Innovation and Stock Prices:
a review of some recent work

Mariana Mazzucato
(Open University)

This paper was published in *Revue de L'Observatoire Francais de Conjonctures Economiques*," June 2006, Special Issue on *Industrial Dynamics, Productivity and Growth.*

Abstract :
The paper reviews work which draws a link between the dynamics of innovation and the dynamics of stock prices. One of the key findings is the relationship between innovation intensity (e.g. radical innovation) and the *volatility* of firm level stock returns. By connecting the analysis of risk and uncertainty— often left in the finance literature to explanations related to 'animal spirits' and other stochastic factors— to changes in *real* production conditions at the firm and industry level, the paper provides the foundation for a Schumpetarian analysis of time varying risk.

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

Correspondence: Economics Dept, Open University, Walton Hall, Milton Keynes, MK7 6AA, United Kingdom. Email: m.mazzucato@open.ac.uk, Tel. +44-1908-654437; Fax. +44-1908-654488.

1. Introduction

The standard approach to industrial economics assumes that innovation is determined principally by firm size and the intensity of market competition. Yet after controlling for the effects of industry-specific conditions, empirical studies have found that the intensity of R&D spending is not statistically influenced by the size of the firm (Cohen, Leven and Mowery 1987). Furthermore, ex-ante and ex-post market power have been found to explain very little of the inter-industry differences in innovation (Geroski 1994).

In fact, most inter-firm differences in innovative activity appear to originate in industry-fixed effects related to the characteristics of the underlying technology, for example the conditions of technological opportunity, appropriability of innovation, knowledge base conditions (Cohen et al. 1987). This has led researchers to investigate inter-industry differences in the sources and evolution of innovation, and how these differences evolve over time (Pavitt 1984; Malerba and Orsenigo 1996).

Given the importance of innovation in determining the long-run growth of firms, one should expect inter-industry differences in innovation to result in differences in *performance*. Much has in fact been written on the relationship between innovation and profits (Geroski et al. 1993), and innovation and market value (Pakes 1985; Hall et al. 2005). The current paper reviews recent results on the empirical relationship between innovation and the volatility of stock returns asking whether inter-industry and inter-firm differences in innovation patterns are translated into inter-industry and inter-firm differences in the volatility of returns. Since stock returns are meant to capture the dynamics of *expected* firm growth, the relationship between innovation and stock returns provides us with insights regarding the way that innovation dynamics affect expectations about future firm growth (i.e. expectations based on fundamentals, bandwagon behavior, irrational exuberance etc.).

In fact, by linking innovation dynamics to stock price dynamics, the paper highlights the importance of connecting our understanding of risk and uncertainty— often left in the finance literature to explanations related to 'animal spirits' and other stochastic factors— to changes in *real* production conditions at the firm and industry level. It thus provides a foundation for a Schumpetarian interpretation of time varying risk.

2. Innovation as Uncertainty

Both Frank Knight (1921)—an early pioneer of risk theory—and John Maynard Keynes (1973) 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":

"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)

"By 'uncertain' knowledge, let me explain, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty…The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence, or the obsolescence of a new invention …. About these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know!" (Keynes, 1973, pp. 114-15)

Both economists used technological innovation as an example of true uncertainty. Innovation is an uncertain *process* and has uncertain *outcomes*. Large investments in R&D often lead to "dry holes". The reasons for the uncertainty behind the innovation process include that: (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, sometimes random interaction between firm-specific capabilities and institutions (see discussion of innovation and "serendipity" in Nelson 2004); and (3) radical innovations cause changes to the status quo, rendering knowledge in the current period a bad predictor of knowledge in the next period (Tushman and Anderson, 1986).

Capitalism, in fact, distinguishes itself from other modes of production such as feudalism by the prevalence of technological innovation. Both Marx and Schumpeter emphasized the central role of innovation in the competitive process: competition is not a ballet, as emphasized in neoclassical theory (e.g. 'perfect' competition), but a fierce battle between firms whose goal is to distinguish themselves so to increase market share. When innovation is "radical" or "competence destroying" the economic environment undergoes fundamental change so that current conditions are no longer useful for making expectations about the future. In a similar vein, and building on intuitions found Shackle (1955), Davidson (1983) emphasizes how since the very function of entrepreneurs is to *change* the economic environment via "crucial decision making" (*strategy* in business school talk), not only to *adapt* to it, it does not make sense to model this decision making in a Bayesian manner based on priors:

> "Shackle has developed the principle of cruciality to distinguish situations involving historical time, nonergodic worlds from ergodic processes. When agents make crucial decisions, they necessarily destroy any ergodic stochastic processes that may have existed at the point of time of the decision. An agent engages in *crucial* decision-making when the person concerned cannot exclude from his mind the possibility that the very act of performing the experiment may destroy forever the

circumstances in which the choice is made….In other words, crucial choice involves, by definition, situations where the very performance of choice destroys the existing distribution functions. ..the future is created by crucial choice decisions, it is not discovered by Bayes-LaPlace theorem. " (Davidson, 1982-83, p. 192)

That is, the rational expectations hypothesis assumes that information 'exists' and agents make expectations using this data by calculating probability distributions of actual outcomes today and for all future dates. Yet it is evident that in a capitalist system characterized by constant technological change, agents will purposely (and rationally) *not* use existing information regarding the current probability structure since this information is not useful in a *dynamic* context where dynamic refers to the fact that the environment is not static but changing. If they do, they will make persistent errors. As discussed in Davidson (1982-83), for the rational expectations hypothesis to hold, the economy must be ergodic, i.e. stationary and independent of time. Yet in a world of constant technological change, conditions are non-ergodic[1].

If stock prices reflect *expectations* about (discounted) future profits, then one should expect a relationship between innovation—which if successful can have a positive impact on a firm's profits (and growth)—and stock prices. In particular, during uncertain times, such as those characterized by radical innovation and "crucial" decision making, those firms that are seen as both probable winners and losers (e.g. the next Microsoft), will experience volatility in their stock prices (Pastor and Veronesi 2004). This is because innovation often 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. In such uncertain periods investors are 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. In fact, Mazzucato and Semmler (1999) find a strong correlation between the volatility of market shares and the volatility of stock prices during early industry evolution when technology is uncertain[2].

Notwithstanding the obvious relationship between uncertainty and innovation and how this might affect the dynamics of stock prices, there are very few studies which link stock price dynamics to innovation. The rest of the paper provides a review of this work, focusing primarily on work which

---

[1] As discussed in Davidson (1983), an ergodic situation is one where the *statistical average* of a series (i.e. the space averages that refer to a fixed time point) is the same as the *time average* (i.e. the phase averages referring to a fixed point as averages over an indefinite time space.

[2] Similarly, Geroski and Mazzucato (2002) find unit roots in firm growth rates during these early uncertain periods (and less so when the industry is more stable driven by economies of scale).

looks at stock price *volatility* since it is the volatility of stock prices that captures the dynamics of risk and uncertainty tied to innovation.

3. Some Empirical Work on Stock Prices and Innovation

There is a missing link between the industrial economics literature on innovation and uncertainty and the finance literature on risk and the volatility of stock prices. There are, however, various studies that focus on the effect of innovation on the *level* of stock prices. These come principally from the applied industrial economics literature that model growth, innovation and stock prices over the industry life-cycle (Jovanovic and MacDonald 1994; Jovanovic and Greenwood 1999; Mazzucato and Semmler 1999) and the work on market values and patents (Pakes 1985; Griliches, Hall and Pakes 1991; Hall, Jaffe and Trajtenberg 2005 from now on HJT).

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.[3] They predict that just before the shakeout occurs the average stock price will fall because the new innovation precipitates a fall in product price which is bad news for incumbents. Building on this work, Jovanovic and Greenwood (1999) 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 by new start-ups cause the stock market to decline immediately since rational investors with perfect foresight foresee the future damage to old capital (competence destroying innovations in the words of Tushman and Anderson 1986). 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).

Interestingly, in both of these papers, it is assumed that agents make expectations through Bayesian updating, which can only occur in an ergodic situation where current information is useful for making predictions about the future. Yet, as discussed above, it is precisely in situations characterized by innovation and "crucial decision making" by entrepreneurs that current probability structures are least useful.

Another body of literature that connects stock price *levels* to innovation is that on the relationship between market values and patents (Pakes 1985; Griliches, Hall and Pakes 1991).

---

[3] 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).

Pakes (1985) starts with the presupposition that looking at patents and stock prices is a way to better understand the relationship between inducements to engage in inventive activity, the relationship between inventive inputs and outputs, and the effects of those outputs. The reasoning is that if patent statistics contain information about *shifts in technological opportunities,* then they should be correlated with current changes in market value since market values are driven by the expectations about future growth. Hence the question investigated is to what degree the stock market valuation of a firm is good proxy for inventive output (Pakes 1985). To do so, he investigates the relationship between the *number* of successful patent application of firms (*unweighted* by citations), a measure of the firm's investment in inventive activity (R&D expenditure), and an indicator of its inventive output (stock market value of the firm)[4]. He finds that indeed unexpected changes in patents and R&D are associated with large changes in the market value of a firm. Yet there is a large variance to the increases in the value of the firm that are associated with a given patent. This is most likely due to the skewed distribution of the value of patents that has been found in the innovation literature.

Griliches, Hall and Pakes (2001) make use of patent citation data to account for this large variance in the value of patents (as explained below, citations are an indicator of value/contribution as with academic publications). This study finds that while a reasonable fraction of the variance of market value can be explained by R&D spending and/or the stock of R&D, patents are informative above and beyond R&D, only when *citation weighted* patents are used (unweighted patent numbers are less significant). Using a Tobin q equation, they find a significant relationship between citation-weighted patent stocks and the market value of firms where market value increases with citation intensity, at an increasing rate. The market premium associated with citations is found to be due mostly to the high valuation of the upper tail of cited patents (as opposed to a smoother increase in value as citation intensity increases)[5].

While these papers provide some extremely useful insights on the relation between the market valuation process and innovation, they focus on the *level* of stock prices not on the *volatility* of stock

---

[4] The logic is clearly stated by Pakes: "The assumptions that management chooses an R&D program to maximize the expected discounted value of the net cash flows from the firm's activities, that the stock market measures this expectation subject to error, and that patents are an error-ridden measure of current and past values of the inputs to and the outputs from the firm's R&D activity were used to suggest a testable interpretation of the dynamic relationships among the three observable variables". (Pakes 1985, p. 406).

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

prices[6]. Yet it is the volatility, not the level, of stock prices that reflects the dynamics of risk and uncertainty.

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. Figure 1 (from Shiller 2000) indicates that prices peaked in relation to earnings precisely during the second and third industrial revolutions.

Figure 1 the relation between excess volatility and technological revolutions (source: Shiller, 2000)
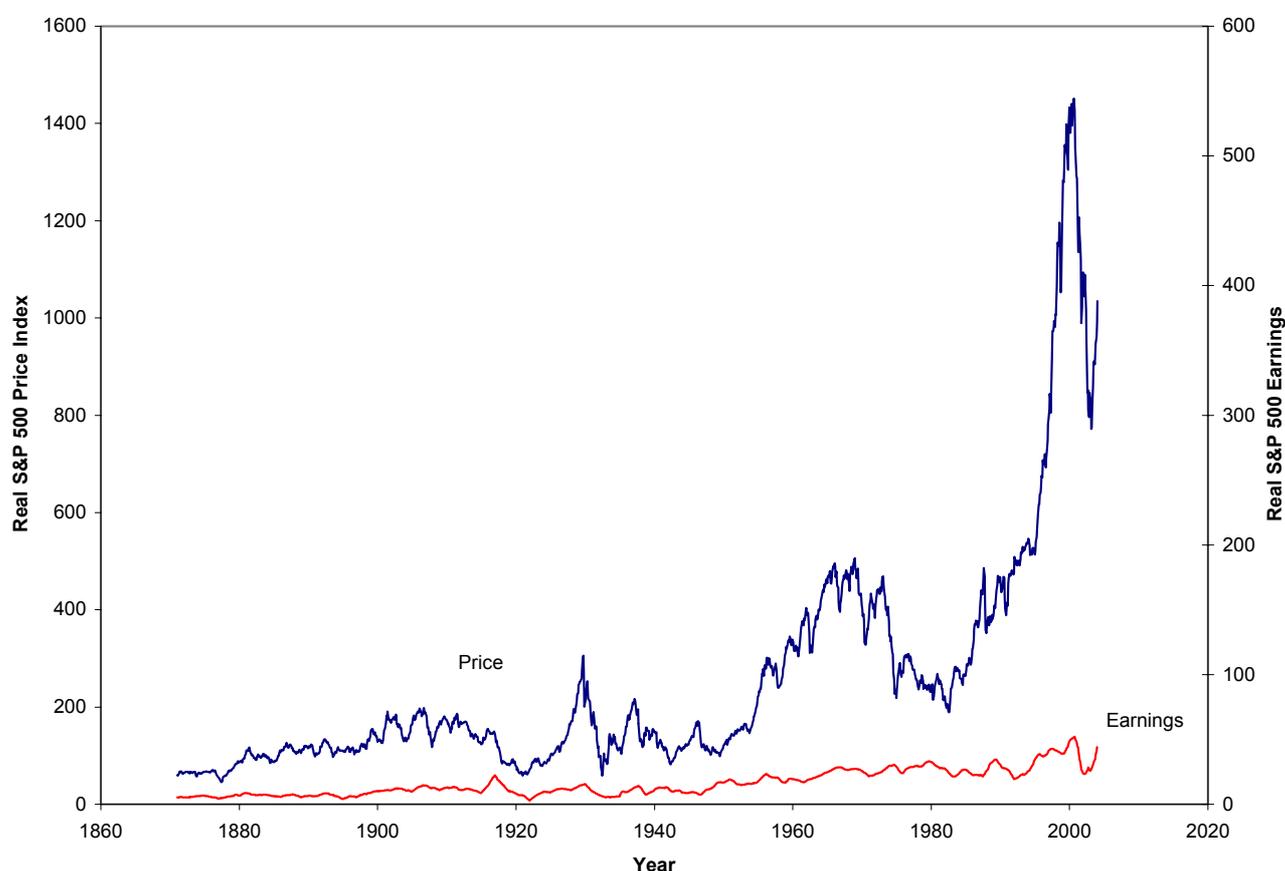
Shiller's work on the excess volatility of stock prices emphasizes the role of herd effects, bandwagon effects and animal spirits in agents behavior. That is, he suggests that it is precisely in

---

[6] Nevertheless, the level and volatility of stock prices are related, e.g. via a "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 between level and volatility 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).

uncertain situations such as those characterized by radical technological change, that current information about 'fundamentals' (i.e. current profits, dividends etc.) are less useful for making predictions about future market values. Hence the reason that the volatility of actual stock prices are so different from those that would emerge from the efficient market model (and the CAPM) is due to the fact that agents make use of other strategies to form expectations about the future under those situations (e.g. copying others). Although Shiller's work is complementary to that of economists who emphases the non-ergodic characteristics of the economy, and hence its lack of compatibility with rational expectations (Davidson 1983), Shiller for the most part does not question the behavioral foundations of the theory, focusing mainly on implications of the empirical dynamics.

Shiller's study uses aggregate data. Uncertainty, however, is better studied at the microeconomic level, as 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). For this reason, Mazzucato and Semmler (1999) and Mazzucato (2002; 2003) study the relationship between innovation and stock price volatility at the firm level over the i*ndustry life-cycle* when the characteristics of innovation are changing (Gort and Klepper 1982) These studies (focused on the auto and computer industries) find that both idiosyncratic risk and excess volatility were highest precisely during the periods in which innovation was the most radical and market shares the most unstable. "Excess volatility" is measured here following the method used in Shiller (1981), i.e. the difference between the standard deviation of actual stock prices (vt below) and "*efficient market prices*" (v*t):

$$v_t = E_t v_t^* \quad \text{and}$$

$$v_t^* = \sum_{k=0}^{\infty} D_{t+k} \prod_{j=0}^{k} \gamma_{t+j}$$

where v_t^* is the ex-post rational or perfect-foresight price (expected value of discounted future dividends), 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*.

Figures 2-3 below (from Mazzucato, 2002) plots excess volatility over time: the difference between the standard deviation of actual stock prices (vt) and the efficient market prices (vt*). The difference between the two lines is greatest in both industries during the periods in which innovation was the most radical: the early 20th century in the case of autos, and the early 1990's in the case of PCs[7]. In the latter case, Bresnahan and Greenstein (1997) attribute the higher degree of

---

[7] In Mazzucato (2002), radical innovation is measured through a quality change index (derived by dividing hedonic prices in both industries by BEA actual prices, a method used in Filson 2001), as well as through the

competitive innovation in this third decade of the PC industry to the "vertically disintegrated" structure of innovation—spread out between the makers of the PCs (e.g. Dell), the makers of microprocessors (e.g. Intel), the makers of the operating systems (e.g. Microsoft), and the makers of application software (e.g. Lotus). From 1980-1988, innovation in the PC industry was more of the "competence-enhancing" type (Tushman and Anderson 1986): it served to enhance the existing competencies and lead of IBM. From 1989-1996, innovation in the PC industry was of the "competence-destroying" type: new radical innovations destroyed the lead of IBM.

The exercise above suggests that it is precisely in periods of "crucial decision making", as emphasized by Shackle (1955) and Davidson (1983), that the efficient market hypothesis will fail to predict the volatility of stock prices. Yet it does not mean that in the absence of such radical change the EMM will work. What we argue is that it will fail *the most* under those conditions, and hence excess volatility will be highest precisely in periods of radical change. One could argue that even in the situation of relative stability the theory will fail. This is due to other criticisms of the Bayesian-LaPlace assumptions regarding expectations formation (see Marengo, 1996).

4. Idiosyncratic Risk: Sectoral Taxonomies and Stock Prices?

A recent study by Mazzucato and Tancioni (2005a) asks whether these results can be generalized to many different sectors. That is, do sectors with different innovation dynamics have different patterns of stock price volatility? To analyze inter-sectoral differences in innovation, we make use of the sectoral taxonomy of innovation literature (Pavitt 1984; Marsili 2001) as well as the industry life-cycle literature (Gort and Klepper 1982). Since innovation tends to be more radical during early industry evolution where there are more technological opportunities available, a testable hypothesis is whether idiosyncratic risk is in fact higher in new and/or high-tech industries, such as biotechnology. We focus on "idiosyncratic risk" (rather than excess volatility), i.e. the ratio between the returns volatility of a particular firm (or industry) and that of the general market, due to its ability to capture firm and industry specific volatility. The term idiosyncratic here is used in an objective not a subjective sense, i.e. it is not referring to how an investor "perceives" risk but simply to the empirical difference between volatility at the firm or industry level and the volatility at the market level. In the firm level analysis we will test whether this variable is related to R&D dynamics (i.e. whether it is highest when R&D intensity is highest). We abstain from making any theoretical assumptions on where idiosyncratic risk originates[8].

---

more qualitative information provided in industry case studies (case study for autos: Abernathy et al. 1983; case study for PCs: Bresnahan and Greenstein 1997).

[8] Future research may be dedicated to linking the study of idiosyncratic risk more closely with the (post-keynesian) discussion of non-ergodicity in financial markets, and the impact of this on macroeconomic policy.
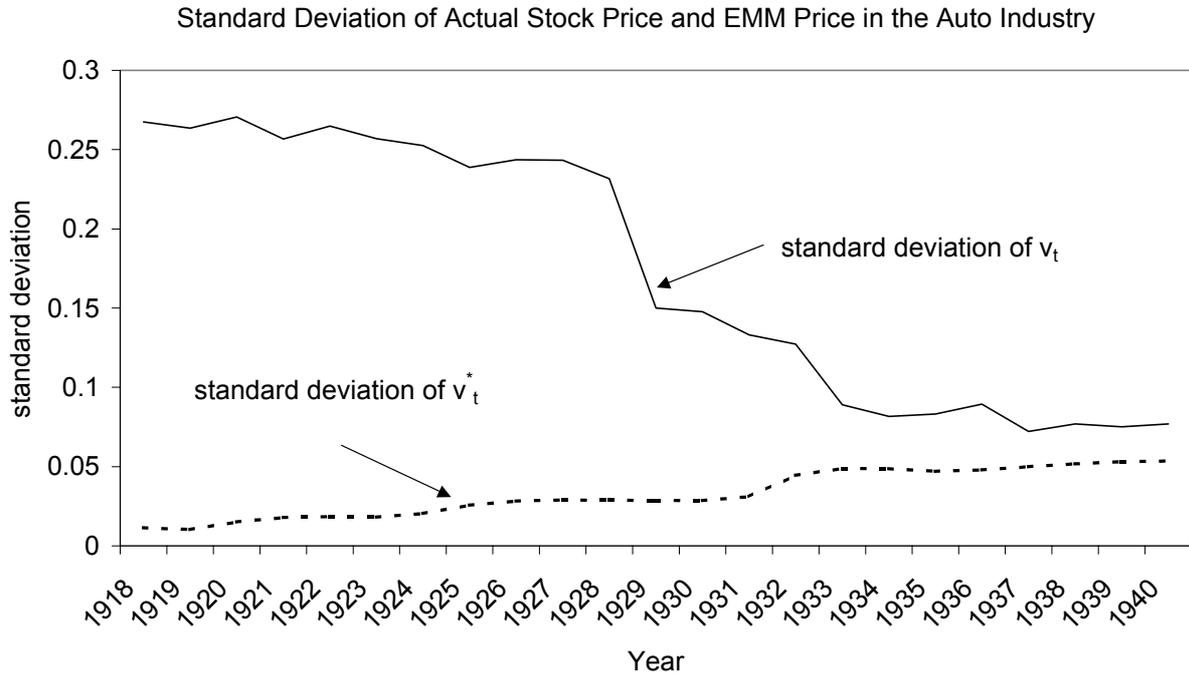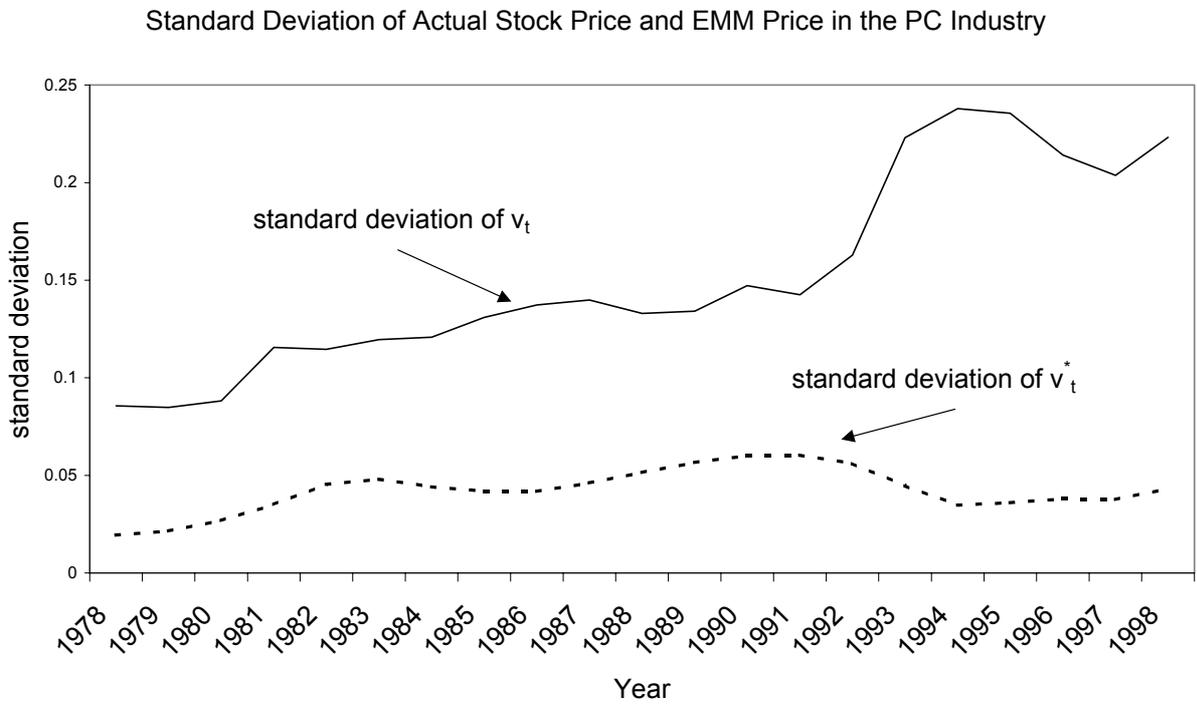
Figure 2

Standard Deviation of Actual Stock Price and EMM Price in the Auto Industry

Figure 3

Standard Deviation of Actual Stock Price and EMM Price in the PC Industry

First some words on a recent benchmark study on idiosyncratic risk. Campbell et al. (2000) conduct an 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 to the IT revolution (and some abstract notion of the New Economy)—an implication often found in both academic studies and the popular business media. They use high-frequency time series data on daily stock returns for the general market (S&P500), industries and firms for the period 1963-1997[9]. Volatility is measured through the sample's variance calculated on a monthly base. While the industry level results are inconclusive, the firm level results confirm the hypothesis of increased idiosyncratic risk. Specifically, their main findings are:

   I.evidence of a positive deterministic time trend in stock return variances for individual firms; no such evidence for market and industry return variances;

   II.evidence of declining correlations among individual stock returns in the past decades[10];

   III.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; (i) companies have begun to issue stock earlier in their life cycle when there is more uncertainty about future profits; (ii) leverage effects; (iii) improved information about future cash flows due to IT revolution; (iv) improved information via financial innovation (new derivative markets). The authors spend some time reviewing the inconclusive 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.

Following Campbell et al. (2000), Mazzucato and Tancioni (2005a) study idiosyncratic risk across different industries and firms. Our aim is to test whether more innovative industries and firms are characterized by higher idiosyncratic risk (regardless of whether it is a New Economy period or not). At the industry level, we study the aggregate behavior of returns in 34 industries using quarterly returns data

---

[9] 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.

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

from1976-1999 (list of industries is found in Table 1). At the firm level, we study the
behavior of monthly firm level returns and quarterly firm level R&D intensity in five
industries from 1974-2003 (in order from lowest to highest R&D intensity: agriculture,
textiles, pharmaceutical, computers and biotechnology).

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*

Using information from various sectoral taxonomies of innovation (Pavitt 1984;
Marsili 2001, EC 1996), the 34 industries in the industry level analysis are divided into
'very innovative', 'innovative' and 'low innovative'. Table 2 contains an example of this
taxonomy using data from Marsili (2001) on R&D intensity as well as other patent
related indicators of technological opportunity. It is important to note that this
taxonomy is *static*, i.e. unlike the industry level study in Mazzucato (2002) where the
focus is how innovation and stock prices evolve over the industry life-cycle, here an
industry is characterized as either innovative or not innovative during the entire period
studied.

Due to the 'review' nature of the current article, only the methodology and results
from Mazzucato and Tancioni (2005a; 2005b) are discussed below. In the first step of
the analysis, Mazzucato and Tancioni (2005a) 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. As long as 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[11].

Table 2: Sectoral Taxonomy of Innovation Intensity (Marsili 2001)

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

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, a test of the cross-sectional *heterogeneity*. In line with the results obtained by Campbell et al. (2000), we 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.

---

[11] When running the bi-variate VAR the residuals are linear combinations of structural shocks. To distinguish between different types of shocks we use a Choleski ordering, entering *first* the industry specific returns variable. We also check for robustness with respect to other orderings and find that the results are not qualitatively different.

In the firm-level analysis, the empirical investigation is developed by directly testing the existence of a positive relationship between idiosyncratic risk and the firm-level degree of innovativeness, proxied by R&D intensity (R&D expenditures divided by sales). R&D intensity of course only captures innovative *effort* (innovation input rather than output). But since in the literature on market value and 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) the results should not be overly biased.

Results prove that the relationship between innovativeness and stock return volatility is rather mixed. In line with the findings found in Campbell et al. (2000), the analysis using industry level data suggest that there is 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, expectations seem to be only fulfilled in the extremes of the categorization (for very innovative industries or for very low innovative industries).

As in Campbell et al (2000), more clear results concerning idiosyncratic risk emerge with firm level data. Here it is found that firms with the highest R&D intensity clearly have the highest idiosyncratic risk. 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, the relationship is not found to be stronger for firms in industries that are more "innovative". We find, for example, that the relationship holds stronger for firms in textiles (low-innovative) than for firms in pharmaceuticals (high innovative). 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. Hence, it appears that R&D intensive firms in very new industries (e.g. nanotechnology) and very old industries (e.g. textiles),

provoke a stronger reaction than R&D intensive firms in innovative mature industries (such as pharma).

Mazzucato and Tancioni (2005a) find that the discrepancy in results obtained with the industry and firm-level analyses are not attributable to aggregation biases. Instead, the inconclusiveness of the industry level results is mostly attributable to the fact that the innovation measure used (the sectoral taxonomy of innovation) is *static*, so that it does not allow consideration of how innovation changes over time, 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 (e.g. for a discussion of the change in knowledge regime from one of "random search" to one of "guided search" in the pharmaceutical industry, see Gambardella 1995).

In fact, as emphasized in Mazzucato (2002;2003), the *dynamic* structure of this relationship is fundamental. For example, Figures 4-5 illustrate that idiosyncratic risk is highest precisely during those decades when innovation in those industries is particularly intense: e.g. computers (1989-1997) and biotechnology (1995-2003).

Figure 4
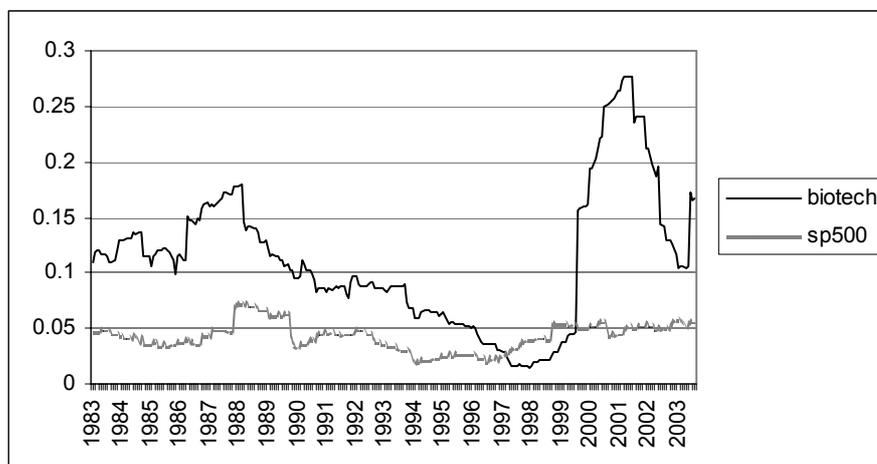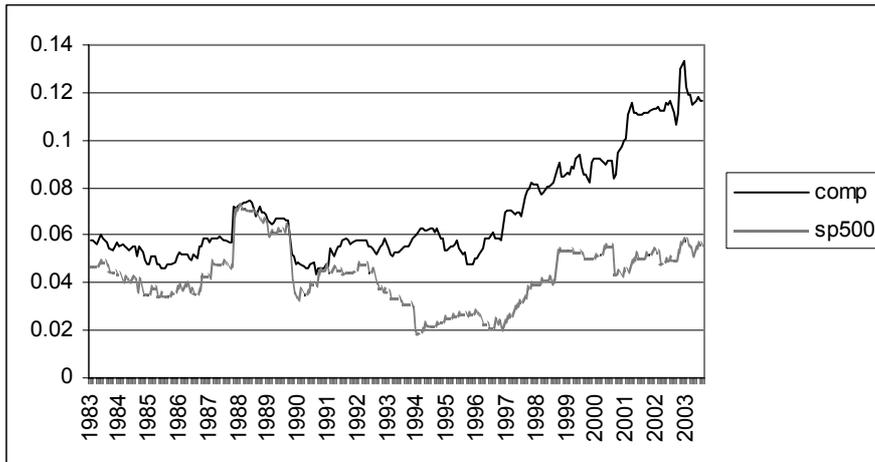**Returns volatility: Biotechnology vs. SP500 (1983-2003)**

Figure 5
Returns volatility: Computers vs. SP500 (1983-2003)

Although in the firm level analysis Mazzucato and Tancioni (2005a) establish the existence of a direct link between R&D intensity and volatility, the analysis cannot explain 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, these 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*, Mazzucato and Tancioni (2005b) incorporate patent citation data into stock price volatility analysis. Rather than using indirect or input measures of innovation as in our previous work (e.g. dividing industries by their level of innovativeness using sectoral innovation taxonomies, employing hedonic based quality change data or using R&D intensity), we use firm level patent citation data which captures the "importance" of an innovation (as in the work discussed above on market value and patent citations; Pakes 1985 and HJT 2005). In a study which focuses on firms in the pharma-biotech sector, we find a strong relationship between the volatility of stock returns, price-earnings ratios and citation weighted patents.

5. Conclusion

The studies discussed in this review piece illustrate that the uncertainty inherent in the innovation process (Knight 1921; Keynes 1973), is reflected n the dynamic behavior of stock price volatility. Hence, unlike the claim that stock prices are driven

primarily by "animal spirits" (and related irrational exuberance), this analysis has shed light on how stock price volatility is fundamentally linked to the *real* (not imaginary) structure of technological change during industry evolution.

The point, however, is not that irrational exuberance isn't important. Rather that this type of *bandwagon* behavior is more important in periods of radical change when there is greater uncertainty about the future, or in the words of Davidson (1983) in periods of "crucial decision making". This might be related to the presence of *information cascades* (Bikhchandani, Hishleifer, and Welch, 1992). An information cascade is a situation where investors are influenced by the behavior of other agents, leading them to "follow the crowd" rather than using their own private information (e.g. on fundamentals). Information cascades are more likely to occur the less certain each individual is about the quality of his or her own information (e.g. in periods of radical technological change when no one knows who the next Microsoft will be).

Information cascades can cause the social outcome to be history – dependent, i.e. non-ergodic. Convergence of behavior to a certain trend can be very idiosyncratic and fragile, characterized by short-lived fluctuations: fads, fashions, booms and crashes. Information cascades can explain why people will place themselves on the borderline between fads so that very small events can cause a radical switch in behavior[12]. In relation to our discussion on innovation and uncertainty, it may be that in the early stage of a new technology, changes in a firm's market share may signal either changes in firm knowledge or a fortuitous shock-- the investor does not know. In other stages, in contrast, the investor knows with almost certainty that the change in market shares is a result of a random shock (and hence is not a result of changes in fundamentals). Thus information cascades are more likely to happen at early stages of the industry life-cycle.

Our results in fact suggest that such 'herd' behavior is not totally random since it is more likely to occur during periods of radical innovation (i.e. in the early stage of the industry life cycle). That is, the pricing of a stock differently from its real value is more likely to happen in unstable periods when 'own information' is less reliable and hence herd or cascade behavior is more likely. This means that we

---

[12] Sequential choices are especially subject to information cascades since previous decisions/behavior can get reinforced, notwithstanding any new private information. As long as a new individual's decisions are drawn independently from the same distribution as that of previous individuals, the new individual will also ignore his/her own information and takes the same actions as previous individuals (Bikhchandani, Hishleifer, and Welch, 1992).

should expect more excess volatility in the beginning of the industry life cycle when innovation, output and market shares are much more unstable.

The work reviewed in this paper provides a foundation for a Schumpetarian understanding of the relationship between innovation and expectations formation under uncertainty. More theoretical and empirical work needs to be done on the dynamic *feedback* between innovation and uncertainty and the impact of this on the market valuation process, i.e. how on the one hand periods of (radical) innovation cause the environment to be more uncertain (the focus of most of the papers above) and on the other hand how innovation itself would not arise without uncertainty (emphasized in the work of Knight)[13]. The dynamics of the stock market, and emergence of bubbles, is obviously related to both these mechanisms.

References

The Analyst Handbook. Standard and Poor's, New York: purchased summary editions from 1995 and 2001.

Black, F. (1976), "Studies of Stock Price Volatility Changes," Proceedings of the 1976 Meetings of the Business and Economic Statistics Section, 177-188, American Statistical Association.

Bikhchandani, S. D. Hirshleifer and I. Welch (1992), "A Theory of Fads, Fashion, Custom and Cultural Change as Information Cascades," *Journal of Political Economy,* 100 (5): 992-1026.

Bresnahan, T. F. and Greenstein, S. (1997). "Technological Competition and the Structure of the Computer Industry," *Journal of Industrial Economics*, 47 (1): 1-40.

Campbell, J.Y., and Shiller, R. J. (1988). "Stock Prices, Earnings and Expected Dividends," Journal of Finance, 43: 661-76.

Campbell, J.Y. (2000), "Asset Pricing at the Millennium," *NBER working paper no. 7589,* March 2000.

Christie, A. (1981), "The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects," *Journal of Financial Economics,* 10: 407-432.

Cohen, W.M, Levin, R. and D.C. Mowery (1987), "Firm Size and R&D Intensity: A Re-Examination," Journal of Industrial Economics, 35(4): 543-565.

Davidson, P. (1982-3), "Rational Expectations: A Fallacious Foundation For Studying Crucial Decision-Making Processes," Journal of Post-Keynesian Economics," Winter 1982-1983, 182-198.

---

[13] This is in fact the point in the famous quote by Knight that "*Without uncertainty it is doubtful whether intelligence itself would exist.*" (Knight, 1921).

Davis, S.J. and Haltiwanger, J. (1992), "Gross Job Creation, Gross Job Destruction , and Employment Reallocation," *Quarterly Journal of Economics,* 107: 819-64.

Duffie, D. (1992), *Dynamic Asset Pricing*, Princeton University Press, Princeton, NJ.

Filson, D. (2001). "The Nature and Effects of Technological Change over the Industry Life Cyle," *Review of Economic Dynamics*, 4(2): 460-94.

Gambardella (1995), "Science and Innovation: The US Pharmaceutical Industry During the 1980s", Cambridge University Press, Cambridge, UK.

Geroski P. A. (1994), *Market Structure, Corporate Performance and Innovative Activity,* Oxford, Oxford University Press.

Geroski, P. A. and Mazzucato, M. (2002), "Learning and the Sources of Corporate Growth," *Industrial and Corporate Change*, Vol. 11 (4): 623-644.
Geroski P. A. , Machin, S. and J. Van Reenan (1993), "The Profitability of Innovating Firms", *RAND Journal of Economics,* 24, 198-21.

Gort, M. and Klepper, S. (1982). "Time Paths in the Diffusion of Product Innovations," *Economic Journal*, 92: 630-653.

Greenwood, J. and Jovanovic, B. (1999). "The IT Revolution and the Stock Market,"*American Economic Review*, 89(2): 116-122.

Griliches, Z., Hall. B., and Pakes, A. (1991), R&D, Patents and Market Value Revisited: Is There ad Second (Technological Opportunity) Factor?," *Economics, Innovation and New Technology,* Vol. 1: 1983-201.

Hall, B., A. Jaffe, and M. Rotenberg (2005) "Market value and patent citations," *Rand Journal of Economics*, Vol. 36(5)

Jovanovic, B., and MacDonald, G.M. (1994). "The Life Cycle of a Competitive Industry," *Journal of Political Economy,* 102 (2): 322-347.

Keynes, J. M. (1973), "A Treatise on Probability," in Moggridge, D. (Ed.). *The Collected Writings of John Maynard Keynes*. London, MacMillan Press, V 8, 1973.

Knight, F.H. (1921). *Risk, Uncertainty and Profit*, Boston: Houghton Mifflin*.*

Marengo, L. (1996), "Structure, Competences and Learning in an Adaptive Model of the Firm," in Dosi, G. and Malerba, F. (eds) Organization and Strategy in the Evolution of the Enterprise. MacMillan, London.

Marsili, O. (2001), *The Anatomy And Evolution of Industries*, Northampton, MA, Edward Elgar.

Mazzucato, M. (2002), "The PC Industry: New Economy or Early Life-Cycle," *Review of Economic ,Dynamics,* 5: pp. 318-345.

Mazzucato, M. (2003), "Risk, Variety and Volatility: Innovation, Growth and Stock Prices in Old and New Industries," *Journal of Evolutionary Economics*, Vol. 13 (5), 2003: pp. 491-512.

Mazzucato, M., and Semmler, W. (1999). "Stock Market Volatility and Market Share Instability during the US Auto industry Life-Cycle," *Journal of Evolutionary Economics*, 9 (1): 67-96.

Mazzucato and Tancioni (2005a), ""Innovation and Idiosyncratic Risk: an Industry and Firm Level Analysis", *Open University Working Paper 50.*

Mazzucato and Tancioni (2005b), "Idiosyncratic Risk and Patent Citations: the case of the pharmaceutical and biotech industry," *Work in progress.*

Nelson R.R. (2004), "The Market Economy and the Scientific Commons", *Research Policy*, 33, 455-472.

Nelson, R., Winter, S. (1982), An Evolutionary Theory of Economic Change, Cambridge Harvard University Press

Pakes, A. (1985), "On Patents, R&D, and the Stock Market Rate of Return," *Journal of Political Economy*, Vol. 93(2): 390-409.

Pastor, L. and Veronesi, P. (2004), "Was There a Nasdaq Bubble in the Late 1990's" Paper presented at the NBER workshop on entrepreneurship and innovation, October 15, 2004, NBER, Boston.

Pavitt, K. (1984), "Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory," *Research Policy,* Vol. 13: 342-373.

Pindyck, R. (1984), "Risk, Inflation and the Stock Market," *American Economic Review,* 74: 334-351.

Shiller, R.J. (1981). "Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends," *American Economic Review*, 71: 421-435.

Shiller, R.J. (2000), *Irrational Exuberance* Princeton University Press, Princeton.

Tushman, M., and Anderson, P. (1986). "Technological Discontinuities and Organizational Environments," *Administrative Science Quarterly*, 31: 439-465.