# Idiosyncratic Risk in Innovative Industries

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**Abstract**
The paper studies whether "idiosyncratic risk", i.e. the degree to which firm and industry specific returns are more volatile than aggregate market returns, is higher in innovative industries which are characterized by more risk and uncertainty. Volatility is studied both at the industry level (for 34 different industries from 1974-2003) and at the firm level (for 5 industries with different levels of innovativeness: biotech, pharmaceuticals, computers, textile, agriculture). Findings are mixed. A relationship between innovation and volatility emerges most strongly with firm level data, when firm dimension is accounted for, and when time varying volatility is explicitly studied via GARCH analysis. The latter highlights the distinctive behavior of returns during the course of the industry life-cycle.

**Key words:** idiosyncratic risk, volatility, innovation, industry life cycle.

**JEL Classification** G12 (Asset Pricing); L11 (Market Structure: Size Distributions of Firms), 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. The central idea is that since innovation is a risky and uncertain process, and since asset pricing is a function of the stochastic discount factor which incorporates firm level risk, the behavior of returns of innovative firms should be different from that of non-innovative firms.

By positing a relationship between changing patterns of innovation and changing patterns of firm and industry specific volatility, the study provides the foundations for an analysis of time-varying risk premium which emphasizes *real* changes in production. This lies in contrast with volatility studies which place emphasis on stochastic factors (e.g. herd effects and animal spirits in Shiller 1981) and/or on aggregate economic characteristics (e.g. aggregate consumption patterns in Campbell and Cochrane 1995). The results provide new insights on the relationship between risk, innovation and volatility, of potential interest to both industrial economists and finance economists.

The paper is organized as follows. Section II reviews the literature on idiosyncratic risk and situates the present work within that body. Section III reviews some stylized facts about what we know about inter-sectoral patterns of innovation and hypothesizes how these patterns might relate to different patterns of stock price volatility. It also reviews results from a related study which finds that stock price "excess volatility" (Shiller, 1981) and "idiosyncratic risk" in specific industries (autos and computers) were highest during the decades in which innovation was most "radical" and "competence-destroying". Sections IV-VI evaluate volatility employing econometric tools (e.g. VAR, G/ARCH) on industry level data (Section V) and firm level data (Section VI) to see whether this result can be generalized, i.e. whether firms and industries with different levels of innovativeness have different patterns of idiosyncratic risk. The methodology is similar to that used in Campbell et al. (2000). Section VII uses panel estimation procedures to test this relationship more directly using firm level data on R&D intensity. Section VIII summarizes the main results.

## II. Uncertainty and Idiosyncratic Risk

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

Modelling of uncertainty in finance models occurs 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:

$$P_{it} = E_t\left[M_{t+1} X_{i,t+1} \mid I_t\right] \qquad (1)$$

where Pit is the price of an asset i at time *t* (today); Et 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.

Uncertainty in models of finance is principally about the variance of *expected* future profits and/or growth. This can be caused by changes in consumer tastes, technology or institutions. Some models of uncertainty emphasize the variance of some aspect of the firm's environment (e.g. GDP) and others emphasize the co-variances in the returns between investment projects[1]. The role of the co-variances is the focus of the Capital Asset Pricing Model which measures risk by the covariance of a firm's returns and the returns of the general market (e.g. S&P 500). According to CAPM, there is a positive relationship between risk and the required rate of return on an investment. Since asset returns capture, at least in theory, the effects of any aspect of a firm's environment, uncertainty can be measured by the variance of firm level stock returns.

Given the inability of the efficient market model (EMM) to reproduce the real volatility of stock returns with a constant discount rate (Shiller, 1981 and 2000, and for connections with IO literature see Mazzucato 2002), finance economists have for a long time been interested in modelling time varying risk premia, often making it a function of some exogenously changing macro variable. For example, if it is assumed that the economy has a representative agent with a well-defined utility function, then the stochastic discount factor can be related to the marginal utility of aggregate consumption—calculated using time series of aggregate consumption (Campbell and Cochrane 1995).

While it is appropriate to use such aggregate series to understand aggregate volatility, the study of firm and industry specific risk requires understandings of risk and uncertainty at the level of the firm and industry. Since innovation is one of the main sources of such uncertainty—through its disruptive effect on market structure and future growth potentials—finance studies could greatly benefit from analyses of how innovation behaviour differs across industries and across time. The paper contributes to this objective by testing whether volatility of stock returns differ systematically

[1] The effect of uncertainty on the incentive to invest depends on the assumption of the convexity or concavity of the marginal revenue product.

in industries and periods in the industry life-cycle that are characterised by different innovation dynamics.

Idiosyncratic risk measures the degree to which firm level volatility differs from aggregate market level volatility, where the latter is in most cases taken to be the S&P 500 index. It is an element of price risk that can, in theory, be largely eliminated by diversification within an asset class[2]. In factor models estimated by regression analysis, it is equal to the standard error. It is sometimes called security specific risk or unsystematic risk. In a regression of a firm's (or industry's) return against the market level return, the *beta* in the CAPM model captures this idiosyncratic component: the higher is beta, the higher is the covariance between the two returns hence the lower is the idiosyncratic component of risk and the higher is the systematic component.

Why do economists care about idiosyncratic risk? Financial economists are interested in idiosyncratic risk for various reasons outlined in Campbell et al (2000): (1) the effect it has on aggregate volatility; (2) the information it provides to investors who want to diversify their portfolio; (3) the effect that it has on pricing *errors*; and (4) the effect it has on the price of options. The current study adds a 5th reason to this list: the study of idiosyncratic risk at the industry level and with a focus on its relation to innovation dynamics provides important insights on the time varying dimension of risk and how it is related not only to stochastic and exogenous factors but also to structural changes in production conditions.

When analyzing the variance of stock returns it is important to distinguish the shocks to expected future cash flows, discounted at a constant rate, and shocks to the discount rates themselves. Stock returns are driven by both, unless one believes that they are driven completely by bubble behavior, e.g. by herd behavior and fads. Random walk models of stock prices imply that stock returns are driven completely by shocks to expected future cash flows.

In this paper we do not enter the debate on whether stock prices follow a random walk or not (Mazzucato 2003). We start from the presumption that innovation does indeed cause more uncertainty and shocks to expected future cash flows and study whether those firms and industries which are more innovative are in fact characterized by more idiosyncratic risk. In doing so it provides insights on how empirical regularities about innovation, such as sectoral differences in innovation behavior (Pavitt 1984) and the evolution of innovation over the industry life-cycle (Klepper 1996), can provide insights on the time varying dynamics of idiosyncratic risk.

[2] The more idiosyncratic risk there is the more assets must be included to achieve diversification.

There are very few industry level studies of volatility. The few that exist focus on the reallocation of resources across sectors. [3] 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—due, for example, to the IT revolution and dynamics related to the New Economy. They use high-frequency (daily) time series data on daily stock returns for the general market, industries and firms during the period 1963-1997. The approach is both descriptive and analytic. The chosen measure for volatility is the sample variance calculated on a monthly base. While the industry level data is inconclusive, the firm level data confirms the hypothesis of increased idiosyncratic risk. 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[4];
3. evidence that volatility moves counter-cyclically and tends to lead variations in GDP.

In the conclusion of their study, 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 the empirical validity of these effects as well as their inconclusive causation. For example, while improved information might increase the volatility of 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). It is this effect—the life-cycle effect—that provides the motivation for the present paper. Since innovation tends to be more radical during early industry evolution when there are more technological opportunities available, we test the hypothesis whether idiosyncratic risk is higher in new and/or

[3] 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).

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

high-tech industries (e.g. biotechnology). Before reviewing the model, we first consider some reasons why innovation and stock price volatility might be related.

## III. Innovation and Idiosyncratic Risk

Both Frank Knight (1921)—an early pioneer of risk theory—and John Maynard Keynes distinguished risk from uncertainty. They argued that while a risky event can be evaluated via probabilities based on priors (e.g. a lottery), an uncertain event cannot be since a truly uncertain situation is "unique" [5]. Both economists used technological innovation as an example of true uncertainty.

Innovation is an uncertain process both from the point of view of the process by which it comes about and its outcome. Reasons for this include: (1) knowledge evolves in a *tacit non-codifiable* manner, embodied in firm-specific capabilities and competencies (Nelson and Winter, 1982); (2) innovation is an outcome of the complex interaction between firm-specific capabilities and institution like scientific institutions (Nelson 1993); (3) innovations cause changes to the status quo, rendering knowledge in the current period not a good predictor of knowledge in the next period (Cohen and Levinthal 1989); (4) the fact that innovators might be incumbents (as is often the case for incremental innovations) or a new entrants (as is often the case for radical innovations) means that the effect on market structure is uncertain; and (5) investment in the innovation process does not always lead to an actual innovation (as is evidenced by recent data on the pharmaceutical industry).

The relationship between innovation and stock prices is determined by the effect of these types of uncertainty on stock prices. Innovation often (not always) causes a shake-up of market shares, diminishing the power of the incumbents who have an invested interest in the status quo. In this situation, current performance is not a good indicator of future performance. Hence, it is especially in such unstable periods that investors will be more likely to be influenced by the speculation of other investors, leading to herd effects and the type of over-reactions emphasized by Campbell and Shiller (1981) in their analysis of excess volatility.

There are not many studies which link stock price dynamics to innovation. Jovanovic and MacDonald (1994) make predictions concerning the evolution of the average industry stock price 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

[5] *"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)

shakeout occurs as a result of one major refinement to that invention.[6] 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.

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).

Although both these papers connect innovation to the evolution of stock prices, they focus on the *level* of stock prices not on the *volatility* of stock prices[7]. One well known 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 (i.e. the underlying fundamentals that they are supposed to be tracking according to the efficient market model), peaks precisely during the second and third industrial revolutions. However, the link between volatility and uncertainty is better studied at the level of the firm since this allows it to be related to the firm's environment. The fact that most shocks are idiosyncratic to the firm or plant makes this imperative (Davis and Haltiwanger, 1992)

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. They find that both idiosyncratic risk and excess volatility were highest precisely during the periods in which innovation in these industries was the most radical (using quality change data in Filson 2001)[8]. This was also the period in which market shares were most unstable—due to the "destruction" of incumbents' advantages after "creative" innovations.

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[6] 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).

[7] 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)

[8] 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-

In this paper we ask whether these results can be generalized to different industries. To posit a (hypothetical) mapping between sectoral stock price dynamics and sectoral innovation dynamics we make use of the literature on sectoral taxonomies of innovation (Pavitt 1984, Marsili 2001) and the literature on the industry life-cycle (Gort and Klepper 1982; Klepper 1996). These works provide insights into how innovation processes and outcomes differ between industries/sectors and between different periods in industry evolution[9].

**IV. Methodology**

Like Campbell et al. (2000) we study idiosyncratic risk across different firms and industries. In particular, we study the aggregate behavior of 34 industries and, at the firm level, the evolution of 5 particular industries. Our aim is test whether the more innovative industries are characterized by more excess volatility and idiosyncratic risk. We first study quarterly data on industry level stock returns for the period 1976-1997. Later, the analysis is extended to the firm level, employing monthly data for the period 1981-2003 on 34 firms belonging to 5 industries with different levels of innovativeness (biotechnologies, computers, pharmaceuticals, textiles and agriculture).

The 34 industries included in the industry level analysis are listed in Table 1 below. The 5 different industries for which monthly firm level data is analyzed between 1981 and 2003 are:

1. Biotechnology (very innovative)
2. Pharmaceutical (innovative)
3. Computers (innovative)
4. Textile (low innovative)
5. Agricultural (low innovative)

Using R&D intensity data, we have divided these industries into 'very innovative', 'innovative' and 'low innovative'. This classification is confirmed by the sectoral taxonomy of innovation found in the (Marsili, 2001). The industry level data comes from Standard and Poor's

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foresight price, $D_{t+k}$ is the dividend stream, $\gamma_{t+j}$ 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.*

[9] Pavitt's (1984) sectoral taxonomy of innovation categorizes sectors by the way that innovation is introduced (e.g. via suppliers, via scale, via science), by the type of innovating firms (large, small), and by the type of innovation (product vs. process). Gort and Klepper (1982) and Klepper (1996) emphasize how innovation dynamics change during the course of industry evolution: innovation during the early stage tends to be more product oriented and radical, while innovation in the mature phase is more process oriented, incremental and led by large firms. Other authors have divided sectors and/or periods of sectoral evolution into Schumpeter Mark I and II, where Mark I (II) represents industries with high (low) entry, less (more) persistence in firms' ability to innovate, and a more codifiable (tacit) knowledge base (Malerba and Orsenigo, 1996). For example, chemicals falls more into Mark II while mechanical engineering falls more into Mark I. Likewise, the early auto industry falls more into Mark I while the mature phase of autos falls more into Mark II.

*Analysts Handbooks* while the firm level data comes from Standard and Poor's *Compustat* database.

As stated above, we are interested in linking differences in volatility and hypothesized differences in innovation. In line with other studies of idiosyncratic risk (Campbell et al. 2000), the volatility of firm and industry returns is compared with market returns (S&P 500 index). For both the industry level and firm level data, we analyze volatility using the following methods: basic descriptive statistics of the standard deviations; deterministic and stochastic trend analysis of volatility; Granger causality analysis to see whether the general market returns have predictive capabilities for the innovative industries and firms; variance decomposition analysis to study the relative contributions of unit-specific and unspecific variances to the single units volatilities; and regression analysis with the CAPM model to evaluate the degree to which the average market return explains the industry and firm level returns.

The higher frequency of the data in the firm-level analysis (monthly instead of quarterly) allows us to use GARCH methods to study time varying volatility. GARCH analysis allows a direct consideration of time varying volatility through the use of the ARCH/GARCH modeling strategy. Under the ARCH/GARCH model perspective, the variance of the series is directly modeled and the responsiveness to idiosyncratic shocks is evaluated by confronting the dimensions of the AR and MA terms in the variance equation.

**V. Industry level results**

This section contains the empirical evaluation of industry level stock returns. The approach adopted here is both descriptive and econometric. We briefly present the method, the expected results and the outcomes of the analysis.

**V.a. Descriptive statistics**

The descriptive analysis looks at the distributions of the different industry level time series. Information is given on specific max/min values and correlations between general market (SP500) returns and industry level rates of returns. 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. Table 1 contains some results for this first descriptive approach to the data.

**Table 1**
**Industry level stock return, descriptive statistics**

| Industry | Mean | Maximum | Minimum | Std. Dev. | Industry | Mean | Maximum | Minimum | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|
| TRANSPORT | 0.1007 | 3.4089 | -0.2685 | 0.3831 | FOREST PROD. PUBL. | 0.0690 | 0.3300 | -0.2166 | 0.1074 |
| SEMICONDUCTORS | 0.0768 | 1.6463 | -0.6776 | 0.2619 | HOSPITAL SUPPLIES | 0.0529 | 0.2607 | -0.1699 | 0.1064 |
| NAT. GAS PIPELINES | 0.0798 | 0.9588 | -0.3777 | 0.1502 | INSURANCE MULTIL. | 0.0669 | 0.2992 | -0.2170 | 0.1053 |
| BUILD. MATERIALS | 0.0674 | 0.4662 | -0.2613 | 0.1367 | FINANCIAL | 0.0705 | 0.3073 | -0.2450 | 0.1041 |
| ELECTRONIC INSTR. | 0.0480 | 0.5427 | -0.2612 | 0.1367 | FOOD CHAINS RETAIL | 0.0724 | 0.3119 | -0.1619 | 0.1014 |
| AUTOMOBILES | 0.0782 | 0.4403 | -0.2328 | 0.1331 | INSURANCE PROPERTY | 0.0752 | 0.2985 | -0.1443 | 0.1012 |
| TRUCKER TRANSP. | 0.0416 | 0.3759 | -0.2406 | 0.1275 | FOREST PROD. PAPER | 0.0599 | 0.3327 | -0.1864 | 0.1001 |
| BANKS NY | 0.0816 | 0.3975 | -0.2884 | 0.1251 | CHEMICALS AND COAL | 0.0684 | 0.3070 | -0.1955 | 0.0992 |
| DEPT. STORE RETAIL | 0.0666 | 0.4930 | -0.3635 | 0.1250 | INTEGR. DOMESTICS | 0.0678 | 0.3539 | -0.2083 | 0.0950 |
| AEROSP. DEFENCE | 0.0736 | 0.5037 | -0.3964 | 0.1246 | METAL AND GLASS CONF. | 0.0676 | 0.2514 | -0.2093 | 0.0946 |
| PAPER CONFECT | 0.0646 | 0.4118 | -0.2364 | 0.1210 | BREWERS AND ALCOOL | 0.0573 | 0.2766 | -0.1325 | 0.0940 |
| ENTERTAINMENT | 0.0584 | 0.3630 | -0.2835 | 0.1196 | SOFT DRINKS NON ALC. | 0.0758 | 0.2685 | -0.1836 | 0.0926 |
| ALLUMINIUM | 0.0593 | 0.4188 | -0.2328 | 0.1193 | ELECRICAL EQUIPMENT | 0.0643 | 0.2536 | -0.2529 | 0.0870 |
| TOBACCO | 0.0930 | 0.3754 | -0.2496 | 0.1177 | COMPOSIT OIL | 0.0790 | 0.2893 | -0.1575 | 0.0800 |
| RETAIL COMP. | 0.0523 | 0.2879 | -0.3449 | 0.1145 | ELECTRIC POWER COMP. | 0.0992 | 0.3333 | -0.0794 | 0.0740 |
| PUBLISHING NEWSP. | 0.0629 | 0.4078 | -0.2308 | 0.1128 | SP500 | 0.0657 | 0.2390 | -0.2049 | 0.0713 |
| RESTAURANTS | 0.0525 | 0.2843 | -0.2503 | 0.1081 | PUBLIC UTILITIES | 0.0930 | 0.2724 | -0.0650 | 0.0684 |

Evidence in favor of the expected results is found only for transports, semi-conductors and, to a minor extent, for electronic instruments. More traditional but innovative industries signaling high variability are automobiles and other vehicles industries. The natural gas pipelines and building materials industries, even if not strictly innovative according to the tables in the appendix, show high sample means and variability. At the bottom, low variability and levels are signaled for more traditional and low innovative industries such as public utilities, electric power companies, oil, electrical equipment, food chains and beverage (alcoholic and non alcoholic) industries. Hence, the evidence from the descriptive analysis is rather mixed. Expectations appear satisfied only at the very extremes of the taxonomy.

In the attempt to achieve more clear-cut conclusions, we conduct variance tests of equality. We expect to obtain a figure of global heterogeneity particularly in the volatility measures, with stronger results for the innovative industries. Persistent rejections of the pair wise variance equality hypothesis are expected when the reference term is the general market stock returns series. The equality tests employed are the ones from Bartlett, Levene and Brown-Forsythe.

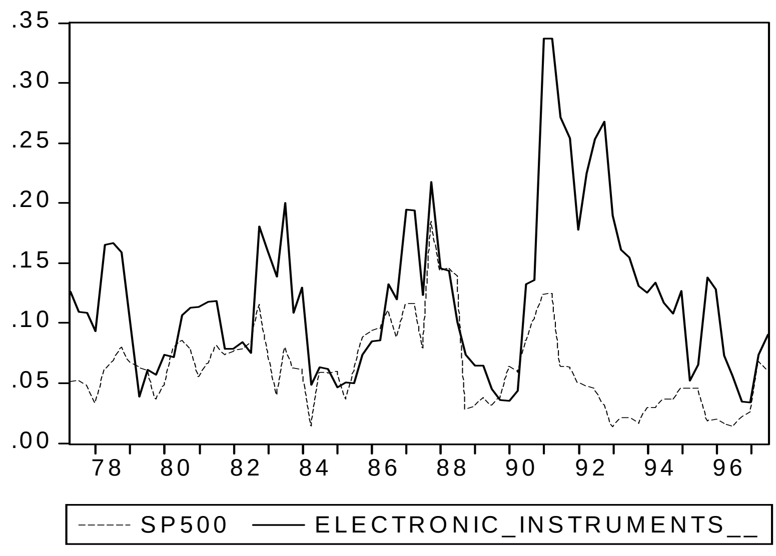
The evidence of global heterogeneity results strongly, independently of the test statistic employed. Also, different variance equality tests[10] between couples of series strongly reject the null hypothesis of homogeneity in all the high and mid innovative industries except the transport sector, for which a surprising (but weak) equivalence in variability appears established under the Levene (1960) and Brown-Forsythe (1974) formulations of the test.

The variance equality hypothesis is strongly accepted only for public utilities, electric power companies, the electric equipment and the oil sectors, all belonging to a low innovative-cluster.

Correlation analysis only partially corroborates our expectations, at least for the innovative industries. The smallest correlation with the S&P500 behavior is correctly signaled by the transport and semi-conductor industries (respectively 0.07 and 0.19), the others being all above the value of 0.25. The higher correlations are obtained, in line with the expectations, (but not strictly with the previous results) for chemicals and coal, paper and forest products, publishing, electrical and financial industries, all traditional, low-innovative industries and all above the value of 0.75.

The behavior of standard deviations (SD) over time, calculated as four terms (quarterly) moving averages of yearly SD, provides some general insight of the supposed excess volatility in innovative industries. Figs. 1-2 below show the SD dynamics for two particularly innovative industries: semiconductors and electrical instruments. Interestingly, in both cases, the periods of greatest volatility as compared to the S&P 500, are precisely in the periods which the case study literature on those industries identify as being particularly innovative periods (see Malerba 1985 for semiconductors, and Bresnahan 1998 for electrical instruments). That is, the mid 1980's for semiconductors and the 1990s for electrical instruments.

**Fgure 1**
**Standard deviations (moving averages)**

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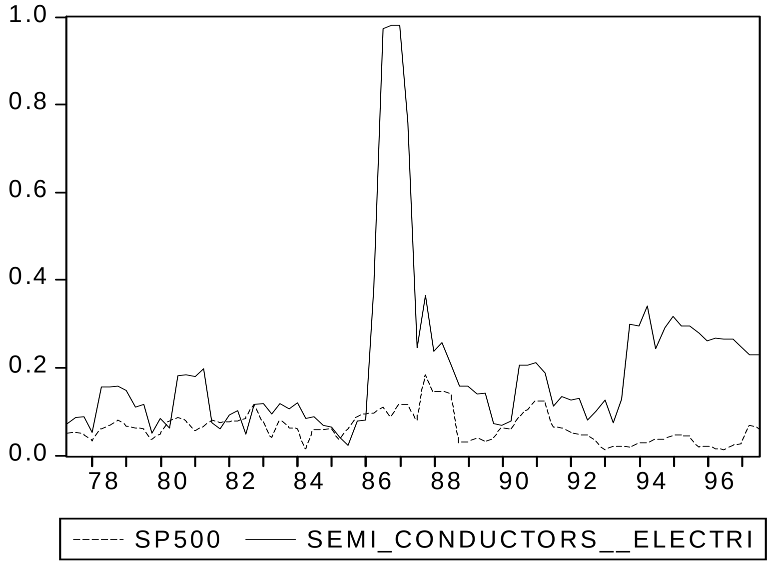
[10] The different formulations employed for the tests of equality of variances are the standard *F*-test, the Siegel-Tukey with continuity correction (Sheskin, 1997), the adjusted Bartlett statistic (Judge *et al.* 1985), the Levene test (1960) and the Brown-Forsythe (1974) test.

**Figure 2**
**Standard deviations (moving averages)**




**V.b. Descriptive statistics during different periods**

Given the added insight provided by the moving averages above, we look more into the time dimension of volatility by looking separately at different time periods for each of the industries.  The three sub-periods chosen are 1976-1983, 1983-1990, 1990-1997.  Table 2 illustrates the changes in ranking between industries by most volatile to least volatile during the three different periods.  We see that each period has a different ranking, although semiconductors appears first in both the second and third periods (and first in the first period).  Almost all the industries are more volatile than the composite S&P500 index in each of the three periods, with the S&P500 coming out *least* volatile in the third period.  This last result would in fact make it appear that idiosyncratic risk at the level of the industry did in fact increase over time as is maintained in Campbell et al. (2000).  However, as with the previous tests, the results seem quite mixed and make most sense for the industries in the extreme of the categorization (e.g. semiconductors, transports and electrical instruments). We come back to this result in section VII where we study changes in volatility using a panel data estimation model that includes R&D intensity as an independent variable.

**Table 2**

**Changes in rank by standard deviation**

| 1976-1983 | | 1983-1990 | | 1990-1997 | |
|---|---|---|---|---|---|
| TRANSPORT | 0.555272 | SEMI_CONDUCTORS__ELECTRI | 1.331324 | SEMI_CONDUCTORS__ELECTRI | 3.109713 |
| TRUCKER__TRANSPORT_01 | 0.074598 | DEPT_STORE__RETAIL_01 | 0.073531 | SOFT_DRINKS_AND_NON_ALCH | 1.57723 |
| SEMI_CONDUCTORS__ELECTRI | 0.059955 | BANKS__NY__AMP01 | 0.072827 | NATURAL_GAS_PIPELINES01 | 0.161014 |
| AUTOMOBILES | 0.058785 | AEROSPACE_AND_DEFENCE01 | 0.07177 | ELECTRONIC_INSTRUMENTS__ | 0.106181 |
| AEROSPACE_AND_DEFENCE01 | 0.055963 | BUILDING_MATERIALS01 | 0.071655 | TOBACCO | 0.080668 |
| BUILDING_MATERIALS01 | 0.053241 | ENTERTAINMENT__ENTERT_AN | 0.066644 | AUTOMOBILES | 0.077009 |
| ELECTRONIC_INSTRUMENTS__ | 0.05323 | PAPER__CONFECTIONERY_01 | 0.054377 | TRUCKER__TRANSPORT_01 | 0.0722 |
| PUBLISHING__NEWSPAPERS_0 | 0.050872 | AUTOMOBILES | 0.054216 | BUILDING_MATERIALS01 | 0.070122 |
| NATURAL_GAS_PIPELINES01 | 0.047128 | TOBACCO | 0.051932 | PAPER__CONFECTIONERY_01 | 0.06755 |
| ALLUMINIUM | 0.045563 | RETAIL_COMPOSITE01 | 0.044611 | HOSPITAL_SUPPLIES01 | 0.065696 |
| RESTAURANTS | 0.041225 | FINANCIAL | 0.042419 | ALLUMINIUM | 0.058074 |
| DEPT_STORE__RETAIL_01 | 0.040345 | ALLUMINIUM | 0.039866 | INSURANCE__MULTILINE_01 | 0.05075 |
| INTEGRATED_DOMESTIC01 | 0.038554 | PUBLISHING__FOREST_PRODU | 0.038194 | RETAIL_COMPOSITE01 | 0.049765 |
| CHEMICALS__CHEM_AND_COAL | 0.037234 | PUBLISHING__NEWSPAPERS_0 | 0.036728 | METAL_AND_GLASS__CONFECT | 0.049673 |
| PUBLISHING__FOREST_PRODU | 0.036225 | RESTAURANTS | 0.035519 | BANKS__NY__AMP01 | 0.042466 |
| ENTERTAINMENT__ENTERT_AN | 0.035521 | INSURANCE__MULTILINE_01 | 0.034177 | DEPT_STORE__RETAIL_01 | 0.038836 |
| PAPER__FOREST_PRODUCT_01 | 0.034622 | TRUCKER__TRANSPORT_01 | 0.032235 | FOOD_CHAINS__RETAIL_01 | 0.038654 |
| RETAIL_COMPOSITE01 | 0.033912 | HOSPITAL_SUPPLIES01 | 0.02607 | INSURANCE__PROPERTY_01 | 0.03648 |
| INSURANCE__PROPERTY_01 | 0.032948 | CHEMICALS__CHEM_AND_COAL | 0.025641 | PAPER__FOREST_PRODUCT_01 | 0.032258 |
| BANKS__NY__AMP01 | 0.032902 | TRANSPORT | 0.025231 | FINANCIAL | 0.031021 |
| BREWERS_AND_ALCOOLICS__B | 0.027502 | SOFT_DRINKS_AND_NON_ALCH | 0.024981 | RESTAURANTS | 0.029783 |
| FOOD_CHAINS__RETAIL_01 | 0.02629 | ELECTRONIC_INSTRUMENTS__ | 0.024191 | ENTERTAINMENT__ENTERT_AN | 0.029018 |
| PAPER__CONFECTIONERY_01 | 0.026214 | FOOD_CHAINS__RETAIL_01 | 0.023654 | PUBLISHING__NEWSPAPERS_0 | 0.027596 |
| INSURANCE__MULTILINE_01 | 0.021646 | BREWERS_AND_ALCOOLICS__B | 0.023278 | INTEGRATED_DOMESTIC01 | 0.021308 |
| COMPOSITE_OIL__OIL1_01 | 0.020669 | PAPER__FOREST_PRODUCT_01 | 0.021616 | ELECTR_POWER_COMP__UTILI | 0.020884 |
| METAL_AND_GLASS__CONFECT | 0.019989 | INSURANCE__PROPERTY_01 | 0.019874 | ELECTRICAL_EQUIPMENT__EL | 0.02033 |
| FINANCIAL | 0.019298 | ELECTRICAL_EQUIPMENT__EL | 0.01987 | TRANSPORT | 0.018335 |
| HOSPITAL_SUPPLIES01 | 0.018166 | INTEGRATED_DOMESTIC01 | 0.008686 | PUBLISHING__FOREST_PRODU | 0.018006 |
| ELECTRICAL_EQUIPMENT__EL | 0.013383 | NATURAL_GAS_PIPELINES01 | 0.008037 | CHEMICALS__CHEM_AND_COAL | 0.015391 |
| SP500 | 0 | METAL_AND_GLASS__CONFECT | 0.004168 | PUBLIC_UTILITIES01 | 0.014353 |
| TOBACCO | -0.000437 | SP500 | 0 | AEROSPACE_AND_DEFENCE01 | 0.012317 |
| ELECTR_POWER_COMP__UTILI | -0.001617 | COMPOSITE_OIL__OIL1_01 | -0.005905 | BREWERS_AND_ALCOOLICS__B | 0.009579 |
| SOFT_DRINKS_AND_NON_ALCH | -0.003019 | ELECTR_POWER_COMP__UTILI | -0.011679 | COMPOSITE_OIL__OIL1_01 | 0.00848 |
| PUBLIC_UTILITIES01 | -0.012124 | PUBLIC_UTILITIES01 | -0.012265 | SP500 | 0 |

## V.c. Trend analysis

Campbell et al. (2000) find some evidence of a (positive) trend in the individual firms stock returns variances. In order to check if this is the case for the industry level data (in particular for the innovative industries), we employ a battery of DF-ADF tests on the industry level time varying SDs. All SDs are stationary except for the natural gas pipelines and the transport industries, and the presence of a deterministic trend is always rejected except for brewer and alcoholics, publishing, restaurants, trucker (transports), all low innovative industries, presenting statistically meaningful, but negative, trends. The presence of a unit root for the two “mature” industries, hence of nonstationarity in mean and variance, is due to the presence of two structural breaks in the series located, respectively in 1995 and 1982. The breaks in the SD series are potentially due to outliers, since the shocks appear to be quite local. When a dummy was introduced, and when the Perron-Ng (1996) test was employed, both the series resulted stationary, and no deterministic trend emerged. This evidence is consistent with the hypothesis of an almost stable variability over time at the industry level (Campbell et al. 2000). Akin to the results in Campbell et al. (2000), the trending hypothesis, conditional to the strategy adopted, is not confirmed at the industry level.

**Table 3**

**DF ADF tests on industry stock returns***

| | DF/ADF | | trend | | |
|---|---|---|---|---|---|
| | stat | prob | coeff | t-stat | prob |
| Aerospace and defence | -4.137 | 0.008 | -0.0004 | -1.591 | 0.116 |
| Alluminium | -3.929 | 0.015 | -0.0001 | -0.582 | 0.562 |
| Automobiles | -3.215 | 0.089 | -0.0001 | -0.642 | 0.523 |
| Banks (NY) amp | -4.021 | 0.012 | -0.0001 | -0.483 | 0.630 |
| Brewers and alcoolics (bev) | -3.594 | 0.037 | -0.0003 | -2.123 | 0.037 |
| Building materials | -4.324 | 0.005 | 0.0000 | -0.231 | 0.818 |
| Chemicals (chem and coal) | -3.768 | 0.023 | -0.0002 | -1.416 | 0.161 |
| Composite oil (oil1) | -3.464 | 0.050 | -0.0002 | -1.587 | 0.117 |
| Dept store (retail) | -3.963 | 0.014 | -0.0001 | -0.452 | 0.653 |
| Electronic instruments (electronics) | -4.180 | 0.007 | 0.0000 | -0.316 | 0.753 |
| Electrical equipment (electrical) | -3.797 | 0.022 | -0.0001 | -0.779 | 0.438 |
| Electr Power comp (utilities1) | -3.179 | 0.096 | 0.0001 | 0.333 | 0.740 |
| Entertainment (entert and fert) | -3.661 | 0.031 | -0.0002 | -1.016 | 0.313 |
| Financial | -3.924 | 0.015 | -0.0001 | -0.837 | 0.405 |
| Food chains (retail) | -3.353 | 0.065 | -0.0001 | -0.756 | 0.452 |
| Hospital supplies | -4.156 | 0.008 | 0.0001 | 0.544 | 0.588 |
| Insurance (property) | -3.685 | 0.029 | 0.0000 | -0.296 | 0.768 |
| Integrated domestic | -3.926 | 0.015 | -0.0002 | -1.391 | 0.168 |
| Metal and glass (confectionery) | -3.374 | 0.062 | -0.0001 | -1.129 | 0.262 |
| Insurance (multiline) | -4.820 | 0.001 | 0.0001 | 0.543 | 0.589 |
| Natural gas pipelines | -2.038 | 0.571 | 0.0003 | 1.202 | 0.234 |
| Paper (confectionery) | -4.226 | 0.006 | 0.0000 | 0.130 | 0.897 |
| Paper (forest product) | -4.138 | 0.008 | -0.0001 | -0.794 | 0.430 |
| Public utilities | -4.789 | 0.001 | 0.0000 | 0.118 | 0.907 |
| Publishing (forest products) | -3.909 | 0.016 | -0.0003 | -1.878 | 0.064 |
| Publishing (newspapers) | -4.540 | 0.002 | -0.0004 | -2.190 | 0.032 |
| Restaurants | -4.404 | 0.004 | -0.0002 | -1.529 | 0.131 |
| Retail composite | -3.174 | 0.097 | -0.0001 | -0.366 | 0.715 |
| Semi conductors (electrical) | -3.624 | 0.034 | 0.0004 | 0.778 | 0.439 |
| Soft drinks and non alchoolics | -3.276 | 0.078 | 0.0000 | 0.322 | 0.748 |
| Tobacco | -3.235 | 0.085 | 0.0002 | 1.338 | 0.185 |
| Transport | -2.901 | 0.168 | -0.0015 | -1.271 | 0.208 |
| trucker (transport) | -5.552 | 0.000 | -0.0004 | -2.109 | 0.038 |
| SP500 | -3.741 | 0.025 | -0.0001 | -1.150 | 0.254 |

*The lag order is chosen according to the Schwartz Bayesian Criterion (SBC).

### V.d. VAR representation: Granger Causality and Variance Decomposition analysis

In order to analyze the dynamic relationships between the general market and the industry specific stock returns, a bi-variate Vector Autoregressive (VAR) representation between couples—SP500 and industry returns— is established and estimated. The lag order *p* is defined according to the indications of the commonly used information criteria, such as SBC and AIC. The VARs are then employed as the basic structure for testing the Granger non causality hypothesis and for implementing variance decomposition exercises.

It is important to emphasize that the causality approach is not fully legitimate, given the perspective assumed here. In fact, the absence of Granger causality is not by itself a corroboration of our hypotheses. First, because industry specificities may exist independently from the existence of particular dynamic relationships between the series. Second, because quarterly observations are not the ideal reference time interval on which to base conclusive considerations on financial interrelations. Our hypothesis is that if idiosyncratic risk affects the volatility of stock returns (hence the dispersion around the estimated dynamic coefficients of the UVAR), then we expect the general market dynamics not to be a valid predictor for them. We expect, in fact, the general market returns to have no predictive capabilities (i.e. are not Granger causal) for the innovative industries' stock returns.

From variance decomposition we further expect to find a lower percentage contribution of S&P 500 variance in forecast variances decompositions of the more innovative industries' returns, in other terms, a bigger presence of the industry specific variance. Even under this perspective, the results are not very clear. Evidence of no Granger causality is found both for some of the innovative industries (transports, semiconductors, electronic instruments) as well as for some of the low innovative industries. Hence, Granger non causality is not an exclusive attribute of the innovative industries. Even assuming an opposite perspective, i.e. expecting Granger causality between SP500 and lower innovative industries, the results are still inconclusive.

From variance decomposition analysis expectations are decisively satisfied, again, only for semiconductors and transports, but some favorable evidence emerges also for other industries deemed to be quite innovative (automobiles, integrated domestics) according to the tables in the appendix. For the two industries mentioned above, the forecast variance at a 1 quarter horizon appears dominated almost entirely by idiosyncratic variability, on average explaining, respectively, about 96% and 99% of the total variability. The values at a 10 quarters horizon are still high, respectively 95% and 94%. The evidence remains mixed for all the other industries partially following the behavior emerging from the descriptive analysis presented in table 1. Table 4 below contains the results from forecast error variance decomposition for the bivariate VARs including the industry specific rate of return and the SP500 rate of return. The values reported are for the autonomous (thus idiosyncratic) industry specific variance contribution.

**Table 4**

**Forecast error variance decomposition for the industry level rates of return**

| Industry | Forecast period 1 | 2 | 3 | 4 | Industry | Forecast period 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|---|---|---|
| TRANSPORT | 99.620 | 98.563 | 94.666 | 94.612 | FOREST PROD. PUBL. | 39.733 | 39.733 | 39.733 | 39.733 |
| SEMICONDUCTORS | 95.674 | 95.143 | 95.137 | 95.136 | HOSPITAL SUPPLIES | 47.143 | 47.143 | 47.143 | 47.143 |
| NAT. GAS PIPELINES | 85.250 | 85.250 | 85.250 | 85.250 | INSURANCE MULTIL. | 46.971 | 46.971 | 46.971 | 46.971 |
| BUILD. MATERIALS | 46.919 | 46.919 | 46.919 | 46.919 | FINANCIAL | 27.704 | 27.773 | 26.496 | 26.988 |
| ELECTRONIC INSTR. | 54.911 | 54.526 | 53.744 | 53.502 | FOOD CHAINS RETAIL | 60.073 | 59.912 | 59.821 | 59.275 |
| AUTOMOBILES | 69.496 | 69.693 | 68.836 | 67.975 | INSURANCE PROPERTY | 51.890 | 51.890 | 51.890 | 51.890 |
| TRUCKER TRANSP. | 61.469 | 61.469 | 61.469 | 61.469 | FOREST PROD. PAPER | 40.693 | 44.092 | 44.253 | 44.261 |
| BANKS NY | 51.069 | 51.069 | 51.069 | 51.069 | CHEMICALS AND COAL | 39.986 | 39.986 | 39.986 | 39.986 |
| DEPT. STORE RETAIL | 52.870 | 53.781 | 54.415 | 54.477 | INTEGR. DOMESTICS | 74.996 | 75.054 | 74.978 | 75.032 |
| AEROSP. DEFENCE | 56.058 | 56.440 | 56.443 | 49.873 | METAL AND GLASS CONF. | 58.784 | 58.580 | 60.014 | 60.954 |
| PAPER CONFECT | 55.474 | 55.474 | 55.474 | 55.474 | BREWERS AND ALCOOL | 59.072 | 59.072 | 59.072 | 59.072 |
| ENTERTAINMENT | 59.428 | 59.428 | 59.428 | 59.428 | SOFT DRINKS NON ALC. | 51.987 | 51.987 | 51.987 | 51.987 |
| ALLUMINIUM | 69.752 | 64.744 | 64.653 | 64.634 | ELECRICAL EQUIPMENT | 32.259 | 34.260 | 35.112 | 35.178 |
| TOBACCO | 63.237 | 63.237 | 63.237 | 63.237 | COMPOSIT OIL | 66.749 | 66.747 | 66.945 | 66.944 |
| RETAIL COMP. | 58.085 | 58.085 | 58.085 | 58.085 | ELECTRIC POWER COMP. | 75.948 | 75.948 | 75.948 | 75.948 |
| PUBLISHING NEWSP. | 40.097 | 40.097 | 40.097 | 40.097 | SP500 | | | | |
| RESTAURANTS | 48.892 | 48.892 | 48.892 | 48.892 | PUBLIC UTILITIES | 58.466 | 58.466 | 58.466 | 58.466 |

Note: Industries are presented according to the variability ordering of table 1

Note: The forecast error decomposition for the SP500 contribution on the industry level variance is the complement to 100 of the autonomous contribution

## V.e. CAPM system estimation of betas

We now estimate the CAPM structural parameters in order to obtain both a test of the efficient market hypothesis and, particularly, a measure of the heterogeneity in alphas, betas and excess returns. Equation 2 below is estimated by employing both single equations methods (OLS) and simultaneous system estimation methods (FGLS, SURE, iterative SURE).

$$R_{it} = \beta_{mi} R_{mt} + \varepsilon_{it} \qquad (2)$$

$R_{it}$ = avg. rate of return for industry *i*: $(P_{it} + D_{it}) / P_{i,t-1}$

$R_{mt}$ =avg. market rate of return (S&P 500 index)

$\beta_{mi}$ = beta for industry *i* with respect to market return

$\varepsilon_{it}$ = industry specific residual

Under the non-diagonal variance-covariance errors matrix (i.e. cross dependencies between equations of the system), a simultaneous estimation is needed and also resolves more efficiently. Furthermore, it allows for a straightforward implementation of a testing strategy (Wald) for the evaluation of the heterogeneity in parameters, with particular reference to the betasn general, for the cross equations assumptions on the estimated parameters. We thus expect the betas for the innovative industries to be different from unity or statistically meaningless. The finding of betas inequality is a signal of global heterogeneity, possibly related to idiosyncratic factors that are inconsistent with the EMM hypothesis. Furthermore, in line with the results obtained by Campbell et al. (2000), we expect to find a decreased Rbar sq. statistic for the equations relative to the innovative sectors.

Results are substantially identical under the different methodologies employed and appears in line with those obtained with the other empirical approaches. The variance explained by the regressions is in fact approximately zero for semiconductors and transports, and almost irrelevant for the natural gas pipelines industry. The maximum values are obtained by the publishing industry, the paper and forest products, the electrical equipment industry, the chemical and coal industries and the financial industry.

From the coefficients test analysis we obtain that, for most of the considered sectors, the hypothesis of unit beta value cannot be rejected except for semiconductors and transport, where downsized, meaningless betas are obtained. In any case, the global heterogeneity hypothesis is confirmed by the Wald test of equality of beta parameters (equality is strictly rejected). The same hypothesis is instead accepted if the industries at the extremes of the taxonomy are excluded from the equality assumption. Thus, distinctive behaviors for different rankings of the innovative industries emerges only for some of the high and low innovative industries considered in the analysis. Table 5 below presents the results of the industry level SURE estimation of the CAPM formulation, reporting (for sake of simplicity) only the R bar sq. and the betas statistics .

**Table 5**
**CAPM industry level betas estimation**

| Industry | Beta coeff | Std. Error | t-Statistic | Adj R-sq | Industry | Beta coeff | Std. Error | t-Statistic | Adj R-sq |
|---|---|---|---|---|---|---|---|---|---|
| TRANSPORT | 0.4051 | 0.5705 | 0.7101 | -0.0061 | FOREST PROD. PUBL. | 1.1522 | 0.1014 | 11.3678 | 0.5979 |
| SEMICONDUCTORS | 0.6998 | 0.3852 | 1.8169 | 0.0262 | HOSPITAL SUPPLIES | 1.0814 | 0.1105 | 9.7861 | 0.5229 |
| NAT. GAS PIPELINES | 0.8049 | 0.2058 | 3.9108 | 0.1372 | INSURANCE MULTIL. | 1.0801 | 0.1099 | 9.8292 | 0.5246 |
| BUILD. MATERIALS | 1.3756 | 0.1403 | 9.8019 | 0.5252 | FINANCIAL | 1.2229 | 0.0843 | 14.4997 | 0.7087 |
| ELECTRONIC INSTR. | 1.2247 | 0.1566 | 7.8211 | 0.4118 | FOOD CHAINS RETAIL | 0.9097 | 0.1157 | 7.8640 | 0.4143 |
| AUTOMOBILES | 0.9740 | 0.1694 | 5.7486 | 0.2716 | INSURANCE PROPERTY | 0.9683 | 0.1090 | 8.8809 | 0.4749 |
| TRUCKER TRANSP. | 1.1188 | 0.1532 | 7.3019 | 0.3779 | FOREST PROD. PAPER | 1.0680 | 0.0953 | 11.2070 | 0.5864 |
| BANKS NY | 1.2106 | 0.1342 | 9.0190 | 0.4832 | CHEMICALS AND COAL | 1.0623 | 0.0931 | 11.4123 | 0.5953 |
| DEPT. STORE RETAIL | 1.1886 | 0.1368 | 8.6884 | 0.4643 | INTEGR. DOMESTICS | 0.6531 | 0.1247 | 5.2384 | 0.2325 |
| AEROSP. DEFENCE | 1.1427 | 0.1409 | 8.1104 | 0.4272 | METAL AND GLASS CONF. | 0.7951 | 0.1152 | 6.9041 | 0.3520 |
| PAPER CONFECT | 1.1114 | 0.1330 | 8.3577 | 0.4385 | BREWERS AND ALCOOL | 0.8270 | 0.1079 | 7.6675 | 0.4022 |
| ENTERTAINMENT | 1.0459 | 0.1374 | 7.6098 | 0.3986 | SOFT DRINKS NON ALC. | 0.9021 | 0.1018 | 8.8643 | 0.4739 |
| ALLUMINIUM | 0.8348 | 0.1530 | 5.4556 | 0.2512 | ELECRICAL EQUIPMENT | 1.0308 | 0.0757 | 13.6087 | 0.6817 |
| TOBACCO | 0.9943 | 0.1410 | 7.0496 | 0.3600 | COMPOSIT OIL | 0.6380 | 0.0978 | 6.5240 | 0.3212 |
| RETAIL COMP. | 1.0268 | 0.1312 | 7.8240 | 0.4121 | ELECTRIC POWER COMP. | 0.5052 | 0.0971 | 5.2054 | 0.2314 |
| PUBLISHING NEWSP. | 1.2119 | 0.1076 | 11.2636 | 0.5942 | SP500 | | | | |
| RESTAURANTS | 1.0648 | 0.1130 | 9.4216 | 0.5052 | PUBLIC UTILITIES | 0.6151 | 0.0786 | 7.8282 | 0.4083 |

Note: Industries are presented according to the variability ordering of table 1

## VI. Firm level results

We now check if the hypothesis of a link between idiosyncratic risk (i.e. volatility) and innovative activity can be better sustained with firm level data.

We employ monthly observations of individual stock returns for a selection of 34 firms belonging to 5 industries with different levels of "innovativeness" (agriculture, biotechnologies, computers, pharmaceuticals and textiles). According to (average) R&D intensity data, the order of innovativeness from most to least is: biotechnology, computers, pharmaceutical, textiles, agriculture. This order is confirmed in the taxonomy found in the appendix.

The number of selected firms per industry was chosen according to the need of having continuous price and dividends information for an adequate time span. By adequate we mean both one guaranteeing a satisfactory and up to date number of observations for the implementation of our analysis, and the one allowing the number of firms in each industry to be greater than unity. The chosen period is 1981m1 2003m7.

The approach is substantially analogous to the one employed at the industry level, but the CAPM model analysis is also extended to the *explicit* consideration of *time varying volatility*. In fact, the availability of observations at higher frequency (monthly series) allows the implementation of the CAPM analysis in the context of the GARCH approach to the direct representation of the series volatility.

### VI.a. Descriptive analysis at the firm level

The descriptive analysis is conducted via the same methodologies and aims described in the industry level analysis. Thus, the considerations expressed there remain valid. Table 6 below contains some basic descriptive statistics for the firm level series.

**Table 6**

**Descriptive statistics for the firm level monthly series**

| **S** | **Firm** | Mean | Maximum | Minimum | Std. Dev. | rel weight | R&D/Sales |
|---|---|---|---|---|---|---|---|
| A | ADM | 0.010 | 0.275 | -0.274 | 0.080 | 0.919 | 0.001 |
| A | ALCO | 0.007 | 0.620 | -0.341 | 0.085 | 0.054 | NA |
| A | ZAP | 0.003 | 1.006 | -0.413 | 0.183 | 0.027 | NA |
| B | DNA | 0.023 | 0.726 | -0.296 | 0.137 | 0.912 | 0.428 |
| B | ENZ | 0.028 | 1.500 | -0.550 | 0.226 | 0.067 | 0.624 |
| B | LIPD | 0.002 | 0.756 | -0.458 | 0.137 | 0.021 | NA |
| C | 3CTLE | 0.011 | 1.778 | -0.666 | 0.285 | 0.002 | 0.042 |
| C | 3SOCR | 0.015 | 1.500 | -0.538 | 0.230 | 0.000 | 0.101 |
| C | AAPL | 0.016 | 0.454 | -0.577 | 0.152 | 0.036 | 0.064 |
| C | DBD | 0.013 | 0.420 | -0.283 | 0.091 | 0.009 | 0.037 |
| C | HPQ | 0.014 | 0.345 | -0.320 | 0.107 | 0.199 | 0.084 |
| C | IBM | 0.010 | 0.354 | -0.275 | 0.084 | 0.633 | 0.066 |
| C | NIPNY | 0.010 | 0.483 | -0.347 | 0.116 | 0.120 | 0.160 |
| P | 3OXIS01 | 0.014 | 2.643 | -0.670 | 0.294 | 0.000 | 0.624 |
| P | ABT | 0.014 | 0.221 | -0.207 | 0.066 | 0.087 | 0.090 |
| P | BMY | 0.010 | 0.222 | -0.282 | 0.067 | 0.112 | 0.088 |
| P | FRX | 0.025 | 0.525 | -0.382 | 0.112 | 0.005 | 0.087 |
| P | GSK | 0.018 | 0.276 | -0.316 | 0.078 | 0.108 | 0.103 |
| P | JNJ | 0.014 | 0.183 | -0.173 | 0.068 | 0.132 | 0.084 |
| P | KV | 0.034 | 1.156 | -0.506 | 0.189 | 0.000 | 0.081 |
| P | LLY | 0.014 | 0.308 | -0.295 | 0.081 | 0.087 | 0.144 |
| P | MRK | 0.014 | 0.222 | -0.219 | 0.071 | 0.162 | 0.092 |
| P | PFE | 0.016 | 0.259 | -0.240 | 0.074 | 0.117 | 0.113 |
| P | PHA | 0.009 | 0.326 | -1.000 | 0.098 | 0.047 | 0.103 |
| P | SGP | 0.012 | 0.203 | -0.199 | 0.074 | 0.049 | 0.112 |
| P | WYE | 0.012 | 0.259 | -0.261 | 0.071 | 0.094 | 0.079 |
| T | 3BMLS | 0.047 | 6.000 | -0.886 | 0.453 | 0.008 | NA |
| T | 3CRWS | 0.032 | 4.360 | -0.718 | 0.330 | 0.047 | 0.016 |
| T | BOTX | 0.018 | 3.167 | -0.667 | 0.284 | 0.012 | 0.001 |
| T | FIT | 0.008 | 0.430 | -0.564 | 0.084 | 0.139 | 0.022 |
| T | HWG | 0.007 | 0.755 | -0.672 | 0.157 | 0.060 | NA |
| T | UFI | 0.016 | 0.506 | -0.306 | 0.125 | 0.537 | 0.010 |
| T | VELCF | 0.013 | 0.381 | -0.210 | 0.084 | 0.197 | NA |
| . | SP500 | 0.009 | 0.131 | -0.217 | 0.045 | . | NA |

The descriptive statistics present some surprising results: the higher unconditional sample variability is found for the first three firms of the textiles industry and the lower unconditional sample variability for some firms of the pharmaceuticals group. This result is not particularly meaningful at the individual firm level, because volatility may well be induced by idiosyncratic risk factors (or firm specific events) other than those regarding innovation. In order to obtain a more general result, average industry specific figures are calculated by weighting the firm level returns by their relative capitalizations in the time span considered. We assume that the total capitalization of the single industries is the one obtained by summing the capitalization of the firms considered in the analysis. This is the same as assuming we hold a portfolio in which equal shares of the different assets are enclosed.

The effect of firm size on volatility appears clearly if we confront the average relative weight of the single firms in the time span considered with the relative standard deviations. From Table 6, we observe that volatility is persistently smaller the higher the relative weight of the firm. This is particularly evident for those firms with the highest standard deviation. For each industry, the higher volatility is always associated with the smallest firm. Even if controlling for the size effect is beyond the potential of this descriptive analysis, it seems realistic to advance that some evidence of the supposed relationship between innovative activity and volatility can be recuperated once the capitalization factor is included in the analysis. Looking at the last column of Table 6, we can verify the substantial validity of the taxonomy found in the appendix for the period considered in the analysis.

One important aspect of the volatility assessment is its behavior over time. The following figures show the standard deviation movements in the sample period 1983-2003 at the industry level. Time varying volatility is obtained by calculating 24 term moving averages of the standard deviations.

Figures 3-7 illustrate that in 3 of the 5 industries (agriculture, pharmaceutical, textile), idiosyncratic risk did not change very much over time. Instead, for biotech and computers, idiosyncratic risk was highest precisely in the periods when the case study literature claims that there was the most innovation in the industries (see Gambardella 1995 and Bresnahan and Greenstein 1997). We look at this possibility more closely in section VII when we regress volatility on R&D intensity data (R&D/sales), and in future work where we plan to include patent citation data.

**Figure 3**

**Agriculture and SP500 volatility 1983-2003**

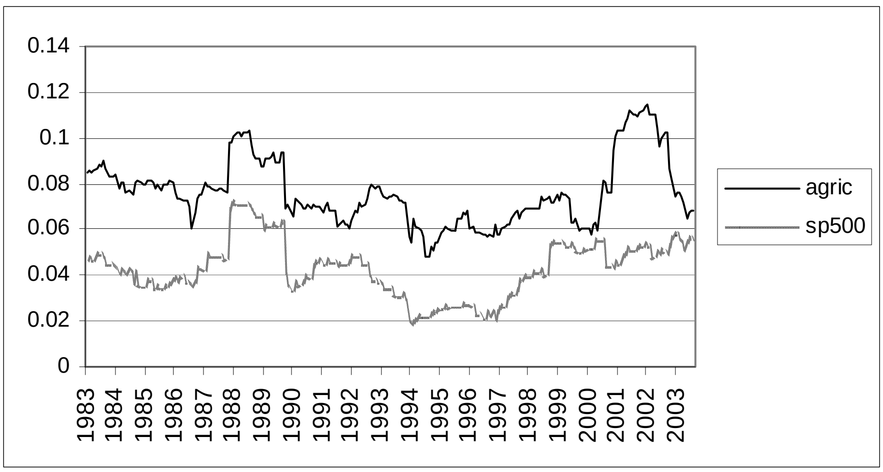


**Figure 4**

**Biotechnology and SP500 volatility 1983-2003**

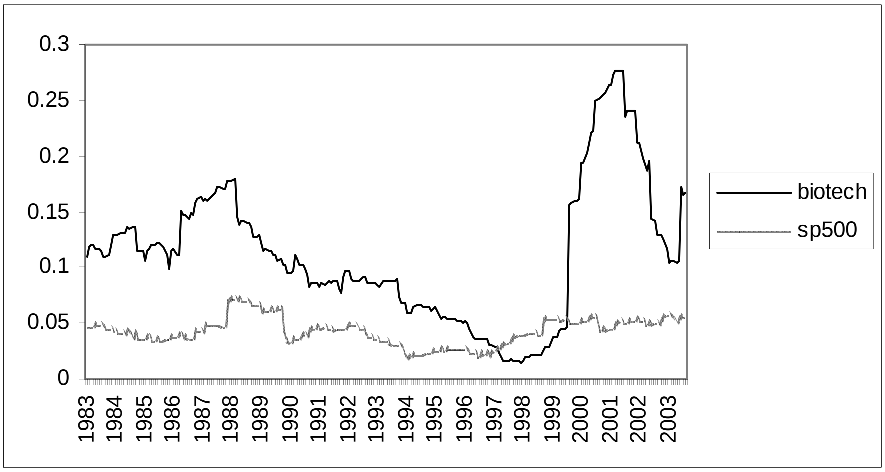



**Figure 5**

**Computers and SP500 volatility 1983-2003**

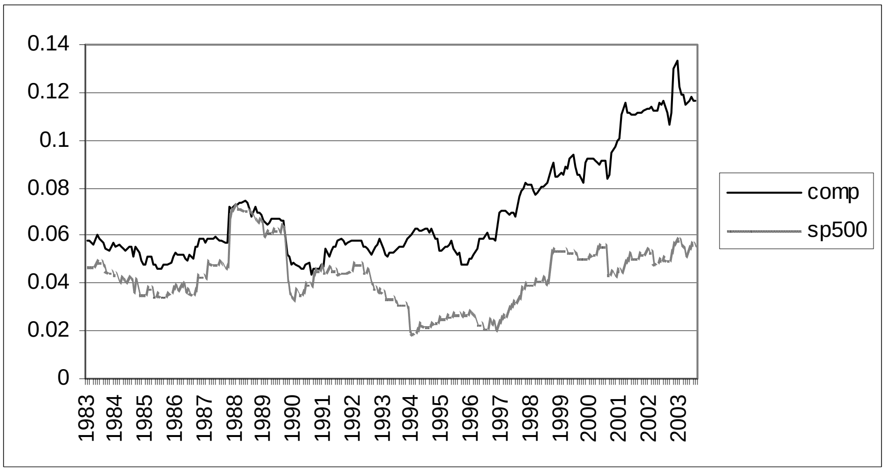



**Figure 6**

**Pharmaceuticals and SP500 volatility 1983-2003**

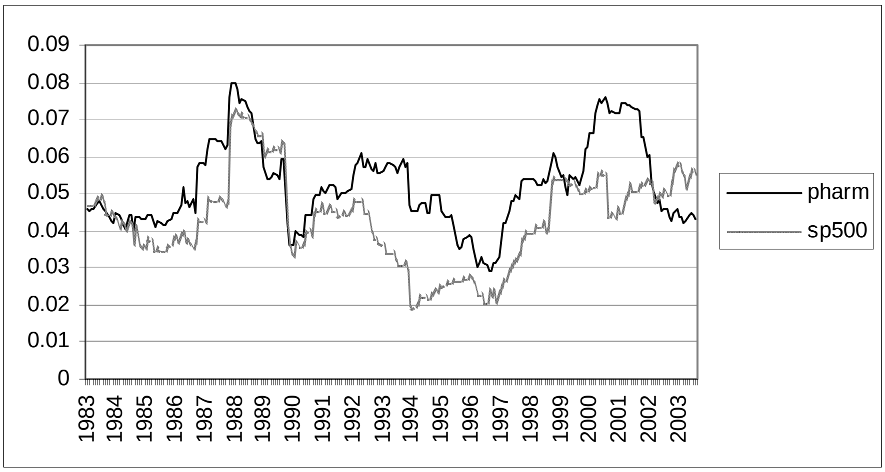
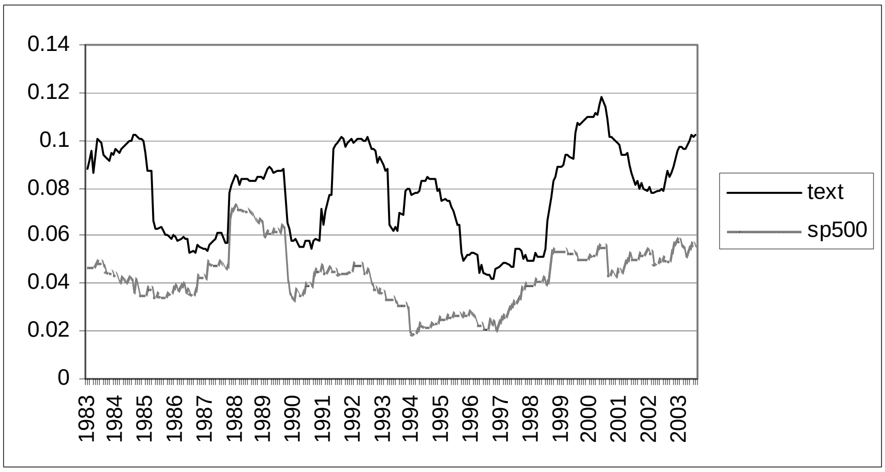


**Figure 7**

**Textile and SP500 volatility 1983-2003**




## VI.b. Results from the firm level, bivariate VAR representations

The same approach used for the industry level analysis is now used for the firm level analysis. The pitfalls cautioned in the industry level analysis for the appropriateness of the use of the Granger Causality (GC) testing approach should be reiterated, even if their strength is stronger due to the higher frequency observations.

The results from GC analysis are quite interesting, for they signal some evidence in favor of our expected result of GC (predictive capabilities) from the general market returns to the firm level returns for the less innovative firms. The hypothesis is that for low innovative firms belonging to mature industries, the news affecting the general market is relevant also at the firm level, while high idiosyncratic elements tend to obscure the effects of general relevance on the innovative side behavior. Table 7 contains the results of the GC testing procedure.

**Table 7**

**Granger non-causality tests at the firm level**

| S | $H_0$: SP500 does not GC: Firm | F-Statistic | Probability | Response | S | $H_0$: SP500 does not GC: Firm | F-Statistic | Probability | Response |
|---|---|---|---|---|---|---|---|---|---|
| A | ADM | 0.643 | 0.526 | A | P | GSK | 0.951 | 0.388 | A |
| A | ALCO | 2.934 | 0.045 | R | P | JNJ | 0.419 | 0.658 | A |
| A | ZAP | 5.396 | 0.005 | R | P | KV | 1.418 | 0.244 | A |
| B | DNA | 0.642 | 0.527 | A | P | LLY | 2.160 | 0.117 | A |
| B | ENZ | 0.353 | 0.703 | A | P | MRK | 1.025 | 0.360 | A |
| B | LIPD | 0.303 | 0.739 | A | P | PFE | 0.413 | 0.662 | A |
| C | 3CTLE | 2.449 | 0.088 | A | P | PHA | 2.051 | 0.131 | A |
| C | 3SOCR | 0.123 | 0.884 | A | P | SGP | 0.033 | 0.967 | A |
| C | AAPL | 3.327 | 0.037 | R | P | WYE | 0.434 | 0.649 | A |
| C | DBD | 1.143 | 0.321 | A | T | 3BMLS | 2.271 | 0.105 | A |
| C | HPQ | 0.905 | 0.406 | A | T | 3CRWS | 1.450 | 0.236 | A |
| C | IBM | 1.895 | 0.152 | A | T | 3GMIL | 2.615 | 0.075 | A |
| C | NIPNY | 0.331 | 0.719 | A | T | BOTX | 3.447 | 0.033 | R |
| P | 3OXIS | 1.163 | 0.314 | A | T | FIT | 1.091 | 0.337 | A |
| P | ABT | 0.178 | 0.837 | A | T | HWG | 1.967 | 0.142 | A |
| P | BMY | 0.547 | 0.579 | A | T | UFI | 3.243 | 0.041 | R |
| P | FRX | 1.853 | 0.159 | A | T | VELCF | 8.044 | 0.000 | R |

Note: A = hypothesis accepted; R = hypothesis rejected
Note B: Underlying VAR orders are selected via the SBC Information Criterion.

With the exception of Apple (AAPL), all the firms for which the NGC hypothesis is rejected belong to the agriculture and textile industries, thus to the low innovative industries in the sample. However, the fact that confirmation of NGC is found both for the innovative firms and for some low innovative firms renders the evidence, again, rather mixed.

Using variance decomposition analysis we find that akin to the outcomes obtained at the industry level, the forecast variance at a 1-quarter horizon appears dominated almost entirely by idiosyncratic variability. This is common to all the firms considered in the analysis and is persistent even during a 6 month horizon. Evidence of slight decay is observable for some of the textile firms and, against our expectations, for a biotechnology firm (ENZO). Table 8 below presents the forecast variance results up to the $6^{th}$month horizon.

**Table 8**

**Forecast variance decomposition at the firm level**

| | | forecast period | | | | | | | | forecast period | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **S** | **Firm** | 1 | 2 | 3 | 4 | 5 | 6 | **S** | **Firm** | 1 | 2 | 3 | 4 | 5 | 6 |
| A | ADM | 99.981 | 99.881 | 97.457 | 96.596 | 96.589 | 96.577 | P | GSK | 99.394 | 98.463 | 98.461 | 98.378 | 97.074 | 94.133 |
| A | ALCO | 99.976 | 99.126 | 99.125 | 98.741 | 98.728 | 98.724 | P | JNJ | 98.690 | 98.234 | 96.984 | 97.016 | 96.612 | 96.604 |
| A | ZAP | 99.540 | 99.362 | 99.230 | 99.236 | 99.227 | 99.001 | P | KV | 99.995 | 97.828 | 97.562 | 97.576 | 96.827 | 92.971 |
| B | DNA | 99.859 | 99.723 | 99.721 | 98.422 | 98.328 | 98.155 | P | LLY | 99.530 | 99.530 | 99.390 | 98.332 | 98.220 | 97.960 |
| B | ENZ | 98.843 | 98.811 | 89.537 | 89.286 | 89.251 | 88.850 | P | MRK | 99.523 | 99.519 | 97.857 | 97.729 | 97.000 | 96.996 |
| B | LIPD | 99.659 | 99.151 | 99.116 | 98.779 | 97.971 | 97.804 | P | PFE | 99.309 | 98.450 | 97.166 | 96.684 | 95.085 | 94.534 |
| C | 3CTLE | 99.720 | 99.718 | 99.718 | 99.484 | 99.326 | 99.246 | P | PHA | 99.996 | 99.929 | 99.929 | 98.477 | 96.665 | 96.503 |
| C | 3SOCR | 99.214 | 98.779 | 98.635 | 97.811 | 96.739 | 94.700 | P | SGP | 99.027 | 98.949 | 98.950 | 98.897 | 98.888 | 98.888 |
| C | AAPL | 99.764 | 99.656 | 99.656 | 99.544 | 99.498 | 98.848 | P | WYE | 98.933 | 98.930 | 98.259 | 98.071 | 98.013 | 95.858 |
| C | DBD | 100.000 | 99.245 | 99.061 | 96.944 | 96.104 | 91.584 | T | 3BMLS | 99.995 | 99.900 | 98.628 | 98.622 | 98.489 | 98.174 |
| C | HPQ | 99.990 | 99.681 | 99.603 | 99.427 | 99.399 | 99.392 | T | 3CRWS | 99.850 | 99.468 | 99.144 | 93.582 | 90.658 | 90.685 |
| C | IBM | 99.473 | 96.921 | 96.947 | 96.981 | 96.839 | 95.558 | T | 3GMIL | 82.933 | 82.971 | 82.961 | 82.982 | 82.990 | 83.055 |
| C | NIPNY | 99.103 | 96.776 | 96.790 | 96.789 | 96.590 | 96.585 | T | BOTX | 99.999 | 99.997 | 99.808 | 99.806 | 99.794 | 99.510 |
| P | 3OXIS | 99.928 | 99.067 | 98.840 | 98.096 | 97.103 | 97.078 | T | FIT | 99.246 | 98.146 | 98.129 | 96.352 | 96.254 | 95.258 |
| P | ABT | 99.852 | 99.822 | 99.799 | 99.751 | 97.677 | 96.438 | T | HWG | 99.947 | 99.584 | 99.570 | 99.469 | 99.248 | 98.391 |
| P | BMY | 98.776 | 98.735 | 98.445 | 98.402 | 98.306 | 98.115 | T | UFI | 99.568 | 97.797 | 97.277 | 95.109 | 92.751 | 92.406 |
| P | FRX | 99.304 | 98.805 | 98.486 | 98.279 | 98.275 | 97.139 | T | VELCF | 97.485 | 97.508 | 96.297 | 95.918 | 95.991 | 95.984 |

Note: Underlying VAR orders are selected via the SBC Information Criterion.

The overall results from the analyses using the bivariate VAR representation are thus weakly informative. Even if some favorable signals are present, they do not provide strong evidence for our hypothesis.

The idiosyncratic elements at work when confining the analysis to the firm level are presumably manifold. Hence, the indirect identification of a clear relationship between volatility and innovativeness is not easily practicable. In Section VII we will see that a more direct identification using R&D data produces better results.

### VI.c. Firm level analysis continued: ARCH and GARCH components in the volatility measure (in CAPM model)

We now approach the question of excess returns and volatility using a CAPM excess returns representation, allowing for a direct formulation and estimation of the variance equation in the context of the ARCH methodology (Engle, 1982, Bollersev, 1986). Before presenting the results, a brief section is dedicated to a quick stylized introduction to the generalized ARCH (GARCH) specification chosen and to the assumptions that we employ in the applications. The connections between this tool for studying time varying volatility and our particular objectives are made explicit.

#### VI.c(1). G/ ARCH-in-Mean and asymmetric volatility modeling

We employ as a general starting point the Threshold ARCH-in-mean GARCH-in-volatility formulation of order ($p$, $q$):

$$y_t = \mu + \beta \mathrm{x}_t + \lambda \sigma_t^2 + \varepsilon_t \qquad (3)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \delta_i \varepsilon_{t-1}^2 + \psi_{t-1} \gamma \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \phi_j \sigma_{t-1}^2 \qquad (4)$$

where $y_t$ is the firm-level stock rate of return, $\mathrm{x}_t$ is the general market rate of return (hence, $\beta$ is the generalisation of the CAPM to the G/ARCH formulation), and $\lambda$ is a coefficient linking returns to volatility[11]. The term $\delta\varepsilon_{t-1}^2$ in the variance equation is the ARCH term (equivalent to a MA term) and $\phi\sigma_{1-t}^2$ its generalization to lagged variance (often defined GARCH, an AR term). The term $\psi_{t-1}\gamma\varepsilon_{t-1}^2$ controls for asymmetric effects, in fact $\psi_t = 1,0$ is a wildcard operating according to the thresholds $\varepsilon_t < 0, \varepsilon_t \geq 0$ respectively[12]. The system (3)-(4) is a highly general mean-variance formulation, since it can account for a number of specificities in the data.

The conditional variance formulation implies that, the bigger the departure from the equilibrium in the mean equation, the larger the conditional variance (one-period ahead forecast variance based on past information). The error terms, or news terms, are in fact excess returns.

Bigger values for the ARCH coefficient produce a greater forecast variance. The ARCH coefficient expresses the conditional variance sensitivity to shocks in the mean equation, while the GARCH, or autoregressive term, is the degree of memory in the variance generating process. The higher the autoregressive coefficient, the smoother the variance behavior[13].

The consideration of possible asymmetries in the variance response expressed by the threshold term is due to the fact that the volatility response to shocking news from the mean equation (the MA term) may be asymmetric, possibly with stronger reactions to negative shocks (Engle and Ng, 1993)[14].

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[11] Under the assumption of risk-adverse individuals, it is possible to advance the hypothesis of a direct relationship between expected returns and expected volatility. The economic rationale is that agents accept higher risks only in the view of higher profits. The generalisation of this idea to the G/ARCH approach produces the G/ARCH-M specification (Engle, Lilien and Robbins, 1987).

[12] Jointly with the mean equation in (2), this formulation is known as the Threshold GARCH model (Zakoian, 1990).

[13] For this reason, in the finance econometric literature the GARCH parameter is often considered as a “defensiveness” measure for it determines the degree of resistance the conditional variance opposes to “shocking news” affecting the mean equation.

[14] The general case is the one of positive values accounting for the presence of the leverage effects.

We will assume that deviations from the systematic relationships are the result of idiosyncratic risk (or news on it), in turn produced, among other factors, by the uncertainty produced by the innovative activity of firms.

Other things equal, the conditional volatility is thus expected to be bigger in those firms displaying higher innovative efforts. This outcome can be assessed via the estimation of the theoretical parameters in the formulation above. We expect to find higher and meaningful coefficients for the MA term values of the highly innovative firms and bigger defensiveness (coefficients on the AR term) for the low innovative.

### VI.c(2). G/ ARCH-in-Mean and asymmetric volatility results

Considering that innovation brings uncertainty and that risk-adverse individuals may adopt different behaviors according to the state of nature they are confronted with, we also expect both the GARCH-in-mean and the threshold asymmetry coefficients to be larger in the innovative firms' equations. Table 9 presents with the results of the CAPM TGARCH estimation.

**Table 9**

**CAPM TGARCH estimation results at the firm level**

| | | mean equation | | variance equation | | | | | mean equation | | variance equation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **S** | **Firm** | **lambda** | **Beta** | **ARCH** | **GARCH** | **gamma** | **S** | **Firm** | **lambda** | **Beta** | **ARCH** | **GARCH** | **gamma** |
| A | ADM | NM | 0.942 | 0.094 | 0.767 | NM | P | GSK | NM | 0.806 | 0.049 | 0.898 | NM |
| A | ALCO | 1.450 | 0.491 | 0.094 | 0.772 | NM | P | JNJ | NM | 0.841 | NM | 0.789 | 0.207 |
| A | ZAP | NM | 0.987 | 0.197 | 0.762 | NM | P | KV | NM | 1.309 | 0.058 | 0.933 | NM |
| B | DNA | NM | 1.023 | 0.067 | 0.879 | 0.314 | P | LLY | NM | 1.006 | 0.039 | 0.953 | NM |
| B | ENZ | 0.562 | 1.555 | 0.110 | 0.744 | 0.257 | P | MRK | NM | 0.895 | 0.110 | 0.847 | NM |
| B | LIPD | 0.271 | 0.822 | 0.337 | -0.232 | NM | P | PFE | NM | 0.907 | 0.048 | 0.848 | NM |
| C | 3CTLE | 0.562 | 1.031 | NM | 0.852 | 0.405 | P | PHA | NM | 0.601 | NM | 0.590 | NM |
| C | 3SOCR | NM | 1.155 | -0.027 | 1.026 | 0.039 | P | SGP | NM | 0.867 | 0.110 | 0.864 | NM |
| C | AAPL | NM | 1.443 | 0.518 | NM | 0.192 | P | WYE | 0.496 | 0.817 | 0.041 | 0.726 | 0.188 |
| C | DBD | NM | 0.702 | -0.059 | 0.626 | 0.150 | T | 3BMLS | 0.799 | 0.398 | 0.083 | 0.265 | 1.044 |
| C | HPQ | 5.023 | 1.459 | 0.003 | 0.857 | 0.053 | T | 3CRWS | NM | 0.530 | 0.434 | 0.611 | NM |
| C | IBM | 0.437 | 0.935 | NM | 1.000 | 0.092 | T | BOTX | 0.651 | 0.872 | -0.053 | 0.891 | 0.324 |
| C | NIPNY | NM | 0.988 | 0.208 | NM | -0.271 | T | FIT | NM | 0.595 | 0.126 | 0.825 | NM |
| P | 3OXIS | 0.627 | 1.687 | 0.030 | 0.599 | 0.688 | T | HWG | NM | 0.981 | -0.020 | 1.020 | NM |
| P | ABT | NM | 0.835 | 0.064 | 0.894 | NM | T | UFI | NM | 0.847 | -0.050 | 1.003 | 0.071 |
| P | BMY | NM | 0.820 | 0.181 | 0.680 | 0.224 | T | VELCF | NM | 0.475 | 0.219 | NM | 0.341 |
| P | FRX | NM | 0.987 | 0.039 | 0.929 | NM | | | | | | | |

Note: ARCH = $\sum_{i=1}^{p}\delta_i$ ; GARCH = $\sum_{i=1}^{q}\phi_i$ .

The estimation is effectuated starting with a (1,1) lag order formulation, then increasing the order until the condition of finding no ARCH components in disturbances is satisfied. A unit lag structure has resolved satisfying for most of the series, with only few needing a higher order structure.

Firms in the agriculture industry do not show meaningful asymmetries in the volatility behaviors. Important asymmetric responses are instead found for most of the biotechnology and computer firms, particularly for those with the smaller dimensions or the higher innovative activity (compare Table 6 with Table 9). The asymmetry parameter resulted meaningful also for some firms in the textile and pharmaceutical industry. We do not find a clear correspondence between volatility and innovativeness or volatility and firm size except for some of the very innovative and very un-innovative firms (e.g. 3OXIS for pharmaceuticals and 3BMLS and BOTX for textiles).

Although the mean/variance relationship is not industry specific, it is found meaningful in particular for the smallest firms in each industry (ALCO in agriculture, ENZ, LIPD in biotechnology, 3CTLE in computers, 3OXIS in pharmaceuticals, and 3BMLS and BOTX in textiles). In the biotechnology and pharmaceutical industries, these firms are also the most innovative.

The ARCH (responsiveness) parameter is particularly high in the computer and biotechnology industries (the ARCH component should be evaluated contextually with its asymmetric component). This is consistent with the results that emerge from the 'asymmetry response' analysis.

The GARCH (variance memory) component tends to be smaller for the firms that have a larger responsiveness to volatility as expressed by the ARCH coefficient. This is what we expected to find, given that GARCH signals for variance smoothness. However, even if the TGARCH analysis produces interpretable results, the mixed evidence prevents us from obtaining clear results. A necessary step is to give importance to firm dimension. To do this, we run the same TGARCH estimations now allowing for the presence of a dimensionality measure in the variance equation.

The standard formulation employed (for each firm independently) is:

$$y_t = \mu + \beta \mathrm{x}_t + \lambda \sigma_t^2 + \varepsilon_t \qquad (2\ )$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \delta_i \varepsilon_{t-1}^2 + \psi_{t-1} \gamma \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \phi_j \sigma_{t-1}^2 + \theta \mathrm{Rk}_t \qquad (5)$$

where $Rk_t$ is a dimensionality measure, i.e. the ratio of the individual firm capital to industry capitalization. Hence $\theta$ is expected to be meaningful and negative, especially for those firms denoting high capitalization movements in the sample period considered. Results are presented in Table 10.

**Table 10**

**CAPM TGARCH estimation results at the firm level: dimensionality in variance equation**

| | | mean equation | | variance equation | | | | | mean equation | | variance equation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **S** | **Firm** | **lambda** | **Beta** | **ARCH** | **GARCH** | **gamma** | **S** | **Firm** | **lambda** | **Beta** | **ARCH** | **GARCH** | **gamma** |
| A | ADM | NM | 0.936 | NM | 0.781 | NM | P | GSK | NM | 0.720 | 0.277 | NM | -0.267 |
| A | ALCO | NM | 0.427 | NM | 0.916 | NM | P | JNJ | NM | 0.853 | 0.11231 | 0.776 | NM |
| A | ZAP | 2.158 | 1.194 | NM | 0.359 | NM | P | KV | NM | 1.233 | -0.099 | 1.010 | 0.078 |
| B | DNA | NM | 1.033 | 0.062 | 0.887 | 0.314 | P | LLY | NM | 1.017 | 0.086 | 0.906 | NM |
| B | ENZ | 1.263 | 1.417 | 0.193 | 0.400 | 0.071 | P | MRK | NM | 0.897 | 0.131 | 0.848 | NM |
| B | LIPD | 1.276 | 0.815 | 0.300 | -0.314 | NM | P | PFE | NM | 0.930 | 0.146 | -0.586 | NM |
| C | 3CTLE | NM | 0.944 | 0.124 | 0.521 | NM | P | PHA | NM | 0.737 | NM | 0.573 | NM |
| C | 3SOCR | MN | 1.171 | -0.020 | 1.007 | 0.095 | P | SGP | -0.466 | 0.858 | 0.043 | 0.936 | NM |
| C | AAPL | 0.746 | 1.413 | 0.079 | 0.815 | NM | P | WYE | 5.188 | 0.763 | -0.056 | 0.736 | 0.264 |
| C | DBD | NM | 0.747 | NM | NM | NM | T | 3BMLS | 0.951 | 0.426 | NM | 0.337 | 0.944 |
| C | HPQ | 1.997 | 1.083 | 0.049 | 0.857 | 0.200 | T | 3CRWS | NM | 1.231 | NM | -0.181 | 1.389 |
| C | IBM | NM | 0.969 | -0.064 | 0.526 | 0.275 | T | BOTX | 0.565 | 0.944 | NM | 0.914 | 0.313 |
| C | NIPNY | 3.829 | 0.910 | 0.054 | 0.875 | NM | T | FIT | NM | 0.583 | NM | 0.558 | NM |
| P | 3OXIS | NM | 1.579 | 0.049 | 0.633 | 1.085 | T | HWG | NM | 1.150 | NM | 0.601 | NM |
| P | ABT | NM | 0.820 | 0.019 | 1.000 | NM | T | UFI | NM | 0.690 | NM | 0.695 | NM |
| P | BMY | NM | 0.849 | 0.101 | 0.811 | NM | T | VELCF | NM | 0.451 | NM | 0.516 | NM |
| P | FRX | NM | 0.958 | NM | 0.928 | NM | | | | | | | |

The introduction of the dimensionality measure in the variance equation produces encouraging results. The ARCH component is meaningless for all the TGARCH of the firms belonging to agriculture and textiles while meaningful results, with the exception of DBD (computers), FRX and PHA (pharmaceuticals), are found for all the firms belonging to the more innovative industries. Furthermore, for DBD a TGARCH volatility model doesn't seem to be a good approximation at all. MA components are often reinforced by asymmetry components, even if they do not appear as industry specific as the ARCH ones. No asymmetry is found for the agricultural industry. Also, no industry specificities are found for the mean variance relationships.

In summary, the hypothesis of a relationship between innovativeness and volatility seems to be favored by the data. The fact that in this section we did not here work with direct observations on innovation (e.g. R&D, patents) and the fact we had to reduce the analysis to a smaller set of firms makes the figures highly exposed to specificities other than those related to innovative capacity. Nonetheless, when controlling for dimensionality, the TGARCH analysis seems able to detect the presence of symptoms of excess volatility for the most innovative firms considered in the analysis.  We now consider innovation more directly.

## VII. Innovation

In sections V and VI innovation was introduced via a sectoral categorization of innovation found in the appendix, inspired by the work of Pavitt (1984). Given the importance in both the industry and firm level analysis of time varying volatility (see Sections Va, Vb, VIa), what is necessary is to gain more insight into the determinants of this variation. We do so here by introducing a limited proxy for innovation, R&D intensity (R&D/sales). It is a limited proxy due to the fact that R&D represents only the *input* to innovation. A better measure would be patent data as this is a good proxy for innovative *output*. However, we leave this to our future work (where we connect NBER patent data with volatility data).

Using annual firm-level R&D intensity data, we evaluate whether these can explain observed changes in firm level volatility of stock returns. Employing monthly observations on stock returns, the annual volatility figures are calculated as 12 term (monthly returns) standard deviations. Given the small time dimension of the sample obtained, the preferred estimators are the pooled OLS and GLS, both with the common constant (C) and Fixed Effects (FE) versions. In order to control, as in the previous analysis, for the effects of dimensionality on volatility, the firms' relative capitalization weights are also entered in the different specifications. The idiosyncratic elements can thus be captured by the GLS weighting, the FE specification and the relative weights in capitalization. The best results are obtained when the R&D intensity measure is entered with 5-year lags. Since R&D is an innovation input rather than output, the high order is not theoretically problematic. It is also consistent with other studies studying the relationship between R&D and performance. Table 11 below shows the results of the analysis under different specifications.

**Table 11**

**Panel estimation of the relationship between volatility and innovative effort**

| Method | Dim. corr. | int coeff | t-stat | dim coeff | t-stat | r&d coeff (-5) | t-stat | Rbar sq |
|---|---|---|---|---|---|---|---|---|
| Pooled OLS | n | 0.106 | 23.586 | - | - | 0.056 | 5.098 | 0.055 |
| GLS | n | 0.086 | 34.856 | - | - | 0.048 | 3.032 | 0.143 |
| FE Pooled OLS | n | CS spec | - | - | - | 0.023 | 2.354 | 0.399 |
| FE GLS | n | CS spec | - | - | - | 0.017 | 0.907 | 0.395 |
| Pooled OLS | y | 0.116 | 22.672 | -0.061 | -3.897 | 0.056 | 5.264 | 0.085 |
| GLS | y | 0.091 | 29.611 | -0.015 | -2.187 | 0.049 | 3.130 | 0.167 |
| FE Pooled OLS | y | CS spec | - | -0.090 | -1.007 | 0.023 | 2.351 | 0.399 |
| FE GLS | y | CS spec | - | -0.065 | -1.659 | 0.018 | 0.957 | 0.401 |
| Pooled OLS | y CS spec | 0.205 | 19.351 | CS spec | - | 0.038 | 3.689 | 0.311 |
| GLS | y CS spec | 0.124 | 16.181 | CS spec | - | 0.037 | 2.207 | 0.291 |

Note: CS spec = Cross Section specific

The hypothesis of a positive relationship between volatility and R&D intensity is not rejected by the data. The innovation effect is statistically meaningful. It is interesting to note that the relationship tends to be weakened by considering different firm-specific factors. In particular, jointly controlling for cross-sectional heteroskedasticity via GLS and for Fixed Effects makes the R&D intensity coefficient statistically meaningless. This potentially happens because the covariation between R&D intensity and volatility may be captured by the two sectional corrections (FE and GLS). The same occurs to the coefficient on the weight for capitalization, resulting statistically meaningless only when entered in a FE-GLS specification. The possibility that the joint consideration of both the corrections for the sectional specificities is responsible for this result is also signaled by the fact that the percentage of variance explained by the regression does not improve when moving from a FE OLS to a FE GLS, while the GLS correction resulted highly effective when the a common constant restriction was imposed. These results are encouraging and suggest that a more direct consideration of innovation activity, for example using patent data, may improve the results.

## VIII. 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, more clear results concerning idiosyncratic risk emerge using firm level data. Here, we find that firms in the most innovative industries (e.g. biotech, computers) clearly have the highest idiosyncratic risk. Furthermore, a look at how volatility changes over time, shows that in fact idiosyncratic risk is highest precisely during those decades when innovation is the most radical: computers (1989-1997) and biotechnology (1995-2003). In particular, results are strongest when firm dimension is included, and when time varying volatility is explicitly accounted for using GARCH analysis.

Results are particularly encouraging when innovation is introduced directly, as opposed to indirectly via the categorization in the appendix. Idiosyncratic risk is clearly the highest for those firms that have the highest R&D intensity. Given this encouraging result, and given that it is important to also take into consideration innovative output, our future work will focus on this area of analysis (e.g. incorporating patent data into the volatility analysis).

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## APPENDIX

**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