-earnings on the various innovation measures (Model 4).

In Model 3 we obtain a positive and statistically significant coefficient for idiosyncratic risk, at the 5% level in the whole sample as well as in the pharma sample. No relevant relationship is found when considering the biotech sample. The best estimates are obtained when IR is entered, respectively for the whole, pharma and biotech samples, with 1 lag, 2 lags and contemporaneously. The lack of evidence in favor of the Pastor and Veronesi (2004) hypothesis in the biotech sample is potentially related to the relevant reduction in

[30] Pastor and Veronesi (2004) use the Market to Book ratio (M/B), which replaces the P/D ratio employed in the theoretical derivations of Gordon's growth formula, on the grounds that dividends are not paid out by small start ups. We instead use P/E instead of P/D since both earnings and dividends, are proxies for the "fundamental" value underlying stock movements.

sample dimension due to missing values for P/E. By relaxing the minimum presence criterion from 8 years to 5 years, the relationship turns out significant, even if only at a 10% level. The relationship between the level of price-earnings and the volatility of firm specific returns, also finds support in the empirical literature on the high frequency relationship between prices (or returns) and market volatility[31].

Model 4 Price earnings and innovation

Finally, we regress P/E on the various innovation variables used above. Considering the whole sample estimates, R&D intensity is always significant at the 5% level, but unlike Model 1 and 2, the patent count variable is insignificant. Weighted patents are instead positive and significant at the 5% level. The lag structure is consistent with that obtained for Models 2 and 3 (see discussion on lag structure above).

As already discussed, the biotech dummy is positive and significant, indicating that on average biotech firms have a P/E ratio 30% higher than the sample mean. This is to be expected given that small innovative biotech firms often have low earnings, so that their stock valuation is determined largely by their investment in innovation (note the higher mean P/E for biotech firms in Table 1).

Considering the pharma section estimates, results are basically unchanged, with both R&D intensity and PATW coefficients (Model 4c) increasing significance from the 5% level to the 1% level. Differently, when the regressions are conducted employing the biotech sample, both PAT and PATW are insignificant, while R&D intensity is significant at the 1% level.

In sum, the positive relationship emerging between P/E and innovation provides support to the rational bubble model in Pastor and Veronesi (2004; 2005) where it is assumed, but not proved, that P/E should be higher for firms that introduce radical technologies.

6. Conclusion

Our study provides empirical support to the assumption found in recent finance literature that the volatility of stock prices (both aggregate and idiosyncratic) is related to innovation. We use firm level R&D and patent data (citation weighted) to test whether firms that are 'more innovative' are characterized by higher (than average) volatility of stock

[31] The rationale is that increasing portfolio risk is compensated by augmented expected returns. The finding of an often significant coefficient for volatility in returns regressions conducted with ARCH-in mean specifications in GARCH modeling for financial time series directly accounts for this relationship.

returns and levels of market value and P/E. We find that both the level and volatility of stock prices is in fact related to innovation. In particular, the positive correlation between innovation and idiosyncratic risk —provides us with important insights on how changes in the 'real' structure of production affect stock price volatility, beyond common explanations related to irrational' exuberance and 'animal spirits'.

The lag structure of the innovation variables provides insights into the speed at which the market reacts to innovation 'signals'. Lags are higher for R&D than for patents, suggesting that the market reacts more quickly to signals regarding innovation outputs than inputs. In fact, it is sensible to think that uncertainty is in fact highest at the time a patent is applied for, since this includes the uncertainty regarding whether the patent will be granted, as well as uncertainty regarding the effect of the patent (if granted) on firm growth. This is especially true in the pharma industry where there is a high patenting rate but a very low rate of new drug discovery (Orsenigo, Dosi and Mazzucato 2006). Pisano (2006), in fact, claims that one way that the pharma and biotech industries differs from other high tech industries, such as computers and software, is the profound and persistent uncertainty of the R&D process due to the limited knowledge of human biological systems (as opposed to chemical or electronic)[32].

We find that volatility is higher in the case of small firms (proxied by market share) and in the post 1985 period, characterized by a more guided search regime (due to scientific and organizational changes discussed in Gambardella 1995). The higher volatility in the latter period is most likely related to the fact that this period is characterized by an 'inflation' of patents (due to the effect of the 1980 Bayh-Dole act on patenting behavior), which reduces their reliability as a 'signal' of real innovation (hence more mistakes made by investors). Though the fact that weighted patents have a stronger effect on volatility (as well as P/E) than simple patent counts, suggests that the market is able to, at least partially, filter through this noise.

Support is found for the 'rational bubble' hypothesis in Pastor and Veronesi (2004), through the positive relationship between the P/E ratio and the innovation variables (as well as through the positive relationship found between P/E and idiosyncratic risk). Interestingly, it is only in Model 4 (with P/E as the dependent variable), that the patent yield variable proves significant, suggesting that of all the dependent variables tested, it is P/E that best captures the 'efficiency' of the innovative process (more output per innovation input). This supports the view that price-earnings are guided by expected future profitability of highly

[32] This is one of the reasons for its low R&D productivity, a delusion for those that hoped that biotech's more nimble structure would save pharma's low turnout of new drugs.

innovative firms. The fact that most biotech companies have no earnings (except the very big ones like Amgen and Genentech), means in fact that their value is determined almost exclusively by expectations regarding their ongoing innovation projects. Yet the fact that the R&D process is so lengthy and the projects so uncertain, means that valuation of firms is full of mistakes. The corrections that emerge from this trial and error process are no doubt partly responsible for the stock return volatility associated with the various innovation variables.

An interesting aspect of our results is that we reproduce the basic findings in the market value and innovation literature (HJT 2005) using flow rather than stock variables (for both R&D and patents), suggesting that more work should be done looking at the different effect of innovation flows and stocks on stock prices. We had conjectured that flows are more relevant when studying *volatility* dynamics, but they are also relevant in explaining changes in the level of market value. Another area that we wish to explore further is how stock price dynamics respond to particular characteristics of innovation, i.e. the degree to which patents are more 'general' or 'original' (as defined in Jaffe and Trajtenberg 2002, see fn 7), and the temporal dimension of patent citations (recent vs. old citations, which is also related to the issue of flows vs. stocks above).

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Figure 1

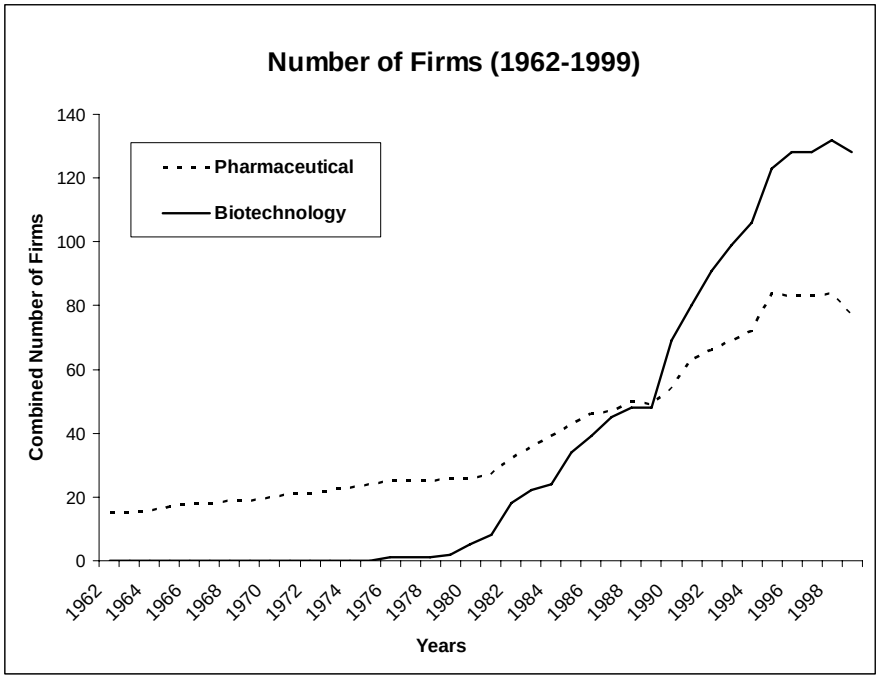
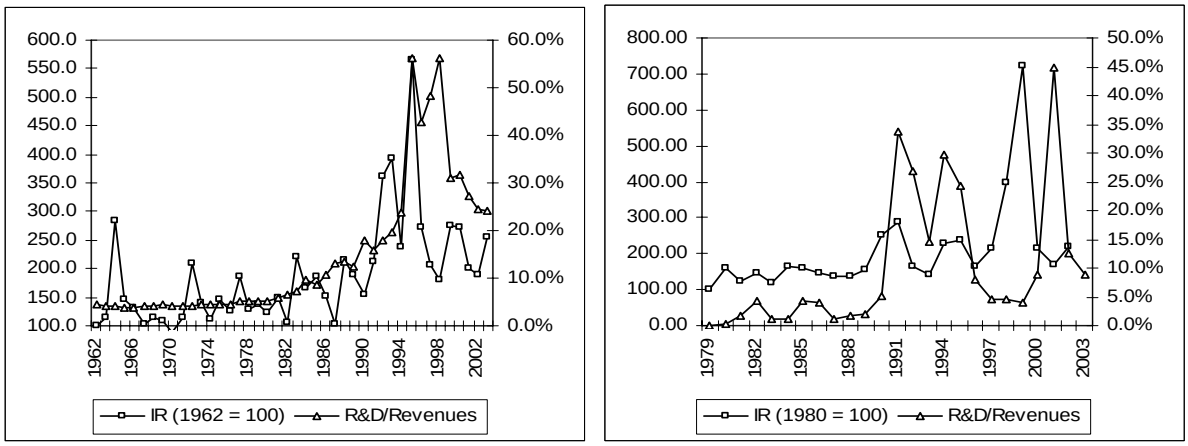
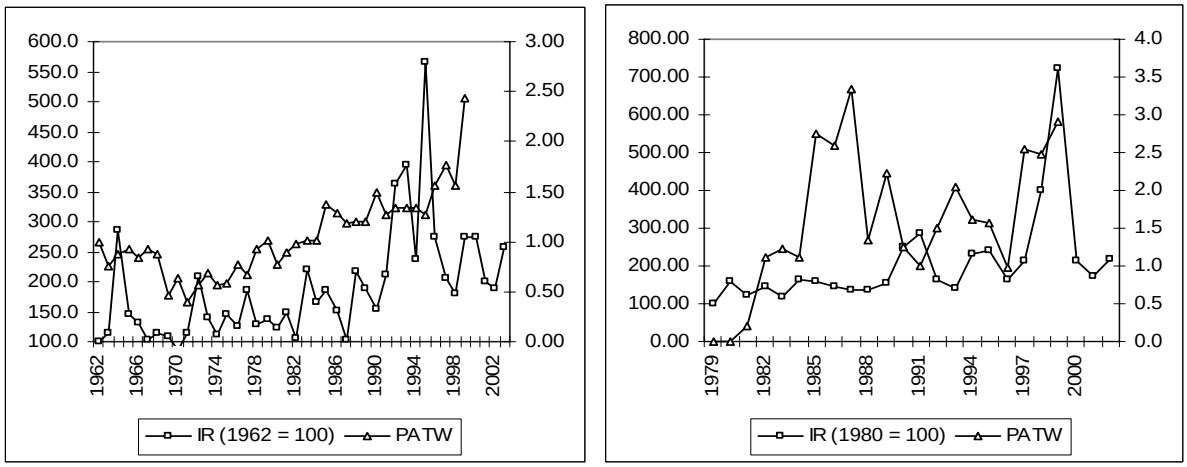

Number of Firms (1962-1999)
Pharmaceutical
Biotechnology
Combined Number of Firms
Years
0
20
40
60
80
100
120
140
1962
1964
1966
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998

Figure 2 Dynamic correlations

Pharma **Biotech**



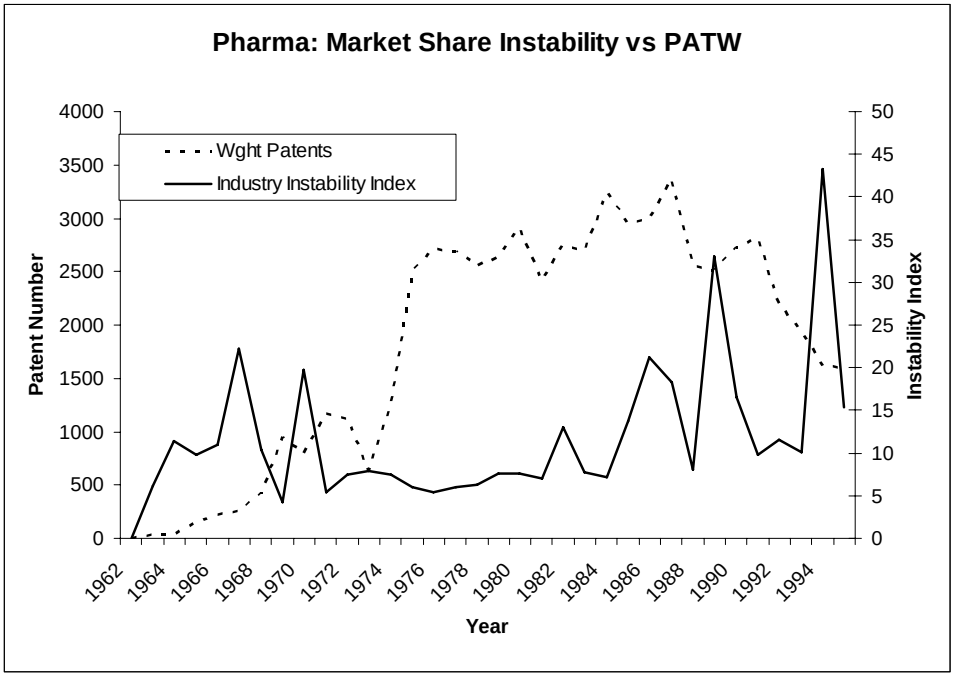
2a) Idiosyncratic risk (IR) and R&D intensity



2b) Idiosyncratic risk (IR) and weighted patents (corrected for truncation)

Figure 3 Innovation and market share instability

3a



3b

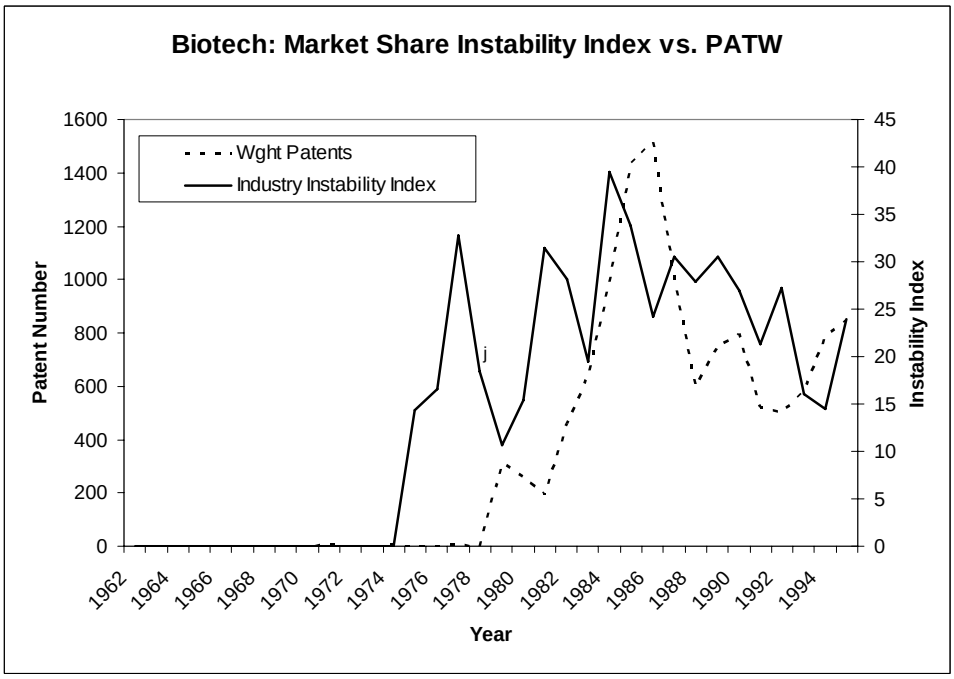


Table 1 Descriptive statistics

WHOLE	MKTVAL	PE	IR_SP500	IR_IND	RD/REV	PAT	PATW	PATYIELD
Mean	5917.147	86.381	0.088	0.085	0.094	8.309	1.457	0.124
Median	787.646	25.408	0.071	0.071	0.054	1.000	0.058	0.001
Maximum	171234.700	9926.505	0.779	2.222	8.413	155.000	69.818	12.870
Minimum	1.697	0.423	-0.029	-0.266	0.000	0.000	0.000	0.000
Std. Dev.	17573.270	427.242	0.072	0.112	0.327	17.527	4.201	0.566
Skewness	5.328	16.312	2.685	9.574	18.844	3.325	9.132	14.757
Kurtosis	35.938	324.173	17.848	167.215	434.910	16.536	121.885	288.691
PHARMA	**MKTVAL**	**PE**	**IR_SP500**	**IR_IND**	**RD/REV**	**PAT**	**PATW**	**PATYIELD**
Mean	7166.306	43.123	0.077	0.081	0.119	9.530	1.237	0.091
Median	998.557	22.768	0.063	0.068	0.078	1.000	0.105	0.003
Maximum	171234.700	4108.527	0.420	0.420	8.413	118.000	22.000	3.890
Minimum	1.697	4.357	-0.029	-0.083	0.000	0.000	0.000	0.000
Std. Dev.	19589.670	158.310	0.058	0.061	0.366	18.407	2.598	0.288
Skewness	4.724	21.204	1.503	1.135	17.009	2.772	3.846	6.548
Kurtosis	28.515	531.733	6.691	6.210	350.434	11.392	21.954	59.816
BIOTECH	**MKTVAL**	**PE**	**IR_SP500**	**IR_IND**	**RD/REV**	**PAT**	**PATW**	**PATYIELD**
Mean	1422.355	242.034	0.126	0.101	0.004	3.913	2.252	0.240
Median	234.938	56.036	0.105	0.082	0.002	0.000	0.000	0.000
Maximum	39131.630	9926.505	0.779	2.222	0.066	155.000	69.818	12.870
Minimum	3.731	0.423	-0.027	-0.266	0.000	0.000	0.000	0.000
Std. Dev.	3708.635	848.918	0.100	0.209	0.006	13.023	7.499	1.077
Skewness	6.007	8.576	2.778	6.393	5.693	8.181	6.559	9.124
Kurtosis	52.096	87.553	14.786	60.349	52.081	85.894	51.626	96.567

Table 2a Model selection tests (whole sample)

Equation	Step	Test	Hypotheses	Chi-sq (5)	P	Selected
1a	1	Breush-Pagan	H0: Pool; H1: RE	3795.39	0.000	RE
1a	2	Hausman	H0: RE; H1: FE	170.37	0.000	**FE**
1b	1	Breush-Pagan	H0: Pool; H1: RE	4041.80	0.000	RE
1b	2	Hausman	H0: RE; H1: FE	114.41	0.000	**FE**
1c	1	Breush-Pagan	H0: Pool; H1: RE	3964.02	0.000	RE
1c	2	Hausman	H0: RE; H1: FE	126.64	0.000	**FE**
2a	1	Breush-Pagan	H0: Pool; H1: RE	4.87	0.027	RE
2a	2	Hausman	H0: RE; H1: FE	2.36	0.501	**RE**
2b	1	Breush-Pagan	H0: Pool; H1: RE	5.75	0.016	RE
2b	2	Hausman	H0: RE; H1: FE	4.20	0.379	**RE**
2c	1	Breush-Pagan	H0: Pool; H1: RE	6.23	0.012	RE
2c	2	Hausman	H0: RE; H1: FE	4.78	0.310	**RE**
3	1	Breush-Pagan	H0: Pool; H1: RE	231.69	0.000	RE
3	2	Hausman	H0: RE; H1: FE	8.21	0.042	**FE**
4a	1	Breush-Pagan	H0: Pool; H1: RE	236.95	0.000	RE
4a	2	Hausman	H0: RE; H1: FE	3.25	0.354	**RE**
4b	1	Breush-Pagan	H0: Pool; H1: RE	237.10	0.000	RE
4b	2	Hausman	H0: RE; H1: FE	3.57	0.467	**RE**
4c	1	Breush-Pagan	H0: Pool; H1: RE	239.06	0.000	RE
4c	2	Hausman	H0: RE; H1: FE	3.85	0.427	**RE**

Table 2b Model selection tests (pharma sample)

Equation	Step	Test	Hypotheses	Chi-sq (5)	P	Selected
1a	1	Breush-Pagan	H0: Pool; H1: RE	2057.92	0.000	RE
1a	2	Hausman	H0: RE; H1: FE	85.86	0.000	**FE**
1b	1	Breush-Pagan	H0: Pool; H1: RE	2503.12	0.000	RE
1b	2	Hausman	H0: RE; H1: FE	85.61	0.000	**FE**
1c	1	Breush-Pagan	H0: Pool; H1: RE	2346.28	0.000	RE
1c	2	Hausman	H0: RE; H1: FE	221.51	0.000	**FE**
2a	1	Breush-Pagan	H0: Pool; H1: RE	195.20	0.000	RE
2a	2	Hausman	H0: RE; H1: FE	27.59	0.000	**FE**
2b	1	Breush-Pagan	H0: Pool; H1: RE	195.50	0.000	RE
2b	2	Hausman	H0: RE; H1: FE	32.87	0.000	**FE**
2c	1	Breush-Pagan	H0: Pool; H1: RE	193.93	0.000	RE
2c	2	Hausman	H0: RE; H1: FE	33.43	0.000	**FE**
3	1	Breush-Pagan	H0: Pool; H1: RE	124.99	0.000	RE
3	2	Hausman	H0: RE; H1: FE	9.49	0.023	**FE**
4a	1	Breush-Pagan	H0: Pool; H1: RE	150.38	0.000	RE
4a	2	Hausman	H0: RE; H1: FE	3.3	0.347	**RE**
4b	1	Breush-Pagan	H0: Pool; H1: RE	150.60	0.000	RE
4b	2	Hausman	H0: RE; H1: FE	4.71	0.318	**RE**
4c	1	Breush-Pagan	H0: Pool; H1: RE	149.78	0.000	RE
4c	2	Hausman	H0: RE; H1: FE	5.66	0.226	**RE**

Table 2c Model selection tests (biotech sample)

Equation	Step	Test	Hypotheses	Chi-sq (5)	P	Selected
1a	1	Breush-Pagan	H0: Pool; H1: RE	1226.74	0.000	RE
1a	2	Hausman	H0: RE; H1: FE	10.92	0.012	**FE**
1b	1	Breush-Pagan	H0: Pool; H1: RE	1091.50	0.000	RE
1b	2	Hausman	H0: RE; H1: FE	9.72	0.045	**FE**
1c	1	Breush-Pagan	H0: Pool; H1: RE	1104.62	0.000	RE
1c	2	Hausman	H0: RE; H1: FE	9.64	0.048	**FE**
2a	1	Breush-Pagan	H0: Pool; H1: RE	0.44	0.505	**POOL**
2b	1	Breush-Pagan	H0: Pool; H1: RE	0.63	0.427	**POOL**
2c	1	Breush-Pagan	H0: Pool; H1: RE	0.59	0.442	**POOL**
3	1	Breush-Pagan	H0: Pool; H1: RE	59.66	0.000	RE
3	2	Hausman	H0: RE; H1: FE	104.82	0.000	**FE**
4a	1	Breush-Pagan	H0: Pool; H1: RE	65.10	0.000	RE
4a	2	Hausman	H0: RE; H1: FE	15.60	0.001	**FE**
4b	1	Breush-Pagan	H0: Pool; H1: RE	70.07	0.000	RE
4b	2	Hausman	H0: RE; H1: FE	15.38	0.004	**FE**
4c	1	Breush-Pagan	H0: Pool; H1: RE	69.00	0.000	RE
4c	2	Hausman	H0: RE; H1: FE	14.53	0.005	**FE**

Table 3 Estimation results (whole sample)

Model (Spec)	Const / [s.e.]	Contr / [s.e.]	Dummy BIO*	Dummy 85	Regr.1 (lag)	Est / [s.e]	Regr.2 (lag)	Est / [s.e]
1 - Dep variable: log MKTVAL; Number of obs = 1591, sectional dimension = 134								
1a (FE)	3.697***	15.794***		1.494***	log RDREV(2)	0.161***	-	-
	[0.070]	[1.305]	[-]	[0.073]		[0.055]		[-]
	R-sq: within = 0.330; between = 0.111; overall = 0.192							
	F(3, 1454) = 238.70, Prob > F = 0.000							
1b (FE)	3.635***	15.498***		1.578***	log RDREV(2)	0.153***	log PAT(1)	0.383***
	[0.071]	[1.294]	[-]	[0.072]		[0.054]		[0.071]
	R-sq: within = 0.343; between = 0.203; overall = 0.271							
	F(4, 1453) = 189.87, Prob > F = 0.000							
1c (FE)	3.651***	15.723***		1.615***	log RDREV(2)	0.151***	log PATW(1)	0.283***
	[0.071]	[1.297]	[-]	[0.072]		[0.055]		[0.065]
	R-sq: within = 0.338; between = 0.182; overall = 0.254							
	F(4, 1453) = 185.88, Prob > F = 0.000							
2 - Dep variable: log IDRISK; Number of obs = 1459, sectional dimension = 134								
2a (RE)	0.114***	-0.475***	0.035**	0.013	log RDREV(2)	0.019**	-	-
	[0.017]	[0.189]	[0.018]	[0.014]		[0.009]		[-]
	R-sq: within = 0.002; between = 0.094; overall = 0.046							
	Wald chi2 (4) = 16.95, Prob > chi2 = 0.000							
2b (RE)	0.112***	-0.637***	0.035**	0.008	log RDREV(2)	0.020**	log PAT(1)	0.027**
	[0.017]	[0.202]	[0.018]	[0.014]		[0.009]		[0.012]
	R-sq: within = 0.004; between = 0.120; overall = 0.046							
	Wald chi2 (5) = 22.27, Prob > chi2 = 0.000							
2c (RE)	0.112***	-0.643***	0.036**	0.008	log RDREV(2)	0.020**	log PATW(1)	0.030***
	[0.014]	[0.197]	[0.018]	[0.014]		[0.009]		[0.012]
	R-sq: within = 0.005; between = 0.138; overall = 0.046							
	Wald chi2 (5) = 24.54, Prob > chi2 = 0.000							
3 - Dep variable: log PE; Number of obs = 764, sectional dimension = 77								
3 (FE)	3.035***	-0.783		0.351***	log IR(1)	1.075**	-	-
	[0.085]	[1.415]	[-]	[0.063]		[0.521]		[-]
	R-sq: within = 0.051; between = 0.091; overall = 0.111							
	F(3, 684) = 12.26, Prob > F = 0.000							
4 - Dep variable: log PE; Number of obs = 775, sectional dimension = 79								
4a (RE)	2.966***	-1.117	0.803***	0.348***	log RDREV(3)	0.552**	-	-
	[0.152]	[1.071]	[0.227]	[0.064]		[0.261]		[-]
	R-sq: within = 0.041; between = 0.208; overall = 0.255							
	Wald chi2 (4) = 51.36, Prob > chi2 = 0.000							
4b (RE)	2.953***	-0.985	0.796***	0.321***	log RDREV(3)	0.558**	log PAT(2)	0.100
	[0.152]	[1.075]	[0.227]	[0.067]		[0.261]		[0.076]
	R-sq: within = 0.043; between = 0213; overall = 0.245							
	Wald chi2 (4) = 53.12, Prob > chi2 = 0.000							
4c (RE)	2.953***	-0.929	0.795***	0.310***	log RDREV(3)	0.534**	log PATW(2)	0.146**
	[0.152]	[1.074]	[0.228]	[0.066]		[0.261]		[0.070]
	R-sq: within = 0.048; between = 0.207; overall = 0.243							
	Wald chi2 (4) = 55.68, Prob > chi2 = 0.000							

Table 4 Estimation results (pharma sample)

Model (Spec)	Const / [s.e.]	Contr / [s.e.]	Dummy 85	Regr.1 (lag)	Est / [s.e]	Regr.2 (lag)	Est / [s.e]
1 - Dep variable: log MKTVAL; Number of obs = 825, sectional dimension = 63							
1a (FE)	4.381***	19.940***	1.781***	log RDREV(3)	0.186***	-	-
	[0.091]	[2.334]	[0.078]		[0.060]		[-]
	R-sq: within = 0.454; between = 0.131; overall = 0.318						
	F(3, 759) = 210.39, Prob > F = 0.000						
1b (FE)	4.170***	19.258***	1.522***	log RDREV(3)	0.157***	log PAT(1)	1.015***
	[0.091]	[2.229]	[0.080]		[0.057]		[0.117]
	R-sq: within = 0.503; between = 0.360; overall = 0.477						
	F(4, 758) = 192.11, Prob > F = 0.000						
1c (FE)	4.257***	19.050***	1.633***	log RDREV(3)	0.158***	log PATW(1)	0.631***
	[0.092]	[2.285]	[0.080]		[0.059]		[0.103]
	R-sq: within = 0.480; between = 0.273; overall = 0.418						
	F(4, 758) = 174.79, Prob > F = 0.000						
2 - Dep variable: log IDRISK; Number of obs = 845, sectional dimension = 63							
2a (FE)	0.091***	-0.169	0.012**	log RDREV(1)	0.019***	-	-
	[0.006]	[0.151]	[0.005]		[0.004]		[-]
	R-sq: within = 0.045; between = 0.264; overall = 0.097						
	F(3, 779) = 12.27, Prob > F = 0.000						
2b (FE)	0.088***	-0.137	0.008	log RDREV(1)	0.019***	log PAT(1)	0.017**
	[0.006]	[0.151]	[0.005]		[0.004]		[0.007]
	R-sq: within = 0.051; between = 0.074; overall = 0.015						
	F(4, 778) = 10.57, Prob > F = 0.000						
2c (FE)	0.088***	-0.133	0.009	log RDREV(1)	0.019***	log PATW(1)	0.016***
	[0.006]	[0.152]	[0.005]		[0.004]		[0.005]
	R-sq: within = 0.052; between = 0.095; overall = 0.023						
	F(4, 778) = 10.65, Prob > F = 0.000						
3 - Dep variable: log PE; Number of obs = 573, sectional dimension = 47							
3 (FE)	2.889***	-3.404	0.398***	log IR(2)	1.278**	-	-
	[0.114]	[2.337]	[0.058]		[0.637]		[-]
	R-sq: within = 0.102; between = 0.204; overall = 0.186						
	F(3, 1454) = 238.70, Prob > F = 0.000						
4 - Dep variable: log PE; Number of obs = 593, sectional dimension = 48							
4a (RE)	3.051***	-4.193**	0.404***	log RDREV(3)	0.453**	-	-
	[0.122]	[1.766]	[0.056]		[0.217]		[-]
	R-sq: within = 0.087; between = 0.290; overall = 0.223						
	Wald chi2 (3) = 70.07, Prob > chi2 = 0.000						
4b (RE)	3.042***	-4.593***	0.374***	log RDREV(3)	0.454**	log PAT(2)	0.112
	[0.123]	[1.792]	[0.060]		[0.218]		[0.081]
	R-sq: within = 0.092; between = 0.286; overall = 0.219						
	Wald chi2 (4) = 71.71, Prob > chi2 = 0.000						
4c (RE)	3.042***	-4.856***	0.357***	log RDREV(3)	0.427***	log PATW(2)	0.186***
	[0.123]	[1.788]	[0.059]		[0.217]		[0.071]
	R-sq: within = 0.100; between = 0.286; overall = 0.220						
	Wald chi2 (4) = 76.64, Prob > chi2 = 0.000						

Table 5 Estimation results (biotech sample)

Model (Spec)	Const / [s.e.]	Contr / [s.e.]	Dummy 85	Regr.1 (lag)	Est / [s.e]	Regr.2 (lag)	Est / [s.e]
1 - Dep variable: log MKTVAL; Number of obs = 728, sectional dimension = 71							
1a (FE)	3.490***	13.048***	0.988***	log RDREV(2)	0.277*	-	-
	[0.187]	[1.545]	[0.184]		[0.171]		[-]
	R-sq: within = 0.123; between = 0.371; overall = 0.347						
	F(3, 654) = 30.65, Prob > F = 0.000						
1b (FE)	4.479***	13.231***	0.887***	log RDREV(2)	0.263	log PAT(2)	0.277***
	[0.186]	[1.537]	[0.186]		[0.176]		[0.092]
	R-sq: within = 0.135; between = 0.411; overall = 0.387						
	F(4, 653) = 25.54, Prob > F = 0.000						
1c (FE)	3.501***	13.570***	0.870***	log RDREV(2)	0.258	log PATW(2)	0.278***
	[0.0186]	[1.542]	[0.187]		[0.176]		[0.086]
	R-sq: within = 0.137; between = 0.411; overall = 0.388						
	F(4, 653) = 25.93, Prob > F = 0.000						
2 - Dep variable: log IDRISK; Number of obs = 636, sectional dimension = 71							
2a (POOL)	0.168***	-0.454*	-0.012	log RDREV(2)	0.015	-	-
	[0.056]	[0.262]	[0.055]		[0.051]		[-]
	Adj R-sq = 0.005						
	F(3, 632) = 1.08, Prob > F = 0.358						
2b (POOL)	0.162***	-0.723**	-0.017	log RDREV(2)	0.020	log PAT(1)	0.045**
	[0.055]	[0.290]	[0.055]		[0.051]		[0.021]
	Adj R-sq = 0.012						
	F(43, 632) = 1.94, Prob > F = 0.102						
2c (POOL)	0.165***	-0.749***	-0.022	log RDREV(2)	0.020	log PATW(1)	0.054***
	[0.055]	[0.284]	[0.055]		[0.050]		[0.020]
	Adj R-sq = 0.016						
	F(4, 631) = 2.56, Prob > F = 0.037						
3 - Dep variable: log PE; Number of obs = 161, sectional dimension = 30							
3 (FE)	4.678***	-6.958***	0.353	log IR(0)	1.307	-	-
	[0.375]	[2.850]	[0.331]		[1.241]		[-]
	R-sq: within = 0.077; between = 0.082; overall = 0.040						
	F(3, 128) = 3.55, Prob > F = 0.016						
4 - Dep variable: log PE; Number of obs = 182, sectional dimension = 31							
4a (FE)	4.261***	-1.602	-0.358	log RDREV(3)	0.495***	-	-
	[0.373]	[2.002]	[0.339]		[0.113]		[-]
	R-sq: within = 0.135; between = 0.001; overall = 0.017						
	F(3, 148) = 7.71, Prob > F = 0.000						
4b (FE)	4.268***	-1.625	-0.352	log RDREV(3)	0.496***	log PAT(2)	-0.018
	[0.379]	[2.021]	[0.345]		[0.113]		[0.173]
	R-sq: within = 0.135; between = 0.001; overall = 0.015						
	F(4, 147) = 5.75, Prob > F = 0.000						
4c (FE)	4.259***	-1.585	-0.363	log RDREV(3)	0.495***	log PATW(2)	0.012
	[0.375]	[2.022]	[0.349]		[0.113]		[0.164]
	R-sq: within = 0.135; between = 0.001; overall = 0.017						
	F(4, 147) = 5.75, Prob > F = 0.000						