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Towards a Richer Specification of the Exploration/Exploitation Trade-off: Hidden Knowledge-based Aspects and Empirical Re-sults for a Set of Large R&D-Performing Firms

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In this paper we describe a richer framework characterizing the trade-off between exploration and exploitation with respect firm performance. Building on a model that complements the notion of organizational learning as a process of inferential learning from the past with an explicit incorporation of a knowledge/information-related theory, by using a panel data set we can show empirically that a firm's innovation activities affect its growth perspectives and its asset base differently, depending on the degree of exploitation/exploration. We also show that competitors' R&D has important diverging effects on other firms which again depend on the degree of exploitation/exploration. Finally, we demonstrate the mediating role of environmental risk. We therefore argue that the trade-off between exploration and exploitation has (at least) three constituent dimensions: an internal dimension relating to performance in terms of increasing sales growth and preservation of the asset base, an external competitive dimension, and a contingency dimension relating to environmental factors such as risk. We conclude that the trade-off between exploration and exploitation can only be fully understood, if all three components are taken into account simultaneously.

1 Introduction

It has often been argued that firms' excessive exploitation activities endanger their future opportunities by not adapting to changing environments, while in the case of excessive exploration, firms discard opportunities offered by their current asset base (March, 1991, Fang and Levinthal, 2008). Closely related to this argument is the ambidexterity hypothesis, which states that firms should be good at both making use of their existing assets via means of exploitation as well as recreating them in order to adapt to changing environments and growth opportunities via exploration (Tushman and O'Reilly, 1996, Benner and Tushman, 2003). Lately, also empirical work on the implied optimal balance between exploration and exploitation has emerged (Uotila et al. 2009, He and Wong, 2004, Jansen et al. 2006, Nerkar, 2003), where a trade-off is usually often either conceptionalized as an inverted u-shape of or a positive complementarity between exploration and exploitation on uni-variate performance measure.

However, there are still many blind spots that relate to theory, empirics as well as an appropriate linkage between them. We will raise three issues here.

First, while theory claims a performance trade-off between exploration and exploitation, it is left unspecified how performance should be measured. Not surprisingly, the empirical research diverges considerably here. While for example He and Li (2004) measure the impact of exploration/exploitation on sales growth, Uotila et al. (2009) use market value as the performance measure.

Second, the competitive aspect has not received much attention. Yet, obviously a firm's innovations impact its competitors, while it is itself affected by its competitors' innovations. Thus, the trade-off between exploration/exploitation is embedded in the competitive environment and should be evaluated against it.

Third, it is likely that the trade-off is contingent on mediating variables. We focus on environmental risk here, but emphasize that there may be other relevant variables.

Organizational learning theory, seeking to understand *how* firms learn, can be very useful in analyzing these issues. However, we argue that it is not self-sufficient. Rather take a step backwards and also ask how exploration and exploitation affect knowledge/information available to the firm as well as its characteristics. Our main theoretical argument is that, if organizational learning is largely an inferential and experiential process of learning from the passed Cyert and March, 1963, Argyris and Schön, 1978, Levitt and March, 1988, March, 1991), the relevant knowledge/information characteristics should be conceptionalized also in inferential (i.e. statistical) terms. However, then the focus is on the information and knowledge dimension and issues such as breadth (variation), dependence (co-variation), and quanity (sample size) of the experiential pool available to the firm become relevant. We use this model to derive testable hypotheses relating to the three guiding issues raised above.

Empirically, we make use of an international panel data set of large R&D-performing firms where we can show that more exploratory innovations conducted by a firm lead to higher sales growth but at the same time also to higher depreciation rates with respect to its asset base (and vice versa). Thus the exploration-exploitation trade-off is rather one of trading off different performance dimensions than one of finding an optimal level with respect to only one as usually postulated in the existing literature (internal performance dimension). Further, we show that the R&D activities of others impact a firm's asset base and growth perspective in ways that potentially differ from the effects that occur internally (competition dimension). Lastly, the implied trade-off seems to be affected by environmental riskiness (contigency dimension).

We therefore argue that the trade-off between exploration/exploitation has (at least) three constituent elements. The first is an internal dimension, because firms' innovations affect their different performance measures in potentially divergent ways. The second is the external dimension of competition: firms impact their competitors' positions by innovating and are impacted by them in return. The third is a contingency dimension, because all this seems to be influenced by environmental variables, in particular, risk.

The remainder of the article is organized as follows. In Section 2 we present the relevant theory and literature linked to exploitation and exploration. Since our estimation strategy hinges on the assumption that the average number of patent backward citations is an appropriate indicator of the degree of exploration/exploitation, we present the theory behind this indicator in Section 3 and a more detailed illustrative example relating to the development of the Compact Disc (CD) that supports this choice. Section 4 describes our empirical results Section 5 concludes.

2 Background and Theory

The trade-off between explorative and exploitative innovation on a firm's performance has often been analyzed in the literature (Fang and Levinthal, 2008, Kane and Alavo, 2007, Siggelkow and Rivkin, 2006). The commonly held belief today seems to be that firms should strive to be ambidextrous, in the sense that they are able to excel in both dimensions (Tushman and O'Reilly, 1996, Benner and Tushman, 2002, 2003). Therefore, firms should have both exploratory and exploitative capabilities.

However, there are still several blind spots, some of which result from the way the trade-off is conceptionalized while another relates to the question of an appropriate theoretical background. Starting with the conceptual domain, though the internal perspective (i.e. how own exploration/exploitation affects performance) has been often addressed (see above), the external competitive domain (how does own exploration/exploitation affect competitors) has not. Yet, neglecting the competitive aspects implies that any analyses of optimal choices that relate only to the internal domain are at best partial. Furthermore the contigency domain was often neglected. I.e. it is not completely clear how environmental or organization factors impact on optimal levels. Without coming up with a single optimal point in this work, we try to explicate a fuller framework.

From a theoretical point of view, the literature of organizational learning has focused its theoretical contributions on how firms learn (including questions of whether they learn effectively and when they fail to do so), while it has not focused equally on the question what firms learn. Therefore, while it is important to ask how firms transform available information into organizational knowledge and how this process is affected by exploration and exploitation, it is not sufficient. We should also ask the more fundamental question of what kinds of information gains are associated with exploration and exploitation.

In our framework, the main argument is that both exploratory and exploitative R&D generate knowledge that differs in its characteristics from each other and thereby lead to the establishment of different kinds of routines within the firm, which are themselves linked to different performance dimensions. This line of reasoning requires three theoretical elements. First, a theory of information characteristics. Second, a theory of how information is transformed into organizational knowledge. And third, a theory of how organizational knowledge may become performance relevant in a broader economic sense. With respect to the second and third issue we can rely on insights from the organizational learning and dynamic capabilities. With respect to the first issue we will develop a framework that goes beyond existing literature.

Based on this notion we will derive our hypotheses separating them by internal, the contigency, and the competitive dimension of the exploration/exploitation trade-off in Section 2.2 and 2.3. Yet, before we do so, we will start by describing relevant aspects of the process of inferential learning that will be relevant for determining the relevant characteristics of information associated with exploration and exploitation.

2.1 Organizational Learning as an Inferential Process and Relation to Value and Performance

Behavioral learning in its original and most simplified version posits that knowledge is accumulated in terms of stimulus and response pairs (Cyert and March, 1963). Therefore, embedded in their environments, organizations act in certain ways that yield either desired or undesired results. The environments provide feedback and this feedback is observed by the organizations which then react adaptively to what they observe.

This mechanistic view of learning has been extended by cognitive theories of learning to include higher order cognition, such as “understanding and interpretation of their environments” (Fiol and Lyles, 1985) that allow claims to “general validity” (Argyris and Schön, 1978, p. 10) or more generally the creation of whole “interpretation systems” (Daft and Weick, 1984). Additionally, this line of research has drawn attention to powerful distorting mechanisms (Bazermann, 1997) among which the most well-known is the attribution bias (Levitt and March, 1988, Meindl and Ehrlich, 1987), which implies humans learn much more slowly than statistical models would suggest (Singer and Benassi, 1981).

Despite these differences, both theories highlight one crucial similarity. This is the emphasis on experiential learning. This pops up in Levitt and March (1988) and March (1991), who even bring it closer to statistical concepts by calling it “inferential learning”, but it also appears in Argyris and Schön (1978, p. 323) when they say that “organizational learning refers to experience-based improvement of thought”.

In both approaches, organizational learning is a process in which organizations interpret and process their past experience in order to adapt and change their future behavior. Therefore, organizational learning has the characteristics of an inherently inferential process of data interpretation in both models.

Organizational learning and the dynamic capabilities approach are linked by Levitt’s and March’s (1988) claim that the results of these learning processes are encoded in a firm’s routines which guide future behavior.

Moreover, Teece et al. (1994) already relate dynamic capabilities to the concept of routines, where they distinguish between static routines that allow firms to replicate or vary previously performed (successful) functions and dynamic routines that allow firms to qualitatively identify new production opportunities.

Since routines (both dynamic and static) are highly unobservable and contingent on the social and organizational context of the firm, they are hard to imitate. That is what makes them valuable.

Therefore, exactly this relationship allows defining a trade-off between exploratory and exploitative R&D, because the combination of organization learning theory and dynamic capabilities provide a means relate learning to different kinds of organizational routines (dynamic and static) to different kinds of firm performance. However, this story is still incomplete, because little is said about why and how exploration and exploitation causes affects different performance dimensions of the firm. It is our claim that this cannot fully be understood without making reference to the characteristics of the information and knowledge potentials that accrue from exploration and exploitation respectively. This has been criticized already by Kogut and Zander (1992, p.386) who claimed somewhat provocatively: “Learning has little significance in the absence of a theory of organization knowledge.”

2.2 The Internal Dimension and Contigency Arguments

2.2.1 The Impact of Exploratory and Exploitative R&D in Inferential Learning

Since organizational learning is understood to be inferential, R&D can be seen as an organized effort to create information, or in statistical parlance, observations from which to learn. Therefore, at the very core of the question how exploratory and exploitative R&D impact firm performance is the question what kind of information they create and whether the information benefits is coded into static or dynamic routines, which are related to different performance dimensions of the firm.

In statistical analysis, there are three dimensions that jointly describe the information content of a set of observations. These are the sample size, the correlation between the observations, and the variance of an individual observation. We argue that exploratory and exploitative R&D generates information flows which differ on these three scores. Therefore, they will benefit the creation of different kinds of routines.

Let us start with dynamic routines that are geared towards prediction-making and the adaptability of the firm. Obviously, organizations with more observations will make better predictions (large n). Furthermore, identification in inferential models is based on variation. Thus, for a given number of observations, the quality of prediction increases with the variance contained in the observations. Finally, since uncorrelated observations contain more distinct information than correlated observations, prediction quality increases with the degree of unrelatedness.

Exploratory innovation yields, by its very nature, precisely this kind of information, while exploitative innovation yields knowledge that has the opposite characteristics. In particular, the latter leads to knowledge that is highly correlated with existing knowledge, i.e. it duplicates old knowledge in parts. Furthermore, it will have less variability because it extends only to a limited domain of all possible technological alternatives. Therefore, little variance in past experience causes firms that suddenly (have to) enter new markets to apply local knowledge to distant domains – statistically speaking to make out-of-sample projections. These are likely to be flawed because of "non-linearities", even if the predicting model was accurate locally. Finally, because entering new technological domains needs a more generalist perspective, it is quite likely that the mere choice of exploration prompts additional and proactive searches, which eventually lead to a higher number of totally available observations, crucially important because of the inherent paucity of historical events (March et al. 1991).

In summary, exploitative innovation yields fewer observations that are highly correlated and display low variability. This limits the creation of dynamic routines, i.e. the organizations' possibilities to make correct predictions about the future. Therefore firm growth should be lower when the innovation strategy is exploitative.

H1: a) Exploratory innovations have a more positive impact on growth than exploitative innovations. b) Completely exploratory innovations have a positive impact in absolute terms.

Yet, H1 is likely to be mediated by the speed of environmental change. If the environment changes its current state quickly, experience (that is knowledge of ideally stable relationships) becomes more important. This will at least hold in ergodic environments, where ergodicity describes an aspect of statistical processes (for example Markov chains) and means that certain states of nature do not become arbitrarily improbable as the system evolves. In our context this simply means that experience of the past remains valuable in the future, because the same state is likely to reoccur. If this is the case, the positive effect of exploratory innovation will be larger in high-risk environments. This corresponds to Brown's and Eisenhardt's (1998) notion of the value of probing in such situations.

H2: The impact of exploratory innovations on sales growth is more positive when the environment is more risky.

This seems to suggest that exploratory innovation leads uniformly to more valuable knowledge. But this is not the case. There are obviously important downsides to the accumulation of a large amount of uncorrelated, high-variance knowledge.

First, organizations do not only learn but also forget. The likelihood that routines are forgotten is larger when they are used less frequently. Thus, collecting too much knowledge is likely to displace old knowledge (Levitt and March, 1988). This also leads to an information overload due to the increased difficulty to differentiate, discriminate and integrate features of a problem as highlighted by complexity theory (Schroder et al. 1967). These arguments are in line with the more standard one according to which excessive exploration leads to a large range of underdeveloped ideas that are unlikely to reach intellectual and technological maturity.

Second, knowledge that scatters over large domains of the possible set of actions does not provide potentials for synergies with existing knowledge. That means, if A and B are related phenomena (e.g. A could be an optimal strategy to sell a car and B could be an optimal strategy to sell a motor cycle) then learning about A also means to learn about B. On the contrary, if A and B are very distant (let A be the same as above and B be a strategy to sell haircuts), then learning about A will teach the organization little about B.

Third, while knowledge that is unrelated provides more information than correlated knowledge, it is hard to make sense of unrelated knowledge, because its diversity may overburden the individuals when they try to access organizational knowledge. This is because the cognitive structures necessary to interpret this knowledge are largely missing. Likewise, unrelated techniques also require new assets and organizational techniques. In this context Henderson and Clark (1990) argue that switches in technologies necessitate architectural change. But this change is exactly the one that turns past investments into sunk costs. Thus, the downside of exploratory innovation and the upside of exploitative innovation should be defined in terms of the existing asset base.

In summary, the same characteristics of exploratory innovation (creation of a large number of uncorrelated, high-variance observations) which have allowed firms to make better inferences about the future and therefore improve their dynamic routines, impact negatively on their static routines which allow firms to replicate or to vary successful actions from the past. This should make the existing knowledge base and all the assets related to it, irrespective of whether they are physical or intangible, less valuable.

H3: a) Exploratory innovations have a more negative impact on the assets base than exploitative innovations. b) Completely exploratory innovations have an impact that is negative in absolute terms.

Also the effects in H3 are probably mediated by risk. The negative effect of exploratory innovation on the asset base is likely to be even stronger in high-risk environments, because here the deliberately induced risks by changes in the technology and the by itself risky environment may multiply and working technological routines are even less likely to prevail.

H4: The impact of exploratory innovations on the asset base is more negative when the environment is riskier.

2.3 The Competitive Dimension

The asset base and the growth opportunities are not only affected by the direction of the firm's own innovation, but also by the actions of the competitors (Herriott et al., 1985).

Yet, the directions of the effects are not necessarily the same. E.g. while the firm's own R&D is likely to benefit the firm competitors' R&D may also become a threat. In order to develop this more clearly, we should pay attention to specifying the channels through which the interdependencies between competitors' R&D and the firm's own performance are transmitted.

Our arguments made above suggested that exploratory innovation creates market-tied dynamic routines that benefit growth, while exploratory innovation creates static routines that are aimed at the internal asset base. According to this duality our main argument here is that there is also a duality of the transmission channels, where the first is market-related and transmits impacts on the growth perspectives while the second is asset-related and transmits the impacts on the asset base. In particular, the first has to do with the relativity of the market position and the second is based on spillovers.

The spillover mechanism tends to bestow the same effects on competitors that have already occurred in the innovating firm, basically because the same innovation or some of its elements spill over. With respect to the asset base, competitors' innovation, be it exploratory or exploitative, should have the same effects as in the originating firm: amelioration of the asset in the case of exploitative innovation and depreciation in the case of exploratory innovation.

The second mechanism that links the performance of one firm to the innovation activities of its competitors are the relativity of competition for supremacy (March, 1991). This entails the evolutionary perspective rather than the absolute position. It is the relative position of a company that determines its success. Furthermore, it is a well-known fact, that in competition for supremacy high risk strategies (at least if they occur in form of a mean-preserving spread) are the better strategies. This is due to the hedge implied by competition for supremacy: if a competitor wins, he claims the total or at least a large part of the market. If he does not emerge as the best the paybacks in the worst case are zero, irrespective of how badly he performed with respect to the best.

Therefore, while mean preserving spreads increase the chances of both coming up with particularly bad as well as particularly good results, firms do not care too much about the downsides, since coming top is all that counts. In any case, in principle both exploitative and exploratory innovations should reduce the growth rates of the competitors in absolute terms. As any progress pushes the competitors down the scale, the negative impact of exploratory innovations is likely to be stronger than that for exploitative innovations, whereas the risk and variance of the outcome distributions of exploratory innovation should be much higher.

By summarizing the results from these two mechanisms, we can conclude with the following two hypotheses.

H5: a) The more exploratory the competitors' innovation activities are, the more it impacts negatively on growth rates of the other firms. b) Completely exploratory innovations have a negative impact in absolute terms.

H6: a) The more exploratory the competitors' innovation activities are, the more it impacts negatively of asset bases of the other firms. b) Completely exploratory innovations have a negative impact in absolute terms.

3 Measuring the Degree of Exploration vs. Exploitation – Rational and an Illustrative Example

In this section we will explain, why we can use patent backward citations as a valid indicator of exploration/exploitation. Despite some theoretical appeal (also highlighted in Rosenkopf and Nerkar, 2001), we will provide a brief illustrative example relating to the development of the CD technology that supports this choice.

Backward citations are listed on a patent document and reflect references made to prior art, most commonly to other patents but also to scientific literature. In any case, we will restrict our attention to earlier patents, because even an exploratory innovation is likely to make use of scientific knowledge.

Both, the applicant and the examiners at the respective patent offices have the option of citing previous patent literature. Applicants primarily cite previous patents in order to show that a patent application goes beyond prior art and therefore merits protection. The motives of patent examiners, on the other hand, are more diverse. They have to decide whether to grant or reject a patent application. Therefore, they either cite previous patents to show that the given patent application actually claims new prior art, eventually leading to the grant of the patent. This is in line with the motive of the applicant. However, previous patents can also be cited by examiners to show that the patent application at hand cannot be considered novel or does not involve an inventive step as compared to previous patents (see for example Frietsch et al. 2010).

Apart from these differing motives, backward citations – either provided by applicants or examiners – give proof of some stock of existing knowledge, upon which a patent application can draw. Thus, it is quite intuitive to state that a small number of references made to previous patents implies that the (commercially used) knowledge stock which can be built upon is rather limited, i.e. resembling a rather explorative innovation strategy underlying the protected invention.

To corroborate our argument, we perform a case study of patent applications and backward citations for the CD technology. This is particularly instructive, because we know that the CD was a result of an exploratory search regime. Therefore, our argument suggests that initially backward citations were low but they should increase as the technology matures.

We also decided to use this particular technology as an example, because a clear life-cycle of products can be found in the audio visual sector, which is based on a change in formats (Shibata 1993). When the market matures, formats are superceded by the next technical innovation, leading to a restructuring of competitive positions in the industry referred to as inter-format competition (Shibata 1993). A change in formats heralds a new technological era and a largely replaced knowledge stock, often rendering existing products obsolete. Innovations can be considered as more exploitative until a new format is developed and the product life-cycle starts anew (Hirsch 1967; Vernon 1966). Thus, there should be identifiable tides of backward citations with the zenith of the tide occurring right before a change of formats.

Additionally, following Rosenkopf and Nerkar’s (2001) analysis of this sector, one could assume that references made to patents from foreign technological fields indicate more explorative innovation strategies, as different sources of knowledge have to be found if there is no stock of knowledge to build upon in one's own technological field.

However, as we do not wish to propose a second indicator which goes beyond the backward citations (backward citations outside the own technology field) but rather to corroborate our choice of the indicator, we will also trace the evolution of the technologically external backward citations.

The CD was introduced to the market in 1982, launching a generation of optical storage media for music and, eventually, other data. However, early research on laser diodes, which were essential for the development of the CD, began as early as 1973. The main players in the field were Sony and Philips/Polygram. Research on CD related technologies, especially on laser diodes, was also done by Bell Labs, Hitachi, IBM, Matsushita, Mitsubishi and others (Wood and Brown 1998).

In order to analyze the evolution of the citing behavior in this technology field in more detail, we searched for the number of patents and backward-citations of the main players in CD technology[1] from 1973 to 2007, also differentiating the references by cited technology fields.

To determine the number of patents and backward citations for the selected firms, we employed the "European Patent Statistical Database" (PATSTAT). We focused our analyses on granted patents[2] at the United States Patent and Trademark Office (USPTO) to keep to a homogeneous patent system for the entire period.[3]

As for the differentiation of technological fields we used the WIPO classes, which include the field of audio-visual technology (Schmoch 2008). We will call citations to the field of audio-

1 The firms taken into account for the analysis were Bell Labs, General Electric, Hitachi, IBM, Matsushita, Mitsubishi, NEC, Philips, Polygram, Sharp and Sony.

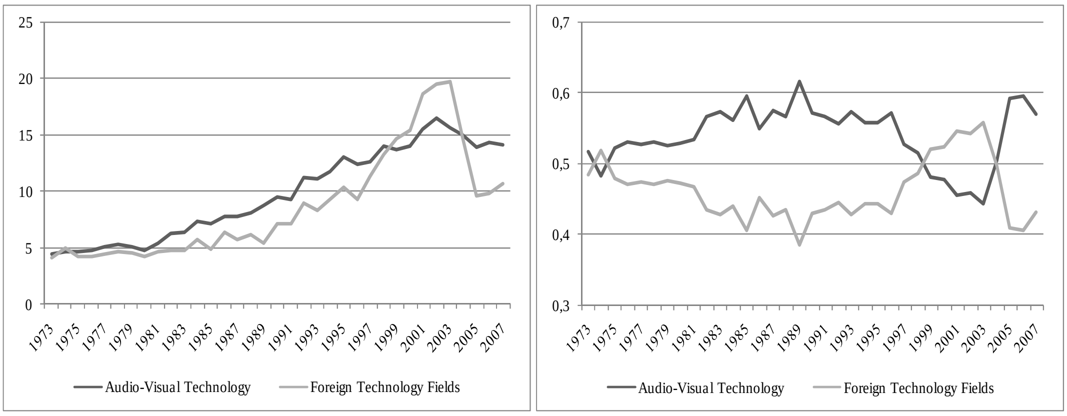
2 Up to the year 2001 the USPTO only published data on granted patents, not on patent applications. Therefore we only report data on granted patents up to the most recent year analyzed.

3 Using the European Patent Office (EPO) would have been an odd choice for several reasons. Besides the US being one of the largest markets for the CD and related technologies, the European Patent Convention (EPC) leading to the introduction of the EPO, came into force as of October 1977 (Stevnsborg/Van Pottelsberghe De La Potterie 2007). Furthermore, mixing EPO and USPTO patent data would also have been potentially fraught with error, because of differing requirements to cite prior art. In the USPTO, citing is mandatory for the applicants; at the EPO it is not.

visual technology home-field citations, as opposed to foreign-field citations, throughout the remainder of this section.

Turning to the results of our analysis, Figure 1 shows the average number of backward citations and the share of home-field citations to all backward citations at the USPTO. In sum, three interesting effects can be observed.

Figure 1: Average number of backward citations and the share of backward citations in audio-visual technology and foreign technology fields to all backward citations at the USPTO, all analyzed firms, 1973-2007



Source: EPO-PATSTAT, own calculations

First, from the year 1970 onwards the average number of backward citations steadily increased, giving a first indication on the accumulating knowledge base, which is made reference to in later phases of the technology life cycle.

Second, at the beginning of the 1980s, the number of home-field citations uncoupled from the number foreign-field citations with home-field citations starting to rise to much higher levels than the foreign citations up to the mid 1990s. Contrary to that, in 1974, one year after the research on laser diodes started, the number of foreign-field citations was even higher than home-field citations. This indicates that backward citations actually are more heavily related to foreign technology fields at the beginning of the product life-cycle. When differentiating the foreign-field citations by all technology fields (not presented), it can be found that mainly telecommunications and computer technologies, as well as the fields of semiconductors and optics were cited. This supports Shibata’s argument (1993) who stated that especially in the audio visual sector new formats are developed in interrelation between hard- and software technology.

Third, from the mid 1990s a sharp increase especially in the number of foreign-field citations and two smaller declines in the number of home field citations (1996-1997 and 1999-2000) can be observed. This pattern of a rising number of backward citations yields to the beginning of a new technological life-cycle, replacing the CD technology by a new one. In fact, two new audio-visual technologies emerged in the mid 1990s, namely the Digital Versatile Disc (DVD), for which a combined format was announced in 1995 (Järvenpää, Mäkinen 2008), and the MPEG-1 or MPEG-2 Audio Layer III (MP3) technology, for which the first patent was filed at the USPTO in 1992, and granted in 1996 (US Patent Number 5,559,834). However, one could see the DVD as an advance in CD technology, but not defining a completely new technology. Thus, maybe more importantly, the development of the MP3 technology, which is a digital audio encoding format which relies even more on developments of software and communication technologies, might have caused the rising trend especially in foreign-field citations.

Particularly important, our results show that backward citations were in our case tightly related to the rise of new technological life-cycles. In the early phases, the number of backward citations was smaller than in later phases.

4 Methodology and Empirical Results

4.1 Methodology

4.1.1 Setting up the model

It seems natural to test our hypotheses based on regression techniques, since they are defined in terms of cause-and-effect relationships. This suggests that we regress the depreciation rate and the sales growth on the relevant innovation variables and on additional control variables. However, following the idea of a trade-off between exploratory and exploitative innovation, which, by our hypotheses, should have divergent effects on the depreciation rate and the sales growth, we should also define a link that allows the determination of a trade-off mediated via these two variables. We therefore set up a sequential model, where the depreciation rate does not only appear as an explained but also as an explanatory variable for the sales growth. Dropping the time subscripts for simplicity (we will work with lag specifications in order to be sure of causality relationships), our benchmark model (suitable for hypotheses H1, H3, H5, H6) looks as follows:

$$\begin{aligned} DP &= \alpha_1 ORD + \alpha_2 ORD \cdot BWC + \alpha_3 CRD + \alpha_4 CRD \cdot CBWC + x'\beta + c + u \\ SG &= \gamma_1 ORD + \gamma_2 ORD \cdot BWC + \gamma_3 CRD + \gamma_4 CRD \cdot CBWC + \gamma_5 DP + x'\eta + z + v \end{aligned} \qquad \text{(1a, b)}$$

where DP and SG denote the depreciation per sales and the one period sales growth. ORD, CRD, BWC, and $CBWC$ are the firm's own R&D expenditures per sales, competitors' R&D expenditures per sales, own backward citations per own patent, and cumulated competitors' backward divided by all competitors' patents. Additionally, x is a vector of control variables that is common to both equations. c and z are unobserved individual effects that are allowed to be correlated with unobserved idiosyncratic error terms u and v.

With respect to H2 and H4 we introduce risk as a third mediation effect. However, due to multicollinearity we drop the influence of the competitors as explaining factors. The model then looks quite similar:

$$\begin{aligned} DP &= \delta_1 ORD + \delta_2 \cdot ORD \cdot BWC + \delta_3 ORD \cdot SDSG + \delta_4 ORD \cdot BWC \cdot SDSG + x'\beta + c + u \\ SG &= \varphi_1 ORD + \varphi_2 \cdot ORD \cdot BWC + \varphi_3 ORD \cdot SDSG + \varphi_4 ORD \cdot BWC \cdot SDSG + \varphi_5 DP + x'\eta + z + v \end{aligned} \qquad \text{(2a, b)}$$

where $SDSG$ denotes the variation of the firm's sales growth over time measuring risk.

It should be noted that both models define simultaneous equation models (SEM), in which DP, which is the explained variable in Eqs. (1a) and (2a), is a covariate in Eqs. (1b) and (2b). Since we believe that the depreciation is an antecedent of changes in sales, we assume that there is no feedback effect of sales growth on the depreciations. Thus, Eqs. (1a, b) and (2a, b) basically define models that are triangular, which allow for both simultaneous and separate estimation of both equations under quite general conditions, while we do not have to correct for endogeneity bias resulting from a potential simultaneous determination of depreciations and sales growth. The exact estimation methods will be described below, but for now we should have a look at the effects which are of potential relevance for the hypotheses.

4.1.2 Definition of the Effects of R&D on Depreciations and Sales Growth

Using Eqs. (1a) and (1b), it is easy to see that H1-H4 are defined in terms of the signs associated with the baseline coefficients $\alpha_1,...,\alpha_4,\gamma_1,...,\gamma_4$. Taken in isolation these measure the impact of own R&D, competitors' R&D, and the respective interaction terms with own backward citations and competitors' backward citations on both depreciations and sales growth. We call these effects isolated (Type I) effects. H1a postulates that the impact of exploratory innovation on sales growth is more positive than that of exploratory innovation, which requires that $\gamma_2 < 0$ because then, irrespective of whether the effect of a completely exploratory innovation is positive or not, the effect of exploitative innovation is more negative. Looking at H1b, which implies that the overall impact of a completely exploratory is positive in absolute terms (instead of just more positive than exploratory innovations) also requires $\gamma_1 > 0$. Comparable arguments hold for the other hypotheses, where obviously with respect to H2 and H4 we do not make a statement about absolute levels. Therefore in these cases only the relative statements pertain. A summary can be found in Table 1.

Table 1 Summary of the hypotheses

	H1a, b	H2	H3a, b	H4	H5	H6
Depreciation per sales	$\gamma_1 > 0$ $\gamma_2 < 0$	$\delta_3 > 0$	---	---	$\gamma_3 > 0$ $\gamma_4 < 0$	---
Sales growth	---	---	$\alpha_1 > 0$ $\alpha_2 < 0$	$\varphi_3 > 0$	---	$\alpha_3 > 0$ $\alpha_4 < 0$

However, adding to the pure testing of the hypotheses, it is interesting to investigate the mediation effects in more detail. In particular, the models allow us to define effects that do not only compare the effect of exploratory relative to exploitative R&D. Focusing on model (1a, b), we are also able to estimate the effect on the depreciation rate and the sales growth of any given R&D portfolio (that is more or less exploratory). These are simply the regression-specific direct marginal (Type II) effects, which are defined as the partial derivatives $\partial \mathrm{E}(DP \mid \cdot)/\partial ORD$,

$\partial\,\mathrm{E}(DP\,|\,\cdot)/\partial CRD$, $\partial\,\mathrm{E}(SG\,|\,\cdot,DP)/\partial ORD$, $\partial\,\mathrm{E}(SG\,|\,\cdot,DP)/\partial CRD$. It is easy to see from Table 2 that they will depend on the level of BWC and $CBWC$, where the effects are evaluated. That means whether for example own R&D destroys or creates assets, will depend on the degree to which the R&D builds on existing knowledge.

Finally, there is the third type of effect that is of interest. In particular, while the Type II effects consider the direct impact of own R&D and competitors R&D on depreciation and sales growth, at least for the latter we also have an indirect effect, because R&D does not only directly affect sales growth but also indirectly via its impact on the antecedent variable depreciation rate. Thus with respect to sales growth, this total (Type III) effect is defined as $\partial\,\mathrm{E}(SG\,|\,\cdot)/\partial ORD$, $\partial\,\mathrm{E}(SG\,|\,\cdot)/\partial CRD$, where we should note that this differs from the Type II effect inasmuch we do not condition the deprecation anymore. The formula-expressions for the Type II-III effects are given in Table 2. They follow directly from the respective derivatives of Eqs. (1a) and (1b).

Table 2 Definition of the effect of own and competitors' R&D

	Type II	Type III
Depreciation per sales	$\alpha_1+\alpha_2 BWC$, $\alpha_3+\alpha_4 CBWC$	
Sales growth	$\gamma_1+\gamma_2 BWC$, $\gamma_3+\gamma_4 CBWC$	$\gamma_1+\gamma_2 BWC+\gamma_5\left(\alpha_1+\alpha_2 BWC\right)$ $\gamma_3+\gamma_4 CBWC+\gamma_5\left(\alpha_3+\alpha_4 CBWC\right)$

We should note here that the Type II and Type III effects are identical for the depreciation because there is no feedback from sales growth.

4.1.3 Estimation Method

Estimation of the Type I and Type II effects which include valid inference for them only requires us to find consistent ways to estimate Eqs. (1a, b) and (2a, b) separately. In the light of potentially endogenous individual effects, this is most easily done by using the within estimator (sometimes loosely called fixed effects estimator), which eliminates the fixed effects by centering each variable on its individual-specific mean. From this regression we can directly read off the Type I effects together with their inference. The Type II effects are obviously non-constant and depend on the value for the backward citations that we plug in. The inference differs for each specific value – some interesting ones such as the mean are discussed later on – but can be derived from an application of the delta method (compare Wooldridge, 2002) that takes into account the covariance between the estimated coefficients.

Even though a point estimate for the Type III can also be calculated from separately performed regressions, the inference will only be available after a simultaneous estimation, because the Type III effect for sales growth also refers to coefficients that come from the depreciation-per-sales-regression. As argued above Eqs. (1a) and (1b) are recursive. Therefore we can estimate both equations simultaneously by seemingly unrelated regression (SURE). A particularly simple way to implement this is to use the least square dummy variable estimator (LSDV) in a SURE approach, which mimics the within estimator (Wooldridge, 2002, Ch. 10.5.3). The inference for the Type III effect than follows once again as an application of the delta method, which now also makes use of the cross-correlations of the coefficients in different equations.

A final note on the variance estimates of the coefficients is in order. By construction, the SURE estimator uses “Sandwich-like” robust estimates. The separate within regression estimates leave the choice of imposing homoscedasticity. In fact, all the results hold, irrespective of variance structure that we impose. That is why we will mainly present the results using the classic variance structure. The other results are available upon request.

4.2 Data Set and Choice of Variables

For the empirical study, a panel data set, including 479 firms from 1990 to 2007 based on the DTI-Scoreboard[4] was constructed, which contains firm-specific data on R&D expenditures, and further information such as the number of employees or sales. The basis year for the construction of the data set is 2001, where 500 companies in total were listed on the DTI-Scoreboard. Data on preceding and following years were added to this data set. If any of the 500 companies had not been listed in the years before or after 2001, the respective observations were treated as missing. Therefore, the panel is unbalanced.

In case of mergers and acquisitions (M&A) between the firms listed on the DTI-Scoreboard, the data for the respective firms was added up in one observation for each year. Using this method, the firms were treated as if they had been merged from the beginning of the observation period. This approach was chosen to preserve comparability over time as no separation of information is possible after the merger.[5] M&A activities with companies not listed on the scoreboard had to be left uncontrolled. However, since unlisted enterprises are not major R&D performers, distortions should be limited.

In a second step, the various key financials, like depreciation rates or capital expenditures, were added from Standard & Poor’s COMPUSTAT Global and North America databases. All mone-

4 For more details on the dataset compare http://www.innovation.gov.uk/rd_scoreboard/.

5 Clearly, this treats merged companies as being the sum of their parts, which may be problematic, if mergers and acquisitions caused for example synergy effects.

tary measures were converted to British pounds (GBP) based on a yearly averaged exchange rate which was taken from the COMPUSTAT Global Currency database. The relevant patent data was extracted from the EPO Worldwide Patent Statistical Database (PATSTAT), which provides published patent information from 81 patent offices worldwide. We restricted the analyses to EPO data. All patent data reported are dated by their priorities, i.e. the year of world-wide first filing. The companies were identified via keyword searches in PATSTAT. The key-words also included the names of subsidiaries, which were directly held to at least 25 percent. The information on the names of the relevant subsidiaries was derived from the LexisNexis (http://www.lexisnexis.com) and Creditreform Amadeus (http://www.creditreform.com). This leaves us with a final sample of 8622 observations from 479 companies world-wide.

Table 3: Overview of the variables and summary statistics

Variable	Mean	Std. Dev.	Min	Max	# Obs.	# Firms
Sales growth	0.12	0.89	-0.96	30.81	4752	458
Depreciation per sales	0.07	0.10	0.00	2.95	4899	455
Sales	10902.77	17409.95	5.00	184879.00	5375	479
Employees	45.85	62.49	0.00	484.00	6392	456
Patent stock	0.39	0.76	0.00	10.74	4769	417
Intangibles/sales	0.18	0.46	0.00	15.42	4833	451
Debt/sales	0.24	0.88	0.00	37.62	5087	456
Capital Expenditures/sales	0.07	0.13	0.00	7.29	4550	453
EBIT/sales	0.09	0.29	-10.94	6.88	5102	456
R&D/sales	0.08	0.22	0.00	11.14	5358	479
Industry R&D/industry sales	0.06	0.04	0.00	0.45	5299	479
R&D/sales (bw-cit)	0.00	0.00	0.00	0.07	4749	442
Industry R&D/industry sales (bw-cit industry)	0.00	0.00	0.00	0.00	4695	440
R&D/sales (bw-cit)	0.05	0.37	0.00	18.29	5322	453
R&D/sales (bw-cit, sd)	0.00	0.00	0.00	0.13	4737	431

We now briefly discuss the variables to be used in regressions presented in the subsequent sub-sections, where descriptive statistics can be found in Table 3. Following the theoretical discussion from Section 2, we use the current sales growth rate as a measure of firm growth while we use the depreciation per sales as a measure of the relative losses on current assets.

Turning to the control variables, we included time dummies to account for confounding level effects that occur over our panel period. Sector dummies need not be included because they are time constant and drop out in fixed effects regression. Furthermore, we included accounting standard dummies because in this international data set not all companies followed identical standards. While those from the US are more likely to do accounting following US-GAAP, European companies are more likely to follow the IFRS or other national standards. However, since most of these standards converged to common principles (e.g. fair value valuation instead of valuation with historical prices), this heterogeneity should not invalidate our results, in particular, after level effects have been controlled. Further control variables include size measures (sales and employees), technology intensiveness (as measured by the patent stock), the importance of intangibles and tangibles (intangibles per sales and the capital expenditures per sales), which could affect, particularly the depreciation rates, as well as profitability and measures of indebtedness EBIT per sales and debts per sales.

The variables of interest (i.e. exploratory and exploitative R&D) allow that the influence of R&D (as measured by R&D per sales) is mediated by the degree of exploitation/exploration (which we approximate based on the average backward citations of the patent portfolio). Therefore, additionally to R&D per sales, we include an interaction effect of with the year-wise portfolio average of the backward citations. This goes for H1 and H3. A measure of risk to which H2 and H3 refer is obtained by calculating the intertemporal standard deviation of each firms sales growth rates. With respect to H5 and H6, we calculate the same measures as for H1 and H3 with respect to the competitors, identifying the latter by being active in the same sector.

4.3 Estimation Results

4.3.1 Testing the Hypotheses – Type I Effects

As argued above, the hypotheses are defined in terms of the actual estimation coefficients. Therefore the results for hypotheses H1-H6 can be read in Table 4, presenting the main regression results.

Additionally to the baseline model in Section 4.1.1, we have also included the past innovation variables in order to account for potential time lags.[6]

Focusing on the first column we clearly see support for the expectation that more exploratory innovations are associated with higher growth rates (H1). This is because the positive coefficient on the R&D per sales variable indicates a generally positive impact of R&D on sales growth which, however, declines with the degree of exploitation as indicated by the negative coefficient on the interaction term ‘R&D/sales (bw-cit)’.

Concerning H5, the results can be found in the same column. The negative effect on the competitors’ R&D variable (in t-1) and the positive effect of the interaction with the backward citations indicate that completely exploratory competitors’ R&D activities impact negatively on the other firms’ growth rates. Yet this negative effect is less pronounced when the competitors’ R&D

6 A one year lag should be enough in most cases. As He and Wong (2004, p. 485) report, based on a sample of 206 manufacturing firms from Singapore, 68% of the R&D-projects were reported to take one year or less.

activities are more exploitative. As explained in Section 4.1.1, this may have to do with the effect that (successful) competitors' innovation activities are likely to push the other firms down the competitive scale. Furthermore, since risk is actually desirable in competition for supremacy, which can be hypothesized for most high-tech industries, exploratory R&D and innovation are even more so, because their outcome is likely to be more uncertain.

The results for 'companion' hypotheses with respect to the depreciation of the asset base are presented in the third column. As expected we find that exploratory R&D impacts negatively on the asset base by increasing the depreciation rate. That is because 'long jumps' instead of a local search (Levinthal, 1997) should devalue the assets related to the production processes based on old technologies while many of the assets related to the new technology still need to be created. In line with this we also find that the negative impact on the asset base declines with the degree of exploitation. Taken together this corroborates the expectations in H3.

Concerning H6 we find the same pattern with respect to competitors' R&D activities on the other firms' asset base. If competitors engage in exploratory R&D, this increases the other firms' depreciations. The negative effect on their assets declines when the R&D becomes more exploitative. This is probably connected to two mechanisms. The first has been described above and relates to the competition of supremacy. If competitors engage in riskier R&D they will not only change their relative competitive position to their favor but will also devalue assets held by the other firms. A second argument relates to the spillovers. Since a spilling over technology should bestow the same kinds of effects on the firm to which it spills over, we would expect that exploratory innovations increase the depreciations on old assets while for more exploitative innovations this effect should be much less pronounced.

Now turning to the impact of risk measured by the standard deviation of the sales growth rate of each firm, H2 hypothesizes that the positive effect of exploratory R&D is likely to be much more prevalent when the risk is high and changes in technologies and markets are profound and abrupt. In this case exploitative innovation is likely to quickly lead to situations in which the firm is improving already outdated technologies. Indeed we see that the positive effect of exploratory R&D can even be negative when the firms operate in very stable environments as can be seen from the negative effect on the R&D/sales variable in t-1 in the second column. The positive effect that was observed in the first column seems to be solely due to firms that operate in riskier environments, which follows from the observation that the effect of interaction with the standard deviation of the growth rate is significantly positive.

A similar effect can be found with respect to the asset base. The depreciation increasing mechanism of exploratory innovation seems to be absent in stable environments, while it occurs only in more volatile situations. In addition, we observe that more exploitative innovations have an asset-appreciating effect also in stable situations, while this effect grows even stronger if the environment is volatile.

In summary, we find that effects of innovation on the asset base and on the growth perspectives can be divergent. The effects are governed by the degree of exploration/exploitation. While more exploitative innovation tends to impact more positively on already existing assets, it does not promote firm growth to the same degree as do exploratory innovations. These relationships seem to be mediated by the volatility that the firm is subjected to.

Up to now we have not paid particular attention to the question of whether sector differences might play a role. In the next subsection we will therefore analyze to which extent the most important results (H1 and H3) vary for manufacturing and service firms.

Table 4: The Main Regression Results (fixed effect regressions)

	H1+H5			*H2*			*H3+H6*			*H4*		
	Sales growth			*Sales growth*			*Depreciation per sales*			*Depreciation per sales*		
	coef.		*t-stat.*	*coef.*		*t-stat.*	*coef.*		*t-stat.*	*coef.*		*t-stat.*
Sales	0.00	***	4.37	0.00	***	7.88	0.00	***	-2.94	0.00	***	-5.45
Employees	0.00		0.83	0.00		0.73	0.00		0.77	0.00	**	2.14
Patent stock	-0.20	***	-3.10	-0.05		-1.08	0.00		-1.36	0.00		0.84
Intangibles/sales	0.09		1.29	0.05		1.05	0.02	***	6.79	0.03	***	9.62
Debts/sales	-0.56	***	-7.35	-0.11	**	-2.10	-0.04	***	-10.91	-0.02	***	-5.81
Capital expenditures/sales	-1.13	**	-2.10	-1.76	***	-4.49	0.67	***	34.17	0.38	***	16.82
EBIT/sales	-0.62	***	-5.38	-0.37	***	-3.66	-0.05	***	-10.42	-0.09	***	-15.68
R&D/sales												
t	2.97	***	6.09	0.42		0.94	0.21	***	9.83	0.01		0.44
t-1	4.89	***	11.60	-1.26	***	-3.48	-0.02		-0.91	0.00		0.07
Industry R&D/industry sales												
t	-3.26		-1.03	---			0.02		0.16	---		
t-1	-9.52	***	-3.08	---			0.59	***	4.35	---		
R&D/sales (bw-cit)												
t	-417.51	***	-6.89	-145.07	***	-2.81	-11.30	***	-4.26	-10.36	***	-3.33
t-1	-363.61	***	-5.90	27.97		0.54	2.49		0.92	-0.07		-0.02
Industry R&D/industry sales (bw-cit industry)												
t	1158.32	***	3.71	---			12.31		0.90	---		
t-1	77.27		0.23	---			-51.23	***	-3.48	---		
R&D/sales (sd)												
t	---			0.04		0.14	---			0.11	***	7.02
t-1	---			2.20	***	11.57	---			0.01		0.82
R&D/sales (bw-cit, sd)												
t	---			48.67		1.34	---			-4.28	*	-1.94
t-1	---			-24.56		-0.86	---			-1.37		-0.79
Depreciation per sales	-0.62		-1.38	-1.22	***	-3.70	---			---		
Year dummies	YES			YES			YES			YES		
Accounting standard dummies	YES			YES			YES			YES		
Constant	YES			YES			YES			YES		
R^2 overall	0.11			0.55			0.49			0.56		
N total	2913			2929			2913			2929		
N firms	372			374			372			374		
F-test	30.34	***		155.73	***		99.43	***		130.03	***	

4.3.2 Sector Differences

Concerning sector differences that may potentially confound our results, we will now test our core results again where we allow coefficients to differ for service and manufacturing firms. The results can be found in Table 5, where the specific pattern that we have observed before seems to be primarily due to firms in the manufacturing sector. The service sector firms differ in two respects. First, competitors' R&D activities do neither affect the sales growth nor the asset base of the other firms. Second, although own R&D both increases the depreciations and the sales growth these effects are not significantly influenced by the degree of exploration.

There might be several explanations for this that range from content over measurement to statistical issues, that relate to inherent differences in the service sector or more trivial ones such as small sample size in this sector, but the most compelling is certainly related an important measurement problem. Since we have used the backward citations as a measure, we of course implicitly suppose that the major outcomes of R&D processes are patented, implying that their characteristics can be measured by patent indicators. This is probably an unreasonable assumption in the service sector, where a much larger part of innovations remain unpatented. In any case, whatever the reason for the largely missing effects may be, we have to constitute that what we have observed in the last subsection is due to manufacturing and not to services.

Table 5: Main regression results by sector (fixed effects regression)

	H1 Sales growth		*H3* Depreciation per sales	
	coef.	*t-stat.*	*coef.*	*t-stat.*
Sales	0.00 ***	4.47	0.00 ***	-2.90
Employees	0.00	1.01	0.00	0.84
Patent stock	-0.20 ***	-3.05	0.00	-1.31
Intangibles/sales	0.09	1.29	0.02 ***	6.64
Debts/sales	-0.51 ***	-6.77	-0.04 ***	-10.61
Capital expenditures/sales	-1.62 ***	-2.98	0.66 ***	32.28
EBIT/sales	-0.49 ***	-3.70	-0.05 ***	-8.50
Manfacturing				
R&D/sales				
t	3.73 ***	6.47	0.22 ***	8.38
t-1	3.01 ***	6.05	-0.03	-1.27
Industry R&D/industry sales				
t	-9.77 **	-2.58	-0.04	-0.23
t-1	-7.03 *	-1.95	0.77 ***	4.74
R&D/sales (bw-cit)				
t	-480.25 ***	-7.12	-12.01 ***	-3.95
t-1	-119.18 *	-1.66	4.16	1.28
Industry R&D/industry sales (bw-cit industry)				
t	1429.87 ***	3.82	20.50	1.21
t-1	-734.62 *	-1.85	-52.35 ***	-2.92
Service				
R&D/sales				
t	0.90	1.07	0.20 ***	5.17
t-1	6.55 ***	8.34	0.00	-0.07
Industry R&D/industry sales				
t	6.04	1.06	0.16	0.62
t-1	-0.33	-0.06	0.22	0.84
R&D/sales (bw-cit)				
t	0.06	0.00	-9.98	-1.40
t-1	41.63	0.27	1.04	0.15
Industry R&D/industry sales (bw-cit industry)				
t	43.39	0.08	2.99	0.13
t-1	-203.89	-0.34	-30.77	-1.15
Depreciation per sales	-0.64	-1.45		
Year dummies	YES		YES	
Accounting standard dummies	YES		YES	
Constant	YES		YES	
R^2 overall	0.10		0.46	
N total	2913		2913	
N firms	372		372	

As we have so far only made statements about the impact of one type of innovation on the asset base/sales growth relative to the other (e.g. exploitative innovations impact less positively on the sales growth than exploratory innovations), we do not know whether the degree of exploitation can in practice be so large that the effect becomes negative in absolute terms. In order to determine this we have to plot the effects of innovation as functions of the degree of exploitation/exploration. This will be done in the next subsection.

4.3.3 The Type II and III Effects

By plugging in mean values for the backward citations into the formulae for the Type II effects (see Section 4.1.2), in Table 6 we present the effects of own and competitors' R&D that are averagely exploitative/exploratory. As we can see, the average R&D increases sales growth and impacts negatively on the asset base. With respect to sales growth this holds true when we take into account the indirect effect that is mediated via the impact on the depreciation rate (compare Table 3). Thus, we can say that the average innovation is demand creating and asset destroying. While there are concerns in the literature, suggesting that firms can easily be trapped in search modes that are local rather than exploratory (among others Levitt and March, 1988), this result suggests that, at least for the sample of the largest R&D performers worldwide, the firms are willing to sacrifice current assets for higher sales growth.

Table 6: Average Effects of Innovation (Type II Effects)

	Sales growth		***Depreciation per sales***	
R&D/sales				
t	2.90 ***	10.30	0.13 ***	11.07
t-1	2.54 ***	24.71	0.00	-0.18
Industry R&D/Industry sales				
t	-5.22 **	2.19	0.37 ***	3.59
t-1	-9.04 ***	-3.86	0.27 ***	2.66

Table 7: Average total Effects of Innovation (Type III Effects)

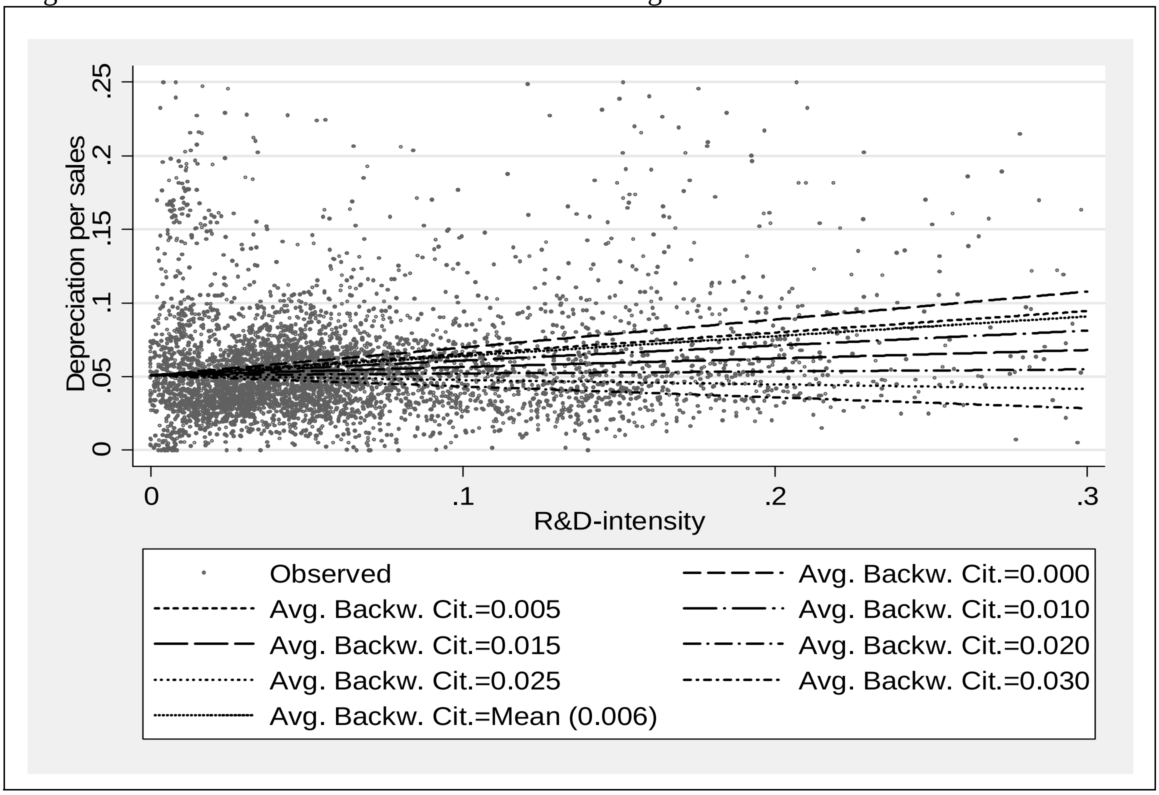
	Sales growth	
R&D/sales		
t	0.2356	0.26
t-1	2.58	2.93 *
Industry R&D/Industry sales		
t	3.77	0.62
t-1	-9.22	4.49 **

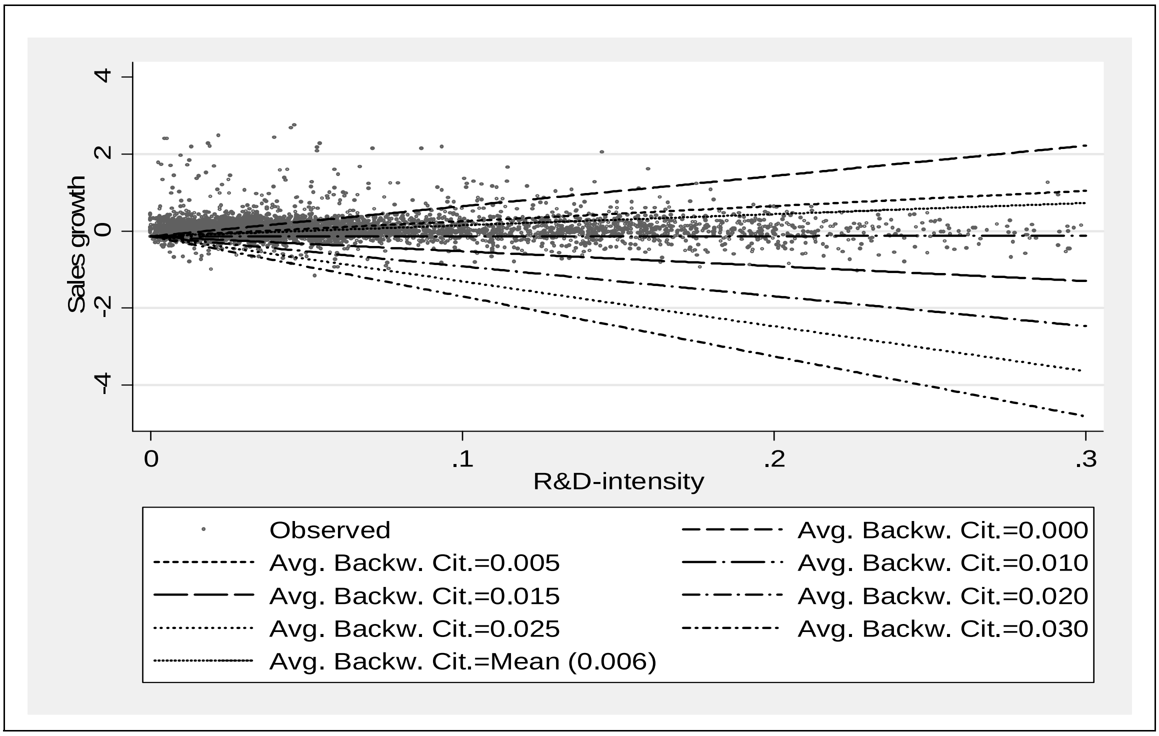
In addition to this observation about average innovations, the results are also useful in another respect. In particular, although the exploration vs. exploitation is measured on a continuous scale, we are able to derive an almost natural classification. This is because the effects of innovation on sales growth and the asset base can switch signs. To illustrate this we have plotted the total effects of innovation on the asset base for various degrees of exploration/exploitation in Figure 2.

Because of the linear interactions these functions are straight lines. Additionally, while a positive slope for one level of exploitation indicates that the innovation has a positive impact on the response variables (either depreciations or sales growth), a negative slope implies a negative effect.

It is easy to see that we can determine three types of innovations. The first are those that are both asset destroying and sales increasing. As we see, the average innovation (with a backward citation rate of 0.006) belongs to this category. Then, at the value of 0.015, innovations become so exploratory that they start to negatively impact on the market growth in absolute terms. Still innovations with this level of exploitation are, even though only slightly, asset destroying. These innovations may therefore to be thought of as an intermediate category of exploitation/exploration. At a value of 0.02, the absolute effect on the asset base also switches signs, implying that firms with such high values can actually appreciate their existing assets. These types of innovation may be thought off as exploitative. It is very compelling to see that about 97% of the firms fall in the first category. 2% fall in the second and only 1% in the last.

Figure 2: Effects of Innovation as Functions of Average Backward Citations





4.3.4 Characterizing the Exploration/Exploitation Trade-off

The previous highlights one of Schumpeter's most fundamental notions of innovation, i.e. that innovation sets off a process of creative destruction by which old assets are sacrificed in order to generate new and strengthened market positions. However, going beyond Schumpeter, who thought that new entrants replace the incumbents, these results show that also the established firms recreate themselves continuously. This pattern holds for about 97% of the firms in our sample, i.e. for an overwhelming majority.

Additionally, the results in the preceding sections show that the trade-off between exploration on exploitation on firm performance is not so much about finding the optimal tipping point with respect to, say, sales growth, but rather that firms trade off their very asset base and future growth perspectives. This trade-off seems to tilt towards the latter in riskier environments and towards the former in environments which are less so. Furthermore, this trade-off seems to be affected by competitors' R&D.

Therefore, the trade-off between exploration/exploitation has at least three constituent elements. The first is an internal dimension, because firms' innovation affects themselves in divergent ways. The second is the external dimension of competition, according to which firms' affect their competitors' positions by innovating and are affected by them in turn. The third is a contingency dimension, because all this seems to be affect by environmental variables. We have focused here on risk, but of course their may be others.

5 Conclusions

This paper argues that understanding the trade-off between exploratory and exploitative R&D requires specifying in terms of which performance measures this trade-off is defined. Based on a framework of inferential learning from the past we propose that firm growth and asset depreciation are two particularly important dimensions.

Our results suggest that while exploratory R&D increases firms' abilities to adapt to changing environments and therefore its growth perspectives, it impacts negatively on the current assets. This is because their usefulness is reduced when new procedures and knowledge are introduced in the firms' technology portfolio. The effect of exploitative R&D has the opposite characteristics. It is much more beneficial for the current asset base while it reduces firms' growth perspectives.

This relationship seems to be affected by environmental risk. In particular, we can show that exploratory R&D becomes more crucial in volatile environments.

Additionally to these results we can show that competitors' R&D, in particular, if it is very exploratory, impacts negatively both on the other firms' asset base as well as their prospective growth rates.

All this suggests a complex trade-off relationship between exploitation and exploration, because, first, firms need to trade-off the effects of exploration/exploitation on two fundamentally different performance measures (internal dimension). Second, they need to take into account that their own R&D has a competitive component (external dimension) as it impacts on their rivals. Third, it is mediated by risk (contingency dimension). Thus, this paper argues that the trade-off between exploitation/exploration is considerably more complicated than finding the optimal level (in the sense of a tipping point of an inverted u-shape) with respect to a univariate performance dimension.

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