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Innovation and Idiosyncratic Risk: An Industry and Firm Level Analysis

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Innovation and Idiosyncratic Risk: an Industry and Firm Level Analysis

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Abstract
Recent studies find that idiosyncratic risk (IR), the degree to which firm specific returns are more volatile than aggregate market returns, has increased since the 1960's and attribute this to economy wide factors such as the role of the IT revolution. To gain further insights into why IR has increased over time, our paper uses industry level data and firm level data to study if firms and industries that are more R&D intensive are characterized by higher IR due to how the process of innovation affects the uncertainty of expected future profits. While the industry level results prove inconclusive, the firm level results are encouraging: a clear relationship is found between a firm's R&D intensity and the volatility of its returns.

Key words: Idiosyncratic Risk; Volatility; Technological Change; Industry Life Cycle.
JEL Classification G12 (Asset Pricing); 030 (Technological Change).

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I. Introduction

The paper studies whether idiosyncratic risk— the degree to which firm and industry specific returns are more volatile than aggregate market returns— is higher in innovative industries and firms which are characterized by greater uncertainty regarding their expected future profits. The central idea is that since innovation is a process characterized by uncertainty (in the Knightian sense, hence beyond just the risk of a lottery), and since asset pricing is a function of the stochastic discount factor which incorporates firm level risk, the behavior of returns of innovative firms and industries should be higher than that of non-innovative firms and industries. Are they?

The study is motivated by the fact that most finance studies of stock price volatility do not look at innovation characteristics of the firms or industries in question. When innovation is considered it is referred to in more general terms, such as the potential effect of the IT revolution or the New Economy on firm conduct and performance. For example, Shiller finds that excess volatility, i.e. the degree to which stock prices are more volatile than the underlying fundamentals, is much higher during periods of technological revolutions when animal spirits, herd behavior and 'bandwagon effects' (on the part of investors) are strong (Shiller 2001). And Campbell et al (2005) find that idiosyncratic risk has increased at the firm level since the 1960's and attribute this to various factors including the effect of the IT revolution on (a) the speed at which investors receive new information, and on (b) the speed at which new firms can go public (earlier than before). But here again, the effect of innovation (at neither the macro nor micro level) is not actually measured.

The paper studies whether the variance of stock returns is in fact higher for industries and firms which have higher R&D intensity (in comparison to the general market). The logic is that since a firm's investment in innovation creates both high expectations for its future growth as well as fears that the investment will lead to a 'dry hole', those firms and industries which invest more in innovation should in theory be characterized by more uncertainty and hence more volatility of their returns. Furthermore, as innovation tends to be more radical in the early phase of industry evolution where there is a large presence of small firms rather than the more mature phase where firms are larger and more concerned with incremental process innovation (Gort and Klepper 1982), we ask whether stock price volatility in younger industries, such as biotechnology, is higher than in older industries such as textiles. In order to be precise from the start with our terms, the exact relationship we are testing for is that between innovation (R&D intensity) and volatility of returns, where the latter is measured in relation to the volatility of aggregate market returns. We focus on a *relative* measure of volatility: the ratio between the variance of firm specific returns and the returns of the general market, as we think this is a good proxy for idiosyncratic risk.

The analysis in the paper finds that at the industry level, it is not possible to say that more innovative industries have higher idiosyncratic risk (from now on denoted by IR). That is, ranking industries by their R&D intensity (at the high end industries like aerospace and pharma, and at the low end industries like textiles and construction) does not predict their ranking in terms of IR. At the firm level, instead, it is found that those firms that have higher R&D intensity are in fact the ones with highest IR. We hypothesize that this is because high R&D spending by firms indicates to market analysts the high growth potential of these firms, however these expectations are not always met since investment in innovation has uncertain outcomes. Interestingly, however, we find that this result does not hold more strongly for firms in highly innovative industries. In fact, it holds strongest for firms in new innovative sectors like Biotech *and* in old non innovative sectors like textiles, more so than in sectors like pharma and computers which are innovative but not new, i.e. in a relatively mature phase of their industry life-cycle (Klepper 1997). This may be because the market reacts more strongly to innovative firms in stagnant sectors (since these firms "stick out" from the crowd, i.e. their competitors), and innovative firms in very new sectors because there are higher hopes in such sectors. Innovation by firms in dynamic but mature industries, like pharma and computers, instead produce less of a reaction since they are not necessarily more innovative than their peers, and also the technology is at a relatively certain stage of its development (there is a core of persistent innovators and less market share instability, Mazzucato 2002).

The paper is organized as follows. Section II contains a review of recent work which links stock price dynamics to *innovation*. Section III provides background on the particular measure of volatility used in the paper: idiosyncratic risk. Section IV discusses our data and methodology,. Section V presents the results from our industry level analysis of 34 industries and Section VI the results from our firm level analysis of five industries with different levels of innovativeness: biotechnology, computers, pharmaceuticals, textiles and agriculture. Section VII concludes by considering possible reasons why our results differ at the industry and firm level.

II. Innovation and stock prices

Uncertainty in finance models refers to how *expectations* about a firm's future growth affects its market valuation, hence its stock prices (Pastor and Veronesi 2004)[i]. Yet few of these models link stock price dynamics to innovation variables at the level of the firm and industry (Mazzucato 2002). This is surprising given that most shocks are idiosyncratic to the firm or plant (Davis and Haltiwanger, 1992) and investment in innovation is expensive and its outcome very uncertain. The uncertainty associated with innovation is why Frank Knight (1921)—an early pioneer of risk theory—and John Maynard Keynes (1973), both distinguished 'risk' from 'uncertainty' in their works, often using technological innovation as an example of *true uncertainty*. They argued that while a *risky* event can be evaluated via probabilities based on priors (e.g. a lottery), an *uncertain* event, such as a new invention, cannot[ii].

The few studies that do relate stock price dynamics to innovation, do so mainly by linking changes in the stock price *level*[iii] to innovation, rather than changes in volatility of stock prices to innovation. Furthermore, they are mainly concerned with *aggregate* innovation dynamics (e.g. the effect of the New Economy or the IT revolution) rather than with firm or industry level innovation dynamics. For example, 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. Focusing on the US tire industry, they build a model which assumes that an industry is born as a result of a basic invention and that the shakeout occurs as a result of one major refinement to that invention.[iv] 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[v].

An example of a study that links stock price *volatility* to innovation is Shiller (2000), where it is shown that 'excess volatility', the degree to which stock prices are more volatile than the present value of discounted future dividends, peaks precisely during the second and third industrial revolutions when innovative activity was high (e.g. new GPTs). Furthermore, Campbell et al. (2000), reviewed further below, relate the dynamics of "idiosyncratic risk" to general changes in the economy associated with the IT revolution.

In this paper, we take the position that the link between volatility, innovation and uncertainty is better studied at the level of the firm since this allows it to be related to the firm's specific environment. In this same spirit, Mazzucato and Semmler (1999) and Mazzucato (2002) extend Shiller's work to the industry level by studying the relationship between innovation and stock price volatility in two specific industries: autos and PCs. There we find that both idiosyncratic risk and excess volatility were highest precisely during the periods in which innovation in these industries was the most 'radical' as measured by a *quality change* index (derived by dividing BEA prices by quality adjusted prices as in Filson 2001)[vi]. This was also the period in which market shares were most unstable—due to the 'destructive' effect of technological change on the advantage of incumbents.

In the current paper we ask whether these results can be generalized to different industries. In particular, we ask whether firms and industries that spend more money on R&D, and hence are more innovative (at least as regards the input to innovation) experience more volatility of their stock returns. If so, this provides further support to our claim that finance studies should pay more attention to the effect of firm and industry specific innovation dynamics on the dynamics of financial risk.

We focus specifically on the dynamics of idiosyncratic risk due to its ability to capture the firm specific and industry specific nature of uncertainty, as reflected in the *volatility* of stock prices. Thus rather than *assuming* that greater volatility implies more uncertainty (as is done in the various studies cited above as well as in more microeconomic finance studies such as Pastor and Veronesi 2004), we see whether one of the most uncertain activities a firm can do (e.g. innovation) is in fact linked to volatility. It is important to note that due to our interest in highlighting the role of innovation in increasing uncertainty and hence volatility, we ignore other sources of volatility, such as monetary policy, globalization of financial services, and globalization of output and input markets (a review of these sources can be found in Eichengreen and Bordo 1991, and Scheve and Slaughter 2004).

III. Idiosyncratic risk

The volatility of individual stock returns can be broken down into three components: the market wide return, the industry specific residual and a firm specific residual. Idiosyncratic risk usually refers to this latter firm specific component. It is an element of price risk that can, in theory, be largely eliminated by diversification within an asset class[vii]. It is sometimes called security specific risk or unsystematic risk. In the Capital Asset Pricing Model, a regression of a firm's (or industry's) return against the market level return, the *beta* coefficient, denoting the *covariance* between individual returns and general market returns, captures the *systematic* component which varies inversely with idiosyncratic risk: the higher is beta, the higher is the covariance between the two returns hence the higher is the systematic component and the lower the idiosyncratic component of risk.

As discussed above, there are very few industry level studies of volatility. The few that exist focus on the reallocation of resources across sectors. [viii] Motivated by this lacuna, Campbell et al. (2000) conduct a rigorous empirical study of idiosyncratic risk on firm level and industry level data. Their aim is to test whether idiosyncratic risk has increased over time. They analyze the volatility of returns, at the firm level, industry level and market level, from 1963 to 1997. Volatility is calculated on a monthly base, through the sample variance of the daily data. While the industry level analysis proves inconclusive, the firm level analysis suggests *increased* idiosyncratic risk since the 1960's. Specifically, their main findings are:

1. evidence of a positive deterministic time trend in stock return variances for individual firms, and no such evidence for market and industry return variances;
2. evidence of declining correlations among individual stock returns[ix];
3. evidence that volatility moves counter-cyclically and tends to lead variations in GDP.

In their conclusion, Campbell et al offer various explanations of why idiosyncratic risk might have increased. These are:

a) companies have begun to issue stock earlier in their life cycle when there is more uncertainty about future profits;

b) leverage effects;

c) improved information about future cash flows due to the IT revolution;

d) improved and quicker information via financial innovations (e.g. new derivative markets).

The authors spend some time reviewing the mixed evidence on these effects. For example, while improved information might increase the volatility of the stock price *level*, it should (at least in the case of constant discount rates) decrease the volatility of stock *returns* since it allows news to arrive earlier when cash flows are more heavily discounted. In fact, the only explanation above whose effect is not ambiguous is the first one (a): since innovation tends to be more radical during early industry evolution when there are more technological opportunities available, it is assumed that idiosyncratic risk should be higher in new and/or high-tech industries which are characterized by greater uncertainty in expected future profits. This assumption is also found in other works such as that of Pástor and Veronesi (2003, 2004) who find that uncertainty (proxied by volatility) increases the firm's fundamental value and use this to explain the high value of technology stocks in the late 1990's during the peak of the IT revolution—without actually having any information on innovation itself. Our aim is to provide more substance to these types of assumptions by investigating directly the relationship between innovation and volatility (first using a sectoral taxonomy of innovation, and then using R&D intensity data).

Unlike Campbell et al. (2000) to measure idiosyncratic risk we do not decompose the return of a 'typical' stock into its three components above (which sum up to the total return volatility), rather we calculate the ratio between the variance of a firm's return and the variance of the return of the general market as a proxy for idiosyncratic risk and apply it to both firms and industries to capture the relative volatility (compared to the S&P500 index). Specifically, if *rit* is the return of firm *i* at time *t* (where P is the firm's stock price and D is dividend):

$$r_{i,t} = \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} - 1 \qquad (1)$$

then, idiosyncratic risk, $IR_{i,t}$, is the standard deviation of r_{it}=[r_{it}] divided by the standard deviation of the market return, $R_{SP500,t}$:

$$IR_{i,t} = \frac{[r_{i,t}]}{[R_{SP500,t}]} \qquad (2)$$

To calculate *industry* specific idiosyncratic risk, firm *i* in Eqs 1-2 is replaced with industry *j.*

Our goal is to see whether this proxy for idiosyncratic risk is in fact higher for innovative firms and industries.

IV. Data and methodology

Following Campbell et al. (2000) we study idiosyncratic risk across different industries and firms. Our aim is to test whether more innovative organisations are characterized by higher idiosyncratic risk. At the industry level, we study the aggregate behavior of returns in 34 industries using quarterly returns data from 1976-1999. At the firm level, we study the behavior of monthly returns and quarterly R&D intensity in five industries from 1974-2003: agriculture, textiles, pharmaceutical, computers and biotechnology. The 5 industries were chosen based on their clear ranking across the innovation spectrum: highly innovative (biotech); innovative (pharma and computer); and low innovative (textiles, agriculture). We decided to use monthly S&P financial data, rather than daily data (e.g. CRSP), since it would be exaggerated to expect that quarterly R&D figures have an impact on a daily basis. For this reason annual volatility figures calculated using monthly returns data, were compared with quarterly R&D data.

Using information from various sectoral classifications found in the literature on sectoral taxonomies of innovation (Pavitt 1984; Marsili 2001, EC 1996), the 34 industries used in our industry level analysis are divided into 'very innovative', 'innovative' and 'low innovative'. Although we focus the discussion in the paper solely to *manufacturing* industries, we retain the results that pertain to the *services* industries (insurance, retail, banks, dept. stores, food chains, financial, restaurants, entertainment, electrical utilities, public utilities), and assume that they fall into the 'low innovative' category due to empirical studies that have shown R&D intensity to be very low in these sectors (EC, 1996). Table A1 and A2 (from Marsili 2001) include all the manufacturing industries included in our data set, except for aluminum, integrated domestics and natural gas pipelines. We thus do not discuss these three industries in our results as we are not sure regarding their "innovativeness" (and assume that all service industries are included in low innovativeness).

After discussing the descriptive statistics on the sample employed, in a first step of the analysis we develop 34 bivariate VAR representations of the industry-level and market-level stock returns, and perform a Forecast Error Variance Decomposition (FEVD) analysis in order to capture the degree of idiosyncratic risk of the series. Assuming that the expected behavior of profits and/or growth is more uncertain - and thus volatile - in innovative firms/sectors, we expect to find that the percentage of the industry-level predictive error variance is mostly explained by the idiosyncratic shock, i.e. by the industry-specific shock. This also implies that the forecast error variance explained by the generic (i.e. SP500) shock should be lower in innovative sectors and higher in less innovative sectors.

In a second step, following the approach developed in Campbell *et al* (2000), the analysis is conducted in the context of the CAPM model. We pool the industry-level sample information obtaining a balanced panel with *time* dimension T (88 observations) and *sectional* dimension N (34 observations), and regress the industry-level stock returns on industry-specific dummies (Fixed Effects) and the SP500 returns. This set up allows a test of the efficient market hypothesis and, particularly, testing the heterogeneity in the sectional dimension. In line with the results obtained by Campbell et al. (2000), we also obtain a measure of the percentage of variability explained by the regression. As long as the behavior of stock prices and returns in innovative sectors is mostly affected by idiosyncratic factors, the variability explained by the regression should result higher for the low innovative industries and lower for the more innovative industries.

In the firm-level analysis, the empirical investigation is developed by directly testing the existence of a positive relationship between idiosyncratic risk[x] and the firm-level degree of innovativeness, proxied by R&D intensity (R&D expenditures divided by sales). By focusing on R&D intensity we are focusing on innovative *effort* (innovation input rather than innovation output such as patents). Yet since in the literature on patents, R&D intensity has also been found to be highly correlated with both patent counts and patent citations (Pakes 1985, Hall et al. 2005) we don't think the results are overly biased. Nevertheless, in our work in progress, focused on the pharmaceutical industry, we consider the patent based information as well (Mazzucato and Tancioni 2005).

We estimate panel regressions in which firm-level idiosyncratic risk depends on R&D intensity and a proxy for firm size: the log ratio between the average market capitalization of the firm and the average capitalization of the S&P500, both calculated on an annual basis (the ratio includes the annual industry average capitalization when the analysis is conducted on the industry-specific sub-samples). We control for firm size (using market value) to avoid spurious results, i.e. that the volatility of returns of small and innovative firms is higher because they are small instead of the fact that they are innovative. We also introduced other control variables such as earnings and employment but found that these did not vary the significance of the results in any way. Although it would be interesting, we do not control for more complex phenomena like the effect of globalization of output or input markets since we do not have data on which firms in a given industry, or which industries in the economy, are affected more by globalization (Scheve and Slaughter 2004). In our future work we plan to partially capture these phenomena by adding a control which accounts for the degree to which industries utilize new technologies such as IT.

The dimension of the *unbalanced* panel[xi] employed is quite big, as we have 30 observations in the time dimension T (yearly, 1974-2003) and 965 observations in the sectional dimension N (firms). The analysis is conducted both employing the pooled panel sample and the five different industry-specific panels of firms. The strategy of analysis is discussed in greater detail in each section.

The industry level data comes from hard copies of the annual editions of the Standard and Poor's *Analysts Handbooks* while the firm level data, including annual R&D expenditures, comes from the electronic Standard and Poor's *Compustat* database (purchased via custom order from S&P). While the industry level data is available on a quarterly basis, the firm level data is available on a monthly basis—a higher frequency that is more appropriate for volatility studies. Unfortunately, we did not have access to continuous R&D data for the industry level analysis. But since the sectoral taxonomy of innovation used in Tables A1-A2 was constructed using average R&D intensity data (as well as other technology indicators related to patents, entry barriers etc., see Marsili 2001), comparison of return volatility with the level of innovativeness suggested in the taxonomy indirectly captures the R&D intensity information.

For the firm level analysis the volatility of returns is calculated annually, through the standard deviations between 12 (month) terms. In this way, the monthly frequency of the financial information collapses to the annual frequency. The firm-level intensity of innovation is proxied by R&D intensity, i.e. by the log ratio between R&D expenditure and total sales. Since sales and R&D firm-level data are both available on a quarterly basis, quarterly flows are summed and collapsed to the annual frequency.

V. Industry level analysis

Table 1 provides a descriptive analysis of the sample. It focuses on the standard two moments of the different industry level time series as well as the contemporaneous sample correlations between general market (SP500) and industry level rates of returns. On the basis of the discussion above, we expect variability in the innovative industries to be higher than average, and correlations between industry-level and market returns to be higher for the more traditional, less innovative industries.

If we look at the standard deviations in Table 1, evidence in favor of the expected results is found only for semi-conductors, transports and, to a minor extent, for aerospace and defense. Surprisingly, high variability is also displayed by tobacco and the forest product (publishing), natural gas pipelines and building materials, all considered "low-innovative" according to Table A1 and A2. As expected, low variability is found for more traditional and low innovative industries such as public utilities, metal and glass confectionery, brewers and alcoholics, electrical equipment and food chains. However, against our expectations, very low variability is found for the more innovative electronic instruments industry.

With respect to the correlations between each industry's returns with the average market returns, moderate values are obtained for semiconductors, transports, electronic instruments and natural gas pipelines, all below 0.5. The higher correlations are instead found for electrical equipment, chemicals and coal, financial and retail stores industries, all above the value of 0.8.

Hence, the evidence from the descriptive analysis is rather mixed. Expectations appear satisfied only for some industries at the very extremes of the taxonomy but not for others. Since one of the reasons why we find these mixed results might be related to the fact that we are averaging across periods that have different levels of innovativeness (for both the innovative and the less innovative industries), we look briefly to the dynamics over time.

The behavior of standard deviations (SD) of returns *over time*, calculated as four terms (yearly) SDs, provides some insight into the reason for our mixed results. Fig 1 illustrates the SD dynamics for two innovative industries (semiconductors and electronic instruments), one medium-innovative industry (chemicals and coal) and one low-innovative industries (food chains). We are encouraged to find that for both the innovative industries, the periods of greatest volatility as compared to the S&P 500, are precisely the periods that the more qualitative and in-depth case study literature on those industries identify as being particularly innovative periods (see Malerba 1985 for semiconductors, and Bresnahan and Greenstein 1997 for electronic instruments). That is, the mid 1980's for semiconductors and the 1990s for electrical equipment. This suggests that the effect of innovation on idiosyncratic risk is both industry-specific and time-specific, hence it cannot be studied with respect to single time dimensions of the sample information (by focusing the analysis on one dimension only, results are likely to be biased, as it implies averaging over the other dimension). On the contrary, for the low-innovative industries, the SDs closely follow the behavior of the SP500 returns, signaling no period specificities for which an innovation-related explanation can be advanced[xii].

Hence, apart from some selected industries at the extreme of the innovation-sectoral taxonomy, the descriptive analysis appears unable to give clear results. It makes most sense for the industries in the extreme of the categorization while for the others it is difficult to derive some reasonable interpretation of their descriptive measures. Looking, however, at the dynamic dimension of the relationship, we gather some initial insights on why the industry analysis is so inconclusive.

Another reason behind our mixed results might be the fact that we have not included controls for changes in monetary policy, globalization of financial services, and globalization of output and input markets. Not only do we not have this data, but as we have no information (or hypotheses) on why such forces should affect specific industries more than others, we do not think this would have necessarily been useful.

Before moving on to the firm level analysis, we try to gain further insights first through variance decomposition analysis and then by testing for the relationship between innovation and IR within a CAPM model, both methods used in Campbell et al. (2005).

Va. VAR representation: forecast error variance decomposition (FEVD) analysis

As briefly discussed above, as a first step we analyze the dynamic relationships between the general market and the industry specific stock returns volatility employing a bi-variate Vector Auto Regressive (VAR) representation between SP500 and industry returns. A VAR is estimated for each of the 34 industries considered in the sample.

The starting VAR formulation for the different industries is the following:

$$\mathbf{y}_t = \sum_{l=1}^{p} \mathbf{\Pi}_l \mathbf{y}_{t-l} + \boldsymbol{\varepsilon}_t, \quad E(\boldsymbol{\varepsilon}_t) = \mathbf{0}, \quad E(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') = \mathbf{\Sigma} \quad \forall\, t \neq s \tag{3}$$

where, according to the single industry *j* being modelled, $\mathbf{y}_{jt} = \left[R_{jt}, RSP500_t\right]'$, $j = 1 \ldots 34$, R_j are industry-specific returns and $RSP500$ market returns. They are obtained as logs of returns (see Eq. 2).

The lag order *p* of each VAR is selected according to the Schwartz Bayesian Criterion (SBC) and the condition of spherical errors. The VARs are then employed as the basic structure for running the Forecast Error Variance Decomposition (FEVD) analyses. The FEVD analysis provides a decomposition of the relative weight of one variable's (*m*) shock in explaining the predictive error variability of another variable (*n*) at different time leads[xiii]. If the FEVD of a variable at a given horizon is explained entirely by the idiosyncratic shock, then its forecast at that horizon does not improve when considering the behaviour of the other variable's shock. Symmetrical considerations are valid in the case in which the FEV of the first variable is dominated by the second variable's shock[xiv].

Our hypothesis is that if idiosyncratic risk affects the volatility of industry specific stock returns, then the general market dynamics is not a valid predictor for them. We expect, in fact, the general market shocks to have low predictive capabilities for the innovative industries' stock returns volatility. In other words, from FEVDs we expect to find a lower contribution of S&P500 shocks in generating the forecast error variances of the more innovative industries' returns, hence, a bigger presence of industry specific variance.

Table 2 contains the results from the FEVD analysis, obtained with the industry-specific bivariate VARs described above. The values reported are valid for the idiosyncratic shock contribution to the industry-specific forecast error variance. The results are again not very clear. The expectations are clearly satisfied, again, only for semiconductors and transports, even if some favorable evidence emerges also for other industries deemed to be innovative in Tables A1-A2 (automobiles, integrated domestics). For semiconductors and transports, the forecast variance at a 1 quarter horizon is dominated almost entirely by idiosyncratic shocks, on average explaining, respectively, about 96% and 99% of the total variability of the series. The values at a 10 quarter horizon are still high, respectively 95% and 94%. The lowest contribution of idiosyncratic shocks to the 1-quarter FEV is found for the financial industry (nearly 28%), electrical equipment (32%) and forest products (both publishing and paper nearly 40%).

Even if for this limited group outcomes are substantially in line with the expectations, we are still far from having obtained a favorable result for our hypothesis of higher variability in innovative industries. The main problem is that, even with the VAR-FEVD analysis, the evidence remains again mixed for all the industries that are not classified at the extremes of the innovation sectoral taxonomy employed here.

Vb. The CAPM hypothesis and industry-level innovation intensity

In this section we adopt a different point of view. We evaluate the empirical relevance of the CAPM predictions by directly testing the relationships between industry and market level returns. The CAPM postulates the existence of a linear relationship between the expected risk and the returns of holding a portfolio of financial assets. If markets are efficient, the ratio between a portfolio premium on a risk-free asset and its standard deviation (which is a measure of perceived risk) equals the ratio between market premium and market risk, i.e.: $\left(r_p - r_f\right)/\sigma_p = \left(r_m - r_f\right)/\sigma_m$, where *r* are portfolio *p*, market *m* and risk-free asset *f* returns and $\sigma_{p,m}$ are standard deviations. The equality above can be re-written as $\left(r_p - r_f\right) = \frac{\sigma_p}{\sigma_m}\left(r_m - r_f\right)$, which justifies the well-known alpha-beta CAPM relation $R_p = \alpha + \beta R_m + u$. The estimate of the beta coefficient is $Cov\left(R_p, R_m\right)/Var\left(R_m\right)$, hence its dimension is directly related to the co-variation between returns. If a particular industry denotes specific volatility patterns over time, this affects the "betas" dimension and, if specificities are systematic, these result in statistically significant "alphas".

For the scope of our analysis, we test whether the hypothesis of unit slope coefficients (i.e. the "betas", denoting the covariance between the individual firm or industry returns and the average market returns) can be empirically established. Our conjecture is that departures from CAPM, i.e. from optimal behavior assumed in the efficient market model (EMM), are the result of perceived uncertainty regarding expected future profits. As a consequence, as long as uncertainty and idiosyncratic risk are related to the innovative activity - which is our basic assumption in this work – we should observe that departures from CAPM are more likely for those sectors that are more innovative according to our classification. Our specific aim is thus to obtain a test of the efficient market hypothesis and, in particular, a measure of heterogeneity in the relationship between industry-level and market level rates of return. This requires testing the equality of the intercepts and the slope coefficients in the CAPM regressions. Specifically, we expect to find bigger intercepts and non-unit, or statistically meaningless, betas for the innovative industries. Following Campbell *et al* (2000), further indications on the empirical relevance of the CAPM can be obtained with the evaluation of the variability explained by the sectional regressions. Given our assumptions, we thus expect the percentage of variability explained by the regression to be lower for the innovative industries.

The data base employed here is a well-dimensioned panel, which has been obtained by pooling the industry-level data previously employed for the VAR estimates. The resulting sample contains 88 observations in the time dimension and 34 observations in the sectional (industry) dimension, for a total of nearly 3,000 observations.

The structure of the sample thus allows a flexible and detailed modeling of the relationship under question. Since the aim of the analysis is to test whether there are *systematic* differences in the relationship between industry level returns and market returns, a natural model candidate is the Fixed Effects (FE) representation of the CAPM hypothesis:

$$R_{jt} = \alpha_j + \beta RSP500_t + \varepsilon_{jt}, \qquad (4)$$

where, α_j's are the FE coefficients and β is the common beta coefficient (covariance) of the CAPM. The FE model assumes that the section-specific effects on the dependent variable can be described by heterogeneous constant terms only, in other words, by dummies operating as intercept shifters of the linear relations. This represents a standard assumption for panel samples with T fixed and N large. Given the availability of a panel with moderate sectional (N) dimension and a sufficiently large time dimension, we can generalize the reference specification to an heterogeneous panel model in which the betas are not restricted to be the same across industries:

$$R_{jt} = \alpha_j + \beta_j RSP500_t + \varepsilon_{jt}, \qquad (5)$$

This specification, that represents our reference model for testing the CAPM, allows a straightforward implementation of a testing strategy (Wald) for the evaluation of the heterogeneity in parameters, with particular reference to the betas.

As regards the estimation approach, we base our choice on the particular cross-correlation structure of the data. We first test the diagonality of the variance-covariance errors matrix[xv] (i.e. the absence of cross-dependencies between equations of the system) by implementing a likelihood ratio test (LR) for the null hypothesis that the off-diagonal elements of the variance-covariance system errors matrix are zero[xvi]. If the hypothesis is accepted, the model is estimated with Ordinary or Weighted Least Squares methods (OLS-FGLS). If it is rejected, we assume that relevant cross-dependencies are present, opting for a Seemingly Unrelated Regression Estimator (SURE).

The LR test of diagonality of the system errors variance-covariance matrix gives a value of 1,951.7 which, compared with a chi-sq. distribution with 528 degrees of freedom, strongly rejects the null hypothesis of a diagonal error structure. The reference estimator is thus the SURE.

The FE dummies are generally statistically significant and the hypothesis of common intercepts is strongly rejected[xvii]. The slopes coefficients (the betas) are always significant at the standard critical values, while the hypotheses of common unit betas and of equality of the betas are decisively rejected[xviii], signaling strong heterogeneity also for the slope coefficients. The hypothesis of unit betas can be accepted for some industries only (See Table 3). Even if some of the most innovative industries belong to this group, it is impossible to detect clear regularities that can be considered significantly aligned with our predictions.

In their study on trends in idiosyncratic risk Campbell *et al.* (2000) analyzed the behavior over time of the variability explained by CAPM regressions. They obtain that the R-bar sq. of the regressions between individual firm returns and market returns decreased *over time*. Amongst the possible explanations of why this is (and in general why there is a positive deterministic time trend in stock return variances for individual firms), they suggest the fact that companies have begun to issue stock earlier in their life cycle when there is more uncertainty about future profits. We build on this in our assumption that differences in the CAPM model's ability to account for the variability of results can be the outcome of shifts in perceived idiosyncratic risk and uncertainty, in turn related to the degree of innovativeness of the single industry/firm. Consequently, we are interested in analyzing if differences in the industry specific R-bar sq. *over the cross-section* can be explained by differences in the innovative intensities of the specific industries.

Table 3 summarizes the results of the industry level SUR estimation of the CAPM formulation, reporting (for sake of simplicity) only the R bar sq. and the betas statistics (with standard errors). The variance explained by the regressions partly confirms the expectations, being approximately zero for semiconductors and transports and low for electronic instruments, and automobiles, all classified as relatively innovative sectors. Expectedly, the maximum values are obtained with the regressions of the paper, forest and publishing industries, the banking and financial sector, the electrical equipment and chemicals and coal sectors. These are classified in Tables A1-A2 as low innovative industries, showing again that our hypothesis meets some empirical support if the attention is focused on only some industries at the extremes of the classification.

Vc. Conclusion of industry level analysis

In sum, the industry level analysis has not produced clear-cut results. A common finding in this section is that, independently of the method of investigation employed, our expectations seem to be only fulfilled in the extremes of the innovativeness categorization. A possible explanation for our inconclusive industry level results is the effect of looking at industry *averages*, i.e. of *aggregating* firms to get industry level values (e.g. variance of industry returns), when in actuality within each industry (both innovative and non-innovative) there is a great deal of variety between firms in their returns, R&D intensity, profits (i.e. persistent inter-firm 'variety' emphasized in evolutionary economics, Nelson and Winter 1982). This drawback is particularly relevant for those industries classified as "intermediate" in the innovation categorization, as their internal composition is less homogeneous in terms of innovativeness. However, as will be seen at the end of the firm level analysis in Section VI, when we test for this aggregation problem we find it not to be significant.

Another factor which might have contributed to our mixed results, already briefly discussed above, concerns the time dimension: some periods are more innovative than others (for both innovative and non-innovative industries). That is, even if an industry is relatively innovative on average, this does not mean that it is particularly innovative for the whole period considered in the analysis. In fact, we have seen in the descriptive analysis in Fig. 1 that time-varying standard deviations of returns for some selected industries are especially high during specific periods in which the industries experienced more radical innovation (see also Mazzucato 2002 for discussion).

To get beyond both these problems, we now turn to the firm level analysis. As we have annual R&D data for the firms, we can study more directly the dynamic dimension of the relationship in question.

VI. Firm-level analysis: R&D intensity and idiosyncratic risk

In this section we show that the hypothesis of a positive and relevant relationship between idiosyncratic risk and innovation is not rejected by the data when the analysis is conducted at the firm-level and when innovation intensity is taken into account.

We employ a panel of 822 firms belonging to 5 different industries[xix] - for which we have monthly observations for the period 1974-2003 – and directly test the existence of a positive relationship between idiosyncratic risk and innovative effort (R&D intensity). In particular, we estimate panel regressions in which firm-level idiosyncratic risk depends on R&D effort and the firm's relative weight in terms of market capitalization[xx]. The analysis is conducted both employing the whole panel sample and the five different industry-specific panels of firms.

As discussed in section III, the monthly frequency of the financial information is transformed to the annual frequency. Table 4 includes summary data for different decades. In the last decade (1994-2003), idiosyncratic risk increased in all industries considered in the analysis, while during the decade between the mid eighties and the mid nineties we can detect a contraction for agriculture and textile and an increase for the other industries. Concerning the innovation intensity, for all the industries but agriculture there is a clear positive variation, which is particularly strong for computers during the period 1984-1993 and for the pharmaceutical and the textiles industries during the period 1994-2003. For biotech the increase in innovative intensity is strong in both periods. Agriculture signals a relevant decrease in innovative activity during the last decade.

This evidence is undoubtedly insufficient for deriving objective indications on the role of innovative effort in determining volatility and idiosyncratic risk. The existence of an increase in both innovative intensity and IR appears unquestionable, and constitutes a first indication which is consistent with our hypothesis[xxi]. In the next section we test this relationship directly.

VI a. Model selection

The panel structure of the data-set suggests to employ as natural model alternatives the following 3 specifications: the pooled, the Fixed Effects (FE) and the Random Effects (RE) specifications. After obtaining an appraisal of the results in the pooled estimator case[xxii], the analysis then focuses on the evaluation of the opportunity of introducing either a systematic or random representation of the firm-specific effects.

We have seen that the FE model assumes that the section-specific effects on the dependent variable can be described by heterogeneous constant terms only. The RE model differs from the FE model in that it employs a common intercept and presumes that the sectional specificities are random, even if fixed over time[xxiii]. The rationale of the RE model is that the firm effects are not systematic, i.e. that they are orthogonal to the regressors.

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[xxiv] against the common constant model (pooled estimator), and then testing the orthogonality of the individual effects, i.e. the RE specification, with the FE as alternative hypothesis. In this second step the reference evaluation tool is the Hausman test.

In order to check if relevant dynamic structures are present, the alternative specifications are also estimated with Maximum Likelihood entering up to *four lags* of the R&D intensity variable. Even if we obtain statistically significant results when including one lag of our innovation variable, results are stronger when R&D intensity is entered contemporaneously. This is not particularly surprising as we are employing annual – low frequency - data and our dependent variable is a measure of perceived risk. We are in fact considering a market signal and not a realised market performance (permanent increase in market valuation, sales). In the latter case relevant lag structures between R&D input and real performance are likely and in fact they are often observed in the literature (Hall et al. 2005). Moreover, previous investigations on market volatility have shown that volatility can lead variations in market valuation and price/earning ratios (Engle, Ng and Rothschild, 1990, Engle and Ng, 1993 Pastor and Veronesi, 2003, 2004). Interestingly, the regression of R&D intensity on lagged volatility resulted statistically meaningless, signalling that market volatility does not lead R&D intensity.

VI b. Results

According to the two-step strategy implemented for choosing the appropriate specification of the model, from the Breusch-Pagan test we obtain that the firm specific effects (which at this stage we don't know whether systematic [FE] or random[RE]) are always relevant irrespective of the model (with or without the inclusion of MV) and the industry considered, i.e. the hypothesis of stable variance over section ($H_o : \sigma^2 u$) is always rejected by the data.

Substantial differences among different industries emerge in the second step of the analysis. For both the standard model (the one in which idiosyncratic risk is regressed on R&D intensity only, M1) and the extended model (the one including the dimension variable, M2), the Hausman test suggests selecting a RE specification for the textile, agriculture, biotechnology and computer industries, while a FE specification is preferred when the data-set employed is the whole sample or the pharmaceutical industry sub-sample only[xxv]. Model selection tests are summarized in Table A3.

Estimation results, which are summarized in Table 5, are very encouraging. Except for agriculture, the estimated coefficient for the relationship between idiosyncratic risk and R&D intensity is always positive and statistically significant, irrespective of the model and the sample considered. The statistical significance of results is in fact not affected by the introduction of the control for firm size MV, whose effect on idiosyncratic risk is, in line with the expectations, negative, large and statistically significant for all the different estimates of the extended model[xxvi]. This fact is particularly important as it shows that, even if the firms' dimension plays an important role in explaining the behaviour of our measure of idiosyncratic risk, it is not crucial for obtaining the expected results. Under this perspective, the outcomes are thus robust to the particular model employed.

The size of the various coefficients suggests that there are substantial inter-industry differences. This may be due to various factors (not testable here), for example, that R&D intensity is a weak proxy for innovation (due to the fact it is only an input to innovation), or that its effect on market valuation differs depending on industry specific factors (not entirely captured here), such as the specific phase of the industry life-cycle. Furthermore, there is no guarantee that R&D intensity is stronger in firms that are developing radical projects, as it may happen that bigger resources are placed by firms that are developing a less risky process/product. In this second case, which is likely for firms belonging to mature but innovative sectors (computers, pharmaceuticals), we in fact find firms displaying high R&D intensity and only moderate IR[xxvii].

Even if IR and innovation intensity are, on average, higher in the biotech industry than in the textile industry (see Table 4), this does not imply that the co-variation is higher in the more innovative industry. In fact, it is likely that the co-variation is more evident in *traditional* industries, where the market valuation of firms is more certain (and stable) on average so that being highly innovative makes the firm stand out and have an impact in terms of expectations about future growth. Hence, the fact that the relationship between idiosyncratic risk and R&D intensity is stronger for the textile industry signals that the evidence is more likely to emerge in a low-innovative cluster, in which differences between innovative and non-innovative firms are more evident.

Nevertheless, the relationship between IR and R&D intensity is weaker when we employ the whole sample. This last result is explained by the fact that the relationship of interest is not significant for the firms of the agriculture industry and that it is quite weak for those belonging to the pharmaceutical industry, as their weight in terms of number of sectional observations on total sample sectional observations is relevant (nearly 30%).

It is interesting to note that the correction for firm size (*MV*) is particularly important in the biotechnology industry and only modest in the textile industry. Even if we can suppose that in the early stages of an industry life cycle there is higher probability of observing a population of small and innovative firms, our results do not find any correlation between firm size and innovativeness: the introduction of firm size in the extended model (M2 in Table 5) does not affect the R&D coefficient found in the simple model (M1). Therefore, the large MV coefficient found for biotech is only attributable to the low average relative market value of the firms in terms of capitalization, which in turn constitutes a peculiarity of the early stages in the life cycle of new industries but not of their degree of innovativeness. This finding is most likely a result of the proxy for innovation being used (R&D intensity): as emphasized by Schumpeter (1975), R&D is very costly process, often affordable only to large firms. But since the search for innovation occurs through various routes (e.g. discussion above on “random search” and “guided search” in pharma), then it might be that using a different proxy for innovation (e.g. patents) might have found a stronger relationship. Our work in progress on this subject using patent data will hopefully further illuminate this question (Mazzucato and Tancioni 2005).

To further explore the effect of firm size on our results, we re-estimated Model 1 and Model 2 using two different samples. In the first sample we excluded the leading firm in each industry in terms of MV (the following firms were dropped: Westpoint-Pepperell, Amgen Inc., Bristol Myers Squibb, IBM, Archer-Daniels-Midland), In the second, we excluded those firms whose market value was more more than 10% of the total industry capitalisation (in this case 43 firms out of 822 are dropped, 5 belonging to the agriculture sector, 12 to the textile sector, 10 to the biotech sector and 8 to the pharma and computer sectors). Results remain perfectly in line with those obtained employing the whole sample, signalling that the presence of big firms in the sample does not alter the statistical significance of the relationship.

The general and important result emerging from the firm-level analysis is that a positive relationship between innovative effort and idiosyncratic risk can be empirically established and thus that our hypothesis is not rejected by the data. Moreover, the outcomes are also robust to model extensions and, with the exception of the agriculture industry, to the particular sub-sample employed.

Finally, to understand why the industry analysis proved so inconclusive, we also test for aggregation bias in various ways: (1) by pooling the sectional and time dimensions of the firm sample and controlling for industries, re-running the industry-level analysis of the CAPM hypothesis, with the only difference being the use of firm-level data; and (2) by calculating the industry means from firm-level data, we reproduce the firm-level analysis of the previous section employing industry-level data. We conclude that aggregation bias does not constitute a major problem for the qualitative assessment of the relationship of interest, its only effect being of leading to the irrelevance of the dimension parameter. This means that the major responsibility for the inconclusive outcomes for the industry level analysis must be attributed to the fact that the static sectoral taxonomy, whereby an industry is classified as either innovative or non innovative in a specific time period, neglects the dynamic dimension of innovation at the industry level (either annual R&D intensity information, or annual sectoral taxonomy), i.e. that over that period the industry might change its degree of innovation intensity.

VII Conclusion

The paper has found that results concerning the relationship between innovativeness and stock return volatility is rather mixed. In line with the findings found in Campbell et al. (2000), results using industry level data find no coherent pattern between innovation and idiosyncratic risk. While some of the innovative industries conform to the predicted behavior of higher idiosyncratic risk (e.g. semiconductors), other innovative ones do not (e.g. aircraft). The same holds for the low innovative industries. In fact, our expectations seem to be only fulfilled in the extremes of the categorization.

As in Campbell et al (2000), more clear results concerning idiosyncratic risk emerge using firm level data. Here we find that firms with the highest R&D intensity clearly have the highest idiosyncratic risk, a confirmation of our main hypothesis. A positive and contemporaneous relationship between idiosyncratic risk and innovation intensity is empirically established and this result is robust to model extensions, such as the control for firm dimension, and – with the exception of the agricultural industry - to the particular sub-sample employed.

Interestingly, we find that it is not true that this relationship between R&D intensity and volatility is stronger for firms in industries that are more “innovative” (according to the taxonomy used in Section V). We find, for example, that the relationship holds stronger in a very innovative industry like biotechnology and a low innovative industry like textiles than in pharmaceuticals (high innovative). Concerning the latter, we hypothesize that this is because the low average R&D intensity in textiles makes innovative firms in that industry ‘stick out’, and hence for the reaction (by market analysts) to their innovativeness be stronger. Furthermore, while innovation in a mature but innovative industry, like pharma or computers, may be high (expressed through a high R&D intensity and/or number of patents), it’s commercial outcome is often less *uncertain* than in new emerging sectors (like biotech and nanotechnology) or in old sectors where innovation activity is not intense (textiles), and hence causes less of a reaction by market analysts.

A look at how volatility changes over time, shows that idiosyncratic risk is highest precisely during those decades when innovation is the most radical and “*competence destroying*”: e.g. computers (1989-1997) and biotechnology (1995-2003). However, as we did not have yearly R&D figures at the industry level we were not able to capture this dynamic element in the industry level analysis.

We also show that the discrepancy in results obtained with the industry and firm-level analyses are not attributable to aggregation biases, even if the results obtained here do not rule out their role for other specific aspects of the analysis. Instead, the inconclusiveness of the industry level results is mostly attributable to the fact that the innovation measure used there (the sectoral taxonomy) was static, so that it does not allow consideration of how innovation changes over time, as suggested in Figure 1 (e.g. an industry may be highly innovative in one period and less so in another when the life-cycle becomes mature), or when the knowledge regime changes (Gambardella 1995).

Even if in the firm level analysis it has been possible to establish the existence of a direct link between R&D intensity and volatility, the analysis that we develop cannot be employed for explaining the heterogeneity found across industries, only the heterogeneity within industries, i.e. at the firm level. This may be due to the fact that R&D intensity is only an indicator of innovative *input* not output. Nevertheless, we believe our results represent a further step in linking stock price volatility and innovation dynamics at the firm and industry level. On this basis, and given that it is important to also take into consideration innovative *output,* our future work focuses on incorporating patent citation data into stock price volatility analysis (Mazzucato and Tancioni 2005).

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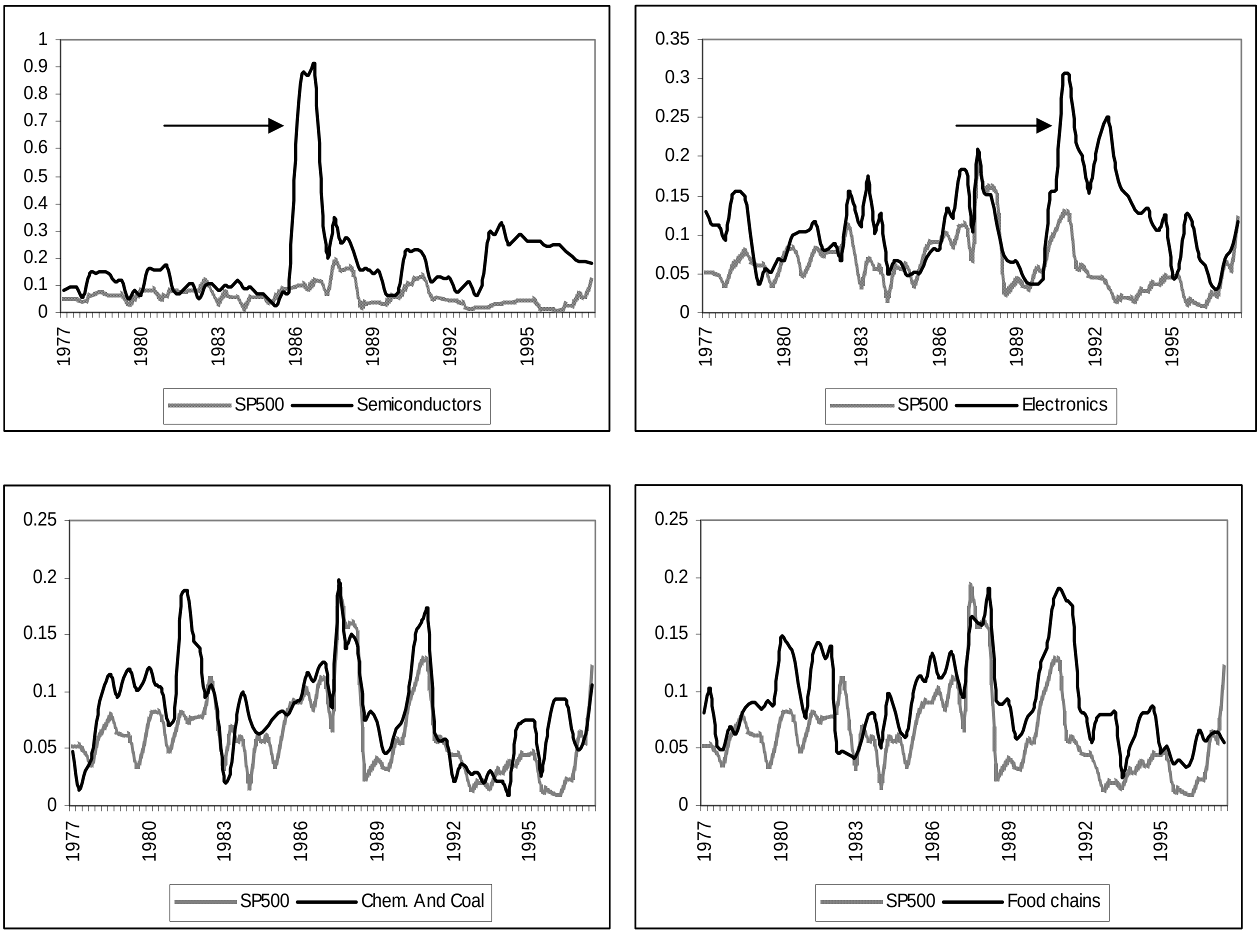
Figure 1: Standard deviations (4 terms moving averages 1977-1999) for four selected industries



Sample: 1976q1-1997q3. Source: Standard and Poor's *Analysts Handbooks*

Table 1: Industry level stock returns, descriptive statistics

Industry	Mean	Std. Dev.	Corr SP500	Industry	Mean	Std. Dev.	Corr SP500
AEROSP. DEFENCE	0.118	0.132	0.722	INSURANCE PROPERTY	0.129	0.099	0.685
ALLUMINIUM	0.077	0.117	0.531	INTEGR. DOMESTICS	0.198	0.111	0.621
AUTOMOBILES	0.079	0.129	0.551	METAL AND GLASS CONF.	0.059	0.092	0.582
BANKS	0.068	0.126	0.750	NAT. GAS PIPELINES	0.151	0.135	0.453
BREWERS AND ALCOOL	0.071	0.096	0.705	PAPER CONFECT	0.178	0.139	0.761
BUILD. MATERIALS	0.065	0.128	0.686	PAPER FOREST	0.173	0.114	0.747
CHEMICALS AND COAL	0.070	0.101	0.816	PUBLIC UTILITIES	0.084	0.064	0.681
COMPOSITE OIL	0.229	0.117	0.719	PUBLISHING FOREST	0.309	0.184	0.785
DEPT. STORE RETAIL	0.178	0.147	0.802	PUBLISHING NEWSP.	0.054	0.109	0.712
ELECRICAL EQUIPMENT	0.238	0.131	0.865	RESTAURANTS	0.050	0.106	0.669
ELECTRIC POWER COMP.	0.040	0.128	0.646	RETAIL COMP.	0.067	0.116	0.569
ELECTRONIC INSTR.	0.051	0.066	0.459	SEMICONDUCTORS	0.042	0.233	0.309
ENTERTAINMENT	0.114	0.118	0.692	SOFT DRINKS NON ALC.	0.154	0.128	0.792
FINANCIAL	0.036	0.103	0.809	TOBACCO	0.236	0.205	0.716
FOOD CHAINS RETAIL	0.091	0.099	0.701	TRANSPORT	0.088	0.183	0.323
HOSPITAL SUPPLIES	0.051	0.104	0.716	TRUCKER TRANSP.	0.063	0.126	0.596
INSURANCE MULTILINE	0.045	0.104	0.667	SP500	0.112	0.081	1.000

Sample: 1976q1-1997q3. Source: Standard and Poor's *Analysts Handbooks*

Table 2: FEVDs of the industry level rates of return, evaluated at different leads

Industry	Forecast horizon (quarters) 1	2	3	4	Industry	Forecast horizon (quarters) 1	2	3	4
AEROSP. DEFENCE	56.1	56.4	56.4	49.9	INSURANCE PROPERTY	51.9	51.9	51.9	51.9
ALLUMINIUM	69.8	64.7	64.7	64.6	INTEGR. DOMESTICS	75.0	75.1	75.0	75.0
AUTOMOBILES	69.5	69.7	68.8	68.0	METAL AND GLASS CONF.	58.8	58.6	60.0	61.0
BANKS	51.1	51.1	51.1	51.1	NAT. GAS PIPELINES	85.2	85.2	85.2	85.2
BREWERS AND ALCOOL	59.1	59.1	59.1	59.1	PAPER CONFECT	55.5	55.5	55.5	55.5
BUILD. MATERIALS	46.9	46.9	46.9	46.9	PAPER FOREST	40.7	44.1	44.3	44.3
CHEMICALS AND COAL	40.0	40.0	40.0	40.0	PUBLIC UTILITIES	58.5	58.5	58.5	58.5
COMPOSITE OIL	66.7	66.7	66.9	66.9	PUBLISHING FOREST	39.7	39.7	39.7	39.7
DEPT. STORE RETAIL	52.9	53.8	54.4	54.5	PUBLISHING NEWSP.	40.1	40.1	40.1	40.1
ELECRICAL EQUIPMENT	32.3	34.3	35.1	35.2	RESTAURANTS	48.9	48.9	48.9	48.9
ELECTRIC POWER COMF	75.9	75.9	75.9	75.9	RETAIL COMP.	58.1	58.1	58.1	58.1
ELECTRONIC INSTR.	54.9	54.5	53.7	53.5	SEMICONDUCTORS	95.7	95.1	95.1	95.1
ENTERTAINMENT	59.4	59.4	59.4	59.4	SOFT DRINKS NON ALC.	52.0	52.0	52.0	52.0
FINANCIAL	27.7	27.8	26.5	27.0	TOBACCO	63.2	63.2	63.2	63.2
FOOD CHAINS RETAIL	60.1	59.9	59.8	59.3	TRANSPORT	99.6	98.6	94.7	94.6
HOSPITAL SUPPLIES	47.1	47.1	47.1	47.1	TRUCKER TRANSP.	61.5	61.5	61.5	61.5
INSURANCE MULTILINE	47.0	47.0	47.0	47.0	SP500	-	-	-	-

Sample: 1976q1-1997q3. Source: Standard and Poor's *Analysts Handbooks*. Computations executed with E-views 4.0. The variables are entered in the VAR as in equation 4 in the text above and the shocks are identified employing a Cholesky triangular structure.

Table 3: Estimation of the CAPM hypothesis: betas and variability explained by the regressions

Industry	Beta coeff	Std. Error	t-Statistic	Adj R-sq	Industry	Beta coeff	Std. Error	t-Statistic	Adj R-sq
AEROSP. DEFENCE	1.169	0.121	9.687	0.516	INSURANCE PROPERTY	0.833	0.096	8.718	0.463
ALLUMINIUM	0.765	0.131	5.818	0.274	INTEGR. DOMESTICS	0.848	0.116	7.338	0.378
AUTOMOBILES	0.873	0.142	6.131	0.296	METAL AND GLASS CONF.	0.662	0.100	6.645	0.331
BANKS	1.159	0.110	10.521	0.558	NAT. GAS PIPELINES	0.754	0.160	4.709	0.196
BREWERS AND ALCOOL	0.833	0.090	9.207	0.490	PAPER CONFECT	1.300	0.119	10.892	0.575
BUILD. MATERIALS	1.080	0.124	8.746	0.464	PAPER FOREST	1.045	0.100	10.421	0.553
CHEMICALS AND COAL	1.016	0.078	13.100	0.662	PUBLIC UTILITIES	0.538	0.062	8.615	0.457
COMPOSITE OIL	1.034	0.108	9.588	0.511	PUBLISHING FOREST	1.774	0.151	11.740	0.611
DEPT. STORE RETAIL	1.450	0.117	12.439	0.639	PUBLISHING NEWSP.	0.958	0.102	9.390	0.500
ELECRICAL EQUIPMENT	1.393	0.087	15.957	0.745	RESTAURANTS	0.869	0.104	8.348	0.441
ELECTRIC POWER COMF	1.015	0.129	7.850	0.411	RETAIL COMP.	0.814	0.127	6.416	0.316
ELECTRONIC INSTR.	0.373	0.078	4.792	0.201	SEMICONDUCTORS	0.886	0.294	3.012	0.085
ENTERTAINMENT	1.006	0.113	8.881	0.472	SOFT DRINKS NON ALC.	1.243	0.103	12.028	0.623
FINANCIAL	1.024	0.080	12.761	0.650	TOBACCO	1.803	0.190	9.499	0.506
FOOD CHAINS RETAIL	0.855	0.094	9.110	0.485	TRANSPORT	0.728	0.230	3.162	0.093
HOSPITAL SUPPLIES	0.918	0.096	9.517	0.507	TRUCKER TRANSP.	0.926	0.134	6.886	0.348
INSURANCE MULTILINE	0.850	0.102	8.300	0.438	SP500	-	-	-	-

	Value	Prob.
System log-Likelyhood	3910.5	-
LR test of diagonality of the var-cov matrix	1951.8	0.000
Wald test for equality of the alpha coefficients	1200.8	0.000
Wald test for equality of the beta coefficients	186.5	0.000
Wald test for unit betas	222.7	0.000

Sample: 1976q1-1997q3. Source: Standard and Poor's *Analysts Handbooks*. Computations executed with E-views 4.0. Method: SURE

Table 4 A summary of the firm-level data, by industry and period. Average values

Variable	whole	agricolture	textile	pharma	computer	biotech
ID. RISK	0.122	0.190	0.156	0.148	0.167	0.181
ID. RISK 74-83	0.094	0.218	0.141	0.120	0.139	0.154
ID. RISK 84-93	0.114	0.161	0.133	0.143	0.158	0.174
ID. RISK 94-03	0.158	0.191	0.197	0.185	0.209	0.218
R&D/Sales %	5.5%	1.8%	0.9%	5.4%	14.6%	4.7%
R&D/Sales 74-83 %	2.8%	1.2%	0.3%	4.1%	6.8%	1.3%
R&D/Sales 84-93 %	6.1%	3.3%	0.5%	4.6%	17.0%	5.0%
R&D/Sales 94-03 %	7.8%	0.7%	2.1%	7.6%	20.5%	8.2%
No of Firms	822	27	74	232	112	377

Source: Standard and Poor's *Compustat* database.

Table 5 Estimation results for the selected model and specifications

				Dependent variable: IR					
Sample	Model	Spec.	Variable	Coefficient	Std Error	t-Statistic	Prob.	*R-sq within*	*R-sq betw.*
Whole	M1	FE	$const.$	0.1297	0.001	123.06	0.000	*0.0009*	*0.0282*
			RDS	0.006	0.003	2.34	0.018		
Whole	M2	FE	$const.$	0.131	0.001	98.20	0.000	*0.0016*	*0.0801*
			RDS	0.006	0.003	2.34	0.018		
			MS	-0.089	0.045	-1.97	0.049		
TEX	M1	RE	$const.$	0.105	0.007	15.78	0.000	*0.0518*	*0.3269*
			RDS	0.571	0.065	8.73	0.000		
TEX	M2	RE	$const.$	0.108	0.006	18.00	0.000	*0.0539*	*0.3322*
			RDS	0.573	0.065	8.82	0.000		
			MS	-0.119	0.076	-1.57	0.117		
AGR	M1	RE	$const.$	0.118	0.011	10.59	0.000	*0.0131*	*0.0144*
			RDS	-0.030	0.031	-0.96	0.338		
AGR	M2	RE	$const.$	0.128	0.011	11.87	0.000	*0.0048*	*0.2137*
			RDS	-0.034	0.030	-1.12	0.265		
			MS	-0.222	0.075	-2.96	0.003		
BIO	M1	RE	$const.$	0.169	0.003	62.54	0.000	*0.0011*	*0.0506*
			RDS	0.014	0.005	3.05	0.002		
BIO	M2	RE	$const.$	0.169	0.003	62.54	0.000	*0.007*	*0.1028*
			RDS	0.012	0.006	2.15	0.045		
			MS	-0.430	0.052	-8.29	0.000		
PHA	M1	FE	$const.$	0.109	0.002	47.22	0.000	*0.0074*	*0.1191*
			RDS	0.008	0.002	3.65	0.000		
PHA	M2	FE	$const.$	0.112	0.003	41.56	0.000	*0.009*	*0.2061*
			RDS	0.008	0.002	3.57	0.000		
			MS	-0.283	0.171	-1.66	0.098		
COMP	M1	RE	$const.$	0.142	0.007	21.85	0.000	*0.0035*	*0.0795*
			RDS	0.019	0.006	2.92	0.003		
COMP	M2	RE	$const.$	0.144	0.006	22.44	0.000	*0.0052*	*0.1376*
			RDS	0.019	0.006	2.94	0.003		
			MS	-0.150	0.063	-2.40	0.016		

Sample: 1974-2003. Source: Standard and Poor's *Compustat* database. Computations executed with Stata 8.

APPENDIX

Table A1

Intensity of R&D expenditure by sector: time average 1980-1992

	INDUSTRY	R&D
HIGH	Aerospace	18.9
	Computers	15.5
	Pharmaceuticals	11.3
	Electronics and telecoms	10.8
	Other transport	8.1
	Instruments	7.2
MED-HIGH	Motor vehicles	4.4
	Chemicals	2.8
	Electrical Machinery	2.7
MEDIUM	Non-electrical machinery	1.7
	Other manufacturing	1.3
	Petroleum	1.3
	Building materials	1.2
	Rubber and plastics	1.2
	Non-ferrous metals	0.8
	Metal products	0.6
	Ferrous metals	0.5
MED-LOW	Paper and printing	0.3
	Food and Tobacco	0.3
	Wood and wood products	0.2
	Textiles	0.2
	TOTAL MANUFACTURING	3.1

source: Marsili (2001), Table 6.2

Level of technological opportunity by industry in the worlds largest fir

	Product group	**Factor**	*Rank R&D int.*	*Rank patent int.*	*Rank % FG pat.*
HIGH	Instruments (photo&)	2.2	*4*	*1*	*2*
	Computers	1.72	*2*	*5*	*1*
	Pharmaceuticals	1.29	*1*	*3*	*5*
	Electrical-electronics	1.19	*3*	*2*	*3*
MED-HIGH	Chemicals	0.25	*7*	*4*	*7*
	Motor vehicles	0.18	*6*	*10*	*4*
	Aircraft	-0.04	*5*	*7*	*12*
MEDIUM	Rubber	-0.4	*8*	*9*	*10*
	Textiles	-0.4	*10*	*11*	*6*
	Machinery	-0.44	*9*	*6*	*15*
MED-LOW	Building materials	-0.56	*11*	*8*	*13*
	Paper and wood	-0.67	*15*	*15*	*8*
	Drink and tobacco	-0.81	*17*	*16*	*9*
	Other transport	-0.85	*12*	*12*	*16*
	Food	-0.87	*14*	*17*	*11*
	Mining and petroleum	-0.87	*16*	*13*	*14*
	Metals	-0.92	*13*	*14*	*17*

Source: Marsili (2001), Table 6.7

Table A2 Industrial classification based on R&D Intensity (source EC, 1996, Green Paper on Innovation)

HIGH	MEDIUM HIGH	MEDIUM LOW	LOW
SEMI CONDUCTORS	AUTOMOBILES	TRUCKER TRANSPORT	SOFT DRINKS AND NON ALCH
AEROSPACE AND DEFENCE	ELECTRICAL EQUIPMENT	BUILDING MATERIALS	TOBACCO
ELECTRONIC INSTRUMENTS	CHEMICALS AND COAL	TRANSPORT	PAPER CONFECTIONERY
		COMPOSITE OIL	METAL AND GLASS CONFECT
			PAPER FOREST PRODUCT
			PUBLISHING FOREST PROD
			BREWERS AND ALCOHOLICS
			PUBLISHING NEWSPAPERS

Table A3: Model selection. Breush-Pagan and Hausman test results

Sample	Model	Breush-Pagan	Prob	Hausman	Prob	Spec
Whole	M1	4578.20	0.000	7.20	0.000	FE
Whole	M2	3478.60	0.000	36.18	0.008	FE
TEX	M1	226.90	0.000	0.75	0.386	RE
TEX	M2	230.80	0.000	0.65	0.724	RE
AGR	M1	64.79	0.000	1.83	0.176	RE
AGR	M2	7.18	0.007	2.60	0.273	RE
BIO	M1	410.03	0.000	4.06	0.091	RE
BIO	M2	231.04	0.000	2.95	0.299	RE
PHA	M1	1762.47	0.000	12.01	0.000	FE
PHA	M2	472.62	0.000	23.69	0.000	FE
COMP	M1	691.61	0.000	2.37	0.124	RE
COMP	M2	870.98	0.000	5.74	0.057	RE
Group Means	M2	20.59	0.000	3.54	0.171	RE

Note: “Group Means” indicates the sample obtained by averaging the firm-level data at the industry-level. Computations executed with Stata 8.

Table A4 Estimation results for the firm-level version of the CAPM

Method: FGLS Dependent variable: *R* (coeff) Variable	Coefficient	Std Error	t-Statistic	Prob.	*Rbar-sq*
(alpha) d_TEX	0.097	0.005	19.02	0.000	*0.84*
(alpha) d_AGR	0.107	0.012	9.20	0.000	
(alpha) d_BIO	0.136	0.003	40.43	0.000	
(alpha) d_PHA	0.111	0.003	36.97	0.000	
(alpha) d_COMP	0.118	0.005	25.91	0.000	
(beta) RSP500_TEX	0.850	0.116	7.33	0.000	
(beta) RSP500_AGR	1.120	0.270	4.15	0.000	
(beta) RSP500_BIO	1.542	0.065	23.62	0.000	
(beta) RSP500_PHA	1.034	0.064	16.21	0.000	
(beta) RSP500_COMP	1.007	0.102	9.90	0.000	

	Value	Prob.
Wald test of equality of the alpha coefficients	52.44	0.000
Wald test of unit beta coefficients	46.93	0.000
Wald test of unit beta coefficients excluding BIO	2.17	0.537

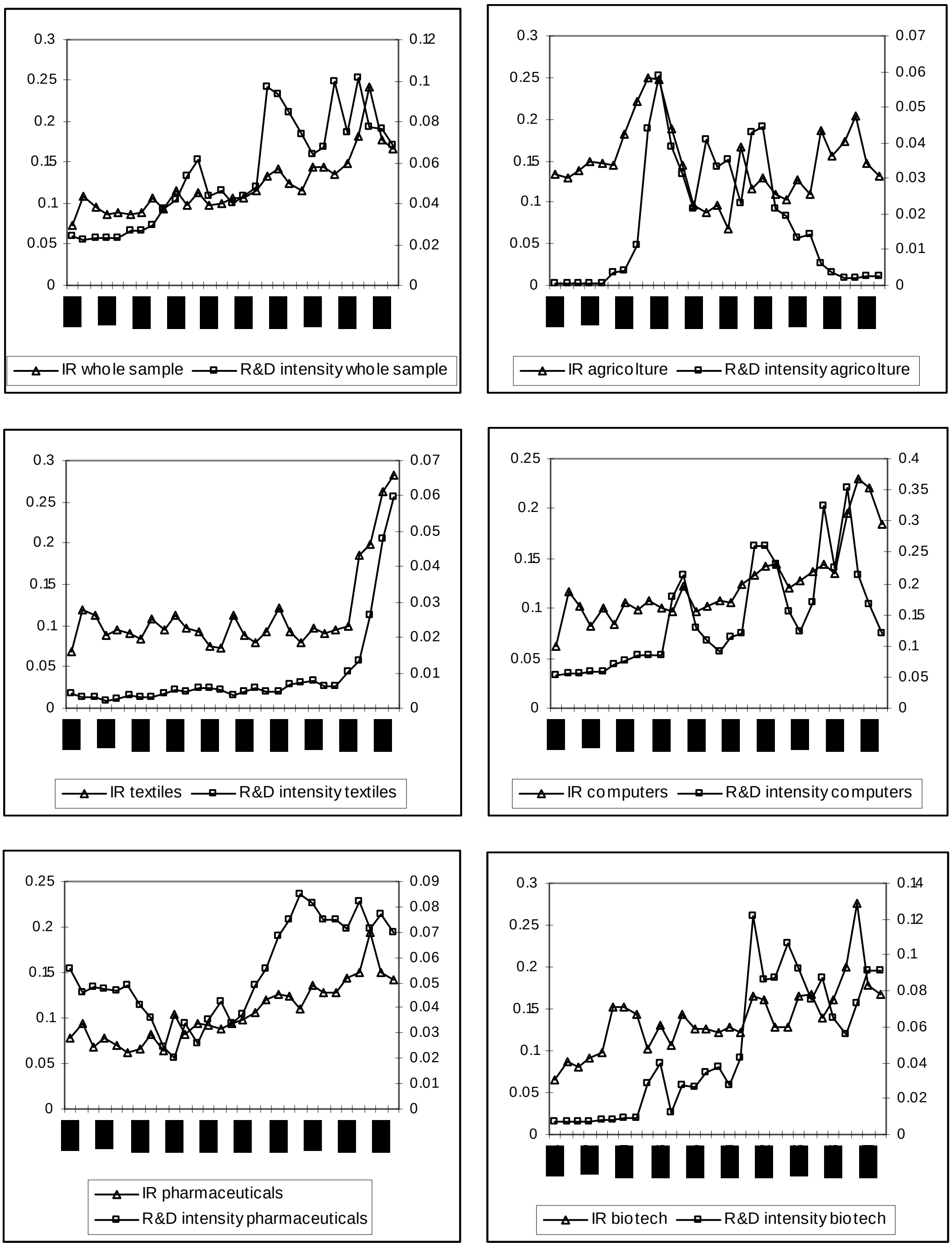
Sample: 1974-2003. Source: Standard and Poor's *Compustat* database. Computations executed with E-views 4.0

Table A5 Results for the industry-level idiosyncratic risk regression.

Method: RE-GLS Dependent variable: IR Variable	Coefficient	Std Error	t-Statistic	Prob.	*R-sq within*	*R-sq betw.*
$const.$	0.088	0.0144	6.11	0.000	*0.1876*	*0.1171*
RDS	0.379	0.071	5.34	0.000		
MS	1.511	0.936	1.61	0.114		

Sample: 1974-2003. Source: Standard and Poor's *Compustat* database. Computations executed with Stata 8

Figure A1 Idiosyncratic risk and R&D intensity 1974-2003 (S&P500, agriculture, textiles, computers, pharmaceuticals, and biotech)



Endnotes

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[i] Uncertainty in finance models appears through the analysis of the risk premia, i.e. the rewards that investors demand for bearing particular risks. In the basic asset pricing equation below (Eq. 1) uncertainty is embodied in the variable M: $P_{it} = E_t\left[M_{t+1}X_{i,t+1} \mid I_t\right]$ where Pit is the price of an asset i at time *t* (today); It is the conditional expectations operator conditioning on today's information i,t+1; Xi,t+1 is the random payoff on asset i at time t+1 (tomorrow); and Mt+1 is the stochastic discount factor (SDF), i.e. a random variable whose realizations are always positive. The inclusion of uncertainty in asset pricing models occurs through the SDF. If there is no uncertainty, then M is simply a constant that converts expected payoffs tomorrow into value today (Campbell 2000). This is the same as when investors are risk neutral. If instead uncertainty is high, then the mapping between expected payoffs into today's value is more complex.

[ii] *"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)

[iii] The relation between the level of a firms' stock price and stock price volatility has also been studied via the "leverage effect": a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity (Black, 1976; Christie, 1982). The relation is also captured by studies of time-varying risk premia which argue that a forecasted increase in return volatility results in an increase in required expected future stock returns and thus an immediate stock price decline (Pindyk, 1984 and others reviewed in Duffie, 1995)

[iv] They admit that this is a strong assumption but motivate it through the fact that a single shakeout is typical in the Gort and Klepper (1982) data and that particularly in the US tire industry there seems to have been one major invention, the Banbury mixer in 1916, which caused the shakeout to occur (Jovanovic and MacDonald, 1994, p. 324-325).

[v] Jovanovic and Greenwood (1999) also link stock prices to innovation by developing a model in which innovation causes new capital to destroy old capital (with a lag). Since it is primarily incumbents who are initially quoted on the stock market, innovations cause the stock market to decline immediately since rational investors with perfect foresight foresee the future damage to old capital. Hence the authors claim that the drop in market value of IT firms in the 1970's was due to the upcoming IT revolution (in the 1990's).

[vi] 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 below) 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.*

[vii] The more idiosyncratic risk there is the more assets must be included to achieve diversification.
[viii] For example, Lilien (1982) studies how increases in industry level volatility of productivity growth reduce output as resources are diverted from production to costly reallocation across sectors, and Cabballero and Hammour (1994) study "cleansing recessions" with reallocation of resources at the firm level. Related are also models which test the firm-level relation between volatility and investment (Leahy and Whited, 1996).

[ix] Evidence for (II) is found in the fact that the R sq. for the CAPM market model estimation have declined accordingly.

[x] Idiosyncratic risk is defined as the ratio between the volatility of firm-level returns over the volatility of market level returns volatility. The volatility of returns is obtained employing firm-level monthly information for calculating the standard deviations at the annual frequency.

[xi] The panel is *unbalanced* as firms are not always present in sample for the whole period 1974-2003.

[xii] Yet even for these low innovative industries, one must ask whether a longer time horizon would show that during the early evolution of these industries there was less correlation with the S&P500, as has been shown, for example, for the early evolution of automobiles in Mazzucato (2002).

[xiii] Formally, $FEV_{mnN} = \dfrac{\sum_{t=0}^{N}\left(\mathbf{e}'_m \mathbf{A}_t \mathbf{T} \mathbf{e}_n\right)^2}{\sum_{t=0}^{N} \mathbf{e}'_m \mathbf{A}_t \mathbf{\Sigma} \mathbf{A}'_t \mathbf{e}_m}$, where, *N* is the lead term (simulation horizon), **A** is the coefficient matrix for the MA representation of the VAR, **T** is a conformable triangular matrix such that $\mathbf{\Sigma} = \mathbf{TT}'$ (Cholesky or triangular decomposition) and **e** is a selection vector for the shocks.

[xiv] It is important to emphasize that this approach is not fully legitimate, given the perspective assumed here. First, because industry specificities may depend on factors that are loosely related to innovation, and the methodology cannot discriminate among them. Second, because quarterly observations are not the ideal reference time frequency upon which to base conclusive considerations on financial interrelations.

[xv] If errors are contemporaneously uncorrelated, i.e. $E\left(\boldsymbol{\varepsilon}_h \boldsymbol{\varepsilon}_k^{'}\right) = \mathbf{0}$, for $h \neq k$, or are contemporaneously correlated with $E\left(\boldsymbol{\varepsilon}_h \boldsymbol{\varepsilon}_k^{'}\right) = \sigma_{hk}\mathbf{I} \neq \mathbf{0}$ and $\mathbf{X}_h = \mathbf{X}_k$ for all h, k, there is no efficiency gain in employing a system estimation method (Zellner, 1962). Diversely, if errors are contemporaneously correlated and $\mathbf{X}_h \neq \mathbf{X}_k$ for some h and k, there are efficiency gains by estimating equation 3 as a system. Note that, for the scopes of this analysis, the matrix **X** contains the sectional binary dummies and the rates of return of the SP500 (RETSP500).

[xvi] The reference statistics is $LR = 2\left[\ell\tilde{\theta} - \sum_{h=1}^{n} \ell_h \tilde{\theta}_h^{OLS}\right]$, which is distributed as a χ^2 with $n(n-1)/2$ degrees of freedom.

[xvii] The Wald statistics for this hypothesis is 1200.7.

[xviii] The Wald statistics are equal to, respectively, 222.6 and 186.5.

[xix] The industries considered in the analysis are (in order from least to most innovative according to R&D intensity figures): agriculture, textiles, pharmaceutical, computers and biotechnologies.

[xx] We have already discussed in Section IV that the introduction of a variable accounting for the dimension of the firm is a reasonable choice, as the variability of returns depends also on the relative weight of the single firm respect to its sector, i.e. by its relative capitalization.

[xxi] Some suggestive indications on the behaviour of the two variables over time can be found in the appendix.

[xxii] The common coefficient model is a panel in which no fixed or random effects are employed as possible determinants of the cross-sectional variability. Results of this preliminary analysis can be obtained on request.

[xxiii] In other terms, the error can be decomposed in a noisy i.i.d. ε component and in a section-specific u component.

[xxiv] The Breusch and Pagan (1980) LM statistic tests whether the variance of individual effects in the error term is zero, hence it actually maintains the RE model under the null hypothesis.

[xxv] A detailed report of the specification selection tests is given in the appendix.

[xxvi] It is interesting to signal that the statistical significance of the dimension factor is weakened in the FE specifications, signalling the presence of substantial correlation with the systematic individual effects dummies.

[xxvii] Gambardella's (1995) analysis of the "random search" versus "guided search" phase of the pharmaceutical industry provides some insight into why there may be less uncertainty associated with high innovation. In what he calls the guided search phase of the pharma industry, dating more or less from the mid 1980's onwards, R&D intensity is high but radical advances in enzymology, biotechnology and computational ability made the search process more "guided" resulting in more scale economies and path-dependency, and less uncertainty.