R&D, Patents and Stock Return Volatility

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Abstract
Recent finance literature highlights the role of technological change in increasing firm specific (idiosyncratic) and aggregate stock return volatility, yet innovation data is not used in these analyses, leaving the direct relationship between innovation and stock return volatility untested. The paper investigates the relationship between volatility and innovation using firm level patent data. The analysis builds on the empirical work by Mazzucato (2002; 2003) where it is found that stock return volatility is highest during periods in the industry life-cycle when innovation is the most ‘radical’. In this paper 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 in their returns. Given that returns should in theory be higher, on average, for higher risk stocks, we also look at the effect of innovation on the level of returns. To take into account the competition between firms within industries, firm returns and volatility are measured relative to the industry average. We focus the analysis on firms in the pharmaceutical industry between 1974 and 1999. Results suggest that there is a positive and significant relationship between volatility, R&D intensity and the various patent related measures—especially when the innovation measures are filtered to distinguish the very innovative firms from the less innovate ones.

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

JEL Classification: G12 (Asset Pricing); 030 (Technological Change).

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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 return volatility. While recent attention has been affected by the bursting of the most recent financial bubble (Frydman and Goldberg, 2011), the attention dates back to different works which have assumed that the New Economy, or the ‘information age’, has affected the stability of the market valuation process, and in so doing increased volatility (Campbell et al. 2001). Shiller’s work (2000) has shown that ‘excess volatility’, i.e. the degree to which stock returns 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. the degree to which firm specific returns are more volatile than average market returns, 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. Mazzucato (2002) and Mazzucato and Semmler (1999) show that, at the sectoral level, the early stage of automobiles was just as volatile as the early stage of the internet and personal computers (underpinning the dot.com era), suggesting that it is not the New Economy but the turbulence that characterizes the early life-cycle of key new industries that causes the volatility to emerge.

The basic idea behind all these works is that innovation, especially when ‘radical’, leads to high uncertainty hence more volatility. This idea provides interesting insights into the debate about whether markets are ‘efficient’. Behavioral economists have recently highlighted the role of animal spirits and herd effects in investment behavior, quite different from the assumptions of perfect foresight and rationality that has been assumed for years in finance theory. What these studies contribute to this debate is that during periods of instability caused by technological change, these behavioral aspects are even stronger causing the departure of stock returns from underlying fundamentals to be greater. Pastor and Veronesi (2004) claim that the reason that high tech firms have returns 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. Yet while hypothesizing a link between return volatility and innovation, none of these studies actually use firm specific innovation data to directly test the relationship. Innovation is alluded to (e.g. the ‘IT revolution’, the New Economy, radical change) but not measured at the firm level.

The aim of our paper is to test for the link between innovation and stock return volatility. Our expectation is that volatility should be affected by such uncertain investments since volatility is commonly perceived as a proxy for uncertainty (Pastor and Veronesi, 2004). And as innovation is a perfect example of true Knightian uncertainty (Knight, 1921), then we expect there to be a
relationship between innovation and volatility. Thus the key hypothesis we test is whether those firms that invest in technological change experience more stock return volatility. Innovation is proxied through R&D spending and patents (weighted by citations in order to distinguish radical innovations from more incremental ones).

Our study focuses on the pharmaceutical industry due to the fact that it has one of the highest sectoral rates of R&D spending and patenting. Focussing on one sector allows us to look at the evolution of the relationship between stock returns and innovation over time, both over the industry’s life-cycle (Mazzucato 2002) and over the course of time as the intensity of innovation investments change. For example, the effect of the 1980 Bayh-Dole act (which allowed publicly funding research in the US to be patented). This would not be possible to do in a study which aggregates different industries, disregarding dynamics which may affect the relationship between innovation and stock returns.

Since we focus on one sector, we focus on how innovation spending by a firm affects the degree to which its stock return is more volatile than the industry average. Comparing the firm to the industry average rather than to the market average (as is more common in studies of idiosyncratic risk) captures the competitive dynamics of the industry since pharma firms are not competing with computer firms but with other pharma firms. We also look at the effect of innovation on the level of firm returns (relative to industry returns). In both cases we test the relationship before and after the mid 1980s.

Our results provide evidence that there is indeed a positive and significant relationship between stock return volatility and innovation. We find that volatility is positively and significantly related to R&D intensity, and to the patent related measures of innovation used in the analysis. We also find that the level of firm returns (compared to the industry average) are positively related with volatility, as is predicted by the ‘rational bubble’ hypothesis (Pastor and Veronesi)—though we provide a very different explanation. We pay particular attention to the lag structure of the independent variables as this provides information on the speed with which the market reacts to news regarding innovation.

The rest of the paper is organized as follows. Section 2 reviews the literature on innovation and stock returns; 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. Risk and Stock Returns over the Industry Life Cycle

Technological innovation is a very risky process: it is extremely expensive ($403 million per drug in pharma), takes a very long time (up to 17 years from the beginning of the research to the commercialization phase), and has a very high failure rate (in pharma only 1 in 10,000 compounds reach market approval phase, i.e. .01% succeed). For these reasons, innovation is often given as an example of true Knightian uncertainty, which unlike ‘risk’ cannot be easily calculated via probability distributions. Figure 1 exemplifies the dangerous consequences of this uncertainty: an exponential rise in the rate of R&D spending has not been accompanied by an increase in new molecular entities.

How are stock returns affected by this uncertainty? As stock prices are driven by future growth expectations, and since innovation is a key driver of firm growth, it can be expected that stock returns and innovation are related. The expectations about a firm’s growth will be positive when the firm in question is a very innovative one, but due to the high uncertainty and failure rate, the expectations will often prove wrong. The correcting behavior will result in volatility. Hence the way that creative destruction affects expectation formation about firm growth will result in volatility. This provides an explanation for Shiller’s (2001) finding that the difference between the volatility of shares and the volatility of the underlying fundamentals is highest during each of the major technological revolutions of the last two centuries. A similar point is made in Perez (2002) where bubble dynamics are related to major technological revolutions.

However, not all innovations are radical. Some are incremental and more process oriented. Hence in thinking about the relationship between stock return volatility and innovation, Mazzucato (2002; 2003) studies whether excess volatility of stock returns and idiosyncratic risk are highest in periods of the industry life-cycle in which innovation is the most ‘radical’ (for a review of the life-cycle perspective see Klepper (1996). Using industry level innovation data (a quality change index that compares Bureau of Economic Prices to hedonic quality adjusted prices), these studies find that in fact it is precisely in the periods of the industry life-cycle which are characterized by the most quality change, that the stock returns are the most volatile. In some industries like autos, this has occurred in the ‘early’ phase of the industry life cycle when innovation was more radical and market shares more unstable. In others, like the personal computer industry, it occurred later on in the industry life-cycle when the departure from a leading incumbent (IBM) allowed both innovation and competition to open up (Bresnahan and Greenstein, 1997). In each case, it appears that it is the phase in the

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1 “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)
industry life-cycle when innovation is the most radical and competition the most intense that stock returns are the most volatile (Mazzucato 2002). Mazzucato and Tancioni (2008) find that in a comparison of 5 different sectors (computers, pharma, biotech, autos and textiles), it is the firms spending the most on R&D that experience the most volatility in their shares. This is especially important in an industry like pharma where there is very high R&D spending but not so many concrete rewards from it as suggested in Figure 1, hence financial markets need to find a way to distinguish the potentially high performers from the low performers.

In this study we introduce firm level patent data and ask whether the firms that spend the most on R&D, have the most patents, and the patents with the most citations, experience the most volatility. The productivity literature on market value and innovation has 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). So 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. We also look at the effect on the level of returns since in theory if returns are on average higher for higher risk shares, then we should see a relationship between returns and innovation as well, since the latter is a good proxy for risk (uncertainty).

As in our previous work, we analyze 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 sector due to the fact that the high R&D and patenting intensity of this industry 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 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 search” characterized by more scale economies and path-dependency2. 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. However, Mowery and Ziedonis (2001) show that the overall effect on patenting activity was small.

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2 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).
Our analysis is carried out in two stages. We first test for a statistical relationship between the volatility of returns and innovation in order to explore the hypothesis that the high uncertainty that underlies innovation is a key source of firm specific volatility (as suggested but not tested in Campbell et al. (2001), and Shiller (2000)). We then test the relationship between innovation and the level of returns. Finally we test directly for the relationship between relative returns and volatility.

3. Data

3.1 Patent data

We study the pharma industry from 1974 to 1999. Our sample of firms is constructed by merging financial data from Compustat with USPTO patent data (extracted from the NBER patent citation database included in the book/CD by Jaffe and Trajtenberg 2002). From now on we will refer to these databases as Compustat and NBER respectively.

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) is available. 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).

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 volatility of returns (relative volatility) and the following innovation variables: R&D intensity (R&D divided by sales), patent counts, and patents weighted by their citations. We also look at the impact of these variables on the level of returns and earnings. The relationship between the level of returns and their volatility is at the basis of financial economics (Campbell et al. 2001). By looking at this relationship at the sectoral level, and relating it to innovation, we are in essence providing an industrial dynamics explanation of this famous relationship.
As many patents in the pharma industry do not result in new drugs (Harris, 2002; Pisano 2006), 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.

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 granted, the patent will lead to a commercialized product etc. And as the approximate lag between the application date and the granted 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.

3.2 Financial data

We use the firm CUSIP code to match firms in the two data bases (Compustat and NBER patent data). Only firms pertaining to the GIC code (which in 2000 replaced the SIC codes) 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, the merged sample contains 126 pharma firms. In order to avoid dealing with highly volatile stock return data, we have omitted firms present in the sample for less than seven years. Since we

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3 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.

4 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.
consider a two-year maximum lag in our estimates, this guarantees that data is available for at least five years. We thus end up studying the dynamics of 63 firms in the pharma industry from 1974-1999. We have verified robustness of results with respect to changes in the selection criterion.

Following Schwert (1989), *monthly* data is used to calculate the volatility of annual returns: the standard deviation is calculated over 12 month observations on returns. We use monthly 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 returns. Furthermore, Campbell et al (2001) analyze volatility using both daily and monthly data and do not find qualitative differences (in trends).

To measure relative volatility 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 which captures the degree to which firm specific returns are more volatile than the average industry returns: the log ratio between the standard deviation of a firm’s return and the standard deviation of the average industry return. We think this is the relevant measure of volatility to look at since firms compete with other firms in their own industry, and hence their growth potential is valued in comparison with their immediate competitors. In fact, in our previous study (Mazzucato and Tancioni 2008) we found that the reaction of returns to R&D is very high for innovative firms in non innovative industries precisely because they ‘stand out’ compared to their competitors. Furthermore, since the pharma industry is a very innovative industry in which R&D spending is very high, financial markets must find a way to distinguish the potential high flyers from the potential losers, even though they are both spending a lot on R&D. For this reason, the relevant measure of volatility is that which compares the firm to its competitors, not to the general market.

To summarize, the financial variables are monthly; R&D is quarterly; and patents are annual. And the volatility of returns and their levels are measured relative to the industry average, as log deviations from industry level volatility and returns.

### 3.3 Stocks vs. flows

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 uses stocks (applying a Permanent Inventory approach with a 15% depreciation assumption). We use flow variables

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5 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.

6 The return of a firm’s stock is defined as: \( \frac{(P_t - P_{t-1}) + D_t}{P_{t-1}} \).

7 The patent application date is listed by year, while patent grant date is listed by month.
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 returns (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 volatility (which is stationary in mean over time), the use of
cumulated and thus trended explanatory variables such as stocks would lead to potentially biased
estimates, because of the unbalanced statistical properties of the data. 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)8.

Nevertheless to make sure the results are robust we also check the results using an R&D
stock measure, obtained by applying a permanent inventory scheme with a standard 15% annual
depreciation assumption.

3.4 Truncation and other data issues

Patent 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 counts9. 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

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8 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).

9 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.
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. 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. 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.

We follow a slightly modified version of the fixed effects approach. We divide the firm-level patent citations received 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, while the innovative activity at the firm-level remains relatively stable, the standard fixed effects correction would bias downward the measure of innovation at the firm-level. 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.

4. Descriptive statistics and econometric results

4.1. Descriptive statistics

Table 1 contains descriptive statistics on the different variables used in the analyses. The table contains first the information for the three financial variables, relative volatility (VOL), relative returns (RET) and then for the two innovation variables, R&D intensity (RD/REV) and weighted patents (PATW). Considering a standardized measure of variability (CV), relative returns exhibit a

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10 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).

11 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).

12 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.

13 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.
large amount of variation, while relative volatility of returns (VOL) appears less variable. Large sample variability is also found for the two measures of innovation (RD/REV and PATW).

Contemporaneous correlations among variables don’t show much significance. This evidence is supported by the regression results (below) which show that the relationships hold mostly dynamically (over time). However, by considering the scatter-plots between variable means, evaluated over section and over time, we obtain a first appreciation of the temporal and sectional correlation among variables. From Figure 3, which refers to the average values evaluated over the section (i.e. firm averages in each year), VOL appears positively correlated with both RD/REV and PATW, while RET shows a negative or moderate correlation with these innovation measures. Considering the average values evaluated over time (i.e. period averages for each firm), Figure 2 shows that VOL is positively correlated with RD/REV only, and a weak negative correlation with PATW is found. Considering RET, the correlation pattern is positive with PATW, and remains negative with RD/REV. These figures provide a first, albeit simplistic, indication of the co-evolution of volatility and innovation—investigated more rigorously below.

It is interesting to see that in Figure 2 the rise in citation weighted patents is accompanied by a rise in market share instability. This is precisely what would be expected by the literature on ‘competence-destroying’ innovations (Tushman and Anderson 1986): the period in which innovation is the most radical is the period in which there is most competition between firms causing a change in their ranking (with more stable periods in market shares being related instead to periods of less technological change). It gives us a preliminary reason to expect that citation weighted patents also affects the volatility of stock returns as these are being driven by the expected growth of firms which in such a period undergo much change for the reasons discussed above.

4.2 Econometric implementation

We first regress relative volatility VOL on the innovation variables R&D/REV and PATW to test whether the volatility of firm returns is affected by investments in innovation (Model 1). Second, we test the impact of innovation on the level of returns (Model 2). Lastly we look at the direct relationship between volatility and returns (Model 3). In all cases we control for the size of the firm as proxied by relative capitalization (SIZEC). Specifically, the relationships we estimate are:

\[ I = \sum_{i=1}^{n} \left| s_i - s_{i-1} \right| \]

where \( s \) is market share of firm \( i \), and \( n \) is number of firms.

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14 The market share instability index is defined in Hymer and Pashigian (1962):
Model 1: Relative volatility and innovation

\[ vol_{i,t} = \alpha + \sum_{h=0}^{p} \beta_{1,h} rdrev_{i,t-h} + \sum_{k=0}^{q} \beta_{2,k} patw_{i,t-k} + \beta_{3} sizec_{i,t} + u_{i} + \epsilon_{i,t} \]

Model 2: Returns and innovation

\[ ret_{i,t} = \alpha + \sum_{h=0}^{p} \beta_{1,h} rdrev_{i,t-h} + \sum_{k=0}^{q} \beta_{2,k} patw_{i,t-k} + \beta_{3} sizec_{i,t} + u_{i} + \epsilon_{i,t} \]

Model 3: Returns and volatility

\[ ret_{i,t} = \alpha + \sum_{j=0}^{r} \beta_{1,j} vol_{i,t-j} + \beta_{2} sizec_{i,t} + u_{i} + \epsilon_{i,t} \]

where lower case letters denote logs.

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, firm level factors systematically enter the relationships, while in the RE model these factors are distributed randomly, i.e. they are an error component which is constant over time.

Individual effects models all presume that there are omitted variables that have section-specific effects such as tacit knowledge and related managerial capabilities. Hall et al. (2005) adopt a pooled model with period and industry dummies. Aside from the fact that their results (on the relation between market value and innovation) become insignificant when individual effects are considered (as also in the related literature), they do not include section-specific controls for two reasons. First, since R&D stocks change slowly over time (by construction), the inclusion of sectional controls would capture those systematic components that are deemed related to firm specific R&D strategies, i.e. to the independent variable. Second, since firms change their strategies over time in response to market signals, an individual effects model in the form of FE 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 individual effects are not likely to be 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.

For these reasons, unlike Hall et al. (2005), we consider section-specific effects in the form of random effects (RE). Even if there isn’t an objective reason to believe that the section specific effects and the explanatory variables are uncorrelated, this choice should reduce the bias implied by the presence of latent variables, as long as they are uncorrelated with the observed regressors.

A further question is endogeneity. We recognize that a firm’s innovative effort is an endogenous strategy that is implemented on the basis of actual and expected outcomes of innovation activity, potentially captured by the financial variables employed in the analysis. Since there are no valid instruments in our sample data to accommodate the potential endogenous nature of R&D investments and patenting activity, we instrument the innovation variables using their lagged values. This basically implies that we are using pre-determined values not only when considering dynamic relations (i.e. lagged regressors), but also when estimating contemporaneous relations.

The preferred lag structure is chosen adopting a ‘general to specific’ procedure in which statistically insignificant lags are removed on the basis of likelihood ratio tests. The errors $u_i$ are entered as we allow for random effects, and the variable $size_{it}$ is a control for firm size, calculated as the log ratio between a firm’s capitalization and total industry capitalization. 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 returns), a result commonly found in the literature.

We run the regressions of Models 1 and 2 for the entire period, and then for the two sub-periods, before and after the Bayh-Dole act (before and after 1982, allowing for the act to have an effect in its first two years). As a further robustness check, we re-estimate models 1 and 2 over a sample in which only above-average innovators are considered, i.e. the firms for which the R&D/REV ratio is above the unrestricted sample mean of 0.12. Finally we look at the role that different levels of R&D spending play, i.e. whether the relationships differ for above and below average R&D spenders.

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15 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.
5. Results

5.1 Dynamic specification and size controls

Before discussing the results for each model, it is worth mentioning that best estimates are obtained with lagged regressors in Models 1 and 2. Only in Model 3 does VOL enter contemporaneously with no lag. Best estimates are obtained when selecting a second order lag for RD/REV and a first order lag for PATW, irrespective of the equation being estimated. This is evidence that RET and VOL are contemporaneously correlated and both depend on lagged measures of innovation, with R&D intensity preceding the patenting activity. Firm size is negatively correlated with relative volatility and positively correlated with relative performances.

The results of the preferred models are summarized in Table 3, and discussed below.

5.2 The effect of innovation on volatility (Model 1)

When relative volatility VOL is regressed on the innovation variables (Eq. 1), it is found that R&D and citation weighted patents have significant and positive effects on relative volatility (5% significance). Unweighted patent numbers are instead insignificant. This suggests that investors in financial markets, when building their expectations about future growth performances, have possibly learned that unweighted patents are very noisy signals about growth in this industry. This is because patents have been increasingly used for strategic reasons (carving out a technological area), and due to the fact that many areas that could not be patented before are being patented now (e.g. public research through the Bayh-Dole act, as well as upstream areas of research)—both leading to patents being a weaker signal of real changes in innovative activity. In this context there is an increased need for patents to be weighted if they are going to really signal potential growth. In fact, when we split the sample into the two periods, before and after the 1982 (to account for the effect of the 1980 Bayh-Dole act), it is indeed found that citation weighted patents are not significant in the first period, but are so in the second. This confirms that this weighting measure becomes relevant in the second period due to the noise that is introduced by the exponential increase in the number of patents.

The coefficient for lagged R&D effort for above average R&D spenders is larger in size and strongly significant. Lagged patents are instead not significant for these firms. Perceived risk is thus not affected by the patenting activity.
5.3 The effect of innovation on returns (Model 2)

When relative returns are regressed on R&D intensity and weighted patents (Eq 2), only citation weighted patents have a significant effect on the dependent variable RET. While R&D has a positive effect on VOL it has a negative effect on RET. One explanation for this negative effect is the fact that R&D costs very much in this industry (approx $403 million per drug) so it is seen as having a negative effect on short run profits driving shares. The positive effect of citation weighted patents on returns is possibly because patents are seen as being closer to the final innovative output (a potential new drug) making the financial markets less impatient with results. Firms with higher innovation activity are thus not expected to display higher returns, unless they are also characterized by higher patenting activity.

Unlike in Model 1, firm size has a positive (significant) sign, suggesting that larger firms have higher returns, as would be predicted16.

Considering the pre-post Bayh-Dole act sub-periods, we obtain that neither citation weighted patents nor R&D effort are significant in the first period, but are in the second. In the latter the R&D effort coefficient is again negative. Consistent with the results from Model 1, this result signals that the relationship between innovation activity and firm performance takes place as the exponential increase in the number of patents makes the information on firm specific innovation more relevant to predict performances. Interestingly, the control for firm size has a negative sign in the first period and a positive sign in the second.

Considering the sample restricted to the highly innovative firms, the coefficients for both lagged R&D effort and lagged patents are not significant according to standard levels. In this case, lagged R&D effort and patenting are not valid predictors for returns.

5.4 The relationship between returns and volatility (Model 3)

Given the positive effect of innovation on both returns and volatility, it is not surprising that there is a positive relationship between these two financial measures. The relationship is found to be contemporaneous.

Results are summarized in Tables 2-5

16 However, out of interest we ran the same equation with Return-Earnings as the dependent variable, the sign is again negative as would be expected. Small innovative firms tend to have higher P/E both because their earnings are lower but also because the growth expectations driving returns is higher.
6. Conclusion

Our study provides empirical support to the assumption found in recent finance literature that
the volatility of stock returns (both aggregate and idiosyncratic) is related to innovation (Shiller 2000;
Campbell et al. 2001). 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 returns
and levels of market value and P/E. We find that both the level and volatility of stock returns is in
fact related to innovation.

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 (citation weighted),
suggesting that the market reacts more quickly to signals regarding innovation outputs than inputs.
In fact, it is sensible to think that uncertainty is 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 industry
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).17

We find that volatility is higher in the case of small firms (proxied by market share) and in the
post 1985 period which is 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). The fact that citation weighted patents
have a stronger effect on volatility than simple patent counts, suggests that the market is able to, at
least partially, filter through this noise.

More broadly, our results confirm that innovation variables are important in capturing the
levels of ‘risk’ embodied in firm performance and as such have an impact on both returns (risk-
return) and volatility (risk-volatility)—as would be expected in the finance literature. However, the
fact that innovation is not just risk but real Knightian uncertainty means that these results should not
be used to justify those finance models that might predict this relationship based on the assumption
of underlying normal distributions of returns. Rather, we have shown that innovation, with all the

17 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.
uncertainty that it embodies, should be taken more seriously in finance models and in doing so help to provide a Schumpetarian foundation to the analysis of bubble dynamics.
References


FIGURE 1 The productivity dilemma: R&D vs. discovery of New Molecular Entities

FIGURE 2 Market share instability and citation weighted patents in pharma
Figure 3 Scatter-plot between average financial and innovation data - Section means and period means

Section means (correlation over time)

Period means (correlation over section)
Table 1 Descriptive statistics

a) Summary

<table>
<thead>
<tr>
<th></th>
<th>VOL</th>
<th>RET</th>
<th>RD/REV</th>
<th>PATW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.116</td>
<td>0.020</td>
<td>0.119</td>
<td>0.648</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.079</td>
<td>0.055</td>
<td>0.366</td>
<td>1.957</td>
</tr>
<tr>
<td>CV</td>
<td>0.678</td>
<td>2.806</td>
<td>3.083</td>
<td>3.020</td>
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</table>

b) Correlations

<table>
<thead>
<tr>
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<th>RET</th>
<th>RD/REV</th>
<th>PATW</th>
</tr>
</thead>
<tbody>
<tr>
<td>VOL</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RET</td>
<td>0.011</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RD/REV</td>
<td>0.238</td>
<td>-0.169</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>PATW</td>
<td>-0.185</td>
<td>0.161</td>
<td>-0.033</td>
<td>1.000</td>
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### Table 2: Estimation results (whole sample)

#### Equation 1

Dependent variable: VOL  
IV Random Effects Panel ML regression  
Obs: 751  
Cross-section dimension (firms): 63

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<td>CONST</td>
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<td>17.9</td>
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<tr>
<td>RD/REV(-2)</td>
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<td>0.005</td>
<td>2.82</td>
<td>0.005</td>
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<td>PATW(-1)</td>
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<td>0.029</td>
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<td>Sigma_u</td>
<td>0.041</td>
<td>0.005</td>
<td>7.38</td>
<td>0.000</td>
</tr>
<tr>
<td>Sigma_e</td>
<td>0.056</td>
<td>0.001</td>
<td>36.19</td>
<td>0.000</td>
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Log likelihood = 1032.306  
LR test of Sigma_u = 0: Chi_sq = 103.60, Prob. = 0.000

#### Equation 2

Dependent variable: RET  
IV Random Effects Panel ML regression  
Obs: 891  
Cross-section dimension (firms): 63

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<td>PATW(-1)</td>
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<td>0.005</td>
<td>4.39</td>
<td>0.000</td>
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<td>Sigma_u</td>
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<td>0.003</td>
<td>7.89</td>
<td>0.000</td>
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<tr>
<td>Sigma_e</td>
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<td>0.001</td>
<td>37.08</td>
<td>0.000</td>
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Log likelihood = 1222.253  
LR test of Sigma_u = 0: Chi_sq = 82.90, Prob. = 0.000
Table 3  Estimation results (pre Bayh-Dole)

Equation 1

Dependent variable: VOL
IV Random Effects Panel ML regression
Obs: 184
Cross-section dimension (firms): 25

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<td>CONST</td>
<td>0.079</td>
<td>0.010</td>
<td>7.90</td>
<td>0.000</td>
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<tr>
<td>SIZE_C</td>
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<td>RD/REV(-1)</td>
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<td>0.037</td>
<td>2.35</td>
<td>0.019</td>
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<tr>
<td>PATW(-1)</td>
<td>-0.011</td>
<td>0.009</td>
<td>-1.25</td>
<td>0.211</td>
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<td>Sigma_u</td>
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<td>0.004</td>
<td>4.87</td>
<td>0.000</td>
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<td>Sigma_e</td>
<td>0.029</td>
<td>0.002</td>
<td>17.4</td>
<td>0.000</td>
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Log likelihood = 368.577
LR test of Sigma_u = 0: Chi_sq = 34.80, Prob. = 0.000

Equation 2

Dependent variable: RET
IV Random Effects Panel ML regression
Obs: 162
Cross-section dimension (firms): 25

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<td>CONST</td>
<td>0.045</td>
<td>0.009</td>
<td>4.87</td>
<td>0.000</td>
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<td>0.134</td>
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<td>PATW(-1)</td>
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<td>0.008</td>
<td>1.11</td>
<td>0.266</td>
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<td>Sigma_u</td>
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<td>0.004</td>
<td>4.77</td>
<td>0.000</td>
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<td>Sigma_e</td>
<td>0.029</td>
<td>0.002</td>
<td>16.51</td>
<td>0.000</td>
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</table>
Table 4 Estimation results (post Bayh-Dole)

Equation 1
Dependent variable: VOL
IV Random Effects Panel ML regression
Obs: 589
Cross-section dimension (firms): 63

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<tr>
<td>CONST</td>
<td>0.135</td>
<td>0.007</td>
<td>18.10</td>
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<td>SIZE_C</td>
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<td>RD/REV(-1)</td>
<td>0.013</td>
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<td>2.33</td>
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<tr>
<td>PATW(-1)</td>
<td>0.016</td>
<td>0.009</td>
<td>1.93</td>
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Sigma_u 0.040 0.005 7.76 0.000
Sigma_e 0.061 0.002 32.04 0.000

Log likelihood  =  767.39
LR test of Sigma_u = 0: Chi_sq = 83.57, Prob. = 0.000

Equation 2
Dependent variable: RET
IV Random Effects Panel ML regression
Obs: 590
Cross-section dimension (firms): 63

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<tr>
<td>CONST</td>
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<td>2.05</td>
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<td>SIZE_C</td>
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<td>-0.010</td>
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<td>PATW(-1)</td>
<td>0.020</td>
<td>0.006</td>
<td>3.18</td>
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</table>

Sigma_u 0.025 0.003 7.30 0.000
Sigma_e 0.047 0.001 32.34 0.000

Log likelihood  =  895.340
LR test of Sigma_u = 0: Chi_sq = 60.53, Prob. = 0.000
Table 5 Estimation results (highly innovative firms)

Equation 1

Dependent variable: VOL
IV Random Effects Panel ML regression
Obs: 158
Cross-section dimension (firms): 28

<table>
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<tbody>
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<td>0.017</td>
<td>0.45</td>
<td>0.651</td>
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</table>

Sigma_u 0.000 0.026 0.00 1.000
Sigma_e 0.078 0.004 17.78 0.000

Log likelihood = 298.421
LR test of Sigma_u = 0: Chi_sq = 28.32, Prob. = 0.000

Equation 2

Dependent variable: RET
IV Random Effects Panel ML regression
Obs: 158
Cross-section dimension (firms): 28

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<tr>
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<tbody>
<tr>
<td>CONST</td>
<td>0.014</td>
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<td>SIZE_C</td>
<td>0.236</td>
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<tr>
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<td>0.011</td>
<td>1.27</td>
<td>0.209</td>
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Sigma_u 0.029 0.004 7.66 0.000
Sigma_e 0.049 0.002 31.6 0.000

Log likelihood = 317.453
LR test of Sigma_u = 0: Chi_sq = 18.74, Prob. = 0.000