Endogenous Knowledge Flows and Sequential Innovation:

Implications for Technology Diffusion, Incentives for R&D and Firm Performance

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Dedicated with love to my parents

Thank you

Abstract

This thesis introduces dynamic considerations and shows that knowledge spillovers (hereafter, spillovers) can also enhance the private returns to innovation (thus, reduce private obsolescence), should they feed back into the dynamic research of the original inventor. However, spillovers will always reduce private returns (thus, intensify private obsolescence) if the original inventor does not technologically benefit from the advancements other inventors build into its spilled knowledge.

The contribution of this thesis broadens the concept of private returns to innovation, by distinguishing between static and dynamic returns. Static returns are defined as the stream of profits directly associated with a single invention, whereas dynamic returns also consider the expected stream of profits the firm can receive from the subsequent developments of its knowledge.

We develop a conceptual framework as well as an empirical methodology that allow us to identify unique patterns of knowledge diffusion, which are defined as lines of research (they are empirically identified as unique sequences of patent citations). We classify the lines of research as two types, based on the feedback they yield to their inventors. A line of research is defined as *Internalized*, if knowledge returns to the boundaries of its inventor, after having been advanced by other firms, whereas a line of research is defined as *Externalized*, if knowledge does not return to the boundaries of its inventor, after having been advanced by other firms.

We find a substantial firm-level variation in the ability to reabsorb spilled knowledge, even within four-digit industries. This variation translates to differential private returns to innovation, where firms that enjoy a more Internalized and less Externalized pattern of diffusion capture higher private returns, as indicated by the effect of their R&D on their market value.

Moreover, we estimate a R&D equation and find preliminary evidence suggesting that firms adjust their R&D expenditures according to their ability to reabsorb their spilled knowledge. Firms that enjoy a more Internalized and less Externalized pattern of diffusion on average invest more in R&D.

We show that firms are able to internalise dynamically some of their knowledge that spills to other firms. To the extent that such internalisation occurs, the underinvestment problem in R&D will be mitigated.

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Contents

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Chapter 1

Introduction and summary of results

Once knowledge leaves the boundaries of its inventor, private returns depreciate, as imitation and subsequent innovation occur[1]. Under cumulative innovation, knowledge is sequentially developed[2], mostly outside the boundaries of its original inventor. The literature refers to this process as knowledge spillovers[3] (hereafter, spillovers). Spillovers are argued to be socially desirable[4], although they enhance private obsolescence (as a more advanced knowledge is now held at the hands of other inventors)[5].

This thesis introduces dynamic considerations and shows that spillovers can also enhance the private returns to innovation (i.e., reduce private obsolescence), should they feed back into the dynamic research of the original inventor. However, spillovers will always intensify private obsolescence, if the original inventor does not technologically benefit from the advancements other inventors build into its

[1]For example, the patent system is designed to mitigate the erosion of private returns as a result of the spread of knowledge, so as to give a sufficient private incentive for innovation.

[2]As Arrow (1962) has stated *"The school of thoughts that emphasizes the determination of invention ... emphasizes strongly the productive role of previous information in the creation of new information"*.

[3]In this thesis, we refer to *spillovers* as the case an inventor builds on prior knowledge that was invented by a different inventor.

[4]Grossman and Helpman (1991) and Romer (1990) model knowledge spillovers as an engine for economic growth.

[5]The obsolescence of private returns to knowledge was addressed, among others, by Griliches (1979), Pakes and Schankerman (1984), Schankerman and Pakes (1986), Caballero and Jaffe (1993) and Lanjouw (1998).

spilled knowledge[6]. We refer to the spilled knowledge as an originating knowledge (as it originates subsequent research) and to its inventor as an originating firm.

The contribution of this thesis broadens the concept of private returns to innovation, by distinguishing between static and dynamic returns. Static returns are defined as the stream of profits directly associated with a single invention, whereas dynamic returns consider also the expected stream of profits the firm can receive from the subsequent developments of its knowledge.

In a static framework, knowledge is not sequentially developed. Hence, static and dynamic returns coincide. However, in a sequential innovation framework, dynamic returns rise with the ability of the firm to exploit the technological opportunities its invention introduces.

Spillovers enhance the technological opportunities of the originating knowledge. The extent to which spillovers raise private returns depends on whether the originating firm benefits from these enhanced technological opportunities. Thus, spillovers can intensify private returns to knowledge through their interaction with the ability of the originating firm to reabsorb its spilled knowledge[7]. We will show, theoretically and empirically, that this ability has a positive effect on private returns in a dynamic framework of sequential innovation.

We develop of a conceptual framework as well as an empirical methodology that identify the ability of firms to reabsorb their spilled knowledge, as described in detail in chapter 2. For this purpose we analyse patents and patent citations data, where patents are our empirical observation for knowledge and patent citations are our empirical observation for knowledge flow from the cited patent to the citing patent[8]. We follow the sequential development of knowledge by extracting sequences of citations, where we interpret every patent in this sequence as a subsequent development of its immediate ancestor. We apply the algorithm we develop

[6]We use the terminology *spilled knowledge,* throughout the thesis, to refer to knowledge that creates spillovers (i.e., the knowledge that is sequentially developed by firms different from the original inventor).

[7]In other words, spillovers can benefit the inventor of the spilled knowledge in a dynamic perspective, through reducing the probability that the line of research it originates will be terminated (once no firm invents). The extent to which these spillovers contribute to the original inventor depends on its ability to build on the inventions of others along the line of research it originates. This ability will be empirically measured, using data on patents and generation of citations.

[8]See, for example, Jaffe, Trajtenberg and Henderson (1993) and Jaffe, and Trajtenberg (1999).

to a high order sequence of citations, which allows us to observe whether knowledge that leaves the boundaries of its inventor, returns to these boundaries after having been advanced by other inventors.

The data we extract are singleton sequences of citations, where *singleton* refers to the fact that every sequence of citations is not fully contained in any longer sequence of citations for the time period we examine (i.e., it is unique). We define these sequences of citations as lines of research, interpreted as unique paths along which the originating knowledge has been developed. We classify these lines of research as two types, based on the feedback they yield to the originating firm. Lines of research are defined as *Internalized*, if the originating knowledge returns to the boundaries of the originating firm, after having been advanced by other firms, whereas lines of research are defined as *Externalized*, if the originating knowledge does not return to the boundaries of the originating firm in the time period we have analysed[9]. Based on the sets of Internalized and Externalized lines of research, we construct diffusion variables that measure the extent to which spilled knowledge is reabsorbed by its inventor.

It should be noted that we assume an inventor desires to exploit the technological opportunities its invention creates by sequentially advancing it (thus, eliminating the case where an inventor retires after making an important discovery). For this purpose, we focus the analysis on a sample of firms that on average remain active for a substantial period of time after having invented the originating knowledge.

The thesis is structured as following: chapters 2 to 5 are mostly empirical and embody the main contribution of the thesis. Chapter 6 is a theoretical analysis of a strategic interaction of firms in managing their spilled knowledge.

In chapter 2 we introduce our conceptual framework and empirical methodology and in chapters 3 and 4 we analyse the circumstances under which a firm is more likely to reabsorb its spilled knowledge; where in chapter 3 we focus on the research environment of the firm and in chapter 4 we focus on the characteristics of the

[9]The terminology Internalized and Externalized refers to whether the spillovers the originating knowledge creates, have been absorbed into the dynamic research of the originating firm.

originating knowledge. Chapter 5 presents the main econometric analysis of the thesis, which estimates the countervailing effect spillovers have on private returns in a market value framework. Finally, in chapter 6 we develop a theoretical model that studies the strategic nature of knowledge flows, by allowing firms to affect the spillovers of their inventions.

We will next turn to explain the findings of this thesis, starting with the main empirical findings, before addressing the findings in each of the chapters of the thesis.

The main findings of this thesis are reported in chapter 5. We find a substantial firm-level variation in the ability to reabsorb spilled knowledge, even within four-digit industries. This variation translates to differential private returns to innovation, as measured by the effect of R&D on the firm market value. Firms that enjoy a more Internalized and less Externalized pattern of diffusion capture higher private returns.

Moreover, we estimate a R&D equation and find preliminary evidence suggesting that firms adjust their R&D expenditures according to their ability to reabsorb their spilled knowledge. Firms that enjoy a more Internalized and less Externalized pattern of diffusion on average invest more in R&D. The importance of this finding extends also to the endogenous nature of knowledge flows, as it motivates developing a framework in which firms not only optimize their R&D activity, but also the diffusion of their knowledge (in chapter 5 we review case-study evidence, suggesting that firms manage the diffusion of their knowledge and in chapter 6 we introduce a theoretical model in which firms simultaneously optimize their R&D and the diffusion of their inventions).

In chapter 2 we introduce our conceptual and empirical framework, which identify the spillovers created by 104,694 patented inventions. We observe that about five percent of these spillovers have been internalized in the dynamic research of their creators. This percentage is stable over time and across technology sectors. Moreover, 7.6 percent of the lines of research (singleton sequences of citations) are Internalized, i.e., represent the case where spilled knowledge is reabsorbed by its inventor. This percentage is also stable across technology sectors and over time.

In chapter 3 we examine the research environment of the originating firm and identify the factors that affect its ability to reabsorb its spilled knowledge. In this chapter, our unit of observation is a line of research. The dependent variable in the econometric analysis is an indicator that receives the value one for an Internalized line of research and zero for an Externalized line of research. We find that firms are more likely to reabsorb their spilled knowledge, if its subsequent developments occur in lines of research that (1) have fewer firms, (2) are less technologically complex and (3) include firms that are more remote in the product market from the originating firm. Findings (1) and (2) are highly robust and evident also within technology sectors. With respect to finding (3), it is less robust to the type of estimation and is less evident within technology sectors (actually, we find a significant effect only in the "Chemicals" sector).

In chapter 4 we investigate the correlation between the diffusion pattern of knowledge and its 'basicness' characteristics. We test the hypothesis that 'basic' knowledge experiences a diffusion pattern which is more Externalized and less Internalized, so that its inventor is likely to face lower private returns. Our unit of observation in this chapter is the originating patent, whereas the dependent variable in the econometric analysis is the share of spillovers that are internalized in the dynamic research of the firm that created them. We find that patents that are more "general" and "original" have a lower share of internalized spillovers. This implies that as knowledge is more 'basic', its inventor is less likely to benefit from the advancement other inventors build into the spilled knowledge by reabsorbing it in a future period.

Chapter 5 includes the main econometric analysis we conduct in this thesis. We analyse the market valuation of the R&D stock of the firm (that proxies its knowledge) and find that the market places a higher valuation on the R&D expenditures of firms that are more able to reabsorb their spilled knowledge (i.e., experience a pattern of diffusion which is more Internalized and less Externalized). Moreover, we find preliminary evidence suggesting that firms adjust their R&D decision according to the diffusion pattern their inventions follow, where firms with a higher ability to reabsorb their spilled knowledge innovate more.

Chapter 6 presents a theoretical model and uses dynamic programming numerical techniques to solve for a game in which firms strategically affect the spillovers that their inventions create, and link this strategic behaviour to the evolution pattern of industries. We theoretically demonstrate the importance of studying the strategic component of knowledge flow for the effect of spillovers on industry evolution, by focusing on the well documented industry event of "producers' shakeout" (which shapes the structure of the industry from fragmented to concentrated).

The mechanism that triggers industry shakeout in our model is based on strategic knowledge flows[10], as follows: at the early periods of the industry evolution firms have a strong incentive to share their knowledge with other firms in order to encourage the expansion of the market. As the industry matures, the positive incentive to share knowledge weakens, relative to the desire of firms to protect their market share, up to a point where firms choose to prevent the flow of their knowledge, thus, diminishing spillovers. This triggers "producer's shakeout", as firms with lower innovative capabilities, which are able to survive only in the presence of spillovers, are forced out of the industry.

In summary, this thesis shows that spillovers can lower private obsolescence of knowledge, if they feed back into the dynamic research of their creator. This depends on the characteristics of the research environment, the type of the knowledge created and the features of the firm. To the extent this internalisation of spilled knowledge occurs, the underinvestment problem in R&D will be mitigated.

[10]In this chapter we explore a different mechanism by which firms can benefit from the spillovers they create. As in the empirical part of thesis firms can benefit from the spillovers they create technologically, in this chapter, the benefit comes from the expansion of the product market.

Chapter 2

Conceptual Framework and Empirical Methodology

Using data on about 600,000 patents and 1.7 million patent citations for the US, we have measured the spillovers created by 104,694 inventions between 1975 and 1995. We identify the extent to which firms reabsorb the knowledge they invent, after it is diffused and is advanced by other firms, and conceptually link it to the private returns to innovation. We find that about 5 percent of the spillovers that have been created by our sample of inventions, contributed to the dynamic research of their inventors. This percentage has been rather stable over time and on average does not vary much across technology sectors.

2.1 Introduction

Using data on about 600,000 patents and 1.7 million patent citations in the US, we have measured the spillovers created by 104,694 inventions, between 1975 and 1995 by tracing the flow of knowledge across patented inventions, in a multiple generations of development framework.

We build on previous studies and identify knowledge flow as a patent citation[1]. We use citations data to follow the diffusion of a piece of knowledge across multiple subsequent developments. In this chapter and throughout the empirical part of the thesis we demonstrate how the data we have developed can be used to address old

[1] See, for example, Jaffe, Trajtenberg and Henderson (1993) and Jaffe, and Trajtenberg (1999).

and new questions in the economics of innovation field, focusing on the effect of knowledge spillovers on private returns to innovation.

Once knowledge leaves the boundaries of its inventor, private returns depreciate, as imitation and subsequent innovation occur. The patent system is designed to mitigate the erosion of the private returns as a result of the spread of knowledge so as to give a sufficient private incentive for innovation. Under cumulative innovation, knowledge is sequentially developed, mostly outside the boundaries of its original inventor. This is addressed in the literature as knowledge spillovers (hereafter, spillovers). Spillovers are argued to be socially desirable[2], although they enhance private obsolescence (as a more advanced knowledge is now held at the hands of other inventors)[3].

This thesis introduces dynamic considerations and shows that spillovers can also enhance the private returns to innovation (i.e., reduce private obsolescence), should they feed back into the dynamic research of the original inventor[4]. However, spillovers will always intensify private obsolescence, if the original inventor does not technologically benefit from the advancements other inventors build into its spilled knowledge.

Identifying the conditions under which spillovers reduce obsolescence and enhance private returns should help in understanding the optimal design of patent policy. Spillovers are both socially and privately desirable when they unambiguously reduce obsolescence, and in such cases public intervention is less required to stimulate innovation[5].

In this thesis we show that there is an empirically identifiable pattern of diffusion that does not necessarily erode private returns, which can also rise through inspiring

[2]Grossman and Helpman (1991) and Romer (1990) model knowledge spillovers as an engine for economic growth.

[3]The obsolescence of the private returns to knowledge was addressed, among others, by Griliches (1979), Pakes and Schankerman (1984), Schankerman and Pakes (1986), Caballero and Jaffe (1993) and Lanjouw (1998).

[4]In chapter 5 we actually show that the positive effect outweighs the negative effect. Thus, in this case spillovers reduce obsolescence.

[5]Spence (1984) relates to the effect of spillovers on the incentive to innovate, by arguing that if firms are not aware of the spread of their inventions, spillovers will not undermine their incentive to innovate. Thus, other firms benefit from spillovers without depressing the *perceived* private returns to the knowledge they are benefiting from.

the ideas of others, that will "feed back" into the dynamic research program of the original inventor.

We decompose the spillovers an invention creates into two components: spillovers that contribute to the dynamic research of the firm that created them, and spillovers that do not make this contribution. We define the first as *Internalized* and the second as *Externalized.* We conceptually link them to the private returns to innovation, where the Internalized pattern reduces private obsolescence (thus, can have a positive net effect on private returns) and the Externalized pattern raises private obsolescence (thus, must have a negative effect on private returns).

The essence of our empirical methodology is as follows: for each patent in our sample we construct a "family-tree", assuming that a patent citation is an indicator for knowledge flow from the cited patent to the citing patent. For example, assume patent j cites patent i and patent k cites patent j. Hence, the "family-tree" of patent i includes both patent j and patent k, where, patent j is the 'child' of patent i and patent k is the 'grandchild' of patent i. Giving this "family-tree", we classify invention k as an offspring invention of patent i, even though knowledge did not transfer directly from invention i to invention k. Applying this method to a high-order sequence of citations allows us to trace the trajectory knowledge has followed, while spreading across inventions and firms. Based on these trajectories, we can determine whether knowledge that leaves the firm and is further advanced by other firms, will have been reabsorbed by the original firm in a future period.

In conclusion, we have broaden the analysis of the dynamic production of knowledge, by identifying two different patterns of diffusion, which have potentially countervailing effects on the private returns to innovation. An Internalized pattern of diffusion is the case where knowledge returns to the boundaries of its inventor, after other inventors have advanced it. Whereas, an Externalized pattern of diffusion is the case where knowledge does not return to the boundaries of its original inventor, after it has been advanced by others. In this chapter we examine the extent to which these two patterns appear in the data and vary across technology sectors and over time periods.

The rest of this chapter continues as following: the methodology is presented in section 2, section 3 describes the data, section 4 discusses the findings and section 5 summarizes and concludes.

2.2 Methodology

We aim at identifying the technological benefit firms receive from the spread of their discoveries to other firms. This section discusses the conceptual issues that underpin our empirical framework, with regard to how we should measure the technological contribution of an invention and the spillovers it creates.

We distinguish between two patterns of knowledge flows: the first pattern is where knowledge leaves the boundaries of its inventor and returns to these boundaries in a future period, after having been advanced by other inventors. The second pattern is where knowledge leaves the boundaries of its inventor and never returns to these boundaries, after others have advanced it. Finally, we describe the empirical strategy that accommodates our conceptual framework.

2.2.1 Identifying the technological contribution of an invention

An invention contributes to technological research only if the knowledge it embodies is diffused and is exploited by other inventions. Thus, the analysis of the technological contribution of an invention is equivalent to that of its diffusion pattern.

We propose measuring the technological contribution of an invention in two dimensions. The first is the proliferation of research opportunities the invention creates and the second is the quality of these research opportunities.

A research opportunity is defined as *a sequence of inventions, where every invention is a follow-up development of its immediate ancestor.* We require that this sequence of inventions be unique over a given time period, i.e., not to be fully contained in a longer sequence of inventions. We define a sequence of inventions that satisfies these requirements as a *line of research*, the first invention in the line of research as an *originating invention* (or an *originating patent)* and the firm that owns this invention as an *originating firm* (or an *originating inventor*).

We link the quality of a line of research to the level of technological progress it provides. A line of research is assumed to be of a higher quality, should the number of subsequent developments of the originating invention it incorporates be larger.

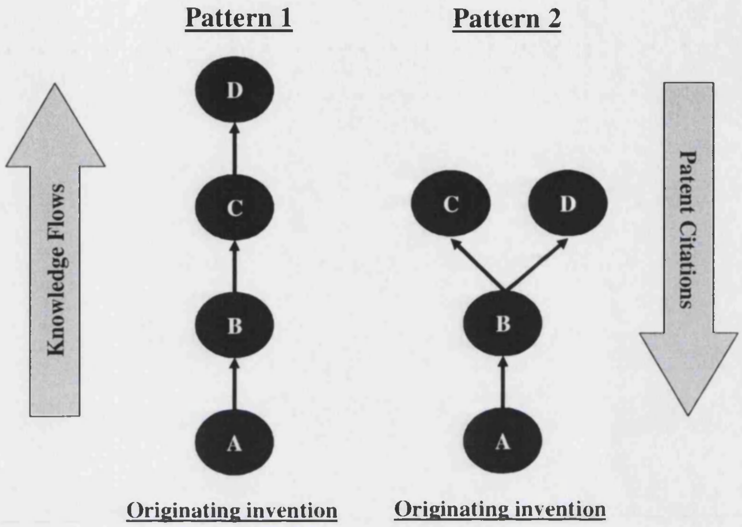


Figure 1: Patterns of diffusion

Figure 1: *Circles in this figure represent inventions and arrows represent the direction of knowledge flow. Pattern 1 illustrates a singleton path of knowledge flow, which is* $A \to B \to C \to D$*, while diffusion pattern 2 illustrates two unique paths of knowledge flows, which are* $A \to B \to C$ *and* $A \to B \to D$*. Determining the technological contribution of invention* A *under the two diffusion patterns requires weighing these lines of research by their quality, by measuring their length in terms of inventions.*

In order to illustrate these two dimensions, it is useful to refer to figure 1, which describes two alternative diffusion patterns of invention A. Circles in this figure represent inventions, whereas arrows represent the direction of knowledge flow. Thus, invention A in patterns 1 and 2 (the originating invention) contributes knowledge to inventions B, C and D, which are developments of the knowledge embodied in invention A. Under pattern 1, invention B benefits directly from invention A, invention C benefits indirectly from invention A, *via* invention B and invention D also benefits indirectly from invention A, *via* inventions B and C.

However, under pattern 2, invention B benefits from invention A directly, whereas inventions C and D benefit from invention A indirectly, *via* invention B.

Focusing first on the proliferation of lines of research originated in invention A, the two patterns of diffusion represent different scenarios. Pattern 1 represents only one unique line of research, which is the sequence of inventions $A \rightarrow B \rightarrow C \rightarrow D$ (the arrows represent the direction of knowledge flow). However, pattern 2 represents two unique lines of research, which are $A \rightarrow B \rightarrow C$ and $A \rightarrow B \rightarrow D$ (since none of them is fully contained in the other). Thus, in terms of research opportunities, pattern 2 is more substantial.

Nonetheless, in order to complete the comparison of the technological contribution between the two patterns of diffusion, we take into consideration the second dimension, which is the quality of the lines of research that are originated in invention A. As described above, we measure the quality of a line of research by the number of subsequent developments of the originating knowledge it incorporates. Therefore, the quality of the singleton line of research $A \rightarrow B \rightarrow C \rightarrow D$ in pattern 1 is 3, as there are 3 subsequent developments of the originating knowledge: B, C and D. The qualities of the lines of research in pattern 2 are 2 for the line of research $A \rightarrow B \rightarrow C$ (inventions B and C) and 2 for the line of research $A \rightarrow B \rightarrow D$ (inventions B and D). Hence, each line of research in pattern 2 is of a lower quality than the singleton line of research in pattern 1. However, pattern 2 is associated with more lines of research. Combining the two dimensions, proliferation of lines of research and their quality, leads to the determination of the technological contribution of invention A, under each of these diffusion patterns.

We propose measuring the technological contribution of an invention as the quality weighted count of the lines of research it originates, as following:

$$TC_i = \sum_{k \in K_i} LR_k \times Q_k \tag{2.1}$$

Where, i is an originating invention, TC_i is the technological contribution of invention i, K_i is the set of lines of research originated in invention i, k indexes lines of research in this set, LR_k is a dummy that receives the value of 1 for line of research k and zero otherwise, and Q_k is the quality of line of research k, as measured by the number of inventions that compose it[6]. Thus, our measure of the technological contribution of invention i is the proliferation of research opportunities it originates, adjusted by the quality of these research opportunities.

Applying this formulation to the diffusion patterns in figure 1 yields:

$$TC_A^1 = (1 \times 3) = 3 \tag{2.2}$$

Where, TC_A^1 is the technological contribution of invention A under pattern 1. The term 1 in the brackets represents the singleton line of research $A \to B \to C \to D$ that is adjusted by its quality, which equals 3 (since it includes three subsequent developments of invention A: B, C and D). Thus, our measure of the technological contribution of invention A under pattern 1 is 3.

Similarly, the technological contribution of invention A under diffusion pattern 2 is:

$$TC_A^2 = (1 \times 2) + (1 \times 2) = 4 \tag{2.3}$$

Where, TC_A^2 is the technological contribution of invention A under pattern 2. The term 1 in the first brackets represents the line of research $A \to B \to C$ that is adjusted by its quality, which equals 2 (since it includes two subsequent developments of invention A: B and C). The term 1 in the second brackets represents the line of research $A \to B \to D$ that is adjusted by its quality, which equals 2 as well (since it includes two subsequent developments of invention A: B and D). Thus,

[6]Simply counting the number of inventions along a line of research may be an overestimate of the technological contribution of the originating invention. A subsequent invention which is a high generation of development of the originating invention is more likely to have benefited from other prior subsequent inventions along the line of research, which may have a more important impact on its creation than the originating invention. Thus, in practice we discount the inventions along a line of research by a discount factor of δ (which we assume to be 15 percent per generation), thus, $Q_k = \sum_{j=1}^{J} \delta^{j-1}$, where, J is the number of offspring inventions in line of research k. Since our choice of the discount factor is arbitrary, we experiment with other values to test the robustness of our findings.

our measure of the technological contribution of invention A under pattern 2 is 4.

From this we conclude that the technological contribution of invention A under diffusion pattern 2 is greater than its technological contribution under diffusion pattern 1 (intuitively, under both patterns of diffusion the number of subsequent developments is equal. However, there are more intense research opportunities under pattern 2, as indicated by the number of lines of research).

2.2.2 Identifying spillovers

After introducing the methodology we have developed in order to identify the technological contribution of an invention, we proceed to discussing our proposed measure of spillovers. We define spillovers as the external exploitation of the technological contribution of an invention, where *external* relates to the set of firms that are different from the originating firm. Following this definition, spillovers are measured as the number of external inventions along the lines of research the originating invention inspires.

For illustration, it is useful to examine a slightly more complicated diffusion pattern, as presented in figure 2. Shapes (denoted by a capital letter) represent inventions, whereas arrows represent the direction of knowledge flow. This figure plots the diffusion pattern of the originating invention A, where the offspring inventions are B, C, D, E, F, G, H, I and J. To complete the presentation, the shape of each figure represents a different firm, i.e., a circle firm (the originating firm), a triangle firm and a square firm.

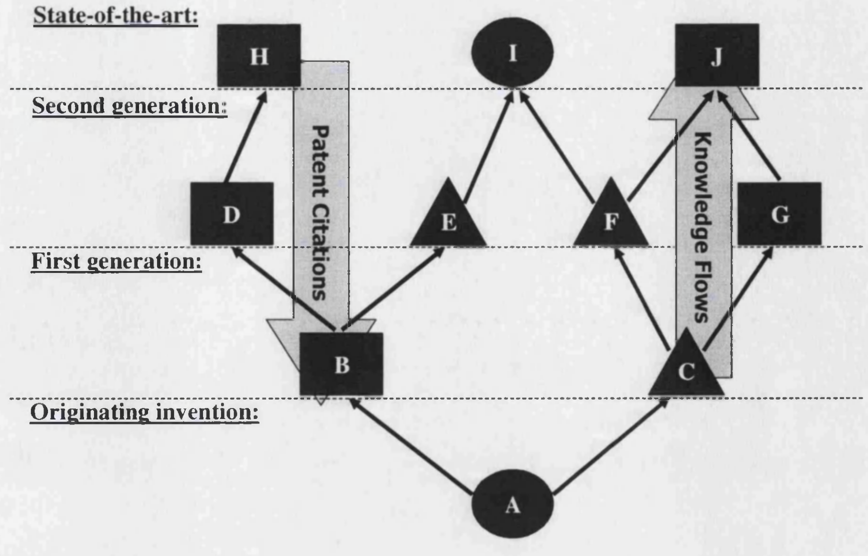


Figure 2: Measuring spillovers

Figure 2: *This figure illustrates the diffusion pattern of the originating invention A. Inventions are represented by a capital letter, while the firm that owns the inventions is represented by a shape (e.g., the originating firm is the circle, since it owns the originating invention A). We define the spillovers created by invention A, given this diffusion pattern, as the number of inventions that are owned by the square and triangle firms (all the firms in the figure which are different from the originating firm) along the lines of research invention A originates.*

Following the methodology we have presented above, in order to measure the technological contribution of invention A, we need to identify the lines of research invention A originates and weigh them by their quality. Since we define a line of research as a singleton sequence of subsequent developments of the originating knowledge, we identify five such lines of research: $A \to B \to D \to H$, $A \to B \to E \to I$, $A \to C \to F \to I$, $A \to C \to F \to J$ and $A \to C \to G \to J$. The technological contribution of invention A following equation (2.1) is given by:

$$TC_A = (1 \times 3) + (1 \times 3) + (1 \times 3) + (1 \times 3) + (1 \times 3) = 15 \qquad (2.4)$$

Since spillovers are defined as the external inventions that compose the lines of research an invention originates, they are formulated as:

$$Spillovers_i = \sum_{k \in K_i} LR_k \times S_k \tag{2.5}$$

Where, i is an originating invention, $Spillovers_i$ denotes the spillovers invention i creates, K_i is the set of lines of research invention i originates, k indexes lines of research in this set, LR_k is a dummy that receives the value 1 for line of research k and zero otherwise and S_k is the number of external inventions included in line of research k. Following this formulation, the spillovers created by invention A are given by:

$$Spillovers_A = (1 \times 3) + (1 \times 2) + (1 \times 2) + (1 \times 3) + (1 \times 3) = 13 \tag{2.6}$$

Where, the second and third terms, (1×2) and (1×2), correspond to the fact that invention I is owned by the originating firm. Thus invention I is excluded from the spillovers measure for invention A (hence, the spillovers along lines of research $A \to B \to E \to I$ and $A \to C \to F \to I$ are based only on inventions B, E, C and F)[7].

Finally, we are interested in distinguishing between two types of spillovers: spillovers that contribute to the dynamic research of the originating firm and spillovers that do not make this contribution.

2.2.3 Internalized and Externalized lines of research

We distinguish between two types of lines of research: the first type is lines of research that are characterized by the originating knowledge leaving the boundaries of its inventor to return to these boundaries after having been further developed by other firms. The second type is lines of research characterized by the originat-

[7] In some patterns of diffusion, the first subsequent development of the originating knowledge is invented by the originating firm (which is identified as a *self-citation*). Hence, knowledge does not immediately spread to other inventors. In this case, the 'in-house' subsequent development is not measured as spillovers.

ing knowledge leaving the boundaries of its inventor so as not to return to these boundaries.

Spillovers along the former type are *internalized* in the dynamic research of the originating firm and, therefore, we define lines of research of this type as *Internalized lines of research.* However, spillovers associated with the latter type do not contribute to the dynamic research of the originating firm. Therefore, we define this type of lines of research as *Externalized lines of research* (since the technological benefit they provide is exploited only by external inventors).

Based on the technological feedback the originating firm receives from the spread of its discovery, we decompose the spillovers created by an invention into two components: spillovers that contribute to the dynamic research of the originating firm and spillovers that do not.

Given this decomposition, the spillovers of an invention can be written as:

$$Spillovers_i \;=\; \sum_{j \in Internalized_i} LR_j \times S_j + \sum_{t \in Externalized_i} LR_t \times S_t \qquad (2.7)$$

Where i denotes an originating invention, $Internalized_i$ is the set of Internalized lines of research originated in invention i, $Externalized_i$ is the set of Externalized lines of research originated in invention i, j indexes lines of research in the $Internalized_i$ set and t indexes lines of research in the $Externalized_i$ set.

We define the first term in the right-hand-side of equation (2.7) as $Internalized\ Spillovers_i$ and the second term in the right-hand-side of equation (2.7) as $Externalized\ Spillovers_i$. Hence, equation (2.7) becomes:

$$Spillovers_i \;=\; Internalized\ Spillovers_i + Externalized\ Spillovers_i \qquad (2.8)$$

Finally, we are interested in computing the share of spillovers that are *internalized* in the dynamic research of the originating firm. This share is computed simply as the ratio between $Internalized\ Spillovers_i$ and $Spillovers_i$, as following:

$$Share\ of\ Internalized\ Spillovers_i \;=\; \frac{Internalized\ Spillovers_i}{Spillovers_i} \qquad (2.9)$$

In order to illustrate this decomposition, we refer back to figure 2. Out of the five lines of research that invention A originates, two are Internalized and three are Externalized. Thus, the set $Internalized_A$ is:

$$Internalized_A = \{A \rightarrow B \rightarrow E \rightarrow I, A \rightarrow C \rightarrow F \rightarrow I\}$$

Similarly, the set $Externalized_A$ is:

$$Externalized_A = \{A \rightarrow B \rightarrow D \rightarrow H, A \rightarrow C \rightarrow F \rightarrow J, A \rightarrow C \rightarrow G \rightarrow J\}$$

Given this decomposition, $Internalized\ Spillovers_A = (1 \times 2) + (1 \times 2) = 4$ (two external inventions in the first line of research and two external inventions in the second line of research in the $Internalized_A$ set).

Similarly, $Externalized\ Spillovers_A = (1 \times 3) + (1 \times 3) + (1 \times 3) = 9$ (three external inventions in each of the three lines of research in the $Externalized_A$ set).

Finally, the $Share\ of\ Internalized\ Spillovers_A$ is $\frac{4}{13}$.

This framework provides three units of analysis, separately addressed in the following chapters.

The smallest unit of observation is a line of research. In chapter 3 we closely examine the characteristics of lines of research and measure their effect on the likelihood that a line of research is Internalized.

The second unit of observation is the patent. In chapter 4 we aggregate the lines of research to the patent level and characterize its diffusion pattern under the Internalized and Externalized criterion. We measure the correlation between the 'basicness' attributes of the patent and its Share of Internalized Spillovers.

Finally, our most aggregated unit of observation is the diffusion pattern at the firm level. In chapter 5 we aggregate the lines of research to the firm level to characterize the diffusion pattern of its inventions. We estimate the effect of the diffusion indices we have constructed on the private returns to innovation in a market value framework.

2.2.4 Empirical strategy

Based on the conceptual framework we have presented above, we turn to discuss our empirical strategy.

We have made two building block assumptions that underpin our empirical methodology. First, patents are empirical observations for inventions. Second, patent citations are empirical observations for knowledge flows from the cited patents to the citing patents. Acknowledging the various noise and biases associated with these two assumptions[8], the only defence we provide for imposing them is that these data are the most comprehensive source of information on the diffusion of knowledge, which have not been explored with regard to the ideas presented in this paper. We believe that the drawbacks of this data source are not large enough to prevent us from posing the questions we address in this research.

Based on data on about 600,000 citing patents (which can appear in the sequences of citations we extract), 570,000 cited patents and 1.7 million citations (links in the sequences of citations), we have constructed the diffusion pattern of 104,694 originating inventions (which are a subset of the cited patents, as explained below) between 1975 and 1995 (we do not have information on citing patents that had been granted before 1975). The task we are facing is to effectively draw figure 2 for these originating inventions.

We identify inventions as patents and flows of knowledge across inventions as patent citations. Thus, the inventions in figures 1 and 2 are empirically identified as patents, whereas the arrows in these figures are empirically identified as citations. For example, an arrow from invention A to invention B in figures 1 and 2 represents the fact that patent B cites patent A.

Further, a unique line of research is empirically identified as a *singleton sequence of citations* (where, each patent cites its direct ancestor). As discussed above, we define that sequence of citations as singleton if it is not fully contained in a longer sequence of citations for the given time period we have been exploring.

[8]See, for example, Trajtenberg (1990) for the potential bias in patents as indicators for innovation output, and Trajtenberg, Jaffe and Fogarty (2001) for a study on the noise component in citations as indicators for knowledge flows.

After extracting the lines of research for our sample of originating patents (i.e., all the singleton sequences of citations), we classify each line of research as either Internalized or Externalized[9], following the methodology we have described above[10].

We have restricted the period for which we extract the diffusion pattern to 15 years after the grant year of the originating patent. Thus, for a patent that was granted in 1975 we have extracted the lines of research it originates as long as the youngest invention in these lines of research has not been granted after 1990.

Furthermore, we stopped exploring the diffusion of knowledge along a given line of research if this line of research had already been classified as Internalized[11].

Thus, our methodology extracts all the unique trajectories in which knowledge had left the boundaries of its inventor and returned to these boundaries in a time period of 15 years after the knowledge had been created[12], as well as all the unique trajectories in which knowledge had left the boundaries of the firm and did not return to these boundaries in the same time period.

The algorithm that was developed to construct the data used in this thesis is described in the appendix. Overall, it has taken about 35 days to run this algorithm on our sample of patents and citations (the running time can be shortened either

[9] However, we find an additional pattern of citations, which is the case where knowledge does not leave the boundaries of the firm that has created it. Thus, all of the subsequent developments of the originating knowledge are invented 'in-house'. Since we assume that technological spillovers can occur only if knowledge drifts outwards from the boundaries in which it has been created, we do not include this pattern in our study.

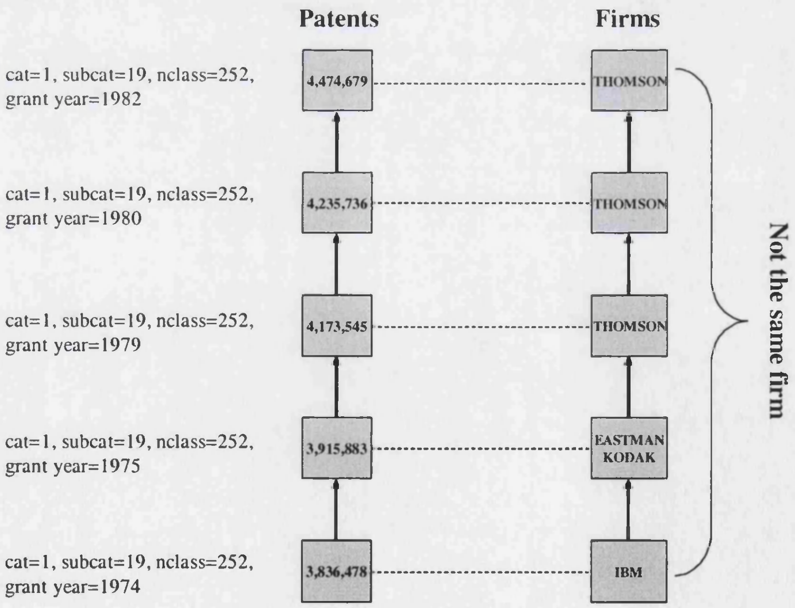
[10] The reader who is familiar with the economics of patents literature can find our definition of an Internalized line of research similar to a self-citation. Where the latter refers to the case in which a firm develops its prior knowledge directly, the former refers to the case in which the firm *indirectly* develops its prior knowledge, after it has been diffused and has been developed by other firms. Thus, an Internalized line of research is a unique *indirect self-citation*, which we associate with a higher appropriability, as the existing literature does with self-citations (for example, see Hall, Jaffe and Trajtenberg, 2005).

[11] E.g., consider the Internalized line of research $A \rightarrow B \rightarrow E \rightarrow I$ that is presented in figure 2. Assume that patent I is cited by patent K, such that this line of research becomes $A \rightarrow B \rightarrow E \rightarrow I \rightarrow K$. The restriction we impose implies that we will extract only the line of research $A \rightarrow B \rightarrow E \rightarrow I$ and will not refer to patent K as being part of the spillovers created by invention A.

[12] Since we refer to the grant year of the patent and not to its application year, the creation date of the patented knowledge is actually earlier. However, even though it may be more reasonable to refer to the application year of the patent rather than to its grant year, we find it technically (in terms of the running time of our algorithm) much more efficient to consider the latter over the former.

by reducing the number of originating patents or the number of citations. Alternatively, one can run the algorithm simultaneously on any number of machines).

We conclude this section with two examples of lines of research that are extracted from our sample, as presented in figures 3 and 4. Figure 3 presents an Externalized line of research originating in patent 3,836,479 which is owned by IBM (the originating firm). This patent was cited by patent 3,915,883, which had been cited by patent 4,173,545. This patent was cited by patent 4,235,736, which had been finally cited by patent 4,474,679. This line of research (sequence of citations) is unique in the sense that it is not fully contained in any other longer sequence of citations within the time period we have been analysing (since the originating patent was granted in 1974, this period is 1974-1989). This line of research is associated with knowledge leaving the boundaries of IBM to other firms and not returning to IBM during the 15 years after this knowledge was created. Therefore, the line of research is classified as Externalized (the spillovers the originating patent created, which are represented by the four external inventions along the line of research, were not technologically exploited by IBM's research).

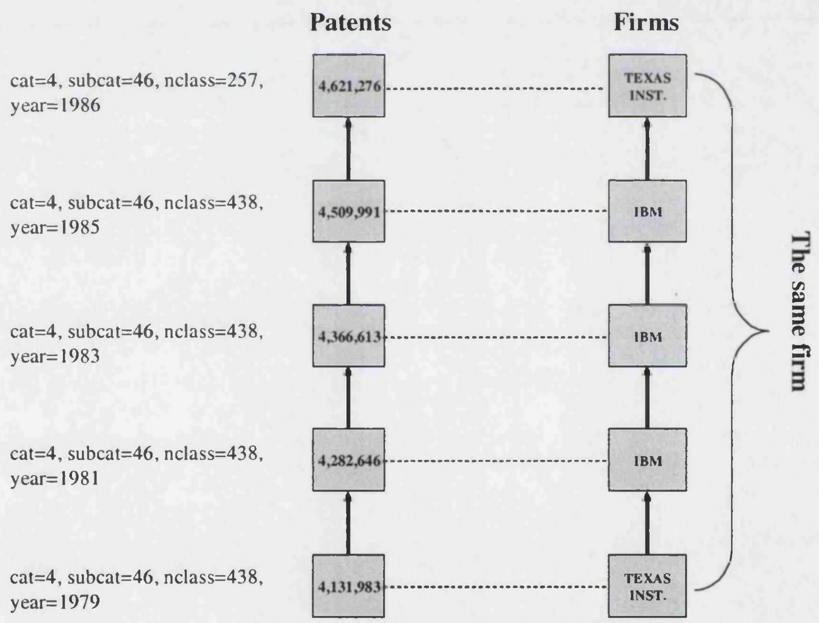


cat refers to one-digit technology sectors, *subcat* refers to two-digits technology sectors and *nclass* refers to three-digits technology sectors.

Figure 3: An example for an Externalized line of research

Figure 3: *This figure presents a unique line of research (a singleton sequence of citations) that is originated in invention 3,836,478 (the originating invention), which is owned by IBM (the originating firm). Since the diffused knowledge along this unique path did not return to the boundaries of IBM in the period 1974-1989 (during 15 years after the grant year of the originating patent), this line of research is Externalized.*

On the other hand, the line of research that is presented in figure 4 is Internalized. The originating patent 4,131,983 was cited by patent 4,282,646, which had been cited by patent 4,366,613. This patent was cited by patent 4,509,991, which had been finally cited by patent 4,621,276. Since the owner of patent 4,621,276 is the same as the owner of the originating patent 4,131,983 (Texas Instruments), the spillovers associated with this line of research are Internalized in the production of the knowledge embodied in patent 4,621,276.



cat refers to one-digit technology sectors, *subcat* refers to two-digits technology sectors and *nclass* refers to three-digits technology sectors.

Figure 4: An example for an Internalized line of research

Figure 4: *This figure presents a unique line of research (a singleton sequence of citations) that is originated in invention 4,131,983 (the originating invention), which is owned by Texas Instruments (the originating firm). Since in this pattern of*

diffusion knowledge returns to the boundaries of its inventor, after being advanced by others (IBM) in the period 1979-1994 (during 15 years after the grant year of the originating patent), this line of research is Internalized.

2.3 Data

The patents and citations data are taken from the NBER USPTO data-set, which is described in details in Hall, Jaffe and Trajtenberg (2001) and in Jaffe and Trajtenberg (2002). Our sample includes all the patents assigned to 2,859 US firms, which had been matched to the patents data by Hall, Jaffe and Trajtenberg (2001). A total of 915,021 patents are included in the sample, out of which, 599,884 patents (owned by 2,606 firms) cite 573,373 patents (owned by 2,696 firms)[13].

We have designed the set of originating patents (the set of inventions whose diffusion pattern we construct) to include all the patents owned by 800 US Compustat firms for which we have complete accounting data for the period of 1980-2001[14]. Further, we included only the patents of these firms that were granted between 1969 and 1980 and received at least one citation from one of the 599,884 citing patents in the sample (since non-cited patents do not experience a diffusion pattern which is empirically identifiable in this framework). This set of patents is defined as the set of 'originating patents', which includes 104,694 patents.

1,760,143 citations are included as technological links in the diffusion trees of the originating patents. The originating patents have received 626,359 direct cita-

[13]We only investigate patents, on which we have ownership information. Since the owner of a patent can be a subsidiary firm, it is important to ensure that a flow of knowledge from one patent to another is not a self-citation, as would be the case if the patent owners were subsidiaries of the same firm. Hall, Jaffe and Trajtenberg (2001) have constructed ownership structure for almost 3,000 patenting firms in the US. We use their ownership information. Since the ownership information is updated up to 1989 and the diffusion pattern we explore goes up to 1995, we are exposed to mistakenly interpreting a citation as an outward flow of knowledge in the period of 1989-1995 (if, for some reason, the ownership information with regard to the cited and citing firms has changed in this period). In order to test the robustness of our findings, we have also constructed the diffusion indices up to 1990. We find our results to be robust for this potential bias.

[14]In chapter 4 we estimate the effect of the diffusion pattern on the private returns to innovation. From that reason, we focus the analysis on the diffusion pattern of patents owned by firms that take part in the econometric analysis.

tions (on average an originating patent receives 3.9 direct citations)[15]. Out of the 1,760,143 citations, 535,596 are self-citations (i.e., the citing and cited firms are identical).

The originating patents have received a total of 194,696 self-citations (out of a total of 626,359 citations these patents receive). 13,978 originating patents have received only self-citations, thus, the knowledge they embody does not leave the boundaries of their inventors directly (*via* the first generation of citation). They create spillovers only if their embodied knowledge leaves the boundaries of their inventors in a future period. In case all of the follow-up developments of these originating patents are created 'in-house', these originating patents do not create spillovers and the lines of research they originate are omitted from the sample. Out of the 13,978 originating patents that receive only self-citations, 6,773 patents do not create spillovers, i.e., the lines of research they inspire are pursued only 'in-house' by the originating inventor.

A well known feature of the citations data is their sensitivity to truncation, as presented in Figure 5. This figure shows that as the grant year of a patent exceeds 1992, the number of citations it has received up to 1999 drops. Obviously, this does not imply that this patent is cited less over its whole life, relative to the older patents in the sample, since for this patent we have observed the citations received in a window of only 7 years. Therefore, we have restricted the grant year of the originating patents not to be greater than 1980, so that their diffusion pattern could be analysed in a wide enough time period[16].

[15]The mean number of citations received by a cited patent in our sample is 4.3, while the mean number of citations made by a citing patent is 4.2. Table *A*1 in the appendix provides more information on the citations made and received by the citing and cited patents.

[16]We can also include the originating patents granted up to 1984, since we have data on their diffusion pattern in a period of 15 years (up to 1999). However, we choose to avoid adding these extra years due to the huge spike in the citations sample between 1995 and 1999 (the number of citations rises by almost 800,000 during these five years). This rise in the number of citations 'explodes' the number of lines of research we have extracted for the originating patents between 1980 and 1984.

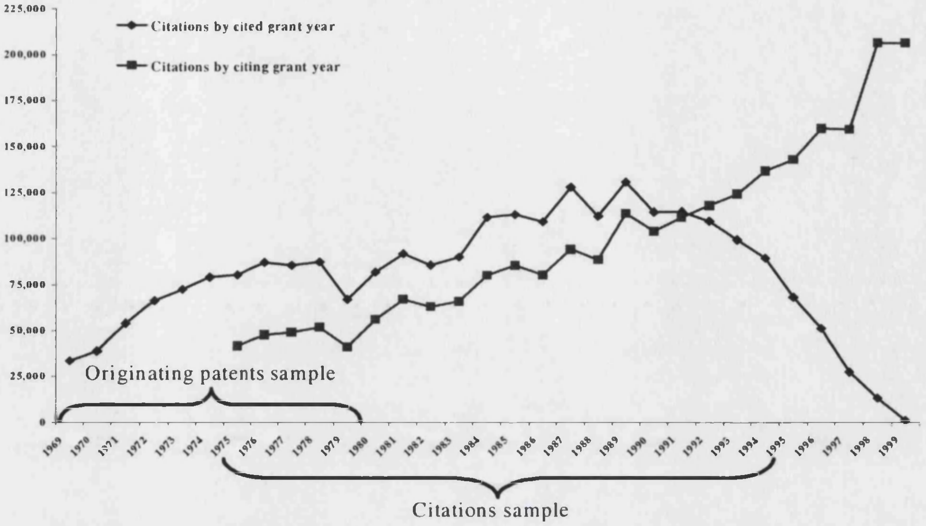


Figure 5: Citations sample

Figure 5: *This figure presents the number of citations made and received by patents in our sample. The upward sloping graph shows the number of citations made each year, where the U shaped curve shows the number of citations received each year.*

Figure 6 presents the distribution of the average number of citations the originating patents receive across years. This figure shows that patents granted in early years were less cited. This pattern is well documented in the literature[17] and might be attributed to increased computerization over time. The rise in the number of citations over time affects the number of lines of research we observe in the data. In order to control for this effect, in chapters 3 and 4 we always include a complete set of dummies for the grant year of the originating patents in the econometric analysis, whereas in this chapter we show that although the number of citations goes up over time, the relative number of Internalized versus Externalized lines of research remains stable over time[18].

[17]See Jaffe and Trajtenberg (2002).

[18]In chapter 5 we construct firm-level diffusion measures based on the aggregated number of Internalized and Externalized lines of research. In the econometric analysis we include the average patent and citation stocks of the originating firms over the period 1969-1980, as controls.

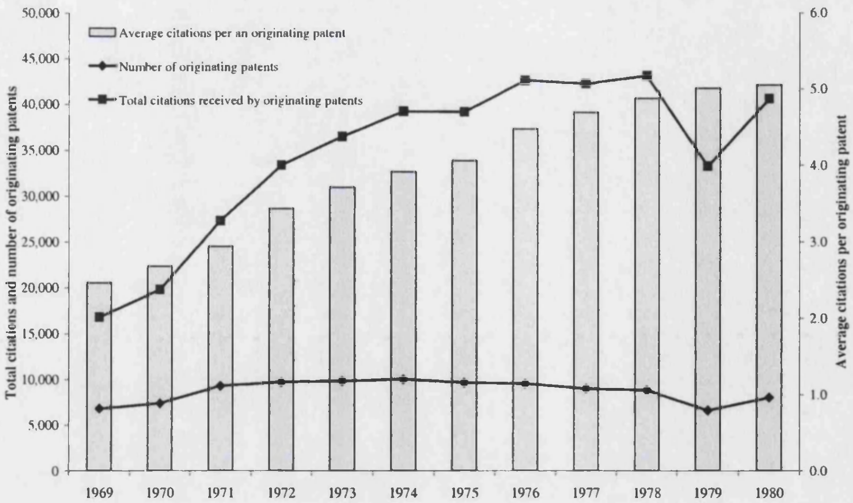


Figure 6: Citations received by originating patents

Figure 6: *This figure presents the citations received by the originating patents in our sample. We observe an increase in the number of citations received by the originating patents over time, although the number of originating patents tends to fall.*

Finally, the sample of originating patents varies across the five main technology sectors, as following: 36,514 originating patents are in the "Chemicals" sector, 10,245 in the "Computers and Communications" sector, 4,481 in the "Drugs and Medicals" sector, 28,951 in the "Electronics and Communications" sector and the remaining 24,503 are in the "Mechanicals" sector.

We will now turn to explore the diffusion pattern of these inventions in further detail.

2.4 Findings

This section discusses our main findings regarding the diffusion pattern of the originating patents. In this chapter we look at the extent to which knowledge that leaves the boundaries of its inventor, will have returned to these boundaries in the form of a future improved invention. We investigate its variation across technology sectors and time.

2.4.1 Lines of research - a first look

We extract 13,107,634 lines of research (singleton sequences of citations), which are originated in 97,921 inventions. 6,773 patents that appear in our initial set of originating patents do not originate Internalized or Externalized lines of research[19]. 999,718 lines of research are classified as Internalized (7.6 percent of the total lines of research) and are originated in 29,964 patents (about 30 percent of the originating patents), while the remainder 12,107,916 lines of research are classified as Externalized and are originated in 97,212 patents[20]. The distribution of the Internalized lines of research across technology sectors and time periods is reported in tables A2 and the same distribution for the Externalized lines of research is reported in table A3, both in the appendix.

On average, about 30 percent of the originating patents have at least one Internalized line of research. This percentage is not stable across technology sectors. For example, in the "Computers and Communications" sector, about 50 percent of the patents have at least one Internalized line of research, whereas it drops to 25 percent in the "Chemicals" sector.

The average number of lines of research per originating patent rises over time. This rise can simply reflect the fact that the number of citations increases over time, as shown in figure 5. Later in this chapter, we report a robustness test in which we control for the number of citations the originating patents receive when calculating the spillovers created by an invention.

Overall, we observe a variation in the number of Internalized and Externalized lines of research across technology sectors and time periods, as indicated by tables A2 and A3. A more interesting question is whether we also observe this kind of variation in the share of Internalized lines of research out of the total number of lines of research. Table 1 summarizes the main findings in this regard.

[19]These patents originate lines of research in which all the follow-up developments of the originating invention is done within the boundaries of the originating firm.

[20]The remaining 709 originating patents inspire only Internalized lines research (thus, all the spillovers these inventions create feed back into the dynamic research of their inventors).

Table 1

Share of Internalized lines of research

	Total lines of research per originating patent[a]	Total sample	1969-1975	1976-1978	1979-1980
Pooled	125.2	7.6%	8.2%	7.6%	7.2%
Chemicals	71.6	6.2%	6.4%	6.3%	5.7%
Computers and Communications	337.2	7.6%	8.8%	7.1%	7.1%
Drugs and Medicals	115.2	15.0%	19.1%	16.8%	8.4%
Electrical and Electronics	182.5	7.4%	7.5%	7.1%	7.5%
Mechanicals	50.6	8.8%	9.1%	9.1%	7.9%

[a]Computed over the entire sample.

As mentioned above, 7.6 percent of the lines of research are Internalized. This percentage does not vary substantially over time[21], ranging from 8.2% at the beginning of the period to 7.2% at the end of the period. As reported in tables A2 and A3, the number of Internalized lines of research and Externalized lines of research rises over time, however, the latter rises mildly faster.

With respect to the variation of the share of Internalized lines of research across technology sectors, we find that in the "Drugs and Medicals" sector, in the entire period, the share is about twice the share in the other technology sectors. With the exception of "Drugs and Medicals", the share of Internalized lines of research is rather stable, ranging from 6.2% in the "Chemicals" sector to 8.8% in the "Mechanicals" sector[22]. At the last period of our sample (1979-1980) we observe a convergence in the share of Internalized lines of research, even when including "Drugs and Medicals". Thus, there is a sharp drop in the share of Internalized lines of research is "Drugs and Medicals". This drop is attributed to a fall in the number of Internalized lines of research in this period, as shown in table A2 (the

[21]We choose to present the variation across the specific time periods in table 1, since the number of total lines of research in each of these periods is similar.

[22]The high stability of the share of Internalized lines of research across technology sectors is rather surprising, in light of the finding we have reported above that the share of originating patents that have at least one Internalized line of research substantially varies across these technology sectors.

average number of Internalized lines of research in this sector drops from 85 in the period 1976-1978 to 39 in the period 1979-1980, whereas, the average number of Externalized lines of research rises in the same period, from 134 to 146).

Table 1 also reports the average number of lines of research (Internalized and Externalized) per originating patent in the whole sample and across technology sectors. We find a high variation in the number of lines of research per originating patent across these sectors, ranging from a low of 50.6 in the "Mechanicals" sector to a high of 337.2 in the "Computers and Communications" sector. However, the high variation in the total number of lines of research does not seem to affect the share of Internalized lines of research across the technology sectors.

So far, we have examined Internalized and Externalized lines of research and found that about 7.6 percent of the lines of research are Internalized. However, this preliminary observation does not fully inform us on spillovers, since the number of external inventions along these lines of research has not been yet considered.

2.4.2 Spillovers - a first look

In the presentation above we have considered only the number of lines research. This can be a misleading and incomplete indicator of spillovers. Assume an originating patent is cited by an external invention, however, this cited patent does not inspire any follow-up research. This will be accounted for an Externalized line of research; however, the spillovers it is associated with are extremely low and cannot be compared to an Externalized line of research that experiences multiple generations of development. In order to capture this, our measure of spillovers is a weighed count of the lines of research a patent inspires, where the weights are the number of external inventions along these lines of research.

We examine four measures of spillovers, which are explained in section 2: Spillovers, Internalized Spillovers, Externalized Spillovers and the Share of Internalized Spillovers. Table A4 (in the appendix) summarizes the main statistics for these measures and presents their breakdown across technology sectors.

Table 2

The Share of Internalized Spillovers

	Spillovers per originating patent[a]	Total sample	1969-1972	1973-1974	1975-1976	1977-1980
Pooled	368.1	4.6%	3.9%	4.8%	4.9%	4.9%
Chemicals	196.6	3.9%	3.4%	4.1%	4.1%	4.2%
Computers and Communications	993.2	5.5%	6.0%	5.3%	5.0%	5.1%
Drugs and Medicals	238.5	5.6%	4.8%	6.3%	6.0%	5.0%
Electrical and Electronics	559.9	4.3%	3.5%	4.6%	4.8%	4.7%
Mechanicals	133.5	5.3%	4.1%	5.7%	6.0%	6.1%

[a]Computed over the entire sample.

Table 2 is equivalent to table 1, however it looks at the Share of Internalized Spillovers (whereas table 1 looks at the share of Internalized lines of research). The Share of Internalized Spillovers over the entire sample is 4.6 percent (compared to a share of 7.6 percent of lines of research which are Internalized). Over time, this share rises, rather moderately from a low of 3.9% in 1969-1972 to a high of 4.9% in 1977-1980[23]. There has been very little change in the Share of Internalized Spillovers in the period 1973-1980. From this we conclude that the Share of Internalized Spillovers has been stable over time.

A comparison of the Share of Internalized Spillovers across technology sectors also shows little variation. The Share of Internalized Spillovers varies from a low of 4.2% in the "Electrical and Electronics" sector to a high of 5.5% in the "Computers and Communications" sector (calculated over the entire sample). The low variation of the Share of Internalized Spillovers across technology sectors is also evident across

[23]A rise in the Share of Internalized lines of research over time is observed, even though the share of Internalized lines of research falls over time (see table 1). A potential explanation is that over time the number of 'short' Externalized lines of research has risen. This is consistent with what we observe in the data. Over time the 'quality' of the citing patents drops, such that citing patents are less likely to be cited themselves (i.e., to be sequentially developed).

This raises the issue of the 'quality' of the citing patent (as opposed to the 'quality' of the cited patent, as measured by the number of citations it receives). We should expect that the quality of the cited patent would be lower if the quality of the patent that cites it is lower. We address this issue in more details in the appendix.

time periods, where we even observe convergence over time (for example, in 1969-1972 the Share of Internalized Spillovers in the "Chemicals" sector is 3.4 percent, compared to 6.0 percent in the "Computers and Communications" sector. This difference falls over time to less than 1 percent in 1977-1980).

An interesting comparison is drawn between the share of Internalized lines of research, reported in table 1, and the Share of Internalized Spillovers, in particular with respect to "Drugs and Medicals". Over the entire sample, the share of Internalized lines of research in the "Drugs and Medicals" sector is 15 percent, whereas the Share of Internalized Spillovers in this sector is only 5.4 percent. In the other sectors, the share of internalized lines of research is much more similar to the Share of Internalized Spillovers.

Moreover, the drastic drop in the share of Internalized lines of research towards the end of the sample (from 16.8 percent to 8.4 percent) is not as strongly evident in the Share of Internalized Spillovers (which only drops from 6.0 percent to 5.0 percent). As the number of Internalized lines of research has drastically fallen, unlike the Share of Internalized Spillovers, this indicates that the remaining Internalized lines of research include more external inventions, compared to earlier periods. We plan to examine this change more seriously in future research.

Finally, tables A5-A7 in the appendix report in more detail the time variations of the diffusion measures across technology sectors. The results are reported in two ways: in absolute terms and normalized by the number of direct citations the originating patents receive (by computing the spillovers measures per direct citation an originating patent receives). This normalization aims to control for the fact that over time there has been an increase in the number of citations (see figure 6), which may affect the Share of Internalized Spillovers.

We find an increase in Spillovers over time, both in absolute terms and per citation received. However, the Share of Internalized Spillovers remains stable, also after controlling for the number of citations received by the originating patents (when controlling for the number of citations the originating patent receives the Share of Internalized Spillovers is 5 percent, over the entire sample).

2.5 Summary and Conclusions

Once knowledge leaves the boundaries of its inventor, private returns depreciate, as imitation and subsequent innovation occur. Under cumulative innovation, knowledge is sequentially developed, mostly outside the boundaries of its original inventor, which raises the obsolescence of the private returns.

This thesis introduces dynamic considerations and shows that spillovers can also enhance the private returns to innovation (i.e., reduce private obsolescence), if they feed back into the dynamic research of the original inventor. However, spillovers will always intensify private obsolescence, if the original inventor does not technologically benefit from the advancements other inventors build into its spilled knowledge. In this chapter we show how we propose to identify the countervailing effects knowledge flows might have on private obsolescence, in a sequential innovation framework, using data on patents and patent citations.

We measure the spillovers created by 104,694 patented inventions in our sample. We define spillovers as the number of external inventions along the lines of research our set of originating patents inspire, where a line of research is defined as a singleton sequence of citations.

We report three main findings: (1) in numerous cases, knowledge returns to boundaries of its original inventor after having been advanced by other inventors (7.6 percent of the lines of research are Internalized). (2) The share of Internalized lines of research is stable over time and across technology sectors. The "Drugs and Medicals" sector is an exception, as it enjoys a much higher share of Internalized lines of research. However, this share converges to the share that is observed in the other sectors towards the end of the sample's period. (3) The Share of Internalized Spillovers is about 5 percent and is highly stable over time and across all technology sectors. This finding is also robust for controlling for the direct citations the originating patents receive (by measuring the Share of Internalized Spillovers per citation).

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2.7 Appendix

2.7.1 The technological contribution of an invention - an alternative interpretation

Our methodology is a generalization of the accepted approach of measuring the quality of patents by counting the number of citations they receive.

In a dynamic framework, we do not simply count the number of citations the patent receives, but weigh these citations by their own quality (hence, link the quality of a patent to the quality of its subsequent inventions). For example, under the patterns of diffusion in figure 1, invention A receives one citation from invention B. However, the quality of invention B differs across diffusion pattern 1 and 2. Invention B is of a higher quality under diffusion pattern 2, it receives two citations, whereas under diffusion pattern 1 it receives only one citation. From this we conclude that we should give a higher weight to the quality of invention A under diffusion pattern 2, since it is cited by a higher quality patent (where, the traditional approach would assign the same quality to invention A, under the two patterns of diffusion).

In addition to weighing citations, our dynamic approach also suggests counting indirect citations when measuring the quality of an invention, thus, taking into account inventions that indirectly benefit from the originating invention. In the example presented in figure 1, this would mean to include patents C and D as offspring inventions of the originating patent A[24].

To summarize, our empirical methodology is essentially weighing the citations the patent receives by the quality of the citing patent (where the weights are the number of direct citations the citing patent receives) and also counting indirect

[24] When doing so, we should be aware of the likelihood that the flow of knowledge from invention A to inventions C and D is lower than the flow of knowledge to invention B, since the former citations are indirect. Currently, there is no satisfactory way to control for the amount of knowledge flow that is associated with indirect citations (and, in fact, also with the amount of knowledge flow that is associated with direct citations). In order to test the robustness of our findings to this bias, we discount every generation of citation by a discount factor (which is 15 percent, so as to be consistent with previous studies, although this value is arbitrary). Moreover, we normalize the citing patents by the number of citations they make, under the assumption that if a patent cites more, its technological link to the originating patent is weaker (representing a lower flow of knowledge).

citations. .

To illustrate, we refer back to figure 1. Under pattern 1 we observe three offspring inventions, and, therefore, we count three citing (direct and indirect) patents, where each citing patent is cited only once. It should be noted that we assume that the last patent in the sequence is counted as if it receives one citation. Thus, $TC_A^1 = (1 \times 1) + (1 \times 1) + (1 \times 1) = 3$. With respect to diffusion pattern 2, there are three offspring inventions as well. However, patent B receives two direct citations and, therefore, it receives the weight of 2. This implies that $TC_A^1 = (1 \times 2) + (1 \times 1) + (1 \times 1) = 4$. In section 2, we show that these measures are identical to the lines of research approach.

A closer look at this methodology would show that the scheme is recursive. Assume patent C in figure 1 under diffusion pattern 1 receives another citation from patent E (thus, it is cited twice, by patent D and patent E). Using the lines of research approach, we observe two lines of research: $A \rightarrow B \rightarrow C \rightarrow D$ and $A \rightarrow B \rightarrow C \rightarrow E$. Thus, $TC_A^1 = (1 \times 3) + (1 \times 3) = 6$. Under the alternative approach discussed above, TC_A^1 is computed as following: starting with patent C (we continue to assume that the edge patents, D and E in this case, are cited only once), it receives two citations, of quality one each (the quality of patents D and E). Regarding patent B, it is cited only once (by patent C). However, since patent C is of quality 2, we treat the citation from patent C to patent B, as if patent B receives two citations. In this case, $TC_A^1 = (1 \times 2) + (1 \times 2) + (1 \times 1) + (1 \times 1) = 6$, which is the same as the technological contribution under the lines of research approach.

More formally, the alternative interpretation of our methodology is the following:

$$TC_i = \sum_{k \in K_i} OS_{ik} \times \widehat{Q}_k \tag{2.10}$$

And $\widehat{Q}_k$ is expressed as:

$$\widehat{Q}_k = \sum_{j \in J} OS_{kj} \times \widehat{Q}_j \tag{2.11}$$

Where, K_i is the set of patents that cite directly or indirectly patent i, OS_{ik} denotes the offspring invention $k \in K_i$, j is another patent in the set K_i, which directly cites invention k, J_k is the set of patents that directly cite invention k (i.e., $j \in J_k \subset K_i$), OS_{kj} denotes the offspring invention which directly cite patent k and $\widehat{Q}_j$ is the quality of invention j. The algorithm that solves this recursive procedure is similar to the algorithm we develop, which is described below.

2.7.2 The Algorithm

Our task in this paper is to develop an algorithm that will generate a "family tree" for every originating patent in our sample. The information we desire to create is not only identifying the originating patent's offspring inventions, but also identifying all the different ways these offspring inventions are linked to the originating patent. For this purpose, it is natural to develop a 'tree' algorithm that stores all the unique sequences of citations the originating patents create.

Since the computational task we face is highly complex and demanding, the efficiency of the algorithm plays a major role in making our task feasible. We turn now to discuss the main steps our algorithm follows. For the interested reader, a more detailed description of our algorithm is available upon request.

Source File

The source file for the algorithm is a file containing the raw data, taken from the NBER Patents and Citations database. This file includes 1,760,143 rows, where each row corresponds to one patent citation, and 7 columns, which are the cited patent number, the citing patent number, the firm owning the cited patent, the firm owning the citing patent, the grant year of the cited patent, the grant year of the citing patent and an indicator to whether the cited patent is an originating patent.

The source file is sorted by the citing patent number. Thus, the first row is the earliest citation made in our sample, the second row is the second earliest citation etc. This sort allows us to save valuable running time due to the fact that a citing patent cannot be cited before it cites. We find that sorting in this way is crucial for the running time of the algorithm. The 'cost' of this sort is conceptual, as we assume that the grant year of the citing patent is the date in which knowledge has been transferred (the sequential number of the patent is determined by its grant year). It would have been preferred to look at the application year rather than the grant year, however, technically it is not applicable (as it will not allow us to sort the file according the 'birth' year of patents).

Data Structure

In order to create an efficient algorithm that will produce the desired output in a reasonable time considering the amount of data, we use a combination of a Tree procedure and a Hash table.

The Tree algorithm is a dynamic procedure that creates a 'tree' of patents without any restrictions on the number of both direct and indirect offspring patents. Each node in the 'tree' contains two types of information: information extracted from the source file, such as citing patent number and citing firm, and information that the algorithm generates, such as the location of the offspring patent in the 'tree'. Note that the 'tree' is not balanced (its branches are not of equal length), thus it does not benefit from the advantages of balanced 'trees', whose maximum length we already know. This leads us to combine a Hash table, which allows us to efficiently store the information on the offspring patents in the diffusion 'tree' and save valuable search time.

The Hash table contains information on all the patents in the source file, both citing and cited, which we define as items. Each item contains the following fields: the depth in the 'tree' (the generation of citation), the place in the 'tree' (how it is linked to the originating patent) and an indictor to whether the patent is an originating patent. The place of the patent in the 'tree' is stored as a vector of numbers, as we explain below.

Running process

The purpose of the algorithm is to create a diffusion 'tree' that holds information on all the unique ways the originating knowledge has been developed. For this reason, it is not enough to identify only the offspring patents, but also all the links between them and the originating knowledge. In other words, we must extract all the branches in the diffusion 'tree', which makes our task harder.

It should be noted that every row in the source file indicates a 'father-child' relationship in the 'tree'. Our searching and updating procedure involves scanning the source file for every originating patent and updating the Hash table for each row according to the location of the citing patent in the diffusion 'tree' (in case a patent does not take part in the diffusion 'tree' of a given originating patent, its line is not updated).

The best way to explain the procedure of the algorithm is by a simple example. The following list of citing and cited patents is a sample taken from the source file (where we do not present the other columns for simplicity).

Citing Patent	**Cited Patent**
3988245	3852388
3988250	3852388
4032309	3852388
4119408	4032309
4174374	4119408
4564373	4174374
4617029	4174374
4629563	3988245
4629570	3988255
4666607	3988245
4737166	4174374

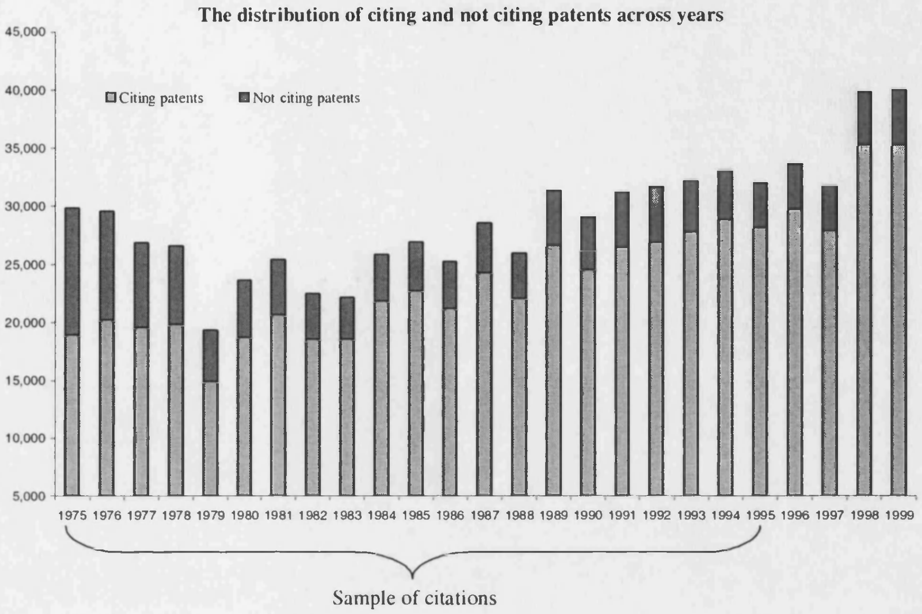
Given this list, the algorithm will first scan the first row in the file, which tells us that patent number 3988245 cites patent number 3852388. As the algorithm starts to construct a new diffusion 'tree', it first checks whether the cited patent in the first row is part of the set of the originating patents. If it is not part of this set, the algorithm skips this row and jumps to the next one. If it does belong to the set of originating patents, the algorithm starts the construction of the diffusion 'tree' for this patent by updating the Hash table for this row and for the next rows in the source file. We will show now how the updating procedure takes place.

The entries in the Hash table at the end on the running and updating procedure is as following (at the beginning of the procedure, the items in the Hash table are initialized to -1):

Patent number	Originating	Place	Depth
...			
3852388	$originating = 1$	$PlaceInTree = 1$	$Depth = 1$
3988245	$originating = 0$	$PlaceInTree = 11$	$Depth = 2$
3988250	$originating = 0$	$PlaceInTree = 12$	$Depth = 2$
4032309	$originating = 0$	$PlaceInTree = 13$	$Depth = 2$
4119408	$originating = 0$	$PlaceInTree = 131$	$Depth = 3$
4174374	$originating = 0$	$PlaceInTree = 1311$	$Depth = 4$
4564373	$originating = 0$	$PlaceInTree = 13111$	$Depth = 5$
4617029	$originating = 0$	$PlaceInTree = 13112$	$Depth = 5$
4629563	$originating = 0$	$PlaceInTree = -1$	$Depth = -1$
3988255	$originating = 0$	$PlaceInTree = -1$	$Depth = -1$
4629570	$originating = 0$	$PlaceInTree = -1$	$Depth = -1$
4666607	$originating = 0$	$PlaceInTree = -1$	$Depth = -1$
4737166	$originating = 0$	$PlaceInTree = 13113$	$Depth = 5$
...			

Once the algorithm finishes scanning the source file, another function is called in to print all the branches of the 'tree' into a file. These branches are unique sequences of patent citations, which we interpret as lines of research. The printed lines of research are than given in a text format ready to be analysed in any statistical package. Determining whether a line of research is Internalized or Externalized is a straightforward task, as we only need to compare the first firm in the sequence of citations to the last firm. If these are identical (and there is at least one external invention along the line of research, such that spillovers are created), the line of research is Internalized. Other wise, it is classified as Externalized.

The next step is to clean the memory and initialize the Hash table before proceeding to the next originating patent, and repeating the same algorithm.


The distribution of citing and not citing patents across years
Citing patents
Not citing patents
45,000
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999
Sample of citations

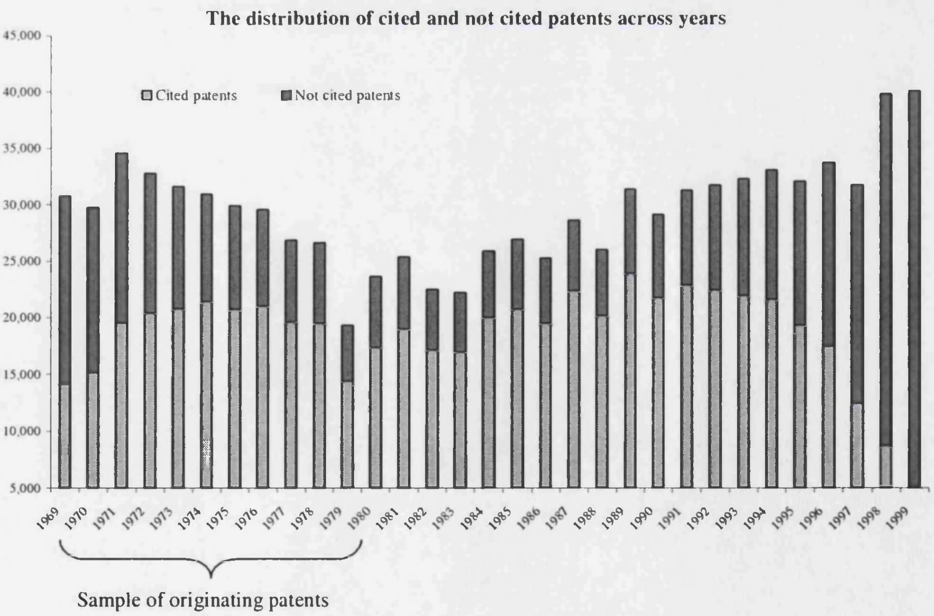

The distribution of cited and not cited patents across years
Cited patents
Not cited patents
45,000
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999
Sample of originating patents

Table A1

Citations received by a cited patent					
	Number of cited patents	Mean	Median	Max	Min
All cited patents	573,373	4.3	3	238	1
Citations received <3	281,884	1.4	1	2	1
2< Citations received <10	234,390	4.9	4	9	3
9< Citations received <50	56,226	16.1	14	49	10
Citations received >49	873	68.7	61	238	50

Citations made by a citing patent					
	Number of cited patents	Mean	Median	Max	Min
All citing patents	599,884	4.2	3	259	1
Citations made <3	259,983	1.5	1	2	1
2< Citations made <10	294,566	4.8	4	3	9
9< Citations made <50	44,796	14.7	13	49	10
Citations made >49	539	72.5	60	259	50

Table A2

Internalized lines of research - distribution across years and main technology sectors

	Total sample	1969-1975	1976-1978	1979-1980
Pooled				
Number of originating patents	104,694	62,673	27,360	14,661
Number of Internalized lines of research	999,718	328,732	387,255	283,731
Internalized lines of research per originating patent	33.4	21.4	41.0	54.8
Chemicals				
Number of originating patents	36,514	22,036	9,536	4,942
Number of Internalized lines of research	161,491	59,611	63,521	38,359
Internalized lines of research per originating patent	17.5	12.4	22.4	24.2
Computers and Communications				
Number of originating patents	10,245	5,931	2,764	1,550
Number of Internalized lines of research	262,723	88,618	89,834	84,271
Internalized lines of research per originating patent	51.3	33.1	56.4	98.3
Drugs and Medicals				
Number of originating patents	4,481	1,945	1,494	1,042
Number of Internalized lines of research	77,547	28,178	36,790	12,579
Internalized lines of research per originating patent	63.8	61.9	84.8	38.5
Electrical and Electronics				
Number of originating patents	28,951	17,641	7,418	3,892
Number of Internalized lines of research	389,128	114,327	154,614	120,187
Internalized lines of research per originating patent	45.7	26.3	55.8	86.2
Mechanicals				
Number of originating patents	24,503	15,120	6,148	3,235
Number of Internalized lines of research	108,829	37,998	42,496	28,335
Internalized lines of research per originating patent	18.5	12.5	23.5	28.0

Table A3

Externalized lines of research - distribution across years and main technology sectors

	Total sample	1969-1975	1976-1978	1979-1980
Pooled				
Number of originating patents	104,694	62,673	27,360	14,661
Number of Externalized lines of research	12,107,916	3,696,270	4,738,837	3,672,809
Externalized lines of research per originating patent	124.6	63.6	185.9	270.2
Chemicals				
Number of originating patents	36,514	22,036	9,536	4,942
Number of Externalized lines of research	2,451,285	875,050	945,533	630,702
Externalized lines of research per originating patent	73.1	43.2	108.4	139.2
Computers and Communications				
Number of originating patents	10,245	5,931	2,764	1,550
Number of Externalized lines of research	3,191,950	920,704	1,175,533	1,095,713
Externalized lines of research per originating patent	319.9	159.9	432.5	729.5
Drugs and Medicals				
Number of originating patents	4,481	1,945	1,494	1,042
Number of Externalized lines of research	438,774	119,084	182,296	137,394
Externalized lines of research per originating patent	107.5	66.9	134.0	146.0
Electrical and Electronics				
Number of originating patents	28,951	17,641	7,418	3,892
Number of Externalized lines of research	4,895,597	1,402,989	2,012,215	1,480,393
Externalized lines of research per originating patent	178.1	84.1	283.5	400.0
Mechanicals				
Number of originating patents	24,503	15,120	6,148	3,235
Number of Externalized lines of research	1,130,310	378,443	423,260	328,607
Externalized lines of research per originating patent	51.0	27.8	75.7	111.9

Table A4

Spillovers per originating patent - summary statistics

	Mean	S.D. Error	Median	Max	Min
Spillovers					
Pooled	368.1	11.5	9.1	545,262	0.72
Chemicals	196.6	8.2	9.1	93,365	0.72
Computers and Communications	993.2	41.8	46.3	104,311	0.85
Drugs and Medicals	238.5	17.1	8.9	29,123	0.72
Electrical and Electronics	559.9	35.7	9.6	545,262	0.72
Mechanicals	133.5	7.8	5.1	73,449	0.72
Internalized Spillovers					
Pooled	20.9	0.8	0	22,921	0.00
Chemicals	8.5	0.5	0	7,860	0.00
Computers and Communications	54.6	2.9	0.9	9,621	0.00
Drugs and Medicals	25.9	2.3	0	2,570	0.00
Electrical and Electronics	33.2	2.3	0	22,921	0.00
Mechanicals	8.3	0.7	0	7,658	0.00
Externalized Spillovers					
Pooled	347.0	11.0	8.7	544,711	0.00
Chemicals	188.1	8.0	8.7	93,216	0.72
Computers and Communications	938.6	40.2	43.1	103,902	0.72
Drugs and Medicals	212.5	16.4	8.5	29,037	0.72
Electrical and Electronics	526.7	34.2	9.1	544,711	0.72
Mechanicals	125.2	7.2	4.7	67,057	0.00
Share of Internalized Spillovers					
Pooled	4.6%	0.0%	0.0%	100.0%	0.0%
Chemicals	3.9%	0.1%	0.0%	100.0%	0.0%
Computers and Communications	5.5%	0.1%	0.2%	100.0%	0.0%
Drugs and Medicals	5.6%	14.3%	0.0%	100.0%	0.0%
Electrical and Electronics	4.3%	11.9%	0.0%	100.0%	0.0%
Mechanicals	5.3%	14.8%	0.0%	100.0%	0.0%

Table A5

Share of Internalized Spillovers per originating patent- variation over time						
	Pooled	Chemicals	Computers and Communications	Drugs and Medicals	Electrical and Electronics	Mechanicals
1969-1972	**3.9%**	**3.4%**	**6.0%**	**4.8%**	**3.5%**	**4.1%**
1969	3.2%	2.4%	6.3%	4.8%	3.4%	3.0%
1970	3.6%	3.2%	6.1%	3.8%	2.9%	4.2%
1971	4.2%	3.9%	6.0%	5.3%	3.7%	4.3%
1972	4.5%	4.0%	5.7%	5.2%	4.0%	5.1%
1975-1976	**4.8%**	**4.1%**	**5.3%**	**6.3%**	**4.6%**	**5.7%**
1973	4.8%	4.2%	7.0%	5.9%	4.6%	4.9%
1974	4.9%	4.3%	4.8%	5.4%	4.3%	6.3%
1975-1976	**4.9%**	**4.1%**	**5.0%**	**6.0%**	**4.8%**	**6.0%**
1975	4.7%	4.0%	4.7%	7.4%	4.5%	5.6%
1976	4.8%	3.9%	4.7%	7.0%	4.8%	5.8%
1977-1980	**4.9%**	**4.2%**	**5.1%**	**5.0%**	**4.7%**	**6.1%**
1977	4.8%	3.6%	5.4%	5.5%	4.9%	5.8%
1978	5.2%	4.7%	5.2%	5.4%	4.9%	6.4%
1979	4.7%	4.1%	5.1%	4.1%	4.6%	5.8%
1980	4.9%	4.5%	4.8%	5.1%	4.2%	6.4%
Total sample	**4.6%**	**3.9%**	**5.5%**	**5.6%**	**4.3%**	**5.3%**

Table A6

Spillovers per originating patent[a] - variation over time

	Pooled		Chemicals		Computers and Communications		Drugs and Medicals		Electronics and Electrical		Mechanicals	
	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations
1969-1972	**62.7**	**14.2**	**48.9**	**11.8**	**137.7**	**27.6**	**35.0**	**7.6**	**86.1**	**19.2**	**26.1**	**6.8**
1969	19.1	6.1	18.4	5.7	39.2	10.6	9.3	2.8	21.7	7.5	11.1	3.8
1970	37.2	10.1	34.4	9.5	74.4	21.6	27.4	6.5	44.4	10.8	17.6	5.5
1971	58.6	14.3	47.2	11.0	137.0	28.1	42.1	8.7	71.9	19.5	22.2	6.3
1972	136.0	26.4	95.5	20.8	300.3	50.2	61.4	12.4	206.4	39.0	53.6	11.5
1973-1974	**313.5**	**53.1**	**181.0**	**34.1**	**805.6**	**112.2**	**261.0**	**35.4**	**478.3**	**84.1**	**111.1**	**21.9**
1973	256.4	42.8	128.6	26.1	614.4	80.1	174.9	28.3	404.9	66.9	104.9	22.4
1974	370.7	63.4	233.5	42.2	996.8	144.4	347.2	42.4	551.7	101.4	117.3	21.4
1975-1976	**415.2**	**59.2**	**205.3**	**36.3**	**1107.3**	**129.6**	**250.0**	**30.2**	**689.0**	**97.0**	**136.7**	**23.9**
1975	334.6	55.6	192.3	38.2	988.6	125.7	270.4	34.6	490.2	88.4	118.0	19.3
1976	495.8	62.8	218.2	34.5	1226.1	133.6	229.7	25.8	887.7	105.7	155.3	28.5
1977-1980	**689.7**	**75.6**	**354.6**	**46.0**	**1840.1**	**173.0**	**299.7**	**36.9**	**1065.0**	**114.5**	**267.5**	**34.6**
1977	562.0	65.1	252.8	32.2	1282.9	138.7	280.3	26.9	973.4	109.8	222.0	31.3
1978	608.1	62.1	388.3	41.4	1518.9	137.2	245.5	40.9	882.0	85.0	256.0	34.6
1979	809.9	86.8	393.3	56.3	1982.8	183.4	214.2	29.2	1352.8	136.8	360.5	39.9
1980	778.9	88.6	383.9	54.3	2575.9	232.8	458.8	50.7	1051.8	126.6	231.3	32.5
Total sample	**392.4**	**51.5**	**208.5**	**32.6**	**1032.7**	**113.4**	**211.5**	**27.5**	**611.4**	**79.5**	**145.7**	**22.5**

[a]Conditional on the originating patent creating spillovers (excluding 6773 patents that do not create spillovers, as explained in the text). From this reason the entries in this table are higher than the entries in tables 2 and A4.

Table A7

Internalized Spillovers per originating patent- variation over time

	Pooled		Chemicals		Computers and Communications		Drugs and Medicals		Electronics and Electrical		Mechanicals	
	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations
1969-1972	**3.6**	**0.7**	**2.0**	**0.4**	**11.8**	**2.0**	**4.8**	**0.7**	**3.9**	**0.8**	**1.9**	**0.3**
1969	0.9	0.3	0.7	0.2	2.9	0.8	1.0	0.2	0.9	0.3	0.5	0.2
1970	2.0	0.5	1.5	0.3	5.9	1.5	2.0	0.5	1.9	0.4	1.1	0.3
1971	3.6	0.7	1.9	0.5	12.8	2.0	8.9	1.2	2.9	0.7	1.9	0.3
1972	7.8	1.3	4.0	0.7	25.8	3.9	7.1	1.1	9.7	1.7	4.0	0.6
1973-1974	**20.1**	**3.0**	**8.8**	**1.4**	**50.7**	**6.8**	**27.1**	**2.9**	**33.3**	**5.1**	**6.7**	**1.1**
1973	17.5	2.7	5.5	0.8	49.5	5.9	15.7	2.6	29.2	5.0	6.1	1.0
1974	22.7	3.3	12.0	2.0	52.0	7.7	38.6	3.2	37.5	5.2	7.4	1.2
1975-1976	**23.4**	**3.2**	**8.2**	**1.2**	**55.7**	**6.4**	**39.0**	**3.2**	**40.8**	**5.9**	**7.9**	**1.3**
1975	19.4	2.7	7.4	1.3	57.1	7.3	36.6	2.9	29.7	4.1	6.8	1.2
1976	27.4	3.7	8.9	1.2	54.3	5.6	41.4	3.5	51.9	7.8	9.1	1.3
1977-1980	**37.5**	**3.6**	**15.0**	**1.7**	**94.6**	**8.8**	**27.6**	**2.7**	**61.2**	**5.5**	**16.6**	**1.7**
1977	33.7	3.6	10.6	1.2	71.9	7.9	43.3	4.1	60.2	6.0	13.7	1.7
1978	34.1	3.0	19.9	1.6	80.8	7.2	25.0	2.4	47.3	4.2	19.6	1.8
1979	41.4	3.8	15.4	1.9	94.0	8.3	17.7	2.1	74.1	6.5	21.3	1.8
1980	40.7	3.9	14.0	2.0	131.7	11.7	24.3	2.2	63.3	5.3	11.7	1.7
Total sample	**20.9**	**2.6**	**8.5**	**1.2**	**54.6**	**6.1**	**25.9**	**2.3**	**33.2**	**4.2**	**8.3**	**1.1**

Table A8

Externalized Spillovers per originating patent- variation over time												
	Pooled		Chemicals		Computers and Communications		Drugs and Medicals		Electronics and Electrical		Mechanicals	
	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations	Total	Normalized by citations
1969-1972	**59.1**	**13.6**	**46.9**	**11.3**	**125.9**	**25.6**	**30.3**	**6.9**	**82.3**	**18.5**	**24.3**	**6.5**
1969	18.2	5.9	17.7	5.5	36.3	9.8	8.3	2.6	20.8	7.3	10.6	3.7
1970	35.2	9.6	32.9	9.2	68.6	20.1	25.4	6.0	42.4	10.4	16.5	5.3
1971	55.0	13.6	45.2	10.5	124.2	26.2	33.2	7.6	69.0	18.8	20.3	6.0
1972	128.2	25.2	91.6	20.1	274.5	46.3	54.3	11.4	196.7	37.3	49.7	10.9
1973-1974	**293.4**	**50.1**	**172.2**	**32.7**	**754.9**	**105.4**	**233.9**	**32.5**	**444.9**	**79.0**	**104.4**	**20.8**
1973	238.8	40.2	123.0	25.3	565.0	74.2	159.2	25.7	375.7	61.8	98.8	21.4
1974	348.0	60.1	221.5	40.2	944.8	136.7	308.6	39.2	514.2	96.2	110.0	20.2
1975-1976	**391.8**	**56.0**	**197.1**	**35.1**	**1051.6**	**123.2**	**211.0**	**27.0**	**648.1**	**91.1**	**128.7**	**22.6**
1975	315.2	52.9	184.9	36.9	931.5	118.4	233.8	31.7	460.5	84.3	111.3	18.1
1976	468.4	59.2	209.3	33.3	1171.8	128.0	188.3	22.3	835.8	97.9	146.2	27.1
1977-1980	**652.3**	**72.1**	**339.6**	**44.4**	**1745.5**	**164.2**	**272.1**	**34.3**	**1003.8**	**109.0**	**250.9**	**32.8**
1977	528.3	61.5	242.1	30.9	1210.9	130.8	236.9	22.9	913.2	103.8	208.4	29.5
1978	574.0	59.1	368.4	39.8	1438.1	130.0	220.5	38.5	834.7	80.7	236.4	32.8
1979	768.5	83.0	377.9	54.4	1888.8	175.1	196.5	27.2	1278.7	130.3	339.3	38.1
1980	738.2	84.7	369.9	52.3	2444.1	221.1	434.6	48.5	988.5	121.3	219.5	30.8
Total	**370.2**	**48.9**	**199.6**	**31.4**	**976.7**	**107.3**	**187.8**	**25.2**	**575.1**	**75.3**	**136.7**	**21.3**

[a]Conditional on the originating patent having at least one Externalized line of research.

Chapter 3

The Diffusion Pattern of Technological Discoveries: Internalized and Externalized lines of research

In this chapter we explore the factors affecting the likelihood that knowledge will return to the boundaries of its inventor, after having been advanced by other firms. We look at the attributes of the research environment of the originating firm, mainly at the level of competition in research it faces and the level of complexity of the line of research it pursues. We find that the firm is more likely to reabsorb its spilled knowledge when: (1) the line of research is more concentrated in terms of firms and (2) the line of research is less technologically complex. Moreover, we find preliminary evidence suggesting that when knowledge spills to firms that are closer to the originating firm in the product market, it is less likely the originating firm will reabsorb this knowledge. Our empirical approach can shed light on the behaviour of firms in a dynamic research environment, where private returns depend on the follow-up research of other firms.

3.1 Introduction

In this chapter we will ask the following question: when knowledge leaves the boundaries of its inventor, under what circumstances it is more likely to return to these boundaries after having been advanced by other firms? We answer this question by exploring the characteristics of Internalized and Externalized lines of research.

Our unit of observation in this chapter is a line of research and in the econometric analysis we perform, the dependent variable is an indicator that receives the value one for an Internalized line of research and the value zero for an Externalized line of research.

The significant of this chapter relates to our argument (which we empirically support in chapter 5) that private obsolescence falls with more Internalized patterns of diffusion and rises with more Externalized patterns of diffusion. Identifying the circumstances under which a pattern of diffusion is Internalized can help in understanding the incentive to innovate in dynamic research environments.

We will focus on two main characteristics of the line of research. The first is the concentration of firms on the line of research, defined as Firm Concentration, and the second is the technological diversification of the line of research, defined as Complexity.

Firm Concentration is interpreted as a measure of competition the originating firm faces along a specific line of research, which is expected to be positively correlated with the likelihood that the line of research is Internalized, since the probability of 'winning' in every development stage falls, as the number of competing firms rises.

Further, we expect to observe a negative correlation between Complexity and the likelihood that a line of research is Internalized, as the originating firm has to possess more diverse innovation capabilities so as to continue inventing along a line of research that is less technologically specialized.

We find that the likelihood of a line of research to be Internalized is positively correlated with Firm Concentration and is negatively correlated with Complexity, as expected.

We also find that the likelihood of a line of research to be Internalized is lower when the originating knowledge spills to firms that are closer to the originating firm in the product market. Some evidence suggests that in case knowledge spills to rivals that are close to the originating firm in the technology space, it becomes less likely that the originating firm will reabsorb its spilled knowledge, as well. We interpret this finding as an indication of a lower ability of the originating firm to 'win' subsequent development stages of its prior knowledge, once its close rivals in the product market and technology space also participate in the development race.

There is vast theoretical literature on sequential innovation that our empirical framework can contribute to. Green and Scotchmer (1995) and Scotchmer (1996) raise the concern that the inventor of the originating patent (the first generation) will capture a lower rent when follow-up developments of other inventors occur. Thus, the firm will have insufficient private incentive for innovation. In this thesis we show how we can empirically address this concern and examine under what circumstance it is more likely to arise. Under an Externalized line of research, this concern is justified, since the originating inventor does not technologically benefit from the subsequent inventions of others. However, under an Internalized line of research, this concern might we weaker, as the originating inventor benefits from the advancements built by others into its prior knowledge, which can raise private returns in a dynamic perspective that takes into account the future developments of the originating inventor.

Importantly, the above argument also holds in the presence of patent protection of both the originating and the subsequent inventions. This can contribute to the design of patent policy[1], by identifying the circumstance under which the incentive to innovate in a dynamic framework is sufficient, even in the presence of spillovers (or to the contrary, the circumstance under which a stronger patent protection is required in order to ensure sufficient incentives to innovate, as might be the case under Externalized patterns of diffusion).

[1]See for example, Klemperer (1990), Gilbert and Shapiro (1990), Scotchmer (1999) and Cornelli and Schankerman (1999).

Moreover, Bessen and Maskin (2002) study the effect of competition on the incentive to innovate in a sequential innovation framework. They argue that competition in research can raise private returns through enhancing the probability that an invention should occur. Our empirical framework can be used to test this argument. Along an Internalized line of research, stronger competition might have this positive effect, however, under Externalized lines of research, stronger competition must have a negative effect on private returns, since even if the probability of inventing a subsequent development rises, the originating firm does not benefit from the inventions of others. Therefore, it should not be positively affected by the higher probability of inventing, due to stronger competition.

This chapter looks at the effect of competition on the pattern of diffusion. We find that stronger competition in research reduces the probability a line of research is Internalized. Thus, even if stronger competition increases the probability of inventing, it reduces the probability the originating firm exploits this invention.

The rest of this chapter proceeds as following: section 2 presents the characteristics of lines of research, section 3 discusses the data, section 4 reports the findings and section 5 summarizes.

3.2 The characteristics of lines of research

We choose to focus the analysis on two main characteristics of the lines of research. The first is concentration of firms and the second is technological complexity. We expect to find that the probability a line of research is Internalized is positively correlated with Firm Concentration and is negatively correlated with Complexity.

We mainly focus on Firm Concentration and Complexity, as the characteristics of the line of research. However, in order to identify their effect on the probability a line of research is Internalized, we ought to introduce other characteristics of the line of research, mostly as controls.

For example, we find it important to control for the length of the line of research in terms of the number of patents it includes, as it is likely that lines of research with more subsequent inventions will also include more firms. In case Externalized lines of research have more patents (which is, indeed, the case as reported in table A1 in the appendix), we will find a positive correlation between Firm Concentration and the probability that a line of research is Internalized, which will be wrongly interpreted.

Moreover, we need to introduce some measures that will inform us on the relevance of the line of research to the research pursued by the originating firm. Failing to do so can lead to another bias in the interpretation of Complexity. A higher level of Complexity could mean that the originating knowledge is being developed in research areas that are irrelevant to the originating firm that chooses not to pursue them. In this case, lines of research with a higher value of Complexity are more likely to be Externalized, simply because they are distant from the research interests of the originating firm.

Due to the above, we will introduce two sets of controls: distance measures and length measures. The distance measures include the distance between the originating patent and its subsequent developments and the proximity between the originating firm and the other firms participating in the given line of research, in the product market and technology space.

The length measures include the number of patents in the line of research and the year lag between the grant year of the youngest patent in the line of research and the grant year of the originating patent.

We will turn now to explain how we construct these variables.

Firm Concentration and Complexity are constructed as following:

$Firm\ Concentration_i$ - we count the number of different firms participating in line of research i, normalized by the number of patents in the line of research, which we define as $Firms\ Per\ Patent_i$. The normalization by the number of patents aims to control for the likelihood that a line of research will include more firms, if it includes more subsequent developments. $Firm\ Concentration_i$ is defined simply as the reciprocal of $Firms\ Per\ Patent_i$.

$$Firms\ Per\ Patent_i = \frac{Firms_i}{Patent_i} \tag{3.1}$$

Where, $Firms_i$ is the number of different firms (other than the originating firm) in line of research i and $Patents_i$ is the number of patents in line of research i. Firm Concentration is computed as:

$$Firm\ Concentration_i = \frac{1}{Firms\ Per\ Patent_i} \tag{3.2}$$

$Complexity_i$ - we count the number of different three-digit technology sectors that take part in line of research i, normalized by the number of patents in this line of research. Thus, $Complexity_i$ is the number of different three-digit technology sectors that appear in line of research i, per patent. The normalization by the number of patents in line of research i aims to control for the higher likelihood that we will observe more three-digit technology sectors in lines of research that include more patents. This measure is constructed as:

$$Complexity_i = \frac{nclass_i}{Patents_i} \tag{3.3}$$

Where, $nclass_i$[2] is the number of different three-digit technology sectors appearing in line of research i.

We construct the distance measure, at the patent level, as following:

$Patent\ Tech\ Distance_i$ - This variable measures the technological *distance* between the originating patent and the offspring patents along line of research i. The technological distance is defined as the average of the technological distance between the originating patent and its subsequent developments along the line of research.

The distance measure is based on Trajtenberg, Henderson and Jaffe (1993) and is constructed as following: the distance between an originating patent and its offspring patent equals 1 if they do not appear in the same one-digit technology sector, 0.66 if they appear in the same one-digit technology sector but not in two-digits technology sector, 0.33 if they appear in two-digits technology sector but not in three-digits technology sector and 0 if they appear in the same three-digits technology sector.

[2] *nclass* is taken from the USPTO and is available in the NBER patents data-set (see Jaffe and Trajtenberg, 2002).

Thus, a higher value of $Patent\ Tech\ Distance_i$ implies that the originating patent is more remote in the technology space from its offspring inventions (direct and indirect).

The distance measures at the firm level include the average proximity between the originating firm and the other firms along the line of research, in the product market and in the technology space. These are constructed as following:

$Firm\ SIC\ Proximity_i$ - This variable measures the average product market proximity between the originating firm and the other firms in line of research i. We construct a pair-wise product market proximity index between the originating firm and each of the other firms on line of research i, in an identical way to Bloom, Schankerman and Van Reenen (2005), as following:

$$SIC_{kj} = \frac{(S_k S_j^{/})}{(S_k S_k^{/})^{\frac{1}{2}} (S_j S_j^{/})^{\frac{1}{2}}} \tag{3.4}$$

Where, k is the originating firm, $j \in J_i$ is a citing (direct or indirect) firm in line of research i and J_i is the set of citing (direct and indirect) firms in line of research i[3]. S is a vector that its elements are the share of the firm's sales in the lines of business at the four-digit industry SIC codes. The normalization by the vector size aims to control for product diversity[4]. After constructing the pair-wise proximity indices between the originating firm and each of the other firms in the line of research, we average these proximities over the number of patents in the line of research, as following:

$$Firms\ SIC\ Proximity_i = \frac{\sum_{j \in J_i} SIC_{kj}}{Patents_i}$$

The technology proximity measure between the originating firm and the other

[3]Note that the set J_i does not necessarily include different firms. If the same citing firm (direct or indirect) appears in the line of research more than once, it will appear the same number of time in the set J_i.

[4]The lines of business data are taken from Compustat 1993 to 2001. We use average share of sales per SIC code within each firm over the period as our measure of activity by product market, $S_i = (S_{i,1}, S_{i,2}, ...S_{i,597})$, where $S_{i,m}$ is the share of sales of firm i in the four-digits SIC code m. We then compute the degree of orthogonality between every pair of firms and interpret this degree of orthogonality as their proximity in the product market (where higher orthogonality implies lower proximity).

firms along the line of research is constructed in a similar way, as following:

Firm TEC Proximity - This variable measures the technological proximity between the originating firm and the other firms in line of research i. We construct a pair-wise technology proximity index, in an identical way to Jaffe (1986), as following:

$$TEC_{kj} = \frac{(T_k T_j^{\prime})}{(T_k T_k^{\prime})^{\frac{1}{2}}(T_j T_j^{\prime})^{\frac{1}{2}}} \tag{3.5}$$

Where, k is the originating firm, $j \in J_i$ is a citing (direct or indirect) firm in line of research i, J_i is the set of citing (direct and indirect) firms in line of research i and T is a vector that its elements are the firm's share of patents in the three-digit technology sectors. The normalization by the vector size aims to control for patenting diversity[5]. After constructing the pair-wise proximity indices between the originating firm and each of the other firms along the line of research, we average these proximities over the number of patents in the line of research, as following:

$$Firms\ TEC\ Proximity_i = \frac{\sum_{j \in J_i} TEC_{kj}}{Patents_i}$$

Finally, our measures of the length of line of research i are the number of patents it includes, which we define as $Patents_i$, and the lag in years between the grant year of the youngest patent in the line of research (the last patent in the sequence of citations) and the grant year of the originating patent, which we define as $Year\ Lag_i$.

As mentioned above, our main focus is on Firm Concentration and Complexity. We interpret Firm Concentration as a proxy for the level of competition the originating firm faces along a given line of research. This interpretation requires assuming a link between the observed number of 'winners' at the different develop-

[5]The technology space information is provided by the allocation of all patents by the USPTO into 426 different technology classes. We use the average share of patents per firm in each technology class over the period 1970 to 1999 to create the following vector for each firm: $T_i = (T_{i,1}, T_{i,2}, ...T_{i,426})$, where $T_{i,m}$ is the share of patents of firm i in technology class m. We then compute the degree of orthogonality between every pair of firms and interpret this degree of orthogonality as their proximity level in the technology space.

ment stages and the number of competitors at each stage. Since we do not observe the number of competitors at every stage of development (which is the first-best measure of competition), we assume that the number of different winners along the line of research proxies the pool of potential winners (so that a less concentrated line of research is more likely to face a larger pool of competing firms at every development stage)[6].

This concludes our set of line of research characteristics. We turn to investigate the correlation between these characteristics and the likelihood that a line of research is Internalized.

3.3 Data

In this chapter our unit of observation is a line of research taken from the sample of lines of research introduced in the previous chapter. For the sake of brevity we will not discuss this sample here and will not refer to the procedure used for its construction (the algorithm is described in the appendix of the chapter 2).

In order to cope with the massive data (about 13 million lines of research), we needed to reduce the size of our sample. Thus, we randomly sampled five percent of the population of lines of research (Internalized and Externalized). This leaves us with 655,377 lines of research that are used in the empirical analysis in this chapter.

Table 1 summarizes the statistics for the set of characteristics of the lines of research discussed above.

On average, a line of research includes 3.6 firms (that are different from the originating firm), where the maximum number of firms in a line of research is 11. The average length of a line of research in terms of patents is 6.5, where the longest line of research includes 15 patents (14 subsequent developments of the originating patent). On average, a firm that participates in a line of research develops about

[6]For example, assume that the probability of winning in one development stage is $p(1-p)^{n-1}$, where p is the probability on inventing, which is equal across firms, and n is the number of competitors. As n rises, the probability of winning drops. Thus, observing many different winners along a line of research would imply n is larger.

1.5 subsequent inventions along this line of research.

Finally, the average year lag of a line of research is 14. This implies that our restriction on the diffusion pattern (the year lag between the youngest patent and the originating patent grant years must be less or equal to 15) is mostly binding.

Table A1 in the appendix provides similar summary statistics, separately for Internalized and Externalized lines of research.

Table 1

Summary statistics for the constructed variables in the sample

	Mean	S.D. Error	Median	Min	Max
Complexity	0.34	0.17	0.33	0.07	0.88
Firm Concentration	2.03	0.96	1.75	1.09	11.00
Firms[a]	3.64	1.52	4.00	1.00	11.00
Patent Tech Distance	0.45	0.28	0.40	0.10	0.00
Year Length	14.17	1.40	15.00	0.00	15.00
Patent Length	6.49	1.82	6.00	2.00	15.00
Firm SIC Proximity	0.07	0.12	0.01	0.00	0.88
Firm TEC Proximity	0.07	0.11	0.01	0.00	0.84

[a]The number of firms in a line of research, as explained in the text.

The share of Internalized lines of research in the sample is 0.076, which is identical to the share in the whole sample (see chapter 2). The share of Internalized lines of research breaks down by technology sectors, as following: 0.062 in "Chemicals", 0.075 in "Computers and Communications", 0.149 in "Drugs and Medicals", 0.074 in "Electrical and Electronics" and 0.088 in "Mechanicals".

3.4 Findings

The empirical analysis starts with simple non-parametric descriptive statistics, such as correlations and comparison of means. We proceed with an econometric estimation of a Probit specification (where the dependent variable is an indicator for an

Internalized line of research), which is followed by robustness tests using a linear probability specification.

Table 2 reports the correlation between Firm Concentration and Complexity and the other set of characteristics used in the estimation.

There is a high correlation between Firm Concentration and Firm SIC Proximity, in contrast with the low and negative correlation between Firm Concentration and Firm TEC Proximity. Thus, the originating firm is likely to be closer in the product market to the other firms along the line of research, if the line of research is more concentrated.

Also, the correlation between Firm Concentration and Patents is positive. This may indicate that lower competition along a line of research raises the probability of inventing, since lines of research including fewer firms tend to include more inventions[7].

With respect to Complexity, it is highly correlated with Patent Tech Distance, as expected from the construction of the two measures (if the originating patent and the subsequent patents are in different three-digits technology sectors, both measures are higher).

Finally, we find a high negative correlation between Complexity and Patents, which implies that longer lines of research tend to include a fewer number of three-digits technology sectors. This finding is interesting as it may indicate that a more rapid scientific development is more technologically localized (a longer sequence of subsequent developments, in a period of 15 years, is more likely to occur in fewer three-digits technology fields).

[7] Which is inconsistent with the theoretical argument of Bessen and Maskin (2002), by which stronger competition raises the probability of inventing.

Table 2

Correlation of Firm Concentration and Complexity with the other controls

	Firm Concentration	Complexity
Firm Concentration		0.002
Complexity	0.002	
Patent Tech Distance	-0.001*	0.500*
Firm SIC Proximity	0.214*	-0.067*
Firm TEC Proximity	-0.024*	-0.218*
Year Length	-0.032*	-0.141*
Patent Length	0.047*	-0.455*

* denotes a significance level of 5 percent (that indicates the correlation is different from zero).

3.4.1 Comparison of means

Table 3 summarizes the results of comparing the means of Firm Concentration and Complexity across Internalized and Externalized lines of research.

A simple comparison of means across the whole sample shows that Internalized lines of research are associated with a significantly higher Firm Concentration relative to Externalized lines of research.

Also, we find that Externalized lines of research are significantly more technologically complex than Internalized lines of research.

This preliminary look at the data supports our prior expectation that Internalized lines of research are associated with a lower degree of competition (a higher Firm Concentration) and with a lower degree of technological complexity (a lower Complexity).

A similar pattern of results also emerges when comparing the means across technology sectors. In all technology sectors, the level of Firm Concentration is higher for Internalized lines of research relative to Externalized lines of research and this difference is always significant at the five percent level.

With the exception of "Computers and Communications", Externalized lines of research have a significantly higher mean of Complexity relative to Internalized lines research.

Table 3

Internalized versus Externalized lines of research - Firms Concentration and Complexity

	Internalized lines of research		Externalized lines of research	
	Firm Concentration	Complexity	Firm Concentration	Complexity
Pooled	2.407*	0.326*	2.002*	0.342*
	(0.004)	(0.001)	(0.001)	(0.0002)
Chemicals	2.692*	0.389*	2.334*	0.408*
	(0.011)	(0.002)	(0.003)	(0.001)
Computers and Communications	2.148*	0.367	1.763*	0.366
	(0.006)	(0.002)	(0.002)	(0.0004)
Drugs and Medicals	2.949*	0.285*	2.424*	0.373*
	(0.014)	(0.002)	(0.007)	(0.001)
Electrical and Electronics	2.204*	0.266*	1.845*	0.278*
	(0.006)	(0.001)	(0.002)	(0.0003)
Mechanicals	2.944*	0.383*	2.475*	0.397*
	(0.018)	(0.002)	(0.006)	(0.001)

Standard errors are in brackets.
* denotes the difference in means is significant at the 5 percent level.

Table 4 reports the comparison of means of the 'distance' measures across Internalized and Externalized lines of research.

With respect to Patent Tech Distance, we find its mean to be significantly higher for Externalized lines of research, in the whole sample, and for each of the technology sectors. This finding may imply that the originating firm is less likely to pursue lines of research that are technologically remote from its original knowledge.

With respect to Firm TEC Proximity and Firm SIC Proximity, their mean is higher for Externalized lines of research. This finding is stronger for Firm TEC Proximity, where for Firm SIC Proximity the pattern is less clear and varies across technology sectors. The implication of this finding is that the originating firm is less likely to reabsorb its knowledge once it spills to firms that are closer in the technology space (and less clearly for firms that are closer in the product market). This is rather puzzling, as we would expect the firm to be able to technologically benefit from firms that are closer in the technology space. A possible explanation would be to consider Firm TEC Proximity as a measure of competition in research the originating firm faces along the line of research (as the originating firm and the other firms in the line of research overlap more in their research areas, it is more likely they compete on similar research projects). Under this interpretation, a higher level of competition reduces the probability of 'winning' in subsequent development stages and, therefore, raises the likelihood that a line of research is Externalized.

Table 4

Internalized versus Externalized lines of research - distance measures

	Internalized lines of research			Externalized lines of research		
	Firm SIC Proximity	Firm TEC Proximity	Patent Tech Distance	Firm SIC Proximity	Firm TEC Proximity	Patent Tech Distance
Pooled	0.066 (0.001)	0.062* (0.001)	0.419* (0.001)	0.065 (0.0001)	0.071* (0.0001)	0.452* (0.0004)
Chemicals	0.058* (0.001)	0.026* (0.001)	0.543 (0.003)	0.065* (0.0004)	0.032* (0.0002)	0.544 (0.001)
Computers and Communications	0.046* (0.0001)	0.053 (0.001)	0.449* (0.002)	0.049* (0.0001)	0.055 (0.0002)	0.463* (0.001)
Drugs and Medicals	0.152* (0.002)	0.045* (0.001)	0.339* (0.003)	0.142* (0.001)	0.055* (0.0006)	0.470* (0.002)
Electrical and Electronics	0.045 (0.001)	0.095* (0.001)	0.341* (0.002)	0.055 (0.0002)	0.109* (0.0002)	0.363* (0.001)
Mechanicals	0.138* (0.003)	0.027* (0.001)	0.499* (0.004)	0.120* (0.001)	0.039* (0.0004)	0.582* (0.001)

Standard errors are in brackets. * denotes the difference in means is significant at the 5 percent level.

From the comparison of means we find that (1) Internalized lines of research are more concentrated (have a higher mean of Firm Concentration), (2) less technologically complex (have a lower mean of Complexity) and (3) include firms that are more remote in the technology space from the originating firm (and less clearly, more remote in the product market).

We will turn to investigate the robustness of these findings in an econometric analysis.

3.4.2 Econometric evidence

In this section the conditional correlation between the characteristics of the lines of research and their likelihood of being Internalized is examined. We estimate a Probit model, in which the probability of a line of research to be Internalized depends on its characteristics. We proceed by reporting robustness tests with a linear probability model, focusing mainly on fixed-effects at the originating patent and originating firm levels.

All the regressions reported in this section include a complete set of dummies for the grant year and one-digit technology sectors of the originating patent. The standard errors are always clustered at the originating firm level, in order to control for serial correlation across originating patents held by the same firm (we also experiment with clustering at the originating patent level, which yields similar results).

Table 5 reports the estimation results for the Probit model. Column 1 reports the estimation results of including only Complexity and Firm Concentration. Consistent with our prior expectations, Complexity has a significant negative effect on the probability that a line of research is Internalized (-0.602 with a standard error of 0.149) and Firm Concentration has a positive and significant effect on the same probability (0.196 with a standard error of 0.022).

In column 2 we add the other control variables that have been discussed above (length and distance measures). The same pattern of results for Complexity and Firm Concentration holds. The effect of Patent Tech Distance on the likelihood that the line of research is Internalized is negative and significant. We interpret this finding as an indication that the originating firm is more likely to pursue sequential research in areas closer to its original knowledge. With respect to Firm TEC Proximity, we find a negative insignificant effect. However, the effect of Firm SIC Proximity is significantly negative. Thus, when knowledge spills to firms that are closer in the product market to the originating firm, the probability that the line of research will be Internalized drops (in the unconditional comparison of means, we found Firm TEC Proximity to be significantly higher in Externalized lines of research, where the mean comparison results for Firm SIC Proximity were less clear).

In column 3 we add two-digit technology sector dummies. The only important change, compared to column 2, is that Patent Tech Distance becomes insignificant. Finally, in column 4 we add three-digit technology sectors dummies, which does not affect the results in an important manner.

Table 5

Internalized and Externalized lines of research characteristics - Probit estimation

Dependent variable: a dummy for an Internalized line of research

	(1)	(2)	(3)	(4)
Complexity	-0.602*	-0.511*	-0.522*	-0.497*
	(0.149)	(0.143)	(0.135)	(0.105)
Firm Concentration	0.196*	0.204*	0.211*	0.222*
	(0.022)	(0.019)	(0.021)	(0.026)
Patent Tech Distance		-0.169*	-0.057	-0.112
		(0.070)	(0.076)	(0.068)
Firm TEC Proximity		-0.259	-0.428	-0.531
		(0.344)	(0.363)	(0.384)
Firm SIC Proximity		-0.352*	-0.439*	-0.591*
		(0.159)	(0.165)	(0.210)
Two-digit technology sector effects[a]	No	No	Yes	No
Three-digit technology sector effects[b]	No	No	No	Yes
Observations	655,377	655,377	655,377	655,377
R^2	0.064	0.066	0.074	0.093

Standard errors are in brackets and are clustered by (421) firms.
* denotes a significance level of 5 percent.
All regressions include a complete set of originating patents grant year dummies and one-digit technology sectors.
All regressions include Patent and Year Length. For example, in column 1 the coefficient on Patents is -0.039 with a standard error of 0.009 and the coefficient on Year Lag is -0.142 with a standard error of 0.009.
[a]Includes 36 two-digit technology sectors.
[b]Includes 379 three-digit technology sectors.

In summary, we have found so far that Internalized lines of research (1) have fewer firms, (2) are more technologically complex and (3) include firms that are remote in the product market from the originating firm. Findings (1) and (2) are consistent with the unconditional comparison of means reported in table 3, while finding 3 is less consistent with the mean comparison.

Quantifying the effects by technology sectors

After having identified the characteristics of the line of research that significantly affect the probability of its being Internalized, we turn to investigate their quantitative effect in the pooled estimation and for each of the main technology sectors, as summarized is table 6 (table A2 in the appendix reports the estimation results for each technology sector, which table 6 builds on). The entries in table 6 are the calculated semi-elasticities, which informs us on the change in the probability that a line of research is Internalized as a response to a percentage change the independent variables.

Table 6

Internalized and Externalized lines of research characteristics: semi-elasticities

Dependent variable: a dummy for an Internalized line of research

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled	Chemicals	Computers and Communications	Drugs and Medicals	Electrical and Electronics	Mechanicals
Complexity	-0.022*	-0.031*	-0.010	-0.108*	-0.016*	-0.012
	(0.006)	(0.008)	(0.009)	(0.034)	(0.005)	(0.015)
Firm Concentration	0.053*	0.041*	0.057*	0.131*	0.061*	0.057*
	(0.010)	(0.007)	(0.016)	(0.037)	(0.015)	(0.013)
Patent Tech Distance	-0.009*	0.006	-0.012	-0.067*	-0.009	-0.031*
	(0.004)	(0.008)	(0.013)	(0.028)	(0.007)	(0.019)
Firm TEC Proximity	-0.002	-0.001	0.002	-0.012	-0.007	-0.005
	(0.003)	(0.001)	(0.003)	(0.009)	(0.008)	(0.004)
Firm SIC Proximity	-0.003*	-0.003*	-0.002	-0.013	-0.001	-0.005
	(0.001)	(0.001)	(0.002)	(0.011)	(0.003)	(0.004)

Calculated from Probit specifications and evaluated at the mean: column (1) is from table 5, and the other columns are from table A2.
* denotes a significance level of 5 percent.
All regressions include Patents and Year Length as controls.

A ten percent increase in Complexity reduces the probability that a line of research is Internalized by 0.2 percent (a one standard deviation increase in Complexity reduces the probability that a line of research is Internalized by 1 percent), as estimated from the pooled sample. This effect varies across technology sectors. In "Drugs and Medicals", the same ten percent increase in Complexity reduces the probability that a line of research is Internalized by 1.1 percent. On the other hand, in "Computers and Communications", a ten percent increase in Complexity reduces the probability that a line of research is Internalized by only 0.1 percent, which is statistically not different from zero.

With respect to Firm Concentration, a ten percent increase in the level of Firm Concentration raises the probability that a line of research is Internalized by 0.5 percent (a one standard deviation increase in Firm Concentration raises the probability that a line of research is Internalized by about 2.5 percent), estimated from the pooled sample. This percentage varies substantially across technology sectors, with the highest effect in "Drugs and Medicals" and the lowest effect in "Electrical and Electronics".

This variation may indicate that the effect of competition on the incentive to innovate (as implied by the ability of the originating inventor to *internalize* the subsequent developments of its original knowledge) varies across technology types. For example, higher competition is more likely to reduce the incentive to innovate in "Drugs and Medicals", compared to "Computers and Communications" (since in the latter sector the ability of firms to reabsorb their spilled knowledge will not be affected much, compared to firms in the former sector).

The effect of Patent Tech Distance is negative and significant in the pooled sample. However, a closer examination across technology sectors shows that it is driven mainly by the "Drugs and Medicals" sector (which is the only sector with a significant effect). Based on our interpretation of Patent Tech Distance, firms in the "Drugs and Medicals" sector are less likely to pursue a line of research that includes subsequent developments that are more remote in the technology space from the originating knowledge. This is consistent with our finding on Complexity, accordingly, in "Drugs and Medicals" the effect of a higher Complexity on the probability that a line of research is Internalized is significantly higher than in the other sectors.

Finally, the effect of the proximity between the originating firm and the other firms along the line of research in the technology space is not significantly different from zero in all technology sectors.

The significant and negative effect of the proximity of the originating firm and the other firms in the line of research in the product market is driven mainly by the "Chemicals" sector.

In order to look closer at the effect of these two proximity measures, we repeat the estimation for each technology sector by including only one proximity measure at a time, since the proximity measures are correlated (a correlation of about 0.3), and their separate effect may be hard to identify in a regression that includes both. Table A3 reports the estimation results. We find Firm SIC Proximity to have a significant and negative effect in "Chemicals", "Drugs and Medicals" and "Mechanicals", and Firm TEC Proximity to have a significant negative effect in "Drugs and Medicals" and "Mechanicals" (both are significant only at the 10 percent level).

3.4.3 Robustness tests

An important robustness test relates to whether the variation we observe across lines of research is indeed attributed to the line of research, or to the characteristics of the originating patent and the originating firm.

For example, the variation in technological complexity can arise from the characteristics of the originating patents, so that a more 'basic' knowledge is likely to originate lines of research that include more technological area[8].

In order to identify whether the source of variation is at the line of research level or at the originating patent level, we estimate an originating patent fixed-effects specification, in which we exploit only the variation across lines of research that are originated in the same originating patent.

[8] In the next chapter we will investigate the correlation between the 'basicness' characteristics of the originating knowledge and the diffusion pattern it experiences.

Similarly, the lines of research variation can be attributed to the characteristics of the firm. For example, if larger firms face a lower competition along their sequential innovation and also have more Internalized lines of research, our interpretation of the effect of Firm Concentration may be biased.

In order to test the robustness of our findings to this potential bias, we estimate an originating firm fixed-effects, using only the variation across lines of research that originate in the same firm.

For this purpose, we estimate a linear probability specification, which is not very applicable in terms of the point estimates it produces. However, we believe the linear specification is useful for testing the significance of our previous results and identifying the sources of variation in the data.

Column 1 in table 7 reports the estimation results without any type of fixed-effect. We find the same pattern of results as in the Probit specification. The effect of Complexity is negative and significant and the effect of Firm Concentration is positive and significant. With respect to the 'distance' measures (Patent Tech Distance, Firm TEC Proximity and Firm SIC Proximity), the same pattern of results holds as well.

Column 2 includes originating patent fixed-effects. The estimate of Complexity more than halves and its significance level drops. However, it remains negative and significant. This is consistent with our concern that the variation in the technological complexity across lines of research is partly related to the 'basicness' attributes of the originating patent (so that more general originating patents are likely to be subsequently developed in more technology sectors).

With respect to Firm Concentration, the estimate actually rises and remains highly significant.

The most striking change occurs in the estimate of Firm TEC Proximity, which becomes highly significant and its effect substantially rises. Similarly, the effect of Firm SIC Proximity rises and it remains highly significant.

In column 3 we add originating firm fixed-effects, which mainly affect Firm SIC Proximity that is no longer significant. Finally, in column 4 we add a complete set of dummies for the two-digits technology sectors of the originating patents to find the same pattern of results.

Table 7

Internalized and Externalized lines of research characteristics - fixed effects robustness tests: linear specification

Dependent variable: a dummy for an internalized line of research

	(1)	(2)	(3)	(4)
Complexity	-0.069*	-0.033*	-0.056*	-0.056*
	(0.016)	(0.012)	(0.014)	(0.014)
Firms Concentration	0.034*	0.046*	0.036*	0.036*
	(0.006)	(0.009)	(0.006)	(0.006)
Patent Tech Distance	-0.022*	-0.034	-0.024*	-0.023*
	(0.009)	(0.008)	(0.009)	(0.010)
Firm TEC Proximity	-0.033	-0.258*	-0.182*	-0.184*
	(0.047)	(0.043)	(0.029)	(0.027)
Firm SIC Proximity	-0.048*	-0.122*	-0.029	-0.032
	(0.024)	(0.047)	(0.026)	(0.026)
Originating patents fixed-effects[a]	No	Yes	No	No
Firm fixed-effects	No	No	Yes	Yes
Two-digit technology sector effects	No	No	No	Yes
Observations	655,377	655,377	655,377	655,377
R^2	0.043	0.197	0.077	0.079

Standard errors are in brackets and are clustered by (421) firms.
* denotes a significance level of 5 percent.
All regressions include a complete set of dummies for grant year and one-digit technology sectors.
All regressions include Patents and Year Lag.
[a]Includes 41,112 originating patents.

Finally, an additional source of concern is associated with the fact that by controlling for the originating patents fixed-effects we do not eliminate all the variation that is attributed to a single invention. It is possible to observe a scenario in which a second generation invention is a 'bottle-neck' for many lines of research (so that many lines of research that can originate in different patents use this second generation as a technological link). In this case, originating patent fixed-effects will not control for this second generation effect. In order to test whether this concern is serious, we have explored specifications with second and third generations fixed-effects. We find our results to hold in these cases as well.

In summary, the fixed-effects robustness tests we have performed in this section provide two main insights: (1) the positive effect of Firm Concentration and negative effect of Complexity on the likelihood of a line of research to be Internalized are strongly evident also within originating patents (lines of research that originate in the same patent) and originating firms (lines of research that originate in the same firm). (2) Once controlling for either originating patent or originating firm fixed-effects, the negative effect of Firm TEC Proximity becomes highly significant.

3.5 Interpretation and summary

In this chapter we have found that firms are more likely to reabsorb their spilled knowledge, if its subsequent developments occur in lines of research that (1) have fewer firms (2), are less technologically complex and (3) include firms that are more remote in the product market from the originating firm.

Findings (1) and (2) are highly robust and evident also within technology sectors. With respect to finding (3), it is less robust to the type of estimation and is less evident within technology sectors (we find a significant effect only in the "Chemicals" sector).

How should we interpret these findings? Regarding our first finding that Internalized lines of research have fewer firms, it is likely to expect that in the case firms compete in subsequent patent races, it would become more difficult for the originating firm to 'win' a development stage if it faces stronger competition.

An alternative interpretation would be to consider an Internalized line of research as a sort of tacit or explicit agreement among firms in sharing their discoveries with one another. Economic theory regarding collusive behaviour of firms would suggest that as the number of participants increases, supporting collusion becomes more difficult.

The importance of this finding relates to the effect of competition on the incentive to innovate in a dynamic framework. In the presence of sequential innovation, an increase in the number of firms will reduce the incentive to innovate, as the likelihood that the firm will benefit in the longer run from its discovery drops. This implies a negative effect of competition in research on the incentive to innovate. Nevertheless, Bessen and Maskin (2002) present an argument in which a higher competition in research raises the probability of inventing and, therefore, raises private incentive to innovate. This argument is applicable only for Internalized lines of research, where the originating firm benefits from the inventions of others. This in principle could be empirically tested by conditioning the analysis on Internalized lines of research (for example, by looking at the effect of competition on R&D expenditures along Internalized lines of research).

Our second finding indicates that an invention that spreads to more technology sectors is less likely to return to the boundaries of its original inventor (a negative effect of Complexity on the probability that a line of research is Internalized). This finding implies a trade-off between the socially desired property that knowledge would spread and benefit inventors in numerous research areas and the desire to provide sufficient private incentive for innovation. In the next chapter we will further investigate the socially desirable attributes of knowledge and examine their relation to the diffusion pattern of knowledge.

Moreover, we find a high variation in the effects of Firm Concentration and Complexity on the likelihood that a line of research is Internalized across technology sectors. This high variation can indicate structural differences in research in these sectors.

For example, a ten percent increase in Complexity lowers the probability that a line of research is Internalized in "Computers and Communications" by only 0.1 percent, where in "Drugs and Medicals", a ten percent increase in Complexity lowers the probability that a line of research is Internalized by 1.1 percent. This huge difference can be associated with the higher technological complexity in "Computers and Communications", compared to "Drugs and Medicals" (for example, the number of three-digits technology sectors in "Computers and Communications" is 44, compared to 14 in "Drugs and Medicals"). Thus, firms that operate in "Computers and Communications" are more likely to possess more diverse innovation capabilities, compared to firms in "Drugs and Medicals" and, therefore, should be less affected in their ability to reabsorb their spilled knowledge by an increase in the complexity of their research environment.

The same argument can be outlined with respect to the differential effect of Firm Concentration across technology sectors.

Finally, our third finding is that once knowledge spills to firms closer to the originating firm in the product market, it is less likely that this knowledge will return to the boundaries of the originating firm. A possible interpretation of this finding is that the originating firm chooses to locate itself further away from its product market competitors, as it is less likely to pursue lines of research it originates that include subsequent developments of its close rivals. This interpretation is consistent with Bloom, Schankerman and Van Reenen (2005), who find the returns to innovation to be negatively affected by the R&D expenditures of close product market rivals. Our finding can add to the above by providing preliminary evidence that the technological location of the firm is determined strategically, depending on the follow-up research of its rivals.

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Table A1

Characteristics of Externalized lines of research

	Chemicals			Computers and Communications			Drugs and Medicals			Electrical and Electronics			Mechanicals		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Complexity	0.41	0.08	0.88	0.37	0.07	0.88	0.37	0.09	0.86	0.28	0.07	0.88	0.40	0.08	0.88
Firm Concentration	2.34	1.11	11.00	1.76	1.10	10.00	2.43	1.13	9.00	1.85	1.09	10.00	2.47	1.11	11.00
Patent Tech Distance	0.55	0.04	1.00	0.46	0.00	1.00	0.47	0.09	1.00	0.36	0.08	1.00	0.58	0.10	1.00
Year Lag	13.98	1.00	15.00	14.39	1.00	15.00	14.18	0.00	15.00	14.31	0.00	15.00	14.04	1.00	15.00
Patents	6.02	2.00	15.00	6.44	2.00	15.00	5.84	2.00	12.00	7.04	2.00	15.00	5.86	2.00	13.00
Firms SIC Proximity	0.07	0.00	0.88	0.05	0.00	0.87	0.14	0.00	0.86	0.06	0.00	0.85	0.12	0.00	0.84
Firms TEC Proximity	0.03	0.00	0.80	0.46	0.00	1.00	0.06	0.00	0.76	0.11	0.00	0.84	0.04	0.00	0.83
Observations	123256	123256	123256	159318	159319	159319	21924	21924	21924	244917	244917	244917	55981	55981	55981

Characteristics of Internalized lines of research

	Chemicals			Computers and Communications			Drugs and Medicals			Electrical and Electronics			Mechanicals		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Complexity	0.39	0.08	0.88	0.37	0.07	0.86	0.29	0.09	0.83	0.27	0.08	0.88	0.38	0.10	0.83
Firm Concentration	2.69	1.29	11.00	2.15	1.22	8.00	2.95	1.40	8.00	2.20	1.22	10.00	2.94	1.29	10.00
Patent Tech Distance	0.54	0.10	1.00	0.45	0.00	1.00	0.34	0.09	1.00	0.34	0.08	1.00	0.50	0.10	1.00
Year Lag	12.99	2.00	15.00	13.58	2.00	15.00	13.19	2.00	15.00	13.65	3.00	15.00	13.10	2.00	15.00
Patents	5.47	3.00	13.00	5.93	3.00	14.00	5.85	3.00	11.00	6.86	3.00	13.00	5.41	3.00	11.00
Firms SIC Proximity	0.06	0.00	0.74	0.05	0.00	0.73	0.15	0.00	0.73	0.05	0.00	0.69	0.14	0.00	0.70
Firms TEC Proximity	0.03	0.00	0.53	0.05	0.00	0.52	0.05	0.00	0.46	0.10	0.00	0.70	0.03	0.00	0.62
Observations	8158	8158	8158	13046	13046	13046	3844	3844	3844	19516	19516	19516	5422	5422	5422

Table A2

Internalized and Externalized lines of research characteristics - Probit estimation by technology sectors

Dependent variable: a dummy for an Internalized line of research

	(1)	(2)	(3)	(4)	(5)
	Chemicals	Computers and Communications	Drugs and Medicals	Electrical and Electronics	Mechanicals
Complexity	-0.701*	-0.210	-1.633*	-0.459*	-0.209
	(0.165)	(0.230)	(0.403)	(0.116)	(0.269)
Firm Concentration	0.160*	0.256*	0.284*	0.258*	0.158
	(0.021)	(0.028)	(0.055)	(0.033)	(0.028)
Patent Tech Distance	0.104	-0.207	-0.813*	-0.195	-0.378
	(0.138)	(0.198)	(0.307)	(0.142)	(0.209)
Firm TEC Proximity	-0.155	0.194	-1.332	-0.487	-1.032
	(0.408)	(0.414)	(1.048)	(0.515)	(0.543)
Firm SIC Proximity	-0.419*	-0.307	-0.515	-0.125	-0.275
	(0.179)	(0.289)	(0.424)	(0.374)	(0.227)

Standard errors are in brackets and are clustered by (421) firms.
* denotes a significance level of 5 percent.
All regressions include Patents and Year Lag as controls.
All regressions include a complete set of dummies for grant year and one-digit technology sectors.

Table A3

Internalized and Externalized lines of research characteristics- Firm SIC Proximity and Firm TEC Proximity

Dependent variable: a dummy for an Internalized line of research

	(1)	(2)	(3)	(4)	(5)
	Chemicals	Computers and Communications	Drugs and Medicals	Electrical and Electronics	Mechanicals
Firm SIC Proximity	-0.003**	-0.002	-0.019**	-0.002*	-0.007**
	(0.001)	(0.002)	(0.009)	(0.003)	(0.004)
Firm TEC Proximity	-0.001	0.001	-0.016*	-0.007	-0.006**
	(0.001)	(0.002)	(0.010)	(0.007)	(0.004)

Standard errors are in brackets and are clustered by (421) firms.
All regressions include Complexity, Firm Concentration, Patent Tech Proximity, Year Lag, Patents and complete sets of dummies for the grant year and one-digit technology sectors of the originating patent.
* and ** denote a significance level of 5 and 10 percent, respectively.

Chapter 4

The Diffusion pattern of 'Basic' Versus Applied Knowledge: Is 'Basic' Research Less Rewarded?

We investigate the correlation between the 'basicness' attributes of knowledge and the technological feedback its inventor receives from its spillovers. We find that private returns should be lower in a dynamic perspective, if the knowledge is more 'basic', as an inventor is less likely to reabsorb this knowledge after its diffusion and benefit from the advancements other inventors build into it. In particular, the spillovers of more "general" and "original" knowledge are less likely to feed back into the dynamic research of the originating inventor. This indicates that there may be insufficient private incentive for 'basic' innovation, which is worrying from a social point of view that values the 'basicness' attributes of knowledge.

4.1 Introduction

Social returns to knowledge outweigh private returns due to the ability of knowledge to spread and contribute to the research of others. A well-accepted notion is that 'basic' knowledge is more socially desirable than applied knowledge[1]. The question we pose in this chapter is whether spillovers have a stronger negative affect on

[1]For example, Griliches (1986) shows that 'basic' research had an important contribution to the productivity growth in the US in the 70's.

private returns as the 'basicness' of knowledge rises. We address this question by studying the effect of the 'basicness' attributes of knowledge on the technological feedback an inventor receives from the spillovers of its discoveries.

As there is no clear definition of 'basicness', it is rather intuitive to think of knowledge characteristics that fall into the 'basicness' category. The most important empirical paper, in our view, that looks into the 'basicness' characteristics of knowledge, using patents and citations data, is Henderson, Jaffe and Trajtenberg (1997). This paper outlines several characteristics of 'basic' knowledge, where the most important ones are Generality and Originality. We have followed their definition of 'basicness' and investigated whether the attributes they outline are systematically correlated with the diffusion pattern knowledge follows. More specifically, we examine whether more General knowledge, as implied by the number of different three-digit technology sectors it contributes to, and more Original knowledge, as implied by the number of different three-digit technology sectors it builds on, experiences a pattern of diffusion that yields a lower Share of Internalized Spillovers[2].

A long debated issue is whether firms have sufficient incentive to invest in 'basic' research rather than in applied research, under the notion that 'basic' research has a higher social value, however, may be less privately rewarded. This concern dates back to Arrow (1962) who argued that *"... basic research, the output of which is only used as an informational input into other inventive activities, is especially unlikely to be rewarded. In fact, it is likely to be of commercial value to the firm undertaking it only if other firms are prevented from using the information obtained."*

Little empirical attention has been devoted to investigate whether inventors face an insufficient incentive to create 'basic' knowledge, or alternatively, whether private returns fall as the 'basicness' of knowledge rises.

In this chapter we offer an indirect way to test this concern, which is based on the technological feedback an inventor receives from the spillovers of its knowledge.

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[2]As a reminder, Share of Internalized Spillovers measures the extent to which spillovers feed back into the dynamic research of the originating firm (see chapter 2).

Our working assumption is that private obsolescence is positively affected by Internalized Spillovers and negatively affected by Externalized Spillovers. Thus, an inventor is likely to face lower private returns and, therefore, a lower incentive to innovate, if more 'basic' knowledge experiences a pattern of diffusion that yields less Internalized Spillovers and more Externalized Spillovers.

We find strong and robust evidence suggesting that in a dynamic perspective, private returns fall as knowledge becomes more 'basic'. This is based on finding a negative correlation between the extent to which knowledge is "general" and "original" and the Share of Internalized Spillovers its diffusion yields. Thus, once more 'basic' knowledge is diffused and is further advanced by other inventors, it is less likely to be reabsorbed by the originating inventor.

We interpret this finding as an indication for insufficient incentive to invest in 'basic' research, as the originating inventor is less likely to enjoy the fruits of its technological success in the long run. Thus, the same mechanism (spillovers) that raises social returns above private returns, especially for 'basic' knowledge, intensifies private obsolescence as knowledge becomes more 'basic'. This leaves room for government intervention, aiming to mitigate the stronger negative effect the diffusion of 'basic' knowledge has on its private returns.

The rest of this chapter proceeds as following: section 2 presents the methodology, section 3 describes the data, section 4 reports the findings and section 5 summarizes.

4.2 Methodology

In chapter 3 the unit of observation is lines of research. In this chapter we move up in the level of aggregation to the originating patent level and decompose the spillovers a patent creates by the Internalized and Externalized criterion, as explained in detail in chapter 2. As a reminder, we briefly review the manner in which we have constructed the spillovers measures, before characterizing the 'basicness' attributes of knowledge.

4.2.1 Diffusion measures

In chapter 2 we have shown how we define and compute the spillovers of an invention. Based on this measure, we have decomposed spillovers into Internalized Spillovers and Externalized Spillovers, where Internalized Spillovers are spillovers that feed back into the dynamic research of the originating firm and Externalized Spillovers are spillovers that do not feed back into the dynamic research of the originating firm.

Internalized Spillovers are constructed following the first term in the right-hand-side of equation (2.7):

$$Internalized\ Spillovers_i = \sum_{j \in Internalized_i} LR_j \times S_j \tag{4.1}$$

Where, i denotes the originating invention, $Internalized_i$ is the set of Internalized lines of research that invention i originates, j indexes lines of research in this set, LR_j is dummy that receives the value 1 for line of research j and zero otherwise, and S_j is the number of external inventions in line of research j, where external refers to the set of firms that do not own invention i.

Externalized Spillovers are constructed following the second term in the right-hand-side of equation (2.7):

$$Externalized\ Spillovers_i = \sum_{t \in Externalized} LR_t \times S_t \tag{4.2}$$

Where, i denotes the originating invention, $Externalized_i$ is the set of Externalized lines of research invention i originates, t indexes lines of research in this set, LR_t is a dummy that receives the value 1 for line of research t and zero otherwise, and S_t is the number of external inventions in line of research t.

Finally, the Share of Internalized Spillovers measures the extent to which spillovers created by an originating invention, contribute to the dynamic research of the originating inventor. The Share of Internalized Spillovers is computed following equation (2.9) and is our preferred spillovers measure in this chapter (it is the dependent variable in the econometric analysis, where the independent variables are the patent characteristics. We assume that private returns rise with a higher Share of Internalized Spillovers and fall with a lower Share of Internalized Spillovers[3].

4.2.2 'Basicness' measures

In defining the characteristics of knowledge we refer to Trajtenberg, Henderson and Jaffe (1997). In particular, we adopt the following characteristics of an invention: Generality, Originality, the technological distance and year lag between an invention and its immediate offspring and ancestor inventions, the number of citations the invention receives and the number of citations it makes. We discuss the way these measures are constructed and their interpretation in this section.

The 'basicness' attributes of an invention can be empirically looked at in various dimensions. However, we find it useful to focus on two main measures, which we find to be the most compelling, and treat the other characteristics of the patent mostly as controls. These two measures are Generality and Originality, which are constructed as following:

$Generality_i$ - This variable measures the extent to which knowledge i is applicable for use in various technology sectors. We associate a 'general' knowledge with being socially desirable. Generality measures the number of different three-digit technology sectors that benefit from the invention. Thus, a higher value of Generality implies more "general" and more 'basic' knowledge. We construct Generality in an identical way to Trajtenberg, Henderson and Jaffe (1997), as one minus the HHI index of concentration across three-digit technology sectors of the citations *received* by patent i, as following:

$$Generality_i = 1 - \sum_j \left(\frac{CR_{ij}}{CR_i}\right)^2 \tag{4.3}$$

Where, i denotes the originating patent, j denotes a three-digits technology sector, CR_{ij} is the number of citations received by patent i from patents in technology sector j and CR_i is the total number of citations received by patent i. Figure 1

[3]This assumption is empirically verified in chapter 5.

illustrates how we construct Generality and it is identical to the one presented in Trajtenberg, Henderson and Jaffe (1997).

Originality$_i$ - This variable measures the extent to which invention i builds on different three-digits technology sectors. Thus, an invention that integrates pieces of knowledge from many different technology sectors is assumed to be more "original", which we associate with a socially desirable knowledge attribute. We construct Originality identically to Trajtenberg, Henderson and Jaffe (1997), as one minus the HHI index for the concentration across technology sectors of the citations *made* by patent i, as following:

$$Originality_i = 1 - \sum_j \left(\frac{CM_{ij}}{CM_i} \right)^2 \tag{4.4}$$

Where, i denotes the originating patent, j denotes a three-digits technology sector, CM_{ij} is the number of citations made by patent i to patents in technology sector j and CM_i is the total number of citations made by patent i. Figure 2 illustrates how we construct Originality and it is identical to the one presented in Trajtenberg, Henderson and Jaffe (1997).

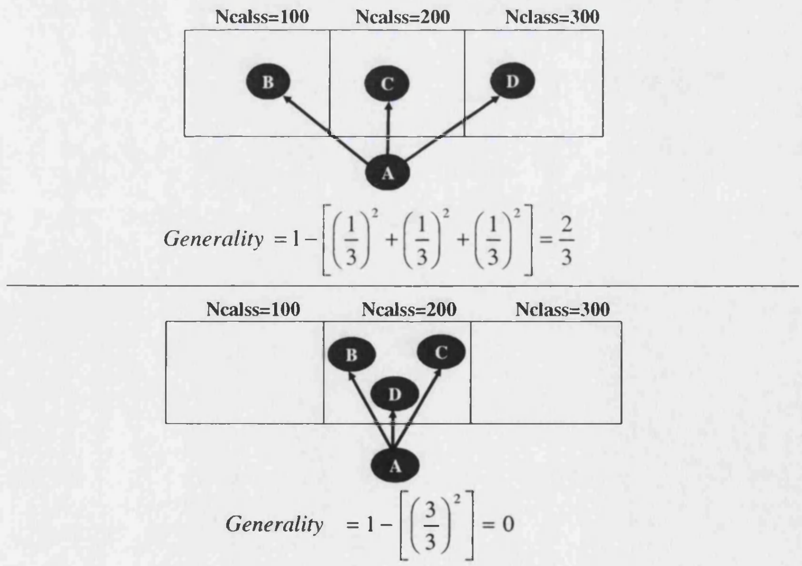

Figure 1: Measuring *Generality*

Figure 1: *This figure illustrates the construction of the Generality measure.*

Patent A in the upper diagram is cited by three patents from different technology fields, whereas, in the lower diagram, patent A is cited by three patents from the same technology field (Nclass 200). Since in the upper diagram patent A is applicable to additional technology fields, the knowledge it embodies is assumed to be more "general".

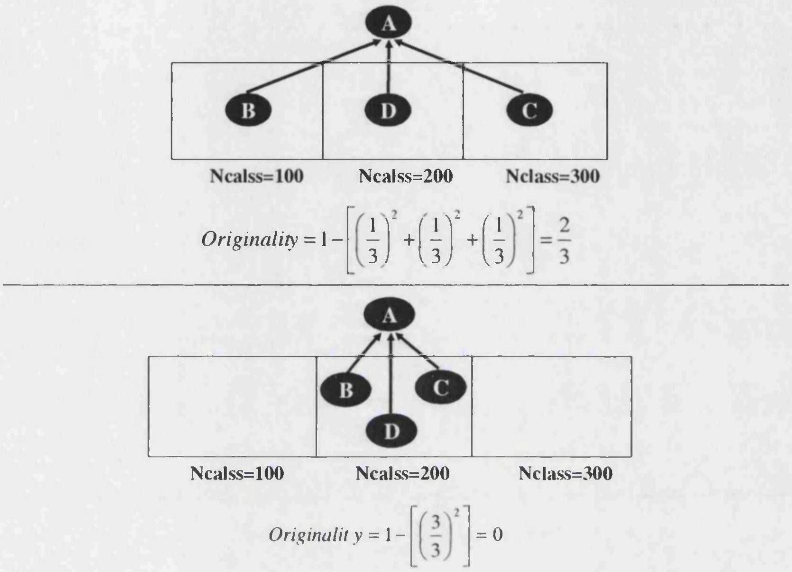

Figure 2: Measuring *Originality*

Figure 2: *This figure illustrates the construction of the Originality measure. The upper diagram in this figure represents the case in which patent A cites three patents from three different technology fields, whereas, the lower diagram represents the case in which patent A cites three patents from the same technology field (Nclass 200). The lower diagram is associated with lower Originality, since the knowledge embodied in patent A does not combine pieces of knowledge from many technology fields.*

In addition to Generality and Originality, we construct measures for the technological distance between the invention and its immediate offspring inventions and immediate ancestors. Intuitively, an invention can be argued to be more 'basic' if its offspring inventions are more distant in the technology space, which can be linked to its level of Generality. Further, an invention that builds on prior inventions that are further away in the technology space can be argued to be more Original and, hence, more 'basic'. Thus, the technological distance variables can be though of as complementary indicators for Generality and Originality, yet, they will not be at the focus of our analysis.

The technological distance measures are constructed as following:

Backward Tech - This variable measures the technological distance between an invention and the knowledge it builds on. This technological distance measure is the mean of the technological distance between the invention and its ancestors. We compute the distance between a pair of patents as following: the distance equals 1 if both patents are not in the same one-digit technology sector, 0.66 if they are in the same one-digit technology sector, but not in the same two-digits technology sector, 0.33 if they are in the same two-digits technology sector, but not in the same three-digits technology sector and 0 if they are in the same three-digits technology sector. After computing the technological distance between the patent and its ancestors, we average these measures. As this variable is backward looking, it is likely to be correlated with the number of citations the patent makes.

Forward Tech - This variable measures the technological distance between an invention and its offspring inventions. The distance between any pair of patents is computed identically to Backward Tech. After computing the technological distance between the patent and its offspring inventions, we average these measures. As this variable is forward looking, it is likely to be correlated with the number of citations the patent receives.

In addition to the technology distance measures, we construct measures of year distance between the invention and its immediate offspring inventions as well as its immediate ancestors, as following:

Backward Lag_i - This variable measures the mean citation lag between an invention and its ancestors (where a citations lag is the difference between the grant year of the citing and cited patents). It can be argued that an invention that builds on 'older' knowledge is more 'basic' in the sense that it is more "original" (whereas, advancing more recent pieces of knowledge is linked to a more applied knowledge).

Forward Lag$_i$ - This variable measures the mean citation lag in years between an invention and its offspring inventions. It measures the speed of diffusion as indicated by the average time is takes to advance the knowledge. Moreover, it is important to control for the speed of citations in the context of the Share of Internalized Spillovers, due to the higher likelihood that a line of research will be Internalized, if the first citation in the sequence of citations arrives sooner (since in this case, there is a longer period in which a line of research can become Internalized, compared to the case where the first citation arrives later).

Finally, we introduce two additional variables which are the number of citations made and received by the patent, as following:

Backward Citations$_i$ - This variable counts the number of citations made by a patent. We expect Backward Citations to be correlated with the backward looking measures, Originality and Backward Tech, which are based on the distribution of citations *made* by the patent. We mainly use Backward Citations as a control for Originality.

Forward Citations$_i$ - This variable counts the number of citations received by a patent, and is mainly used in the literature as a measure for the quality of the patent (the more citations the patent receives, the higher is its perceived quality). Forward Citations are likely to be correlated with Generality and Originality, which are constructed based on the distribution of citations received by the patent.

4.3 Data

In this chapter our unit of observation is an originating invention. In chapter 2 we have described the set of originating patents, which includes 97,921 patents. The summary statistics for Share of Internalized Spillovers (and for the other spillovers measures) are reported in chapter 2 and for the sake of brevity, we do not discuss them here. Table 1 describes the summary statistics for the patent characteristics discussed above.

Table 1

Patents main characteristics

variable	Mean	Median	Std Dev	Minimum	Maximum
Main 'Basicness' Measures					
Generality	0.41	0.48	0.27	0	0.93
Originality[a]	0.32	0.38	0.28	0	0.90
Forward and Backward Citations					
Backward Citations[a]	4.23	4.00	28.8	0	461
Forward Citations	8.02	6.00	8.2	1	239
Technology Distance					
Backward Tech[a]	0.30	0.24	0.31	0	1
Forward Tech	0.35	0.33	0.29	0	1
Time Distance					
Backward Lag[a]	8.64	8.33	3.75	0	26
Forward Lag	9.62	9.50	3.61	0	24

[a]The backward looking variables: Originality, Backward Tech, Backward Citations and Backward Lag, are computed over the period 1975-1980 (and the forward looking variables are computed over the period 1969-1980). The reason is explained in the text.

We do not have information on citations made by patents granted prior to 1975 (however, we have information on patents that were *cited* prior to 1975). Consequently, we observe Originality, Backward Tech, Backward Lag and Backward Citations only for 48,366 patents that were granted between 1975 and 1980. In the econometric analysis we tend to use the smaller sample, which has complete information on patent characteristics.

Table 2 reports the correlation between our two main 'basicness' measures, Generality and Originality, and the other characteristics described above. As expected, we find a high correlation between Generality and the forward looking variables, and a high correlation between Originality and the backward looking variables.

In particular, we are interested in the correlation of Generality and Originality with Forward Citations and Backward Citations, respectively. We find a high correlation between Generality and Forward Citations (although in the construction of Generality we control for the number of citations the patent receives) and a high correlation between Originality and Backward Citations (although in the construction of Originality we control for the number of citations the patent makes). Hence, as we are interested in the correlations between the Share of Internalized Spillovers and Generality and Originality, it is important to control for the number of citations the patent receives for Generality, and for the number of citations the patent makes for Originality.

Table 2

Correlation of Originality and Generality with other 'Basicness' measures

	Generality[a]	Originality[b]
Forward Citations	0.287	0.101
Backward Citations	0.099	0.458
Forward Tech	0.525	0.245
Backward Tech	0.275	0.544
Forward Lag	0.169	0.030
Backward Lag	0.065	0.018

All correlations are greater than zero with a significant level of 1 percent, with the exception of the correlations between Originality with Forward Lag and Backward Lag.
[a]Correlations of Generality with forward looking variables are based on 97,921 patents and the correlations with backward looking variables are based on 48,366 patents (see explanation in the text).
[b]Correlations of Originality with all measures are based on 48,366 patents (see explanation in the text).

As a final note, Hall, Jaffe and Trajtenberg (2001) show that Generality and Originality are biased, and the magnitude of this bias depends on the number of citations received by the patent for Generality, and on the number of citations made by the patent for Originality. Patents that receive few citations are more likely to be considered less "general" than patents that receive many citations. Similarly, patents that make few citations are more likely to be less "original" than patents that make many citations. The intuition for this bias relates to the fact that the HHI index for both variables computes the share of citations made or received in every technology sector based only on observed citations. For patents that receive or make only few citations, the HHI index will not coincide with the true HHI index, since the citations sample for these patents misrepresent the true citations distribution.

Therefore, for Generality, the number of citations the patent receives is positively correlated with Generality. For example, in case the number of citations received by a patent is positively correlated with the Share of Internalized Spillovers, we may find that for patents that receive only few citations, low Share of Internalized Spillovers will be associated with lower Generality. We expect this bias to be eliminated as the number of citations received by a patent rises. The same argument holds for Originality and Backward Citations.

We cope with this bias as following: firstly, we control for the number of citations the patent makes and receives in order to mitigate the above concern (e.g., in the econometric analysis we condition on Forward Citations and Backward Citations). Secondly, we test the robustness of our findings for the correction proposed by Hall, Jaffe and Trajtenberg (2001), i.e., the bias-adjusted $\widehat{HHI}$ is $\widehat{HHI} = \frac{N \cdot HHI - 1}{N-1}$, where N is the number of citations received for Generality and the number of citations made for Originality.

4.4 Findings

We report our findings by first looking at a non-parametric comparison of means of the 'basicness' variables across a set of patents characterized as having a high Share of Internalized Spillovers (hereafter, High) and a set of patents characterized as having a low Share of Internalized Spillovers (hereafter, Low). We proceed to looking at conditional correlations in an econometric analysis.

4.4.1 Non-parametric evidence

We examine the hypothesis that more 'basic' inventions are associated with a lower Share of Internalized Spillovers, as indicated by their pattern of diffusion. Our non-parametric test of this hypothesis is to examine whether the following inequality holds:

$$E(B_k | B_k \in Low) > E(B_k | B_k \in High) \tag{4.5}$$

Where, B_k is the kth 'basicness' indicator (mainly, $k = \{Generality, Originality\}$). The sets *Low* and *High* refer to whether the patent has a low or high Share of Internalized Spillovers.

A natural allocation of the originating patents across the two sets is based on whether they have at least one Internalized line of research. As described in chapter 2, about 30 percent of the originating patents have at least one Internalized line of research, while the remaining patents originate only Externalized lines of research. Thus, the set Low includes patents that do not originate Internalized lines of research and the set High includes patents that originate at least one Internalized line of research[4].

Table 3 summarizes the comparison of means of the patent characteristics across the Low and High sets. With respect to the main 'basicness' measures, Generality and Originality, we find the following results: the mean of Generality is 0.447 with a standard error of 0.002 in the High set and 0.393 with a standard error of 0.001 in the Low set (the difference in means between the two sets is different from zero at the 5 percent significant level). Further, the mean of Originality is 0.336 with a standard error of 0.002 for the High set and 0.303 with a standard error of 0.002 for the Low set (the difference in means between the two sets is different from zero at the 5 percent significant level). These two findings imply that more 'basic' patents have a higher Share of Internalized Spillovers. This contradicts our hypothesis that more 'basic' knowledge has a lower Share of Internalized Spillovers.

Moreover, patents in the High set are cited more and make more citations compared to patents in the Low set. This raises a concern of how we should interpret the above comparison of means. As reported in table 2, there is a high correlation

[4]We test the robustness of the mean comparison results, by allocating patents to the High and Low sets based on the 75 percentile (which equals 0.022) and 90 percentile (which equals 0.142) thresholds. Our results are robust to the alternative allocation of patents.

between Generality and Forward Citations and a high correlation between Originality and Backward Citations. In order to test whether High Share of Internalized Spillovers is associated with a higher Originality and Generality, we should compare the mean of these measures, conditioned on the number of citations the patent receives and the number of citations it makes (the importance of conditioning on Forward Citations and Backward Citations also relates to the potential bias in Generality and Originality, as discussed in the previous section).

Table 3

Comparison of means: High vs. Low Share of Internalized Spillovers

	High share of Internalized Spillovers[1]	Low Share of Internalized Spillovers[1]
Main 'Basicness' Measures		
Generality	0.447*	0.393*
	(0.002)	(0.001)
Originality[a]	0.336*	0.303*
	(0.002)	(0.002)
Forward and Backward Citations		
Backward Citations[a]	4.734*	3.942*
	(0.026)	(0.017)
Forward Citations	12.074*	6.229*
	(0.065)	(0.021)
Technology Distance		
Backward Tech[a]	0.309	0.301
	(0.002)	(0.002)
Forward Tech	0.336*	0.359
	(0.002)	(0.001)
Time Distance		
Backward Lag[a]	8.000*	9.007*
	(0.026)	(0.022)
Forward Lag	8.787*	9.99*
	(0.018)	(0.015)

Standard errors are in brackets. * denotes the difference in means is greater than zero at the 5 percent significant level.

[1]We allocate a patent to the High set if it has at least one Internalized line of research and to the Low set, otherwise.

[a]The backward looking variables: Originality, Backward Tech, Backward Citations and Backward Lag, are computed over 1975-1980, while the forward looking variables are computed over 1969-1980 (see explanation in the text).

For this purpose, table 4 reports the comparison of means for Generality across the High and Low sets, conditioned on the number of citations the originating patents receive. We condition on the patent receiving more than 6 citations, which is the sample median, more than 10 citations, which is the sample 75th percentile and more than 16 citations, which is the sample 90th percentile. If our previous findings are robust, we expect to find a higher mean of Generality in the High set, independently from Forward Citations.

Table 4 shows that the results are not robust. Once conditioning on the patent receiving more than 6 citations, the mean of Generality in the High set is 0.495 with a standard error of 0.002, which is significantly lower than the mean in the Low set, which is 0.513 with a standard error of 0.002. This finding indicates that once conditioning on the quality of the patent (as implied by the number of citations it receives), a higher Generality is associated with a lower Share of Internalized Spillovers. This pattern of results continues to hold when we condition on the patent receiving more than 10 citations and more than 16 citations.

Table 4

Comparison of Generality means: High vs. Low Share of Internalized Spillovers - Conditioning on Forward Citations

	High Share of Internalized Spillovers	Low Share of Internalized Spillovers
Unconditional	0.447*	0.393*
	(0.002)	(0.001)
Observations	29,964	67,957
Forward Citations>6	0.495*	0.513*
	(0.002)	(0.002)
Observations	19,916	23,535
Forward Citations>10	0.516*	0.538*
	(0.002)	(0.002)
Observations	12,714	10,081
Forward Citations>16	0.535*	0.565*
	(0.003)	(0.004)
Observations	6,514	3,219

Forward Citations=6 is the median, Forward Citations=10 is the 75th percentile and Forward Citations=16 is the 90th percentile.
* denotes the difference in means is different from zero at the 5 percent significance level.

We perform a similar analysis for Originality, however, now we condition on the number of citations the patent makes (as Originality is a backward looking measure and is correlated with Backward Citations). We condition on the patent making more than 4 citations, which is the sample median, more than 6 citations, which is the sample 75th percentile and more than 8, which is the sample 90th percentile.

As we condition on the patent making more than 4 citations, our previous finding of a higher Originality in the High set disappears. As we tighten our restriction on Backward Citations, we find that a more Original patent is more likely to be associated with a lower Share of Internalized Spillovers.

Table 5

Comparison of Originality means: High vs. Low Share of Internalized Spillovers - Conditioning on Backward Citations

	High share of Internalized Spillovers	Low share of Internalized Spillovers
Unconditional	0.336*	0.303
	(0.002)	(0.002)
Observations	17,493	30,873
Backward Citations>4	0.450	0.457
	(0.003)	(0.003)
Observations	7,813	10,599
Backwards Citations>6	0.478	0.491
	(0.004)	(0.004)
Observations	4,105	4,879
Backwards Citations>8	0.500	0.511
	(0.006)	(0.005)
Observations	2,023	2,148

Backward Citations=4 is the median, Backward Citations=6 is the 75th percentile and Backward Citations=8 is the 90th percentile.
* denotes the difference in means is different from zero at the 5 percent significance level.

Thus, in both cases, our previous findings, by which more General and Original patents enjoy a higher Share of Internalized Spillovers, are not robust. Once we condition on the number of citations the patent receives, patents that are more "general" have a lower Share of Internalized Spillovers, and once we condition on the number of citations the patent makes, patents that are more "original" have a lower Share of Internalized Spillovers. These two findings imply that private returns are more likely to be negatively affected by spillovers as knowledge is more 'basic'.

We will now turn to investigate the conditional correlations between the Share of Internalized Spillovers and Generality and Originality in an econometric approach to examine whether the same pattern of results still remains.

4.4.2 Econometric evidence

In the previous section we found that a more 'basic' knowledge, as indicated by its degree of Generality and Originality, is more likely to have a lower Share of Internalized Spillovers, once conditioning on the number of citations it receives and makes. In this section we will extend the analysis and adopt an econometric approach of estimating the conditional correlation between the 'basicness' characteristics of patents and their Share of Internalized Spillovers.

Table 6 estimates a Tobit specification, where the dependent variable is the Share of Internalized Spillovers. We have chosen to use the Tobit specification due to the structure of the data, which include zeros for about 70 percent of the observations (as only 30 percent of the originating patents have at least one Internalized line of research)[5].

In column 1 we include only Generality, which has a positive and significant effect on the Share of Internalized Spillovers. This is consistent with the unconditional correlation we report in table 3. In column 2 we control for the number of citations the patent receives. In this case, the effect of Generality becomes negative and significant, consistent with the comparison of means reported in table 4 (where we condition on the number of citations the patent receives).

In column 3 we include only Originality, which has a positive and significant effect on the Share of Internalized Spillovers, consistent with the findings reported

[5] An alternative estimation is Probit, where the dependent variable is an indicator to whether the patent originates Internalized lines of research. The Probit specification does not exploit the variation in the continuous part of the Share of Internalized Spillovers (which includes the patents originating Internalized lines of research), thus, it is less preferable in this case. Moreover, the Tobit specification may be more applicable, as we may suspect that the zeros component in the Share of Internalized Spillovers corresponds to some noise in the data that allows observing positive Internalized Spillovers only when they are greater than a given threshold.

in table 3. However, once we condition on the number of citations the patent makes, as reported in column 4, the effect of Originality becomes negative and significant. This finding is consistent as well with the non-parametric analysis reported in table 5.

Finally, in column 5 we include Generality and Originality, together with the number of citations made and received by the originating patent. We find the same pattern of results, by which Generality and Originality have a negative and significant effect on the Share of Internalized Spillovers.

Thus, so far the econometric results support our previous findings that indicate that more 'basic' knowledge is likely to be associated with a lower Share of Internalized Spillovers.

Table 6

Regressions of Share of Internalized Spillovers on Generality and Originality - Tobit estimation

	(1)	(2)	(3)	(4)	(5)
Generality	0.044*	-0.032*			-0.026*
	(0.004)	(0.005)			(0.006)
Originality			0.191*	-0.019*	-0.022*
			(0.005)	(0.006)	(0.006)
Forward Citations		0.008*			0.007*
		(0.0001)			(0.0002)
Backward Citations				0.008*	0.005*
				(0.001)	(0.001)
Observations	97,921	97,921	48,366	48,366	48,366
R^2	0.06	0.081	0.014	0.021	0.078

Standard errors are in brackets.
All regressions include one-digit technology sector dummies and originating patent grant year dummies.
* denotes a significant level of 5 percent.

Based on the estimates reported in table 6, we quantify the negative effect of Generality and Originality on the Share of Internalized Spillovers (by computing the elasticity of the Share of Internalized Spillovers with respect to Generality and Originality). With respect to Generality, a one standard deviation increase lowers the Share of Internalized Spillovers by 0.7. Thus, evaluated at the mean, the Share of Internalized Spillovers falls from 0.046 (chapter 2, table 2) to 0.039 (alternatively, a 10 percent increase in Generality lowers the Share of Internalized Spillovers by about 2.5 percent).

With respect to Originality, a one standard deviation increase lowers the Share of Internalized Spillovers by 0.6. Thus, evaluated at the mean, the Share of Internalized Spillovers falls from 0.046 to 0.040 (alternatively, a 10 percent increase in Originality lowers the Share of Internalized Spillovers by about 1.6 percent).

Next we will turn to investigate the robustness of our findings to a linear specification with firm fixed-effects. We find it important to control for firm fixed-effects, since the variation we observe across originating patents can be attributed to the originating firms. For example, if larger firms perform more applied research and also have a higher Share of Internalized Spillovers, this will be wrongly interpreted as a negative effect of the 'basicness' of knowledge on the Share of Internalized Spillovers.

Robustness tests

Table 7 reports the estimation results of a linear specification, where the dependent variable is the Share of Internalized Spillovers, as before. In column 1 we include only Generality and Originality, which are both negative and significant, even when not conditioning on Forward Citations and Backward Citations (unlike in the Tobit specification). In Column 2 we add Forward Citations and Backward Citations, which yield a pattern of results similar to the equivalent Tobit specification (column 4 in table 6). The estimate of Generality rises substantially in absolute value from -0.015 to -0.025, once including Forward Citations.

In column 3 we add firm fixed-effects. Rather surprisingly we do not observe a change in the estimates of Generality and Originality. This may indicate that the variation we observe in the 'basicness' attributes of knowledge is independent from firm level attributes that may simultaneously affect 'basicness' and the pattern of diffusion.

In column 4 we include three-digit technology sector effects, instead of firm fixed-effects. This is due to our concern that the 'basicness' attributes of knowledge and its technology type co-vary with the Share of Internalized Spillovers. The pattern of results remains, where Generality and Originality are both negative and significant. The estimate of Generality falls from -0.025 to -0.019, which indicates that some of the effect Generality on the Share of Internalized Spillovers is attributed to technology sectors variation. In column 5 we include firm fixed-effects and three-digit technology sector effects. The same pattern of results remains and we do not observe an important change in the estimates, compared to column 4.

Table 7

Regressions of Share of Internalized Spillovers on Generality and Originality - linear fixed effects estimation

	(1)	(2)	(3)	(4)	(5)
Generality	-0.015*	-0.025*	-0.025*	-0.019*	-0.019*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Originality	-0.007*	-0.011*	-0.011*	-0.008*	-0.009*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Forward Citations		0.001*	0.001*	0.001*	0.001*
		(0.0001)	(0.0001)	(0.0001)	(0.0002)
Backward Citations		0.001*	0.001*	0.0002	0.0001
		(0.0003)	(0.0002)	(0.0002)	(0.0002)
Firm fixed-effects	No	No	Yes	No	Yes
Three digits technology sectors fixed-effects[a]	No	No	No	Yes	Yes
Observations	48,366	48,366	48,366	48,366	48,366
R^2	0.016	0.022	0.072	0.065	0.091

Standard errors are in brackets and are clustered by (480) firms.
* denotes a significance level of 5 percent.
All regressions include one-digit technology sector dummies and originating patent grant year dummies.
[a]Includes 391 technology sectors.

We add the other characteristics of the originating patent into the regressions reported in table 7: Forward Lag, Backward Lag, Forward Tech and Backward Tech. The estimation results are reported in table A1 in the appendix.

The same pattern of results, as reported in tables 6 and 7, holds, where Generality and Originality are negative and significant. Interestingly, we find Forward

Tech, which measures the average distance between the originating patent and its subsequent developments in the technology space, to have a significant and negative effect on the Share of Internalized Spillovers. Similarly, Backward Lag, which is the average lag in years between the originating patent and its immediate ancestors, has a negative and significant effect.

Both findings support our hypothesis that 'basic' knowledge is likely to have a lower Share of Internalized Spillovers, as we interpret Forward Tech as a complementary measure of Generality and Backward Lag as a complementary measure of Originality.

Our final robustness test is to directly correct for the bias in Generality and Originality, as suggested by Hall, Jaffe and Trajtenberg (2001). We recalculate the HHI as $\widehat{HHI} = \frac{N \cdot HHI - 1}{N-1}$ for Generality and Originality (see the discussion in section 3), where N is the number of citations the patent receives for Generality and the number of citations it makes for Originality.

The unconditional comparison of means yields the following results: the mean of Generality in the High Share of Internalized Spillovers set is 0.531 with a standard error of 0.002, whereas the mean in the Low Share of Internalized Spillovers set is 0.563 with a standard error of 0.001 (the difference in means is different from zero at the 5 percent significance level). Similarly, the mean of Originality in the High Share of Internalized Spillovers set is 0.509 with a standard error of 0.003, whereas the mean of Originality in the Low Share of Internalized Spillovers set is 0.524 with a standard error of 0.002 (the difference in means is different from zero at the 5 percent significance level). This indicates that patents that are more "original" are associated with a lower Share of Internalized Spillovers.

Thus, interestingly, we find that in the unconditional comparison of means, more 'basic' patents have a lower Share of Internalized Spillovers, as well. Previously, we have found this pattern of results only once conditioning on the number of citations the patent receives (for Generality) and makes (for Originality).

We repeat the robustness test reported in table 7 with the bias-corrected Generality and Originality. The estimation results are reported in table A2 in the appendix. We find a similar pattern of results to the one reported in table 7, where the only important difference we observe is that in the bias-corrected estimation, adding Forward Citations and Backward Citations has little effect on the estimates of Generality and Originality.

Overall, we find the same pattern of results with the bias-corrected measures and when using the uncorrected measures, but conditioning on the number of direct citations the patent receives and makes. This pattern of results strongly suggests that more 'basic' patents are associated with a lower Share of Internalized Spillovers.

4.5 Summary and conclusions

We have investigated the correlation between the diffusion pattern of knowledge and its 'basicness' attributes and tested whether inventors of 'basic' knowledge are likely to face lower private returns, as implied by the Share of Internalized Spillovers the diffusion of their knowledge yields.

We have found strong and robust evidence that patents that are more General and Original have a lower Share of Internalized Spillovers, once we condition on the number of citations patents receives and the number of citations they make. This implies that as knowledge is more 'basic', its inventor is less likely to benefit from the advancement other inventors build into the spilled knowledge by reabsorbing it in a future period.

We interpret this finding as an indication that inventors face a lower incentive to invest in 'basic' knowledge, as they are less likely to benefit from the fruits of their discoveries in the long run, once other inventors further advance them. This interpretation supports the well-debated concern of a trade-off between private and social incentives for inventing 'basic' knowledge. Society values the spread of knowledge, however, as we have shown in this chapter, this spread of knowledge may come at the expense of the incentive to create knowledge at the first place, as knowledge becomes more 'basic'.

In the next chapter, we will estimate the effect of the diffusion pattern of knowledge on its private returns. Thus, we will investigate whether the ability of an inventor to technologically exploit the spillovers of its inventions, intensifies private returns. Finding that private returns rise with Internalized patterns of diffusion and fall with Externalized patterns of diffusion, will validate the approach we have taken in this chapter and justify the link we have drawn between the Share of Internalized Spillovers and private returns to innovation.

4.6 References

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4.7 Appendix

Table A1

Regressions of Share of Internalized Spillovers on Generality and Originality - linear fixed effects estimation

	(1)	(2)	(3)	(4)
Generality	-0.017*	-0.013*	-0.012*	-0.010*
	(0.006)	(0.005)	(0.004)	(0.004)
Originality	-0.009*	-0.009*	-0.009*	-0.009*
	(0.003)	(0.003)	(0.003)	(0.003)
Forward Citations	0.001*	0.001*	0.001*	0.001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Backward Citations	0.001*	-0.001*	0.0002	0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Forward Tech	-0.014*	-0.016*	-0.008*	-0.011*
	(0.003)	(0.004)	(0.003)	(0.004)
Backward Tech	0.002	0.001	0.004	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Forward Lag	-0.001*	-0.002*	-0.002*	-0.002*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Backward Lag	-0.001*	-0.0003	-0.001*	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Firm fixed-effects	No	Yes	No	Yes
Three-digit technology sector effects[a]	No	No	Yes	Yes
Observations	48,366	48,366	48,366	48,366
R^2	0.016	0.075	0.067	0.110

Standard errors are in brackets and are clustered by (480) firms.

* denotes a significant level of 5 percent.

All regressions include one-digit technology sector dummies and originating patent grant year dummies.

[a]Includes 391 technology sectors.

Table A2

Regressions of Share of Internalized Spillovers on Generality and Originality: bias-corrected

	(1)	(2)	(3)	(4)
Generality	-0.028*	-0.028*	-0.026*	-0.022*
	(0.005)	(0.005)	(0.004)	(0.004)
Originality	-0.004*	-0.006*	-0.006*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Forward Citations		0.001*	0.001*	0.001*
		(0.0001)	(0.0001)	(0.0001)
Backward Citations		0.001	0.0002	-0.0001
		(0.0002)	(0.0002)	(0.0002)
Firm fixed-effects	No	No	Yes	Yes
Three-digit technology sector effects[a]	No	No	No	Yes
Observations	46,017	46,017	46,017	46,017
R^2	0.019	0.024	0.084	0.112

Generality and Originality are bias-corrected. See the text for more details.

Standard errors are in brackets and are clustered by (480) firms.

* denotes a significant level of 5 percent.

All regressions include two-digits technology sector dummies and originating patent grant year dummies.

[a]Includes 391 technology sectors.

Chapter 5

Technology Diffusion, Firm Performance and Incentives for R&D: Theory and Empirical Evidence

We broaden the concept of the private returns to innovation by studying the technological feedback firms receive from the diffusion of their inventions. The objective of this chapter is to exploit the firm-level variation in the ability to reabsorb spilled knowledge, through estimating the effect of Internalized Spillovers and Externalized Spillovers on private returns, as indicated by the market valuation of the R&D stock of the firm. We find that private returns rise with Internalized Spillovers and fall with Externalized Spillovers. Moreover, we find preliminary evidence suggesting that firms raise their R&D expenditures in response to a higher ability to reabsorb their spilled knowledge.

5.1 Introduction

In this chapter we aggregate Internalized Spillovers and Externalized Spillovers from the originating patent level to the originating firm level. We exploit the firm-level variation in the ability of the firm to reabsorb its spilled knowledge, through estimating the market valuation of its R&D activity.

We formalize the dynamic considerations introduced in this thesis, by showing that spillovers can raise private returns, through enhancing the technological opportunities along the lines of research the originating knowledge inspires. The extent to which spillovers raise private returns depends on whether the originating firm benefits from the enhanced technological opportunities. Thus, spillovers can increase private returns via their interaction with the ability of the originating firm to reabsorb its spilled knowledge. In this chapter, we will show, theoretically and empirically, that this ability has a positive effect on private returns in a dynamic framework of sequential innovation.

A famous example that illustrates the importance of the diffusion pattern of a discovery for its private returns is the CT (Computed Tomography) scanners invention. There is no doubt that this invention has great social value (both for consumers and innovators), mainly for health care, as discussed by Trajtenberg (1990). However, private returns to this discovery were low, as it had mostly experienced an Externalized pattern of diffusion[1]. This new technology was developed by EMI (a British electronic company) and was patented in 1973. The new market for CT scanners emerged following rapid innovation aiming at exploiting the new technological opportunities. From 1975 onwards, hundreds of offspring inventions had been created. In the early years, most of these inventions were developed by EMI itself, however, after less than a decade EMI failed to capture any significant portion of the market (which was mainly dominated by General Electric), while not succeeding to remain at the frontier of the technology it had originally introduced. Thus, this implies that the diffusion of knowledge outwards from EMI had a crucial impact on its ability to appropriate any substantial return on its remarkable invention.

In this chapter, we show that knowledge can leave the boundaries of the firm and still have a positive effect on private returns, if it is reabsorbed by the originating firm in a future period.

[1]We investigate the pattern of diffusion of this invention using the generation of citations approach we have developed in this thesis. Interestingly, the pattern of diffusion shows that the immediate subsequent developments were developed 'in-house', however, once knowledge had left the boundaries of EMI and was further developed by other firms, EMI was not able to reabsorb it. Thus, the lines of research the CT scanners invention had originated were mostly Externalized.

The empirical analysis of this chapter exploits the firm-level variation in the extent to which spillovers are Internalized versus Externalized. Thus, we find it important to motivate the existence of this variation by looking at the strategic behaviour of firms optimizing the diffusion of their knowledge. We argue that the variation we observe in the data in the ability of firms to reabsorb their spilled knowledge may represent a differential ability of firms to manage their knowledge flows. We refer to several case-studies to introduce this motivation. We focus on the strategic behaviour of IBM and Intel to demonstrate how firms can affect the diffusion pattern of their knowledge, prior to referring to the case of Xerox, which demonstrates how firms vary in their ability to benefit from the spread of their discoveries[2].

IBM and Intel share a common belief, according to which, knowledge cannot be kept secret and will eventually diffuse into the economy. With this notion in mind, both firms aim at optimizing not only their innovation, but also the diffusion of their knowledge, while choosing different approaches. The intellectual property (IP) strategy of IBM involves massive patenting. The patented inventions are then licensed and sold to external inventors. This method is a formal way of transferring knowledge. Also, in order to improve potential buyers' access to its inventions, IBM has recently invested $35 million in transferring its patents database into the most advanced patents search engine in the world[3].

In contrast, Intel adopts an IP strategy that involves an informal way of managing its knowledge flows. This strategy includes organizing conferences with external scientists, publishing the *Intel Technical Journal*, which is freely available on the web[4] and funding numerous external projects. In addition, patenting is not Intel's favourite way of protecting its inventions. Only the most valuable discoveries are patented. For these, a strict infringement policy is adopted. Other unpatented

[2]These examples are based on Chesbrough (2003).

[3]See IBM's web site: *http://www.ibm.com/ibm/licensing/*. In this site, IBM states its decision guidelines on whether to license its inventions. One of the conditions to license is: *"the relative importance of the technology to IBM's own present and future business"*. This can be an indication for strategic behaviour of firms in managing their knowledge flows. Also, IBM relates to the technological proximity between itself and the licensee: *"whether IBM wishes to have a continued presence in the particular technology field concerned"* and also to the product market proximity between itself and the licensee: *"any potential negative business impact resulting from the licensee's activities"*.

[4]http://developer.intel.com/technology/ITJ/.

knowledge, on the other hand, is published freely on the web.

We interpret our approach as empirically characterizing the 'managerial skill' of firms optimizing the diffusion of their knowledge, by identifying the extent to which they reabsorb their spilled knowledge. Hence, a firm enjoying higher Internalized Spillovers and lower Externalized Spillovers is argued to be better in managing the diffusion of its knowledge.

We estimate the effect of this ability on the market valuation of the R&D activity of the firm and define private returns as the change in market value that is associated with a change in the R&D expenditures of the firm. We find private returns to rise with Internalized Spillovers and fall with Externalized Spillovers. A one standard deviation increase in the firm level measure of Internalized Spillovers[5] raises the market valuation of an additional dollar spent on R&D by 30 percent.

In addition, we introduce a preliminary observation on whether firms internalize their ability to reabsorb their spilled knowledge once setting their R&D expenditures. We estimate a reduced-form R&D equation and estimate the extent to which the R&D decision is affected by the diffusion variables. We find that Internalized Spillovers positively affect the R&D expenditures of the firm, whereas Externalized Spillovers negatively affect R&D expenditures.

The main contribution of this chapter is showing that spillovers can have countervailing effects on private returns, depending on the feedback they give to the originating firm. This supports and validates the findings reported in previous chapters and the policy implications they raise. Most importantly, we demonstrate that spillovers can be both privately and socially desirable, which may imply that under certain circumstances (which are analysed in chapters 3 and 4), firms have sufficient incentive to innovate, even in the absence of public intervention (such as designing the complex patent institution or R&D subsidies).

Moreover, the extent to which the firm-level variation in the diffusion variables we have constructed is attributed to differential managerial skills of firms optimizing

[5]As Internalized Spillovers are a patent level measure, we aggregate them to the firm level by averaging Internalized Spillovers over all the originating patents of the firm. We do the same for Externalized Spillovers and Share of Internalized Spillovers.

the diffusion of their knowledge, has important consequences to the analysis of spillovers. In this case, knowledge flows can no longer be assumed exogenous, but the result of a strategic behaviour of firms.

The rest of the chapter is organized as following: section 2 explores prior studies in the field, section 3 presents the analytical framework, section 4 describes the empirical methodology, section 5 discusses the data, the findings are reported in section 6 and section 7 concludes.

5.2 Prior Studies

This work builds on prior empirical studies on the valuation of innovation activity. In this section, we explore the main empirical studies that are the most relevant to this research, focusing on the use of patents and patent citations in analysing the returns to innovation.

There are two different strands in the literature regarding the role of patent citations in the analysis of innovation: the first is the use of patents and citations in measuring the value of knowledge and the second is the use of citations as indicators of technological links between inventions (i.e., a patent citation is an empirical observation of a flow of knowledge from the citing patent to the cited patent). Since these two strands play a central role in this study, we briefly review their evolution over the past two decades.

5.2.1 Patents, citations and the quality of innovation

For almost three decades, economists have been studying the private value of innovation by investigating data on R&D, patents and patent citations[6]. The most common approach for measuring the value of patented knowledge is by looking at market value data as suggested by Griliches (1981) in his seminal work in the field. This approach is equivalent to the Hedonic prices analysis, in which the value of

[6] There is an extensive literature on estimating the social returns to knowledge, by measuring spillovers in various ways (see Griliches (1992) and Keller (2004) for surveys of the literature). Since the focus of this thesis is mainly on the private returns to innovation (as a function of the mechanism that generates the social returns to innovation) we do not focus on this literature here.

the firm depends on the value of its characteristics, which are assumed to be its tangible (physical) and intangibles (knowledge) assets. The market value approach has been extensively used thereafter, to find that the market places a high valuation on the R&D stock of the firm[7]. For example, Jaffe (1986) finds that the market prices the R&D stock of the firm three times more than its physical stock.

Moreover, In order to investigate whether the value of R&D varies with the ability of the firm to appropriate rents on its discoveries, Griliches and Cockburn (1987) conducted an important study which looks into survey data on industry specific appropriability indices. Although they find low cross-industry variation in their appropriability indices[8], they find some evidence that the appropriability conditions the firm faces have an effect on the value of its innovation activity.

The market value approach has become highly accepted in the field and researchers have adopted it to include measures of the innovation output, as well (in addition to the R&D input measure).

The first indicator to be examined was patents, hoping that it would provide additional information regarding the output of the research efforts of the firm. Griliches, Hall and Pakes (1988) were amongst the first to look into patents in the market value framework. Disappointingly, they find that patents are weakly correlated with the value of the firm, especially, when conditioning on R&D expenditures. They interpret their results by arguing that patents are a highly skewed measure, so that without additional information on the distribution of the quality of patents, they do not provide information regarding the output of the research activity.

However, the disappointment from patents data did not last long. Trajtenberg (1990), in a landmark work, links the social value of a specific invention to the product market, by estimating the increase in consumers surplus as a response to the CT scanners invention. He shows that patents are correlated with consumers surplus only when controlling for their quality, using data on patent citations, under the assumption that more citations represent a higher quality patent.

[7]See Hall, Czarnitzki and Oriani (2005) for a review of the main empirical findings in the market value framework.

[8]Although we use a different approach, the fact that the survey data variation is mainly within industries is encouraging for our research agenda, as it focuses on firm level appropriability indices.

From then onwards, patent citations came into fashion as indicators for the quality distribution of patented inventions. The most recent study that incorporates citations data in the market value framework was conducted by Hall, Jaffe and Trajtenberg (2005), who study the market value of knowledge by using data on patent citations. They construct the knowledge stock of the firm by building a 'stock' of the citations it receives. They find the citations stock to be highly important for the valuation of the firm[9].

In a completely different line of research, a very interesting literature has evolved through the analysis of data on patent renewal fees, aiming to estimate the private value of patented inventions, by examining at the decisions of inventors on whether to renew their patents at various points in their life span. Schankerman and Pakes (1986) and Pakes (1986) were the first to develop this framework, which has been found to be highly informative, mainly with respect to the evaluation of the value of patents over their life cycle and across (European) countries.

5.2.2 Patent citations and knowledge flows

As described above, patent citations are highly useful for recovering the quality distribution of patents. Nonetheless, this is not the only contribution of patent citations. A patent citation is also an empirical observation for a technological link between two patented inventions. This technological link corresponds to some sort of knowledge flow from the cited patent to the citing patent. We believe that the main contribution of patent citations to research in the field nowadays is their ability to shed light on the way knowledge moves in the economy, which has been a 'black box' in past decades.

This thesis adopts the notion that citations represent knowledge flows and sequential developments. Thus, we find it important to briefly review the previous literature we build on in this strand of research, which has been rapidly evolving in the past decade.

The first study that looks at citations as indicators of knowledge flows is Jaffe, Henderson and Trajtenberg (1993). They find that patent citations appear to be

[9]See also Lanjouw and Schankerman (2004).

localized geographically; implying knowledge diffuses quicker within geographical regions.

Their findings have important implications, mainly for the economics of geography, in the sense that physical distance does matter for technological progress. Their finding of a geographic localization was supported by a later study by Jaffe and Trajtenberg (1999), who examined patterns of patent citations among the United States, United Kingdom, France, Germany and Japan. They also find significant evidence for geographical localization of spillovers that fade slowly over time (they estimate the propensity of citations between and within countries and find a 'home-bias' effect in patent citations, which is a higher tendency of an inventor to cite a different inventor from the same country).

Along the 'macro' framework of patent citations, Hu and Jaffe (2001) use patent citations to trace knowledge flows between the United States and Japan to Korea and Taiwan. They find that knowledge flows from the developed countries to Korea and Taiwan boosted their growth rates.

Patent citations were also integrated into a general equilibrium model by Caballero and Jaffe (1993). In our view, the main contribution of their study is the understanding that the rate by which knowledge becomes obsolete is endogenous and determined by the rate of technological developments, which bound the private rent on a technological discovery. In this thesis, we develop this idea by showing that there are two different patterns by which the knowledge of the firm can be sequentially developed by other firms, which have countervailing effects on the private obsolescence of knowledge.

Finally, Jaffe, Trajtenberg and Fogarty (2000) conduct the most important study on the validity of patent citations as indicators of knowledge flows, by surveying 160 patentees who answered questions about their inventions, the relationship of their inventions to patents that were cited by their patents and the relationship to "dummy" patents that were technologically similar to the cited patents but not cited by the patentees. Their findings confirm that citations are a noisy measure, however, they do add substantial information regarding knowledge flows across patented inventions.

5.3 Analytical framework

In this section, we formalize the ideas developed in this thesis in a simple model of sequential innovation. In this model, spillovers enhance the technological opportunities created by the originating knowledge, through reducing the probability that subsequent inventions will not occur (hence, the line of research the originating knowledge inspires will be terminated). The extent to which spillovers raise private returns depends on whether the originating firm benefits from these enhanced technological opportunities.

Thus, spillovers can increase private returns to knowledge, through their interaction with the ability of the originating firm to reabsorb its spilled knowledge. In this section, we represent this ability by a single parameter, θ. We show that there is a direct link between θ and the private returns to the originating knowledge.

Our model assumes that firms do not behave in any strategic manner to affect θ or the flow of their knowledge to other firms (although these might be interesting extensions. In the appendix we present a different model, in which a firm strategically affect the spillovers of its knowledge that yields similar implications).

We model a dynamic innovation process and distinguish between *static* returns and *dynamic* returns to innovation. We define *static* returns to innovation as the one period stream of profits attributed to a single invention. Dynamic returns, however, also consider the stream of profits the originating firm may capture by inventing subsequent developments along the line of research it originates. Its ability to do so will depend on the extent to which it can exploit the technological opportunities that other firms introduce along this line of research.

Assume firm i (the originating firm) holds a piece of knowledge k. The static returns to this knowledge include the stream of profits firm i receives from this invention, until it becomes obsolete, which we assume to occur with the development of the next generation of the knowledge k, i.e., with the introduction of a subsequent stage of development.

Nevertheless, dynamic returns to the knowledge k take into account the expected stream of profits firm i will receive from its subsequent follow-up developments of the knowledge k. Thus, dynamic returns to the knowledge k do not become obsolete once a subsequent development takes place, should the originating firm be able to invent in the future along the line of research knowledge k has originated.

We would like to investigate the value of this invention to firm i, under the assumption that the knowledge k has the potential of being developed an infinite number of times. Denote by v the one-shot pay-off associated with winning a development stage of the knowledge k. In every development stage there are n firms competing in a patent race (while the patent in every development stage provides a stream of profits only until the next generation of knowledge arrives). Denote by S_{-i} the set of $n-1$ firms that participate in the line of research originated by knowledge k excluding firm i, where a line of research is defined as a specific research agenda along which knowledge k is being developed (as defined in chapter 2).

In order to invent an offspring invention, which we define as a *generation of development*, the immediate ancestor of this invention ought to have already been invented. Hence, the dynamic innovation process is sequential, in the sense that one generation of development is the technological grounds for the follow-up generation.

The winner in every development stage is awarded with the prize v, which for simplicity we assume to be constant over time and across generations. I.e., the prize v does not depend on the discovery time of the follow-up generation. This assumption can be justified by assuming symmetry in the time elapsed between two proceeding generations and treating v as the value the patent holder receives in this in-between period.

Further, only one firm is allowed to win a development stage and receive the prize v. If more than one firm makes a discovery, a patent cannot be granted, and both firms engage in Bertrand competition that drives profits to zero. This simplifying assumption implies that a firm is rewarded for the success of its innovation, only if it is the only successful inventor.

Every generation of development requires a constant R&D investment of x, which yields a probability p of making a discovery by firm i (i.e., with probability p firm i discovers a piece of knowledge that awards the static payoff v, if no other firm invents the specific generation). Define q as the probability that at least one of firm i's competitors along the line of research makes a discovery.

Given this set-up, the expected static rent firm i captures from participating in a development stage (which is constant across all stages, as indicated by the above assumptions) is:

$$Z = p(1-q)v - x \tag{5.1}$$

Finally, we assume that the number of firms n is constant across all development stages and that Z is strictly positive.

5.3.1 The Dynamic game and the ability to reabsorb spilled knowledge

Our main interest in this chapter is to link the ability of the firm to benefit from the research of others, which builds on its prior research, to the rent it captures on its discovery. How should we define the rent an inventor captures on its technological discovery? In a static framework, a technological discovery does not inspire follow-up research and, therefore, private returns coincide with the one-shot value of the discovery. Nonetheless, under sequential innovation, a technological discovery inspires follow-up research. Therefore, dynamic returns associated with a sequential innovation should consider the expected valuation of continuing to improve the new technology along the line of research it originates.

We proceed to studying the dynamic returns firm i captures on its knowledge k as a function of its ability to reabsorb the knowledge k into its future research, after it has been further developed by other firms.

We assume the knowledge k has the potential to be sequentially developed an infinite number of times. In computing the dynamic returns firm i captures on its knowledge k, we ought to compute the expected value of the infinite stream of follow-up discoveries it will introduce along the line of research.

As a departure point, assume that once firm i fails to win in a given generation, it cannot continue developing the next generation, even if some other firm has been successful in inventing this generation (thus, the knowledge that is required for the production of the follow-up generation exists in the economy). In this case, we say that firm i has no ability to build on its own spillovers (alternatively, firm i cannot reabsorb its spilled knowledge). Firm i's dynamic returns to the knowledge k are given as:

$$W_i = (p(1-q)v - x) + p(1-q)\left(p(1-q)v - x\right) + p^2(1-q)^2\left(p(1-q)v - x\right) + ... \tag{5.2}$$

The first term on the right hand side of equation (5.2) is the expected static pay-off of winning the first generation of development, the second term is the expected static pay-off of winning the second generation of development, which occurs with probability $p(1-q)$ (the probability of winning the first generation), the third term is the expected static rent of winning the third generation (which is possible if firm i had won the first and second generations of developments that occur with probability $p^2(1-q)^2$) and so forth.

It is straightforward to show that since we assume an infinite number of potential developments, W_i becomes

$$W_i = \frac{vp(1-q) - x}{1 - p(1-q)} \tag{5.3}$$

Next, assume that if firm i does not invent in a given generation, whereas one of its competitors does invent, firm i can still proceed to invent the follow-up generation, while building on the knowledge of its rival. We model the ability as the number of times the firm is allowed not to make a discovery in a development stage, and still remain in the dynamic game, by building on the knowledge that was invented by another firm. Thus, we model the ability of the firm to reabsorb its spilled knowledge along the line of research it originates, as the number of 'second chances' it gets, if it fails to invent in a development stage, but some other firm succeeds. We denote this ability by θ (thus, in equation (5.2), $\theta = 0$, since the firm is not allowed to have any 'second chances', so that once it fails to invent, it is out of the sequential development).

Now consider the case where $\theta = 1$, i.e., if firm i fails to invent more than once, it is forced out from the dynamic race (firm i receives one 'second chance'). In this scenario, the dynamic rent firm i captures on its knowledge k can be written as:

$$\begin{aligned} W_i(\theta &= 1) = p(1-q)v - x + p(1-q)\left(p(1-q)v - x\right) + p^2(1-q)^2\left(p(1-q)v - x\right) + ... \\ &+p(1-q)q(p(1-q)v - x) + 2p(1-q)(1-p)q\left(p(1-q)v - x\right) + ... \qquad (5.4) \end{aligned}$$

Where the second row on the right hand side of equation (5.4) represents the 'second chance' firm i gets (for example, the first term in the second row is the additional expected rent the firm captures due to the fact it is allowed to fail in developing the first generation and still participate in the development race of the second generation). It is easy to show that equation (5.4) can be written as:

$$W_i(\theta = 1) = \frac{(1-q)\,pv - x}{(1-p)\,(1-q)}\left(1 - \left(\frac{q}{1-(1-q)\,p}\right)^2\right) \qquad (5.5)$$

We can generalize this model to any θ, and in the appendix we show that the dynamic rent can be written as a function of θ in the following way:

$$W_i(\theta) = \frac{(1-q)\,pv - x}{(1-p)\,(1-q)}\left(1 - \left(\frac{q}{1-(1-q)\,p}\right)^{\theta+1}\right) \qquad (5.6)$$

This implies that the expected rent firm i faces increases in θ, since $\frac{q}{1-(1-q)p} < 1$[10].

This summarizes our empirical prediction, by which the ability of the firm to build on the research of its rivals along the line of research it originates has a positive effect on its private rent. We have developed a methodology, based on data on patents and citations, aiming to measure θ for firms in our sample (as presented in chapter 2).

Finally, note that by substituting $\theta = 0$ into equation (5.6) we get equation (5.2), which is the dynamic returns firm i captures on its discovery, if it has no

[10] As mentioned in the appendix, q is also the probability an invention occurs, however, firm i is not the 'winner'. Thus, $q = q(1-p) + pq$, which is smaller than $1 - p + pq$, as $q < 1$.

ability to build on the discoveries of other firms along the line of research it originates. Moreover, when the firm has a complete ability to build on the research of its rivals ($\theta = \infty$), the dynamic returns become:

$$W_i(\theta = \infty) = \frac{v\,(1-q)\,p - x}{(1-p)\,(1-q)} \tag{5.7}$$

Hence, the dynamic returns to innovation are the static returns per subsequent invention (Z in equation (5.1)), discounted by the probability that the line of research will be terminated[11] (which occurs with the probability $(1-p)\,(1-q)$, where no firm invents). As the probability that the line of research will be terminated falls, dynamic returns rise.

So far, we have established that when we consider the private value of an invention in a dynamic perspective, this private value rises with the ability of the firm to build on external follow-up developments of its prior knowledge.

In the appendix, we present an alternative model that allows the firm to strategically affect the diffusion pattern of its knowledge. We show that the above theoretical predication holds in that strategic framework as well.

5.3.2 The incentive for innovating along the line of research and θ

Next, we will turn to investigate the relationship between θ and the incentive of firm i to innovate along the line of research it originates (for presentation convenience, the subscript i has been omitted in this section).

Assume the knowledge k can originate two different lines of research. In the first line of research $\theta = 0$, i.e., firm i gets no 'second chances' to remain in the development race, if it fails to invent in previous stages (conditional on others inventing). However, in the second line of research, the firm has a complete ability

[11] Compared to equation (5.3), where Z is divided by the term $1 - p(1-q)$. This term is the probability that the line of research will be terminated *in firm i's perspective*, which occurs when firm i fails to win in a development stage.

to build on the research of others along the line of research it originates (i.e., $\theta = \infty$).

Empirically, the case where $\theta = 0$ can be associated with an Externalized line of research, as the originating firm does not reabsorb its spilled knowledge (i.e., once other firms invent a development stage along the line of research invention k originates, firm i cannot invent a follow-up invention). Similarly, the case where $\theta = \infty$ can be associated with an Internalized line of research, where the originating firm is able to reabsorb its spilled knowledge.

In this section, we investigate the optimal innovation efforts of the firm under each pattern of diffusion (lines of research). We modify the model we present above by letting firms choose the level of their R&D expenditures, x, which affects the probability they will invent, $p(x)$, with $p'(x) > 0$, $p''(x) < 0$, $p(0) = 0$ and $p(\infty) = 1$. The most important assumption we make in this section is of a decreasing return to scales in the production of knowledge (which is necessary to ensure an interior solution for x[12]).

We start by assuming that the firm has no ability to build on the research of others, i.e., $\theta = 0$. For simplicity, we assume that the firm is small in the sense there is no strategic interaction in R&D. In this case, the dynamic returns to the knowledge k are:

$$W(\theta = 0) = \frac{vp(x)(1-q) - x}{1 - p(x)(1-q)} \tag{5.8}$$

The firm maximizes equation (5.8) with respect to its R&D expenditures, x, which yields the following first order condition:

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[12]The second order condition is:

$$\frac{\partial W^2(\cdot)}{\partial^2 x} = p''(x) - \frac{1}{(1-q)}\left[-\frac{\frac{\partial W(\cdot)}{\partial x}}{(W(\cdot)+v)^2}\right] \leq 0$$

Define x^* as the optimal R&D decision, thus:

$$\frac{\partial W^2(\cdot)}{\partial^2 x}|_{x=x^*} = p''(x)$$

For x^* to be a maximum we require $p''(x) < 0$.

$$p'(x|\theta = 0) = \frac{1}{(1-q)(W(\theta = 0) + v)} \tag{5.9}$$

Let $x^*(\theta = 0)$ solve equation (5.9). Thus, the optimality condition equates the marginal benefit from R&D (the increase in the probability of a discovery that is achieved by a marginal increase in the R&D spending, $p'(x)$), adjusted by the probability that the firm will be the sole winner in the research race (while taking into account the one shot pay-off, v, and the total pay-off of winning the race, $W(\theta = 0)$), to the marginal cost of R&D, which is assumed to be 1.

An increase in q reduces the probability of winning the development stage and, consequently, reduces the R&D expenditures of the firm (note that $W(\theta = 0)$ is a decreasing function of q). On the other hand, an increase in the one shot payoff, v, encourages the firm to innovate more (note that $W(\theta = 0)$ is an increasing function of v). More importantly, a rise in the dynamic rent, given by $W(\theta = 0)$, increases the innovation efforts of the firm.

Intuitively, since we have shown above that dynamic returns rise with θ, a higher θ also implies a higher innovation effort of the firm, should we allow firms to optimize their R&D expenditures while internalizing the effect of θ on the private returns they face.

Now consider the case where the knowledge k originates a line of research in which the firm has an infinite number of 'second chances', i.e., its ability to build on the research of others is complete ($\theta = \infty$). Dynamic returns to knowledge k are expressed as:

$$W(\theta = \infty) = \frac{vp(x)(1-q) - x}{(1-p(x))(1-q)} \tag{5.10}$$

The optimality condition for x is given as:

$$p'(x|\theta = \infty) = \frac{1}{(1-q)(W(\theta = \infty) + v)} \tag{5.11}$$

Let $x^*(\theta = \infty)$ solve equation (5.11).

Proposition 5.1 *The firm innovates more when it is able to build on the discover-*

ies of others (i.e., firm i innovates more when it has an infinite number of 'second chances', compared to the case that it has none).

Proposition 5.1 suggests that the innovation efforts of the firm increase with its ability to build on the inventions of others along the line of research it originates. The simple intuition behind this proposition is that the firm is willing to invest more in R&D, when private returns are higher.

Proving proposition 5.1 is straightforward.

It is enough to show that $W(\theta = \infty, x^*(\theta = \infty)) > W(\theta = 0, x^*(\theta = 0))$, since we assume decreasing returns to scale in the production of knowledge ($p''(x) < 0$). Suppose that $W(\theta = 0, x^*(\theta = 0)) > W(\theta = \infty, x^*(\theta = \infty))$. This inequality cannot hold, since we have shown above that $W(\theta = \infty, x) > W(\theta = 0, x)$. Thus, $W(\theta = \infty, x^*(\theta = 0)) > W(\theta = \infty, x^*(\theta = \infty))$, which is a contradiction of $x^*(\theta = \infty)$ being the optimal R&D investment when $\theta = \infty$. Hence, it must be that $W(\theta = \infty, x^*(\theta = \infty)) > W(\theta = 0, x^*(\theta = 0))$[13], which implies that $p'(x|\theta = \infty) < p'(x|\theta = 0)$ and $x^*(\theta = \infty) > x^*(\theta = 0)$.

In conclusion, we have shown that not only the ability of the firm to exploit the research activity of other firms along the line of research it originates has a positive effect on private returns, but also that this ability has a positive effect on its R&D expenditures.

In the rest of the chapter, we turn to empirically estimate the effect of θ on private returns and R&D investment. In the econometric section, we specify private returns as $\frac{\partial V_i}{\partial K_i}$, where V_i is the market value of the originating firm and K_i is its knowledge capital (which is approximated by its current and past stream of R&D expenditures). The theoretical predication outlined in this section is that private returns depend on θ, thus, we specify private returns as $\frac{\partial V_i}{\partial K_i} = \Theta(\theta)$. We empirically identify θ by the measures of Internalized Spillovers and Externalized Spillovers, where θ is assumed to be higher when the firm experiences more Internalized Spillovers and less Externalized Spillovers.

[13] The case where $V(\theta = \infty, x^*(\theta = \infty)) = V(\theta = 0, x^*(\theta = 0))$ cannot hold from exactly the same argument.

Also, we empirically test prediction 5.1, by which the R&D expenditures of the firm rise with θ. In this econometric specification, we estimate the effect of Internalized Spillovers and Externalized Spillovers (which measure θ) on the R&D expenditures of the firm.

5.4 Methodology

The empirical methodology and conceptual framework are identical to the one described in chapter 2. For the sake of brevity, we do not describe them again in this chapter. We aggregate the diffusion variables from the originating patent level to the originating firm level. Thus, every firm in our sample will have three variables that will characterize the pattern of diffusion of its inventions, based on Internalized Spillovers, Externalized Spillovers and Share of Internalized Spillovers.

5.4.1 Firm level diffusion variables

We construct the firm-level diffusion variables in the simplest way possible[14]. The first variable measures the amount of spillovers the firm creates that feed back into its dynamic research. We label this variable as *Internalized Flows* and compute it as the mean of Internalized Spillovers, taken over all the originating inventions of the firm, as following[15]:

$$Internalized\ Flows_i = \frac{1}{J_i} \sum_{j \in P_i} Internalized\ Spillovers_j \qquad (5.12)$$

Where i denotes an originating firm, J_i is the number of originating inventions held by firm i, P_i is the set of originating inventions held by firm i and j is an originating invention in this set.

[14] We have also experimented with more complicated variables that directly control for the number of citations the firm receives and the total number of patents it holds. We have found the same pattern of results when using the complicated and simple indices. Since it is much easier (and intuitive) to interpret the simple indices, we adopt them in the estimation section. Below we explain how we plan to deal with the various potential biases they may be associated with.

[15] In measuring the spillovers created by an invention, we discount each generation of citation by 15 percent, under the notion that a higher generation of citation is associated with less spillovers from the originating invention. Our results are robust for different discount factor values (including not discounting at all).

The second variable measures the amount of spillovers created by the firm that do not feed back into its dynamic research. We label this variable as *Externalized Flows* and compute it as the mean of Externalized Spillovers, taken over all the originating inventions of the firm, as following:

$$Externalized\ Flows_i = \frac{1}{J_i}\sum_{j\in P_i} Externalized\ Spillovers_j \tag{5.13}$$

We also aggregate to the firm level the Share of Internalized Spillovers, which measures the share of spillovers that feed back into the dynamic research of the firm. We label this variable as Internalized Share and compute it as:

$$Internalized\ Share_i = \frac{1}{J_i}\sum_{j\in P_i} Share\ of\ Internalized\ Spillovers_j \tag{5.14}$$

Thus, using the above definitions, the firm level equivalent of Internalized Spillovers is *Internalized Flows*, the firm level equivalent of Externalized Spillovers is *Externalized Flows* and the firm level equivalent of the Share of Internalized Spillovers is *Internalized Share*.

5.5 Data

We have collected accounting data on 800 *US Compustat* firms from 1980 to 2001[16]. We 'cleaned' the data to remove major mergers and acquisitions, accounting periods below ten months and above fourteen months and firms with less than four years of consecutive data, which leaves us with 712 firms.

We match the 800 *Compustat* firms to the *USPTO NBER* patents and citations data-set, described and studies in Hall, Jaffe and Trajtenberg (2001) and Jaffe and Trajtenberg (2002). We drop firms that did not have any cited patents in the period 1969-1980 (where we require a firm to be cited at least once between 1975-1990, by one of the 2466 US firms that are included in our sample of citing firms). We drop

[16]The 800 firms in our original sample perform about 72 percent of the R&D performed by the 2859 firms that had been matched to the US Patent Office by Hall, Jaffe and Trajtenberg (2001), over the period 1980-2001.

firms that were not cited in the period 1969-1980, since we design our sample of originating patents, to include all the cited patents in this time period (see chapter 2 for further details on the design of the originating patents set). This leaves us with 610 firms, whose diffusion pattern we analyse. Finally, after running the algorithm on this set of firms, we find that 502 firms have created spillovers, where the remaining firms have experienced only self-citations (all of their subsequent developments were owned by the originating inventor)[17].

We match these 502 firms to the 'cleaned' accounting data, which leaves us with 476 firms, for which we have information on the diffusion pattern of their inventions and complete accounting data. Thus, our estimation sample includes an unbalanced panel of 476 firms[18] in the period 1980-2001, as we keep exiters in the sample, and a total of 9,454 observations.

The un-weighted patents stock (simple patent count) and R&D stock were calculated using a perpetual inventory method with a 15% depreciation rate, while Tobin's Q was calculated as the total firm value divided by the full book value of assets, following Hall, Jaffe and Trajtenberg (2000)[19]. The citations-weighted patent stock was constructed by normalizing the number of patents the firm owns according to the number of citations it receives and the average number of citations to all patents in the same year. Given this normalized patents count the stock is constructed using the perpetual inventory method. Finally, the citations stock was constructed in an analogous way to the patent and R&D stock.

An important issue in this chapter is how to treat firms that exit the sample. Since the diffusion variables are based on a pre-estimation period (the originating patents are granted in the period 1969-1980 and the estimation period is 1980-2001), a concern rises that once a firm exists, it will not perform R&D, which will

[17]The initial set of 610 cited firms included also firms that had received only self-citations. We did not drop these firms from the sample of originating firms at this stage, since it was possible for their knowledge to leave their boundaries via a subsequent invention.

[18]The 476 firms in our final sample perform about 85 percent of the R&D that is performed by the original sample of 800 firms in the period 1980-2001.

[19]For Tobin's Q firm value is the sum of the values of common stock, preferred stock, long-term debt and short-term debt net of assets. Book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles (other than R&D).

be captured by the diffusion variables (after a firm has exited the sample, it can experience only Externalized patterns of diffusion).

Due to the above, we find it important to focus on firms that are active for a substantial period of time after having invented their originating inventions (nonetheless, our sample is unbalanced, as we allow firms to exit)[20].

The average number of years firms are active in the estimation sample is 18.5. The median number of years firms are active in the estimation sample is 21 (thus, during the entire estimation sample, 1980-2001), the 25th percentile is 18 and the 10th percentile is 12. In order to test the robustness of our empirical findings, we condition our estimations on the firm being active for at least 10 years. Our findings are robust to this condition, but, conditioning on survival may change the interpretation of our results.

Table 1

Descriptive statistics: diffusion Variables: 476 firms

Variable	Mean	Median	Min	Max	Std.
Internalized Flows	5.90	0.14	0	891	45
Externalized Flows*	0.43	0.04	0.001	39	2.5
Internalized Share	0.02	0.004	0	0.246	0.04

Externalized Flows is divided by 1000.

Table 1 summarizes the main statistics of the diffusion variables for the 476 firms in our sample. We find that the mean of Internalized Share is about two percent (compared to about 5 percent at the invention level, as discussed in chapter 2), which implies that only two percent of spillovers technologically contribute to the firms that originated them. However, we find this mean to vary across firms, reaching a maximum of about 25 percent.

[20]However, one should distinguish between two scenarios: first, a firm exists as a result of its not being able to exploit its own inventions and second, a firm exits due to a different reason, unrelated to the diffusion variables. In the first case, it is interesting to attribute the death of the firm to the pattern of diffusion of its knowledge. In the second case, the diffusion variables will capture the fact that the firm is dead, as it will be able to have only Externalized pattern of diffusion.

Finally, table 2 summarizes the main sample statistics of the accounting and patenting variables.

Table 2

Descriptive statistics: accounting and patents variables

9,454 observations and 476 firms

Variable	Mean	Median	Min	Max	Std.
Tobin's Q	2.02	1.32	0.1	20	2.34
Market value	4,689	592	0	485,566	16,782
R&D stock	806	49	0	47343	3195
R&D stock / Assets	0.39	0.20	0	10	1
Capital stock	3,090	392	2.13	199,303	9,736
Patents stock	155	18	0.42	9,848	489
Patents stock weighted by citations	158	16	0.28	12,643	585

The statistics are computed over all the observations that were included in the estimation (1980-2001) and are given in thousands of 1996 USD.

5.6 Estimation

In this section, we present the estimation results of the effect of the diffusion pattern of knowledge on private returns to innovation and the R&D decision of the firm. Our main econometric analysis focuses on the market value framework, where we examine whether the market valuation of the R&D stock rises with the ability of the firm to reabsorb its spilled knowledge.

Further, we present a reduced form estimation of a R&D equation to provide a preliminary test to whether firms internalize their ability to reabsorb their spilled knowledge when making their R&D decisions.

5.6.1 Market value specification

In order to estimate the effect of the diffusion pattern of knowledge on private returns to R&D, we adopt a simple version of the value function approach proposed by Griliches (1981)[21]. The market value of firm i at period t, V_{it}, takes the following form:

$$V_{it} = \kappa_{it}\left(A_{it} + \gamma K_{it}\right) \tag{5.15}$$

Where, A_{it} denotes physical assets, K_{it} is the R&D stock (representing the intangible knowledge assets of the firm), γ is the shadow price of the R&D stock (higher values of γ indicate that the market valuation of the knowledge capital relative to physical capital rises)[22].

The parameter γ will capture the private returns to innovation, which we define as the change in the market value as a response to a change in the R&D stock of the firm.

Since we aim at investigating the effect of the pattern of diffusion on private returns, we model γ as a linear function of Internalized Flows and Externalized Flows[23], as:

$$\gamma = \gamma_0 + \gamma_1\left(Internalized\ Flows_i\right) + \gamma_2\left(Externalized\ Flows_i\right) \tag{5.16}$$

We expect γ_1 to be positive and γ_2 to be negative (the theoretical predication is that private returns rise with θ, which is the ability of the firm to reabsorb its spilled knowledge, as empirically identified by the diffusion variables).

Taking logarithms and dividing by A_{it} gives the traditional average Tobin's Q, where its deviation from unity depends on the ratio between the R&D stock to the tangible stock $\left(\frac{K}{A}\right)$, Internalized Flows and Externalized Flows and κ_{it},

[21] See also Jaffe (1986), Hall et al (2005) or Lanjouw and Schankerman (2004).

[22] Note that we have assumed constant returns in the market value function, consistently with previous studies.

[23] We also report specifications where we include Internalized Share instead of Internalized Flows and Externalized Flows.

$$\log\left(\frac{V_{it}}{A_{it}}\right) = \log\kappa_{it} + \log\left(1+\gamma\frac{K_{it}}{A_{it}}\right) \tag{5.17}$$

When presenting the findings, we refer to γ_0 as the linear term of R&D over assets, γ_1 as the interaction term of R&D over assets with Internalized Flows and γ_2 as the interaction term of R&D over assets with Externalized Flows.

Finally, κ_{it} is specified as:

$$\log\kappa_{it} = Z'_{it}\beta_0+\beta_1\log\left(Internalized\ Flows_i\right)+\beta_2\log\left(Externalized\ Flows_i\right)+\tau_t+\eta_i+\epsilon_{it} \tag{5.18}$$

Where Z_{it} is a vector of controls (such as industry effects, sales, patents stock etc.), τ_t denotes a complete set of time dummies, η_i denotes the firm fixed-effect, which we discuss in detail later in the chapter, and ϵ_{it} is an idiosyncratic error term.

The linear terms of Internalized Flows and Externalized flows are included in the specification, mainly as controls for the interaction terms, as specified in equation (5.16). Our preferred specification is to include only the interaction terms of Internalized Flows and Externalized Flows, as we predict these diffusion variables affect the value of the firm only through their interaction with the R&D stock. Nonetheless, the linear diffusion terms can be regarded as an approximation of the interaction effects and, therefore, we expect β_1 to be positive and β_2 to be negative. In specifications where it would be difficult to identify both the linear and interacted effects of the diffusion variables, we will include only the interaction terms.

Equation (5.17) is estimated by non-linear least squares, where standard errors are clustered by firms (robust to heteroscedacity and serial correlation), which is important due to our long panel (about 19 years per firm).

5.6.2 Identification issues

We interpret Internalized Flows and Externalized flows as measures of the ability of the firm to reabsorb its spilled knowledge. Nonetheless, we face two main concerns regarding this interpretation. The first relates to the correlation between the diffusion variables and other characteristics of the firm (such as patenting volume and product market size). The second relates to our estimation framework, which pools firms across different industries.

Identifying the ability to reabsorb spilled knowledge from patenting volume and product market size

A firm that has a larger patents stock is more likely to have higher Internalized Flows and lower Externalized Flows, as it is more likely to randomly indirectly build on its prior knowledge. In case patents stock has a positive effect on private returns[24], we will find a pattern of results by which Internalized Flows positively affect private returns and Externalized Flows negatively affect private returns.

In order to cope with this identification issue, we make the following argument: if, indeed, the diffusion variables capture the effect of patents stock, it should not have a significant effect on private returns, should we condition on the patents stock of the firm. Thus, we include the patents stock of the firm (adjusted for quality, as indicated by the number of citations received) linearly and interacted with the R&D stock over assets. In case the effects of Internalized Spillovers and Externalized Spillovers will not disappear, the above identification concern will be mitigated[25].

In order to examine the correlation between the diffusion variables and patents stock, figure 4 plots Internalized Share for the top 200 patenting firms (as indicated by their mean of the citations-weighted patents stock over the estimation period), in an ascending order (where firms with higher stock of patents appear to the left of the horizontal scale). We observe a high variation in Internalized Share, which is independent from patenting volume. This further mitigates the concern that all the variation we have observed in the data regarding the diffusion variables is driven by patenting volume.

[24]For example, patents stock can represent the intellectual property protection the firm faces, so that a larger stock of patents indicates stronger appropriability and higher private returns.

[25]We also include the mean of the patents stock of the firm, R&D stock and citations stock, computed over a pre-estimation period, to capture any non-parametric shift in patenting performance between the period that is used to construct the diffusion variables (1969-1980) and the actual estimation period (1980-2001).

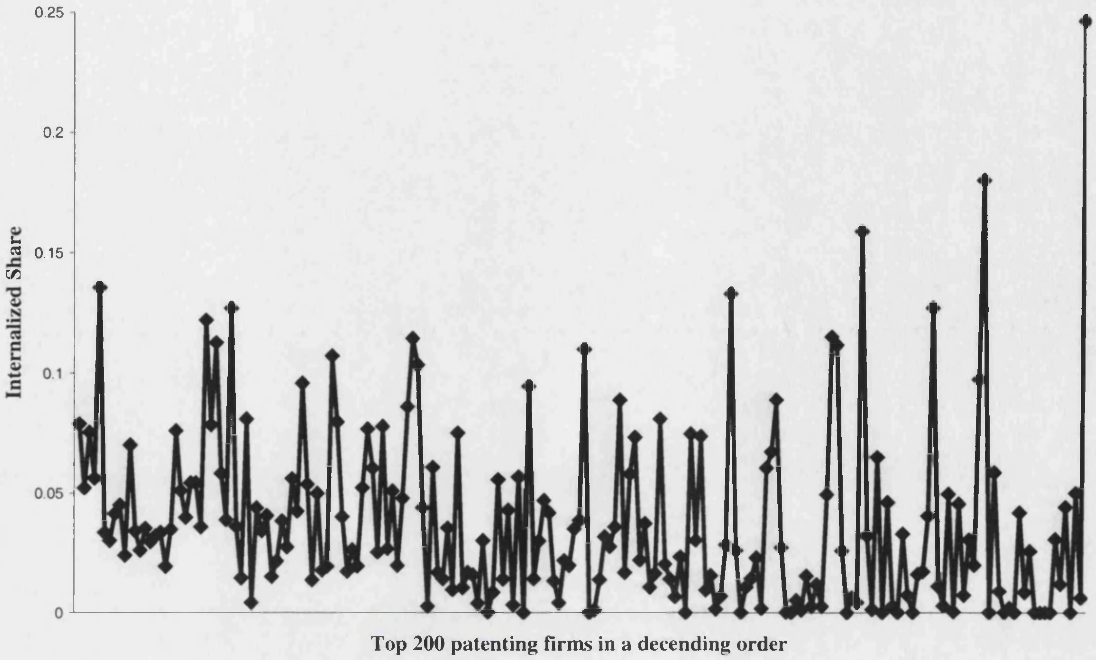

Figure 4: Internalized Share and patents stock

Figure 4: *This figure plots the variation of Internalized Share across the top 200 patenting firms in a descending order (firms with a larger stock of patents appear on the left of the horizontal scale). This illustrates that there is a high variation in Internalized Share, which is independent from the patenting activity of the firm.*

Along this line of concern, we may also think that the diffusion variables capture the size of the firm in the product market, under the notion that larger firms have a higher ability to pursue dynamic research and capture higher private returns. Our strategy of coping with this concern is to include firm size measures, such as the firm market share, number of employees, sales and etc. Similarly to patents stock, in case our diffusion measures capture the size of the firm in the product market, once having controlled for the size of the firm, the diffusion variables should not provide any significant information.

Controlling for cross-industry variation in the diffusion variables

Firms in our sample are located in different industries, which may vary in the private returns to innovation they provide. In case the diffusion variables vary as well across these industries, a pooling estimation across industries may capture industry variation in private returns, via the diffusion variables. For example, in case firms in the Computers industry enjoy higher private returns to innovation and also have higher Internalized Flows, compared to firms in the Chemicals industry, a pooling estimation, once not conditioning on industry effects, will yield a pattern of results by which Internalized Flows have a positive effect on private returns.

We cope with this serious concern in various ways. First, we have shown in chapter 2 that there is a little variation in the extent to which spillovers are Internalized across technology sectors (the Share of Internalized Spillovers and the share of lines of research that are Internalized are stable across technology sectors). This slightly mitigates our concern that the diffusion variables capture industry effects, as they do not vary much across firms that operate in different technological environments.

Furthermore, in all the econometric specifications reported below, we include a complete set of two-digit industry dummies and a complete set of main technology sector indicators, which are the share of the firm's patents in each of the five main technology sectors. Moreover, we test the robustness of our results to including a complete set of four-digit industry dummies.

Finally, we present a case-study on 30 firms that operate in high-tech industries (mainly Computer Hardware), where we expect the diffusion variables to matter the most. As this set of firms is relatively homogenous in terms of the type of innovation they perform, finding the same pattern of results in this restricted sample will mitigate our concern that they are driven by cross-industry variation.

Table 3 offers a look into the variation of the diffusion variables across four levels of industry aggregation. The analysis of the variation of the diffusion variables shows that the main variation comes from within industries, mainly for Internalized Flows and Externalized Flows (Internalized Share seems to be more sensitive to industry effects, however, about 50 percent of its variation is still evident within four-digit industry breakdown). This finding is encouraging, since it is more likely that the source of variation in the ability of firms to reabsorb their spilled knowledge is not strongly associated with cross-industry variation[26].

Table 3

Analysis of Variance - diffusion variables

	One-digit SIC	Two-digits SIC	Three-digits SIC	Four-digits SIC
Internalized Flows	1.51	0.30	0.23	0.24
% Between industries variation	3%	6%	8%	15%
% Within industries variation	97%	94%	92%	85%
Externalized Flows	2.84*	0.54	0.36	0.61
% Between industries variation	5%	9%	12%	31%
% Within industries variation	95%	91%	88%	69%
Internalized Share	1.37	1.71*	1.47*	1.52*
% Between industries variation	3%	25%	36%	52%
% Within industries variation	97%	75%	64%	48%

Table entries are the F-statistics for the null hypothesis of equal mean across the different industry breakdowns. * denotes that the mean varies across industries at the 5 percent significance level.

Finally, it is worth mentioning that if firms internalize the technological feedback they receive from the diffusion of their discoveries, we may find it difficult to identify an effect of the diffusion variables on private returns to innovation. This difficulty is especially likely to arise where we estimate the marginal returns to innovation. For example, in the case of decreasing returns in the production of knowledge, when firms with a higher ability to reabsorb their spilled knowledge

[26]The fact that firms operating in similar product markets differ in their ability to reabsorb their spilled knowledge may hint at a strategic behaviour of firms in managing the diffusion of their inventions.

find it optimal to innovate more (as indicated by the theoretical model in section 3), it would be difficult to recover the expected effect of the diffusion variables on private returns to innovation. Therefore, we believe that finding the expected effect of the diffusion variables will be an underestimate of their importance to private returns.

5.6.3 Econometric issues

The use of firm level accounting data may lead to the classical endogeniety bias. In particular, a higher market value can, indeed, be the result of conducting more R&D, however, the ability to devote more resources to R&D can reflect a higher market value that provides more finance to the innovative activity. Moreover, demand or supply shocks can simultaneously raise the R&D expenditures and the market value of the firm. In order to mitigate this potential bias we include a complete set of year dummies aiming at capturing transitory shocks[27]. Further, our main concern is to recover the effects of the diffusion variables, which are less sensitive to the endogeniety of the accounting variables, as the diffusion variables are time invariant and are constructed over an earlier period.

A more serious endogeniety bias (with respect to the focus of this chapter) may be associated with the diffusion variables themselves, so that they are correlated with omitted variables that affect the market value of the firm. In order to test this potential bias, we experiment with different time periods for the construction of the diffusion variables, so as to reduce the overlap with the estimation period (the endogeniety of the diffusion variables is mitigated, in case they are pre-determined in the estimation period).

For example, in the econometric analysis, the diffusion variables have been constructed in the period 1969-1995, which overlaps with the estimation period (1980-2001). Thus, we also construct the diffusion variables in the period 1969-1990, 1969-1985 and 1969-1980. We find the same pattern of results in each of these cases[28]. Finally, we test the robustness of the results for the potential endogeniety

[27]We also experiment with lagging the R&D stock by one period, which we find not to affect the pattern of results in a significant manner.

[28]Naturally, we are interested in studying a diffusion period which is as long as possible, and,

of the diffusion variables by restricting the estimation sample to the period 1990-2001. Our findings are robust in these cases, as well.

We introduce firm fixed-effects into the Tobin's Q specification using the "mean scaling" method of Blundell, Griffith and Van Reenen (1999). This method assumes that computing the mean of Tobin's Q in a long enough pre-estimation period can be used as an initial condition to proxy for unobserved heterogeneity, if the first moment is stationary. Thus, we assume that the effect of the time-invariant attributes of the firm is captured in a pre-sample mean of Tobin's Q.

In order to amplify the effectiveness of this method and test its robustness, we also include the pre-estimation means of other firm-level variables, such as sales, industry sales, employees, R&D stock, citations-weighted patents stock and citations stock[29].

We do not include the traditional firm fixed-effects by adding a complete set of firm dummies, as the diffusion variables are time invariant and their effect cannot be identified in the presence of firm dummies[30]

In order to construct the pre-sample means of these variables, we refer to *Historical US Compustat*, which gives us an extra 10 years of data (1970-1979) for the 476 firms in our sample, which are used to approximate the initial conditions of the firm fixed-effects.

Although some finite sample bias will exist, Monte Carlo evidence shows that this pre-sample "mean scaling" estimator performs pretty well.

5.6.4 Estimation results

In this section, we present the estimation results of the effect of the diffusion pattern of knowledge on private returns to innovation. All the Tobin's Q specifications

therefore, we decide to construct the diffusion variables from the period 1969-1995 (the probability to find an Internalized line of research increases with the length of the diffusion period).

[29] We also include the mean of these additional variables, as they are computed over the same time period used for the construction of the diffusion variables. Thus, their inclusion mitigates our identification concern, by which the diffusion variables capture the patenting activity of the firm or its size in the product market.

[30] This is obviously the case for the linear terms of Internalized Flows and Externalized Flows. With regard to their interaction terms with R&D stock over assets, their effect could be identified through the variation in the R&D stock over assets (in case the within firm variation in the R&D stock over assets depends on Internalized Flows and Externalized Flows). However, we do not find any significant interaction effect in the presence of firm dummies.

reported in this section include a complete set of two-digit industry dummies (78 dummy variables), a set of indicators for the share of patents the firm has in the five main technology sectors, a complete set of year dummies (20 dummy variables), a dummy variable that receives the value one if the R&D stock of the firm is zero and a dummy variable that receives the value one if Internalized Flows is zero. Further, the firm fixed-effects we use in the econometric analysis is always based on the "mean scaling" approach suggested by Blundell, Griffith and Van Reenen (1999) (thus, we do not use the classical firm fixed-effects of including a complete set of firm dummies).

Table 4

The effect of Internalized Flows and Externalized Flows on private returns to innovation

Nonlinear Least Squares, dependent variable: log(Tobin's-Q)

	(1)	(2)	(3)	(4)	(5)
R&D stock/Assets	0.280*	0.145*	0.152*	0.167*	0.217*
	(0.079)	(0.021)	(0.028)	(0.029)	(0.040)
Internalized Flows x (R&D stock/Assets)	0.208*	0.096*	0.059*	0.059*	0.062*
	(0.095)	(0.029)	(0.010)	(0.009)	(0.012)
Externalized Flows x (R&D stock/Assets)	-0.011*	-0.005*	-0.004*	-0.004*	-0.005*
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
log(Internalized Flows)			0.031*	0.027*	0.028*
			(0.005)	(0.005)	(0.005)
log(Externalized Flows)			-0.023*	-0.026*	-0.026*
			(0.004)	(0.004)	(0.004)
log(Sales)				0.031*	0.028*
				(0.003)	(0.003)
log(Industry Sales)				-0.024*	-0.029*
				(0.006)	(0.006)
Sales Growth					0.533*
					(0.017)
Firm Fixed-Effects[a]	No	Yes	Yes	Yes	Yes[b]
Observations	9,454	9,454	9,454	9,454	9,015
R^2	0.323	0.501	0.509	0.511	0.516

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (clustered at the firm level). * denotes a significant level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero and a dummy variable for Internalized Flows equal zero.

[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

[b]For example, the estimates for the pre-sample mean variables are as following: Market Share -0.106* (0.018), Employees 0.003 (0.002), log(Tobin's Q)* 0.544 (0.011), Sales 0.013 (0.027), Assets -0.856 (0.592), Patents stock -0.009 (0.013), Citations stock 0.029* (0.007) and R&D stock -0.292 (0.335).

Table 4 reports the estimation results of the nonlinear specification (equation (5.17)). In column 1, we include the linear term of R&D over assets and its interaction terms with Internalized Flows and Externalized Flows. The estimate of the linear term of R&D over assets (γ_0) is positive and significant (0.280 with a standard error of 0.079). The interaction term of Internalized Flows with R&D over assets (γ_1) is positive and significant (0.208 with a standard error of 0.095) and the interaction term of Externalized Flows with R&D over assets (γ_2) is negative and significant (-0.011 with a standard error of 0.003). These findings are consistent with our expectations, under which private returns to R&D rise with a higher value of Internalized Flows and fall with a higher value of Externalized Flows.

Given these estimates, the elasticity of market value with respect to the R&D stock is 0.103[31]. This implies that an additional one dollar spent on R&D raises market value by 0.49 cents (which is already net of the R&D costs). A one standard deviation increase in Internalized Flows raises the private gain on an additional dollar spent on R&D to 0.63 (thus, a one standard deviation increase in Internalized Flows raises private returns to an extra dollar spent on R&D by 30 percent). A one standard deviation increase in Externalized Flows lowers these private returns to 0.44 (thus, a one standard deviation increase in Externalized Flows lowers private returns to an additional dollar spent on R&D by 10 percent).

It is important to note that the estimated effects of Internalized Flows and Externalized Flows on private returns are underestimated, as we assume that a change in either measures does not affect the other. For example, it is likely that an increase in Internalized Flows will reduce Externalized Flows as well (thus, a line of research becomes Internalized instead of being Externalized). This indicates that private returns will rise as a result of the increase in Internalized Flows and also as a result of a decrease in Externalized Flows.

In column 2, we add firm fixed-effects, as described above[32]. The linear term of R&D stock over assets halves (from 0.280 to 0.145), however it remains significant. With regard to the interaction term of Internalized Flows with the R&D stock over assets, it drops from 0.208 to 0.096, however it remains significant. As for the interaction term between Externalized Flows and the R&D stock over assets, it

[31] Our estimated elasticity is significantly lower from that reported in previous studies. For example, Bloom, Schankerman and Van Reenen (2005) report an elasticity of 0.24, using a similar estimation sample. However, they do not include industry or technology effects. We find a similar elasticity when including only one-digit industry dummies in our specification.

[32] The set of pre-sample means is jointly significant with a *p-value*<0.001.

drops in absolute value (from -0.011 to -0.005), but remains significant, as well.[33]

Moreover, the R^2 under firm fixed-effects rises substantially from 0.323 to 0.501, which indicates that the set of pre-sample means adds significant explanatory power.

Under firm fixed-effects, the elasticity of market value with respect to the R&D stock is 0.056 (compared to 0.103 without firm fixed-effects). An additional one dollar spent on R&D raises market value by 0.26 (compared to 0.49 without firm fixed-effects). A one standard deviation increase in Internalized Flows raises private returns to an additional dollar spent on R&D to 0.34. Thus, a one standard deviation increase in Internalized Flows raises private returns by about 30 percent, as is the case without firm fixed-effects. A one standard deviation increase in Externalized Flows lowers the private valuation of the additional dollar spent on R&D to 0.24. Thus, private returns fall by about 10 percent, as is the case without firm fixed-effects.

We find that adding firm fixed-effects scales down the estimated shadow price of the R&D stock, however, it does not influence the effect of Internalized Flows and Externalized Flows in relative terms.

In column 3, we add to the firm fixed-effects specification Internalized Flows and Externalized Flows linearly. The same pattern of results holds. The main change we observe is a drop in the interaction term between Internalized Flows and R&D stock over assets (from 0.096 to 0.059), which remains significant. The linear term of Internalized Flows is positive and significant, whereas the linear term of Externalized Flows is negative and significant, both are consistent with our expectations.

Importantly, we are able to identify the positive effect of Internalized Flows and the negative effect of Externalized Flows, both linearly and through their interaction with the R&D stock over assets, which amplifies the robustness of our findings.

[33]We also interact the pre-sample mean of Tobin's Q with R&D over assets, in order to test the robustness of the interaction terms of Internalized Flows and Externalized Flows. The coefficient on the interacted term of Internalized Flows rises to 0.112 with a standard error of 0.019 and the coefficient on the interacted term of Externalized Flows is 0.006 with a standard error of 0.001).

In columns 4 and 5 we add the sales of the firm, the aggregate sales in the industry the firm operates in (industry sales) and the growth in the sales of the firm. We add these variables to capture transitory shocks in demand that may affect the R&D valuation of the firm and its pattern of diffusion.

The same pattern of results with respect to Internalized Flows and Externalized Flows (linear and interacted terms) remains. We find a positive and significant effect of sales and sales growth and a negative and significant effect of industry sales.

In table A5 in the appendix, we report the same estimations for Internalized Share. The interaction term of Internalized Share and R&D stock over assets is always positive and significant, consistent with the findings reported in table 4. Moreover, the linear term of Internalized Share is positive and significant, as well. The elasticity of market value with respect to the R&D stock is 0.154. This implies that an extra dollar spent on R&D raises the value of the firm by 0.73 cents. A one standard deviation increase in Internalized Share raises private returns to this extra dollar to 1 dollar. Thus, at the margin, private returns rise by 40 percent as a response to a one standard deviation increase in Internalized Share[34].

Table 5 summarizes the quantitative effects of Internalized Flows, Externalized Flows and Internalized Share, as reported above (the columns correspond to the same columns in tables 4 and A5). Including firm fixed-effects does not change the effect of Internalized Flows and Externalized Flows (comparing column 1 to column 2), however, it raises the effect of Internalized Share. Adding the linear terms of the diffusion variables (column 3) substantially lowers the effect of the interaction terms.

[34]Interestingly, this 40 percent increase in private returns is equivalent to a simultaneous one standard deviation rise in Internalized Flows and a one standard deviation fall in Externalized Flows.

Table 5

Quantitative effects of the pattern of diffusion on private returns

	Interaction terms	Firm fixed-effects	Linear effects
	(1)	(2)	(3)
One standard deviation increase			
Internalized Flows	+30%	+30%	+16%
Externalized Flows	-10%	-10%	-6%
Internalized Share	+40%	+50%	+37%
Two standard deviations increase			
Internalized Flows	+55%	+53%	+32%
Externalized Flows	-18%	-16%	-12%
Internalized Share	+74%	+96%	+71%

Note: columns (1), (2) and (3) are based on the corresponding columns in tables 4 and A5. Thus, column 1 includes only R&D stock over assets and interactions with Internalized Flows and Externalized Flows, column 2 adds firm fixed-effects and column 3 adds linear terms of Internalized Flows and Externalized Flows.

In conclusion, we find a pattern of results which is highly consistent with our expectations. The effect of Internalized Flows on market value is positive, which is identified linearly and through an interaction with the R&D stock. Similarly, the effect of Externalized Flows on market value is negative and is also identified linearly and through an interaction with the R&D stock. We also find these effects to be quantitatively important.

Robustness tests

This section begins with robustness tests for the nonlinear specification and proceeds by linearizing equation (5.17), using a polynomial series expansion.

Table 6 reports the robustness tests for Internalized Flows and Externalized

Flows in the nonlinear specification, which uses column 5 in table 4 as a benchmark[35].

The first concern we face relates to the interpretation of Internalized Flows and Externalized Flows. Our interpretation of the two variables is that they measure the ability of the firm to reabsorb its spilled knowledge (the parameter θ in the theoretical section).

However, an alternative interpretation would be that these variables capture the patenting activity of the firm, so that firms that have more patents will have higher Internalized Flows and lower Externalized Flows (as the firm has more patents, the probability it will randomly indirectly cite its previous patents is higher). The same pattern of results can arise under this alternative interpretation, if patents have a positive effect on private returns.

In column 1 in table 6, we include the citations-weighted patents stock of the firm (denoted as CW Patents Stock). We argue that if Internalized Flows and Externalized Flows simply capture the patenting activity of the firm, they should be uninformative in this specification.

We find that the same pattern of results regarding Internalized Flows and Externalized Flows holds, for the linear terms and the interacted terms (Internalized Flows is positive and significant and Externalized Flows is negative and significant). However, the effect of the interacted term of Internalized Flows drops from 0.062 to 0.048.

The estimate of the interaction term of the citations-weighted patents stock is positive and significant, whereas the estimate of the linear term is also positive, but not significant.

The second robustness test we perform relates to the size of the firm in the product market, aiming at mitigating the concern that larger firms are better able to perform sequential innovation and capture higher private returns on their R&D. We pursue the same reasoning and argue that if this were the case, Internalized Flows and Externalized Flows would not be informative in the presence of product

[35]We do not report the same robustness tests for Internalized Share for the sake of brevity; however, it is also robust for these tests.

market size variables. As we have already included sales and industry sales, we add the market share of the firm (which is the ratio between sales and industry sales), linearly and interacted with the R&D stock over assets. We find the previous pattern of results to be robust in this case, as well.

Our final test in the nonlinear specification includes the external R&D stock the firm faces, as is reported in column 3. We define this measure as R&D Pool (its construction is explained in the appendix), which is the 'classical' measure widely used in the literature to measure the effect of knowledge spillovers[36].

Our concern with regard to R&D Pool can go in two directions. First, R&D Pool can be negatively correlated with Internalized Flows and positively correlated with Externalized Flows, as a higher R&D Pool indicates that the amount of R&D conducted by the competitors of the firm is larger. Thus, it faces a higher competition in research, which can translate into a lower ability to perform sequential innovation. In case private returns are lower when R&D Pool is higher, the same pattern of results regarding the diffusion variables will be observed.

Nonetheless, a higher R&D Pool also implies higher spillovers. Thus, the firm is more likely to learn from the research of others, which encourages sequential innovation, i.e., R&D Pool should be positively correlated with Internalized Flows and negatively correlated with Externalized Flows. In case private returns are higher when R&D Pool is higher, we will observe the same pattern of results regarding the diffusion variables.

The same pattern of results regarding Internalized Flows and Externalized Flows also remains after the inclusion of R&D Pool linearly and interacted with the R&D stock over assets. The interaction term of R&D Pool is positive, however, not significant, whereas the linear term is negative and significant[37].

Finally, in column 4 we have put together citations-weighted patents stock, market share and R&D Pool (all interacted and linearly). The same pattern of results regarding Internalized Flows and Externalized Flows remains[38].

[36] See, for example, Jaffe (1986, 1988).

[37] Jaffe (1986) finds a similar negative linear effect of R&D Pool on market value, which he interprets as an indication of a negative competition effect in the technology space.

[38] We have also experimented with including a measure of self-citations the firm receives (linearly

Table 6

Robustness tests for the effect of Internalized Flows and Externalized Flows

Nonlinear Least Squares, dependent variable: log(Tobin's-Q)

	(1)	(2)	(3)	(4)
R&D stock/Assets	0.204*	0.222*	0.183*	0.187*
	(0.039)	(0.007)	(0.037)	(0.038)
Internalized Flows x (R&D stock/Assets)	0.048*	0.063*	0.062*	0.052*
	(0.013)	(0.012)	(0.012)	(0.014)
Externalized Flows x (R&D stock/Assets)	-0.004*	-0.005*	-0.005*	-0.005*
	(0.001)	(0.002)	(0.002)	(0.002)
log(Internalized Flows)	0.025*	0.028*	0.024*	0.021*
	(0.005)	(0.005)	(0.005)	(0.005)
log(Externalized Flows)	-0.027*	-0.026*	-0.026*	-0.027*
	(0.004)	(0.004)	(0.004)	(0.004)
CW Patents Stock x (R&D stock/Assets)	0.006*			0.004*
	(0.002)			(0.002)
log(CW Patents Stock)	0.010			0.016*
	(0.006)			(0.006)
Market Share x (R&D stock/Assets)		-0.035		-0.058
		(0.066)		(0.062)
Market Share		0.061		0.073
		(0.049)		(0.051)
R&D Pool x (R&D stock/Assets)			0.074	0.059
			(0.064)	(0.066)
log(R&D Pool)			-0.018*	-0.024*
			(0.009)	(0.009)
Firm Fixed-Effects[a]	Yes	Yes	Yes	Yes
Observations	9,015	9,015	9,015	9,015
R^2	0.516	0.516	0.516	0.516

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (clustered at the firm level). * denotes a significant level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero, a dummy variable for Internalized Flows equal zero, sales and industry sales.

[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

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and interacted with the R&D stock over assets), under the notion that self-citations represent an ability of the firm to pursue dynamic research. In all the specifications, the same pattern of results regarding Internalized Flows and Externalized Flows (linear and interacted) remains. With respect to self-citations, we find the linear term to be positive and significant and the interacted term not to be significant.

Linear approximation Next, we turn to analyse a linear version of equation (5.17) and to test the robustness of our findings to specifications, where the term $log(1+\gamma\frac{K_{it}}{A_{it}})$ is approximated by a polynomial series expansion. The series of functions used for this approximation is denoted by $\gamma\Phi(\frac{K_{it}}{A_{it}})$, which is linear in γ. We experiment with a series expansion of degree one ($\Phi(\frac{K_{it}}{A_{it}})=\frac{K_{it}}{A_{it}}$), two ($\Phi(\frac{K_{it}}{A_{it}})=\sum_{j=1}^{2}\left(\frac{K_{it}}{A_{it}}\right)^{j}$), three ($\Phi(\frac{K_{it}}{A_{it}})=\sum_{j=1}^{3}\left(\frac{K_{it}}{A_{it}}\right)^{j}$) and four ($\Phi(\frac{K_{it}}{A_{it}})=\sum_{j=1}^{4}\left(\frac{K_{it}}{A_{it}}\right)^{j}$). Thus, equation (5.17) becomes:

$$\log\left(\frac{V_{it}}{A_{it}}\right)=\log\kappa_{it}+\gamma\Phi(\frac{K_{it}}{A_{it}}) \tag{5.19}$$

Where, γ and $\log\kappa_{it}$ are specified in equations (5.16) and (5.18) , respectively. Equation (5.19) is estimated by OLS, where the standard errors follow the Newey-West correction (unless mentioned otherwise). We use the Delta method to compute the standard errors of the marginal effects of the linear terms of $\Phi(\frac{K_{it}}{A_{it}})$ and the interacted terms of $\Phi(\frac{K_{it}}{A_{it}})$ with Internalized Flows and Externalized Flows.

Table 7 reports the estimation results with a series expansion of degree one (thus, $log(1+\gamma\frac{K_{it}}{A_{it}})\approx\gamma\frac{K_{it}}{A_{it}}$).

Column 1 reports the estimation results of a specification that includes R&D over assets and interaction terms of Internalized Flows and Externalized Flows with R&D over assets (as in column 1 in table 4 for the nonlinear specification). The pattern of results is similar to the one we have observed in the nonlinear specification. The interaction term between Internalized Flows and R&D stock over assets is positive and significant and the interaction term between Externalized Flows and R&D over assets is negative and significant.

Compared to the equivalent nonlinear specification (column 2 in table 4), the linear specification yields a lower estimate of the interaction term of Internalized Flows (0.089 compared to 0.208) and a lower estimate of the R&D over assets term (0.229 compared to 0.280). The estimate of the interaction term of Externalized Flows is similar to the estimate obtained from the nonlinear specification.

The elasticity of market value with respect to the R&D stock 0.093, compared to 0.103 in the equivalent nonlinear specification. An additional one dollar spent on R&D, raises the market value of the firm by 0.44 cents, compared to 0.49 cents in the nonlinear specification. A one standard deviation increase in Internalized Flows raises private returns by 17 percent (compared to 30 percent in the nonlinear specification), whereas a one standard deviation increase in Externalized Flows lowers private returns by 5 percent (compared to 10 percent in the nonlinear specification). Thus, we observe that in the first-degree linear approximation the effects of Internalized Flows and Externalized Flows are lower, compared to the equivalent non-linear specification[39].

In column 2 we add firm fixed-effects (using the same set of pre-sample means as in the nonlinear specification). The estimates of R&D stock over assets term and the interaction terms of Internalized Flows and Externalized Flows substantially drop, however, their signs do not change and they remain significant.

In column 3 we add the linear terms of Internalized Flows and Externalized Flows. The estimates of the linear terms of Internalized Flows and Externalized Flows are similar to those obtained from the nonlinear specification, i.e., the coefficient on Internalized Flows is positive and significant and the coefficient on Externalized Flows is negative and significant. The estimate of the interaction term of Internalized Flows drops, however it remains significantly positive. The estimate of the interaction term of Externalized Flows remains negative and significant with no important change in its size.

In columns 3 to 5 we repeat similar robustness tests as reported in table 6. Thus, adding linear and interacted terms of citations-weighted patents stock and R&D Pool. The same pattern of results regarding Internalized Flows and Externalized Flows (linear and interacted) remains.

[39]However, the effect of Internalized Share in the linear specification is identical to its effect in the nonlinear specification. A one standard deviation increase in Internalized Share raises private returns to an extra dollar spent on R&D by 39 percent.

Table 7

The effect of Internalized Flows and Externalized Flows on private returns to innovation

Linear estimation (Newey-West standard errors), dependent variable: log(Tobin's-Q)

	(1)	(2)	(2)	(3)	(4)	(5)
R&D stock/Assets	0.229* (0.022)	0.137* (0.025)	0.141* (0.025)	0.185* (0.028)	0.187* (0.038)	0.174* (0.037)
Internalized Flows x (R&D stock/Assets)	0.089* (0.022)	0.044* (0.015)	0.026* (0.012)	0.030* (0.015)	0.029* (0.015)	0.028* (0.014)
Externalized Flows x (R&D stock/Assets)	-0.008* (0.002)	-0.004* (0.002)	-0.004* (0.002)	-0.004* (0.002)	-0.004* (0.002)	-0.004* (0.002)
log(Internalized Flows)			0.032* (0.008)	0.022* (0.008)	0.031* (0.008)	0.020* (0.009)
log(Externalized Flows)			-0.018* (0.007)	-0.026* (0.004)	-0.019* (0.007)	-0.021* (0.007)
CW Patents Stock x (R&D stock/Assets)				0.003 (0.020)		0.003 (0.020)
log(CW Patents Stock)				0.033* (0.009)		0.016* (0.006)
R&D Pool x (R&D stock/Assets)					0.002 (0.032)	0.002 (0.033)
log(R&D Pool)					-0.018 (0.014)	-0.043* (0.015)
Sales Growth				0.556* (0.047)	0.557* (0.048)	0.548* (0.048)
Observations	9,454	9,454	9,454	9,015	9,015	9,015
Firm Fixed-Effects[a]	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation. * denotes a significant level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero and a dummy variable for Internalized Flows equal zero.

[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

In table 8, we experiment with higher degrees of polynomial approximation. For the polynomial approximation we report the computed marginal effects of the linear term of R&D stock over assets and the interaction terms between Internalized Flows and Externalized Flows with R&D stock over assets[40]. The coefficients on

[40]The marginal effects are computed by differentiating equation (5.19) with respect to each variable. Standard errors for the marginal effects are computed using the Delta method.

the series expansion for the linear R&D stock over assets and its interaction terms with Internalized Flows and Externalized Flows are reported as well (below the marginal effects)[41].

In columns 2 to 4, we report the estimation results with a polynomial expansion of degree two, three and four, respectively. We find the same pattern of results regarding the interaction terms of Internalized Flows and Externalized Flows with R&D stock over assets, where the interaction term of Internalized Flows is positive and significant, and the interaction term of Externalized Flows is negative and significant.

With regard to the coefficients size, as the degree of the polynomial expansion rises, the effects of the linear terms of R&D stock over assets and the interaction terms with Internalized Flows and Externalized Flows rise. For example, the elasticity of Tobin's Q with respect to R&D stock over assets in the fourth-degree polynomial approximation is 0.14, compared to 0.09 in the second-degree polynomial approximation. Nevertheless, although the size of the effect changes, the pattern of results is very robust to any form of linear approximation.

[41] In all specifications we have also experimented with including sales data (sales growth, sales and industry sales). The results are robust to adding these controls.

Table 8

The effect of Internalized Flows and Externalized Flows on private returns to innovation

Dependent variable: Log(Tobin's-Q); 9,454 observations

	(1)	(2)	(3)	(4)
R&D stock/Assets[a]	0.137* (0.025)	0.233* (0.041)	0.292* (0.048)	0.353* (0.056)
(R&D stock/Assets)		0.243* (0.045)	0.344* (0.061)	0.484* (0.091)
$(\text{R\&D stock/Assets})^2$		-0.013* (0.005)	-0.069* (0.026)	-0.184* (0.062)
$(\text{R\&D stock/Assets})^3$			0.005* (0.002)	0.029* (0.012)
$(\text{R\&D stock/Assets})^4$				-0.001* (0.001)
Internalized Flows x (R&D stock/Assets)[a]	0.044* (0.015)	0.041* (0.013)	0.059* (0.013)	0.063* (0.015)
Internalized Flows x (R&D stock/Assets)		0.087* (0.031)	0.188* (0.047)	0.266* (0.067)
Internalized Flows x $(\text{R\&D stock/Assets})^2$		-0.022* (0.016)	-0.119* (0.035)	-0.233* (0.070)
Internalized Flows x $(\text{R\&D stock/Assets})^3$			0.016* (0.005)	0.056* (0.021)
Internalized Flows x $(\text{R\&D stock/Assets})^4$				-0.003* (0.001)
Externalized Flows x (R&D stock/Assets)[a]	-0.004* (0.002)	-0.005* (0.001)	-0.007* (0.002)	-0.008* (0.002)
Externalized Flows x (R&D stock/Assets)		-0.012* (0.004)	-0.024* (0.006)	-0.0299* (0.012)
Externalized Flows x $(\text{R\&D stock/Assets})^2$		0.002* (0.001)	0.009* (0.003)	0.016* (0.009)
Externalized Flows x $(\text{R\&D stock/Assets})^3$			-0.001* (0.0002)	-0.002* (0.002)
Externalized Flows x $(\text{R\&D stock/Assets})^4$				0.0001* (0.0001)
Firm Fixed-Effects[b]	Yes	Yes	Yes	Yes

[a]Estimated marginal effects, evaluated at the mean. Standard errors are calculated using the Delta method.

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (Newey-West corrected). * denotes a significance level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero and a dummy variable for Internalized Flows equal zero.

[b]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

Finally, we test the robustness of the above findings to four-digit industry effects. We report the estimation results of including a complete set of four-digit industry dummies in a polynomial expansion of degree one and two. The results are reported in table A9 in the appendix. The same pattern of results hold, where Internalized Flows is positive and significant and Externalized Flows is negative and significant. Interestingly, we find that the effects of the linear term of R&D stock over assets and its interactions with Internalized Flows and Externalized Flows rise when exploiting only the variation within four-digit industry SIC codes.

In conclusion, we have linearized equation (5.17) using a polynomial series expansion of degrees one, two, three and four. We find the same pattern of results regarding the interaction terms between Internalized Flows and Externalized Flows with the R&D stock over assets, where the interaction term of Internalized Flows is positive and significant and the interaction term of Externalized Flows is negative and significant. We also find that the estimated effects in the polynomial approximations tend to be higher as the series expansion degree rises.

5.6.5 A reduced form R&D equation

In this section, we estimate a reduced form R&D equation aiming at finding preliminary evidence suggesting the diffusion variables affect the R&D decision of firms. This may indicate that firms internalize their ability to reabsorb their spilled knowledge when optimizing their R&D.

We estimate the effect of Internalized Flows and Externalized Flows on the R&D decision of the firm in two stages. In the first stage, we estimate the firm fixed-effect component in the R&D equation. In the second stage we project the estimated firm fixed-effects obtained from the first stage of the estimation on Internalized Flows and Externalized Flows.

The R&D equation we estimate in the first stage is:

$$\log R\&D_{it} = \alpha_i + Z'_{it}\beta + \epsilon_{it} \tag{5.20}$$

Where, $R\&D_{it}$ is the R&D expenditures of firm i in period t, α_i is the firm fixed-effect, ϵ_{it} is an idiosyncratic error term and Z_{it} is the following vector of controls: log(citations-weighted patents stock), log(sales) (current period and lagged by one period), log(industry sales) (current period and lagged by one period). We include the sales variables (current and lagged) so as to capture demand shocks that may affect the R&D incentives of the firm. The citations-weighted patent stock can be thought to affect the R&D decision of the firm in various manners. One possibility is that patents represent the intellectual property protection the firm faces, so that a larger patent portfolio (adjusted by its quality) will intensify private returns to R&D.

Finally, we also experiment with a dynamic specification that includes log $R\&D_{it-1}$ in the right-hand-side of equation (5.20). This dynamic specification is an important robustness test, as R&D investment is known to be persistent over time, thus, much of its variation can be explained by its lagged value.

Based on the estimates obtained from the R&D equation, we recover the estimated firm fixed-effects, denoted by $\widehat{\alpha}_i$, and examine in the second stage the extent to which $\widehat{\alpha}_i$ is explained by Internalized Flows, Externalized Flows and Internalized Share, as following:

$$\widehat{\alpha}_i = \gamma_1 \left(Internalized\ Flows_i\right) + \gamma_2 \left(Externalized\ Flows_i\right) + \delta\overline{Z}_i + \nu_i \qquad (5.21)$$

Where, $\widehat{\alpha}_i$ is the estimated firm fixed-effects obtained from equation (5.20), $\overline{Z}_i$ is the mean of Z_{it} over the estimation sample (1980-2001) and ν_i is the error term. We expect γ_1 to be positive and γ_2 to be negative[42].

We estimate three specifications of the firm fixed-effects. Our first specification includes only the diffusion variables. In this specification, we aim at identifying the extent to which cross-firm variation in the time-invariant component in their R&D decision is attributed to the diffusion variables.

[42]In addition, we report specifications where we include Internalized Share instead of Internalized Flows and Externalized Flows. In these specifications, we expect the coefficient on Internalized Share to be positive.

Our second specification adds the mean of the time variant variables used in the first-stage of the estimation, in the period 1980-2001, whereas in the third specification we add the set of pre-sample means of the variables used in the fixed-effects "mean scaling" approach we have adopted throughout this chapter.

Finally, we test whether our results also hold in a dynamic specification that includes the lag of R&D in the right-hand-side of equation (5.20). A well-documented stylized fact is that the R&D expenditures of the firm are strongly correlated over time. Thus, identifying the firm fixed-effect in a specification that already includes the lag of R&D would be a difficult task. Nonetheless, it is an important robustness test, as reported in table 10.

Table 9 reports the estimation results for the static specification (which does not include lagged R&D expenditures). In column ,1 we report the results from the first-stage estimation. Current and lagged sales have a positive effect of R&D expenditures, where the effect of industry sales is positive and significant only for the current term. Citations-weighted patents stock has a positive and significant effect on R&D expenditures.

In column 2, we project the firm fixed-effects that have been obtained from the first-stage estimation. The effect of Internalized Flows is positive and significant, whereas the effect of Externalized Flows is negative and significant, both as expected. The R^2 is 0.39, which indicates that about 40 percent of the variation across firms in their R&D decisions can be explained by Internalized Flows and Externalized Flows.

In column 3, we add the mean across the estimation period of the variables used as controls in the estimation of the R&D equation. The estimates of Internalized Flows and Externalized Flows drop, however, they keep their signs and remain significant.

In column 4, we add the set of pre-sample means. The estimates of Internalized Flows and Externalized Flows continue to fall, however, they keep the 'correct' signs and remain significant.

In columns 5 to 7, we report the equivalent estimation results of projecting the estimated firm fixed-effects on Internalized Share. We find in all specifications the expected result, in which the coefficient on Internalized Share is positive and significant.

Table 9

Reduced form R&D and firm fixed-effects (FE[1]) estimations - static

9,454 observations (in the R&D regression), 476 firms (for the fixed-effects regressions)

	log(R&D)	FE	FE	FE	FE	FE	FE
Internalized Flows		0.028* (0.003)	0.018* (0.003)	0.015* (0.003)			
Externalized Flows		-0.048* (0.014)	-0.035* (0.013)	-0.028* (0.012)			
Internalized Share					11.862* (2.000)	9.531* (1.608)	8..075* (1.392)
mean(Sales)			0.008 (0.007)	0.026 (0.011)		0.019 (0.013)	0.033* (0.001)
mean(Industry Sales)			0.053* (0.008)	0.042* (0.009)		0.059* (0.009)	0.041* (0.008)
mean(CW Patents stock)			0.002 (0.002)	0.006* (0.002)		0.004* (0.002)	0.011* (0.003)
mean(R&D stock)			0.003 (0.004)	-0.016 (0.011)		0.002 (0.005)	0.002* (0.001)
$\log(Sales_t)$	0.146* (0.013)						
$\log(Sales_{t-1})$	0.044* (0.008)						
$\log(\text{Industry Sales}_t)$	0.296* (0.019)						
$\log(\text{Industry Sales}_{t-1})$	-0.033 (0.023)						
log(CW Patents stock)	0.286* (0.011)						
Pre-sample variables mean	No	No	No	Yes	No	Yes	Yes
R^2	0.778	0.391	0.507	0.552	0.113	0.347	0.425

[1]The estimated firm fixed-effects are fitted from the R&D regression that is reported in column 1.
Robust standard errors are in brackets. * denotes a significance level of 5 percent.
The R&D equation includes a complete set of year dummies.

In table 10, we report the estimation results of the dynamic specification (adding the lag of R&D in the right-hand-side of equation (5.20)). The *long-run* fixed-effect term is computed as $\frac{\widehat{\alpha}}{1-0.568}$, where 0.568 is the coefficient on the lag of R&D.

We find the same pattern of results when projecting the estimated firm fixed-effects on the diffusion variables. Thus, Internalized Flows is positive and significant, Externalized Flows is negative and significant and Internalized Share is positive and significant.

Table 10

Reduced form R&D and firm fixed-effects (FE[1]) estimations - dynamics

9,454 observations (in the R&D regression), 476 firms

	log(R&D)	FE	FE	FE	FE	FE	FE
Internalized Flows		0.044* (0.006)	0.028* (0.006)	0.022* (0.061)			
Externalized Flows		-0.110* (0.028)	-0.085* (0.026)	-0.070* (0.025)			
Internalized Share					18.523* (3.436)	14.897* (2.808)	12.156* (2.402)
mean(Sales)			0.049 (0.031)	0.114* (0.029)		0.067* (0.033)	0.001* (0.0001)
mean(Industry Sales)			0.079* (0.014)	0.066* (0.015)		0.084* (0.015)	0.063* (0.014)
mean(CW Patents stock)			0.002 (0.002)	0.001* (0.003)		0.006 (0.005)	0.001* (0.0005)
mean(R&D stock)			-0.002 (0.010)	-0.001* (0.0001)		-0.0005 (0.001)	-0.004* (0.0002)
$\log(R\&D_{t-1})$	0.568* (0.006)						
$\log(Sales_t)$	0.262* (0.007)						
$\log(Sales_{t-1})$	-0.199* (0.007)						
$\log(Industry\ Sales_t)$	0.125* (0.014)						
$\log(Industry\ Sales_{t-1})$	-0.007 (0.008)						
log(CW Patents stock)	0.079* (0.008)						
Pre-sample variables mean	No	No	No	Yes	No	Yes	Yes
R^2	0.949	0.289	0.397	0.469	0.077	0.277	0.375

[1]The estimated firm fixed-effects are fitted from the R&D regression that is reported in column 1.
Robust standard errors are in brackets. * denotes a significance level of 5 percent.
The R&D equation includes a complete set of year dummies.

In conclusion, in this section we have performed a preliminary test to whether the R&D decision of the firm is affected by the diffusion pattern of its inventions, under the hypothesis that the firm would invest more in R&D, should it face higher dynamic private returns (as indicated by the theoretical model we present in section

3).

We find that R&D expenditures rise with higher Internalized Flows and lower Externalized Flows. This finding is also robust to a dynamic specification of the R&D equation, which includes the lag of R&D as an explanatory variable. This amplifies the robustness of our findings, as R&D investment is known to be time-persistence, which implies that identifying the fixed-effect component is this specification becomes a harder task.

In future research we plan to analyse a structural model in which the R&D decision of the firm takes into account dynamic consideration, where private returns to R&D depend on future subsequent developments. In chapter 5, we develop a theoretical model allowing firms to internalize the effect of the spillovers they create on their future profits and strategically manage the diffusion of their knowledge.

A case-study

We conclude the empirical analysis of this chapter with a case-study.

As our findings are based on a pooling estimation across industries, one of our main concerns is that the diffusion measures we have constructed capture variation in private returns across industries.

In order to mitigate this concern, we have controlled for industry effects, by including a complete set of two-digit industry dummies as a default in all specifications (in addition to main technology sector indicators). Furthermore, we have experimented with four-digit industry dummies and found our results to be robust.

Nevertheless, even if the cross-industry variation could be captured by two-digit industry dummies, they are included only linearly and not interacted with the R&D stock over assets (i.e., the linear industry effects are only an approximation of the cross-industry variation in private returns).

In order to further mitigate the above concern, we investigate in this section whether our findings are evident within a small sample of 30 firms that operate in high-tech industries, where we should expect the diffusion pattern of knowledge to matter the most. Encouragingly, we find the pattern of results in this smaller, high-tech sample to strongly confirm our previous findings from the pooled sample.

We focus on a sample of 30 firms, which operate in the Computer Hardware industry (the four-digit SIC codes are listed in the appendix), over a period of about 20 years. Table 11 reports the estimation results, where columns 1 and 2 refer to the Tobin's Q estimation, whereas columns 3 and 4 refer to the R&D estimation.

Column 1 reports the estimation results of a Tobin's Q specification that includes the R&D stock over assets, linearly and interacted with Internalized Flows and Externalized Flows[43]. We find that private returns significantly rise with Internalized Flows and fall with Externalized Flows, as expected.

In column 2 we add firm fixed-effects. The same pattern of results regarding Internalized Flows and Externalized Flows remains, where the former is positive and significant, and the latter is negative and significant.

Columns 3 and 4 report the estimation results of the R&D equation (for the sake of brevity, we report only the second stage estimation). In column 3, we report the estimation results of the static R&D specification (identically to column 2 is table 9). As expected, Internalized Flows is positive and significant, whereas Externalized Flows is negative and significant.

Finally, in column 4, we report the estimation results of the dynamic R&D specification (identically to column 2 in table 10). The pattern of results remains robust to this specification as well.

[43]Internalized Flows and Externalized Flows are not included linearly as well, since the small sample size does not allow us to simultaneously identify the effects of the linear and interacted terms of the diffusion variables. Including only the linear terms yields the same pattern of results reported in columns 1 and 2.

Table 11

The effect of Internalized Flows and Externalized Flows - A case study on R&D intensive firms

	Tobin's Q	Tobin's Q	R&D Static	R&D Dynamics
R&D stock/Assets	0.056*	0.050*		
	(0.029)	(0.025)		
Internalized Flows x (R&D stock/Assets)[c]	0.379*	0.211*		
	(0.098)	(0.085)		
Externalized Flows x (R&D stock/Assets)[c]	-0.011*	-0.016*		
	(0.005)	(0.006)		
Internallized Flows			0.307*	0.288*
			(0.105)	(0.116)
Externalized Flows			0.015*	0.012*
			(0.004)	(0.004)
Firm Fixed-effects	No	Yes		
Observations	594	594	30	30
R^2	0.165	0.287	0.519	0.440

Standard errors in brackets are robust to arbitrary heteroskedacity. * denotes a significance level of 5 percent.

In conclusion, the case-study we have conducted in this section verifies our empirical findings that private returns rise with Internalized Flows and fall with Externalized Flows, and that firms with higher Internalized Flows and lower Externalized Flows innovate more.

This mitigates our concern that our empirical findings are driven merely by cross-industry variation, as may be the case under pooling estimation.

5.7 Summary and conclusions

In this chapter we aggregate Internalized Spillovers and Externalized Spillovers from the originating patent level to the originating firm level (where the firm level measure of Internalized Spillovers is labeled as Internalized Flows and Externalized Spillovers is labeled as Externalized Flows). We exploit the firm-level variation in the ability of the firm to reabsorb its spilled knowledge, through estimating the market valuation of its R&D stock.

We formalize the dynamic considerations introduced in this thesis, by showing that spillovers can raise private returns, through enhancing the technological opportunities along the lines of research the originating knowledge inspires. The extent to which spillovers raise private returns depends on whether the originating firm benefits from the enhanced technological opportunities. Thus, spillovers can increase private returns via their interaction with the ability of the originating firm to reabsorb its spilled knowledge.

The main econometric analysis we have conducted in this chapter is the estimation of a market value specification, in which the market valuation of the knowledge of the firm (which is proxied by its R&D stock) depends on Internalized Flows and Externalized Flows. We expect private returns, as measured by the change in the value of the firm as a response to a change in its R&D expenditures, to rise with Internalized Flows and to fall with Externalized Flows.

Moreover, we have performed a preliminary test to whether firms internalized their ability to reabsorb their spilled knowledge (and, hence, capture higher private returns), by estimating a R&D equation.

We find that private returns rise with Internalized Flows and fall with Externalized Flows, as expected. A one standard deviation increase in Internalized Flows raises the market valuation of an additional dollar spent on R&D by 30 percent (evaluated at the mean).

Furthermore, we find preliminary evidence that firms adjust their R&D expenditures according to their ability to reabsorb their spilled knowledge, where R&D expenditures rise with Internalized Flows and fall with Externalized Flows.

Our empirical findings validate the assumption we have made in chapters 3 and 4, under which private returns are higher when knowledge creates more Internalized Spillovers and less Externalized Spillovers. This confirms the importance of the findings reported in these previous chapters.

Moreover, the extent to which the firm-level variation in the diffusion variables we have constructed is attributed to different managerial skills of firms optimizing the diffusion of their knowledge, has important consequences to the analysis of spillovers, as knowledge flows can no longer be assumed exogenous, but the result of a strategic behaviour of firms. This is further highlighted as our findings hint that firms adjust their R&D spending according to the pattern of diffusion their inventions follow.

In the next and final chapter of this thesis we develop a theoretical model that demonstrates the importance of the strategic nature of knowledge flows for the understanding of the effect of spillovers on economic performance. We design a mechanism that channels through the product market, via which a firm can benefit from the diffusion of its knowledge. We show that this mechanism can explain one of the most important events in the industry life cycle, which the literature refers to as 'producers-shakeout'.

5.8 References

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5.9 Appendix

5.9.1 Data

Our sample combines data mainly from two sources: the patents and citations data are from **The NBER USPTO patents database**[44] and the accounting data for the period 1980-2001 are from the **The Compustat North-America dataset**

For the patents data, we focus only on patents for which we have ownership information, including the patents of 2859 US organizations, out of which 800 US firms are matched to The Compustat North-America dataset (we do not have complete accounting data on the other firms, but only patents data, which we use as technological links in the sequence of citations we have constructed and explained in chapter 2)

The accounting dataset has been 'cleaned' to remove accounting years with extremely large jumps (>+200% or <-66%) in sales, employment or capital signalling merger and acquisition activity. The book value of capital is the net stock of property, plant and equipment (Compustat Mnemonic PPENT); Employment is the number of employees (EMP). R&D (XRD) is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate (Hall et al, 2005). For Tobin's Q, firm value is the sum of the values of common stock, preferred stock, total debt net of current assets (Mnemonics MKVAF, PSTK, DT and ACT). Book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles other than R&D (Mnemonics PPENT, INVT, IVAEQ, IVAO and INTAN). Tobin's Q was set to 0.1 for values below 0.1 and at 20 for values above 20. See also Lanjouw and Schankerman (2004).

We construct the pool of knowledge facing firm i in period t, defined as $R\&D\ Pool_{it}$, as

$$R\&D\ Pool_{it} = \Sigma_{j,j\neq i} TEC_{ij}(R\&D\ Stock_{jt})$$

[44]These data are collected from The US Patent and Trademark Office (PTO) and are described in detail in Hall, Jaffe and Trajtenberg (2001). These data contain detailed information on almost 3 million U.S. patents granted between January 1963 and December 1999 (such as inventor, grant year, technology sector etc.) and a list of all the citations made in the period 1975-1999.

Where TEC_{ij} is defined in equation (3.5) and the index j represents firms that operate in overlapping technology sectors to firm i.

$Industry\ Sales_{it}$ is defined as the aggregate sales of other firms facing firm i (denoted by the index j), which operate in overlapping product markets, as following:

$$Industry\ Sales_{it} = \Sigma_{j,j \neq i} SIC_{ij}(Sales_{jt})$$

Where, SIC_{ij} is defined in equation (3.4). Industry price deflators were taken from Bartelsman, Becker and Gray, 2000, until 1996 and from the BEA 4-digit NAICS Shipment Price Deflators afterwards.

In Table 11, the industries we have included are: SIC 3570 to 3577 (Computer and Office Equipment (3570), Electronic Computers (3571), Computer Storage Devices (3572), Computer Terminals (3575), Computer Communications Equipment (3576) and Computer Peripheral Equipment Not Elsewhere classified (3577).

5.9.2 Estimation tables

Table A1

Analysis of Variance - accounting and patents variables

	One-digit SIC	Two-digits SIC	Three-digits SIC	Four-digits SIC
Log(Tobin's Q)	5.46	2.61	2.58	2.27
	(0.000)	(0.000)	(0.000)	(0.000)
R&D stock/Assets	4.78	1.94	1.33	1.65
	(0.000)	(0.000)	(0.021)	(0.000)
Assets	4.02	1.80	2.44	1.80
	(0.000)	(0.000)	(0.000)	(0.000)
Sales	3.41	0.97	1.06	1.35
	(0.000)	(0.551)	(0.325)	(0.011)
CW Patent stock	1.22	1.05	1.00	1.62
	(0.279)	(0.374)	(0.497)	(0.000)
Citations stock	3.31	1.61	1.31	1.35
	(0.000)	(0.003)	(0.032)	(0.014)

Table entries are the F-statistics for the null hypothesis of equal means across the different industry breakdowns. $Pr[>F]$ is in the brackets.

Table A2

Conditional correlation between the diffusion measures and main variables: OLS estimation

	Internalized Flows	Externalized Flows	Internalized Share
log(mean Sales)	4.162	0.338	-0.002
	(3.585)	(0.209)	(0.003)
log(mean R&D Stock)	-0.127	0.083	0.000
	(1.138)	(0.066)	(0.001)
log(mean Employees)	-5.079	-0.613	0.001
	(3.994)	(0.233)	(0.003)
log(mean CW Patents Stock)	5.274	0.034	0.009
	(1.873)	(0.109)	(0.001)
log(mean Citations Stock)	1.075	0.259	-0.001
	(2.188)	(0.128)	(0.002)

The estimation sample includes the 476 firms that are in our final sample.

Table A3

The effect of Internalized Share on private returns to innovation

Nonlinear Least Squares, dependent variable: log(Tobin's-Q)

	(1)	(2)	(3)	(4)	(5)
R&D stock/Assets	0.330*	0.120*	0.135*	0.141*	0.217*
	(0.101)	(0.024)	(0.026)	(0.026)	(0.040)
Internalized Share x (R&D stock/Assets)	5.624*	2.341*	1.702*	1.379*	1.311*
	(2.295)	(0.507)	(0.533)	(0.498)	(0.586)
log(Internalized Share)			0.016*	0.020*	0.025*
			(0.004)	(0.006)	(0.007)
log(Sales)				0.035*	0.033*
				(0.004)	(0.004)
log(Industry Sales)				-0.005*	-0.011*
				(0.006)	(0.006)
Sales Growth					0.538*
					(0.018)
Firm Fixed-Effects[a]	No	Yes	Yes	Yes	Yes
Observations	9,454	9,454	9,454	9,454	9,015
R^2	0.294	0.496	0.496	0.499	0.504

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (clustered at the firm level). * denotes a significant level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero and a dummy variable for Internalized Flows equal zero.

[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

Table A4

The effect of Internalized Share on private returns to innovation

Linear estimation (Newey-West standard errors), dependent variable: log(Tobin's-Q)

	(1)	(2)	(2)	(3)
R&D stock/Assets	0.175* (0.021)	0.167* (0.021)	0.187* (0.022)	0.190* (0.023)
Internalized Share x (R&D stock/Assets)	2.829* (0.553)	3.306* (0.609)	2.189* (0.605)	1.293* (0.620)
log(Internalized Share)			0.054* (0.012)	0.050* (0.011)
CW Patents Stock x (R&D stock/Assets)				0.013 (0.002)
log(CW Patents Stock)				0.045* (0.009)
Sales Growth				0.767* (0.055)
Observations	9,454	9,454	9,454	9,015
Firm Fixed-Effects[a]	Yes	Yes	Yes	Yes

Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (clustered at the firm level). * denotes a significant level of 5 percent.

All regressions include 78 two-digits industry dummies, 4 technology indicators, a complete set of year dummies, a dummy variable for R&D stock equals zero and a dummy variable for Internalized Flows equal zero.

[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

Table A5

The effect of Internalized Flows and Externalized Flows on private returns to innovation: four-digits industry effects

Dependent variable: Log(Tobin's-Q); 9,015 observations, 475 firms

	(1)	(2)	(3)	(4)
R&D stock/Assets[a]	0.197* (0.042)	0.342* (0.068)	0.199* (0.042)	0.348* (0.068)
R&D stock/Assets		0.366* (0.074)		0.373* (0.074)
(R&D stock/Assets)^2		-0.030* (0.009)		-0.031* (0.009)
Internalized Flows x (R&D stock/Assets)[a]	0.071* (0.021)	0.054* (0.015)	0.072* (0.019)	0.055* (0.014)
Internalized Flows x (R&D stock/Assets)		0.109* (0.041)		0.111* (0.039)
Internalized Flows x (R&D stock/Assets)^2		-0.021 (0.029)		-0.022 (0.029)
Externalized Flows x (R&D stock/Assets)[a]	-0.008* (0.002)	-0.005* (0.002)	-0.007* (0.002)	-0.005* (0.002)
Externalized Flows x (R&D stock/Assets)		-0.014* (0.005)		-0.012* (0.005)
Externalized Flows x (R&D stock/Assets)^2		0.002* (0.0006)		0.002* (0.0006)
log(Internalized Flows)			0.005 (0.019)	0.005 (0.018)
log(Externalized Flows)			-0.009 (0.014)	-0.011 (0.014)
Sales Growth	0.551* (0.055)	0.551* (0.055)	0.549* (0.054)	0.573* (0.054)
Firm Fixed-Effects[b]	Yes	Yes	Yes	Yes
Four-digit Industry effects	Yes	Yes	Yes	Yes
R^2	0.569	0.568	0.569	0.572

[a]Estimated marginal effects, evaluated at the mean. Standard errors are calculated using the Delta method.
Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation (clustered at the firm level). * denotes a significance level of 5 percent.
All regressions include a complete set of year dummies, and a dummy for R&D stock equals zero and a dummy for Internalized Flows equal zero.
[a]Firm Fixed-Effects are approximated according to Blundell, Griffith and Van Reenen (1999). Thus, including a pre-sample mean of: Market Share, Employees, Tobin's Q, Sales, Assets, R&D stock, Patents stock and Citations stock.

5.9.3 Theoretical model - sketch of proof (equation (5.6) in section 3)

In this section, we show how we have derived the expression of the dynamic returns in equation (5.6), as a function of the number of 'second chances' the originating firm receives to stay in the development race, if it fails to win (recall that a win in the case where firm is the sole inventor in a development stage).

The model does not include time, only generation of developments of the originating knowledge k. We assume the model starts from the point in time where knowledge k becomes available for sequential innovation by other firms (and by the originating firm i). All the computations of the expected number of wins relate to the point of view of this starting period.

The probability of winning at generation g is given by:

$$P(g) = \sum_{s=0}^{g-1} \begin{pmatrix} g-1 \\ s \end{pmatrix} [p(1-q)]^{g-s} q^s \tag{5.22}$$

It should be noted that the term q^s reflects the ability of the firm to build on external research along the line of research it originates. The probability that knowledge is created in a given development stage and firm i not winning in this stage is $q(1-p)+pq=q$ (since the firm does not win either if it fails to invent, or if it succeeds to invent, however, at least one other firm succeeds as well).

We aim at computing the expected dynamic returns to knowledge k, given the expected number of development stages won by firm i. For this purpose, we need to compute the following equation for the expected number of development stages won by firm i:

$$E(wins) = \sum_{g=0}^{\infty} P(g) = \sum_{g=0}^{\infty} \sum_{s=0}^{g-1} \begin{pmatrix} g-1 \\ s \end{pmatrix} [p(1-q)]^{g-s} q^s \tag{5.23}$$

We turn now to describe how this summation is computed to yield the expected number of development stages firm i wins.

Taking g to infinity (assuming the knowledge k has the potential of being developed an infinite number of times) and computing the expected number of inventions firm i makes along the line of research can be expressed as following:

$p(1-q)$
$p^2(1-q)^2 \quad p(1-q)q$
$p^3(1-q)^3 \quad 2p^2(1-q)^2q \quad p(1-q)q^2$
$p^4(1-q)^4 \quad 3p^3(1-q)^3q \quad 3p^2(1-q)^2q^2 \quad p(1-q)q^3$
$p^5(1-q)^5 \quad 4p^4(1-q)^4q \quad 6p^3(1-q)^3q^2 \quad 4p^2(1-q)^2q^3 \quad p(1-q)q^4$

Define $h \equiv (1-q)\,p$. The summation of equation (5.23) over g can be computed by first summing each column across its rows and then summing over columns. Also, define s as the number of times the firm failed to win a development stage and then summing over s equals 0 to infinity.

Summation of $s = 0$ (zero failures):

$$S^0 = h + h^2 + h^3 + h^4 + ... \tag{5.24}$$

$$S^0 = \frac{h}{1-h} \tag{5.25}$$

Summation of $s = 1$ (one failure):

$$S^1 = q\left(h + 2h^2 + 3h^3 + 4h^4 + ...\right) \tag{5.26}$$

Which can be written, as following:

$$\begin{array}{lllll} h & h^2 & h^3 & h^4 & \cdots \\ & h^2 & h^3 & h^4 & \cdots \\ & & h^3 & h^4 & \cdots \\ & & & h^4 & \cdots \end{array}$$

Using the same method, we can first sum across rows and then across columns. This yields:

$$S^1 = \frac{q}{1-h}\left[h + h^2 + h^3 ...\right] = \frac{q}{1-h}S^0 \tag{5.27}$$

For $s = 2$ (two failures) we get the following summation:

$$S^2 = q^2\left(h + 3h^2 + 6h^3 + 10h^4 + ...\right)$$

Which can be expressed in the following form:

$$\begin{array}{lllll}
h & h^2 & h^3 & h^4 & \dots \\
 & h^2 & h^3 & h^4 & \dots \\
 & h^2 & h^3 & h^4 & \dots \\
 & & h^3 & h^4 & \dots \\
 & & h^3 & h^4 & \dots \\
 & & h^3 & h^4 & \dots \\
 & & & h^4 & \dots \\
 & & & h^4 & \dots \\
 & & & h^4 & \dots \\
 & & & h^4 & \dots
\end{array}$$

Using the same method described above, this summation becomes:

$$S^2 = \frac{q}{1-h} q \left(h + 2h^2 + 3h^3 + 4h^4 ...\right) = \frac{q}{(1-h)} S^1 \tag{5.28}$$

With $s = 3$ (three failures) the summation is:

$$S^3 = q^3 \left(h + 4h^2 + 10h^3 + ...\right) \tag{5.29}$$

Which can be expressed, as following:

$$\begin{array}{llll}
h & h^2 & h^3 & \dots \\
 & h^2 & h^3 & \dots \\
 & h^2 & h^3 & \dots \\
 & h^2 & h^3 & \dots \\
 & & h^3 & \dots \\
 & & h^3 & \dots \\
 & & h^3 & \dots \\
 & & h^3 & \dots \\
 & & h^3 & \dots \\
 & & h^3 & \dots
\end{array}$$

As before, this summation becomes:

$$S^3 = \frac{q}{1-h} q^2 \left(h + 3h^2 + 6h^3 ...\right) = \frac{q}{(1-h)} S^2 \tag{5.30}$$

Thus, the summation of columns is a geometric series with a multiplicative factor equals $\frac{q}{(1-h)}$ and the first argument in the series is $\frac{h}{1-h}$.

Since we assume that the static payoff of winning every development stage is

$$Z = p(1-q)v - x \tag{5.31}$$

The dynamic returns as a function of the number of 'second chances' the firm gets, θ, are given as (thus, θ informs us on the number of columns we sum, where, for θ equals zero, we sum only the first column and when θ goes to infinity we sum all columns):

$$W_i(\theta) = \frac{(1-q)\,pv - x}{(1-p)\,(1-q)} \left(1 - \left(\frac{q}{1-(1-q)\,p}\right)^{\theta+1}\right) \tag{5.32}$$

And in the limit where θ goes to infinity we get:

$$W_i = \frac{p(1-q)v - x}{(1-p)\,(1-q)} \tag{5.33}$$

5.9.4 A simple model of strategic knowledge flows

We introduce a three stage patent race game that demonstrates the importance of the ability to benefit from own knowledge flows to the private value of innovation in a framework that allows for strategic behaviour in the diffusion of knowledge. This model is complementary to the model presented in section 3, which does not assume firms can affect the diffusion of their inventions.

We consider a model in which an originating firm internalizes the spread of its discovery and optimizes its diffusion by affecting the cost its rivals will incur when accessing it.

Assume firm i (the originating firm) holds the knowledge k. In order to commercialize this knowledge a subsequent invention must occur. Denote by n the number of firms that aim at advancing the knowledge k (including firm i). Further, we consider a patent race framework, in which the first firm to develop the knowledge k gains the prize v, while the rest gain nothing. Let $S = \{1, ..., n\}$ be the set of firms that participate in the patent race that the knowledge k originates and let $S_{-i} = \{1, ..., i-1, i+1, ..., n\}$ be the set of firm i's rivals in this patent race. In order to enter the patent race, firm $j \in S_{-i}$ incurs access cost to the knowledge k, denoted by $\gamma(\tau)$. For example, $\gamma(\tau)$ can represent formal licensing fees or informal searching and learning efforts. τ denotes policy measures firm i can adopt that affect the access cost of its $n-1$ rivals to the knowledge k, with $\frac{\partial \gamma(\tau_i)}{\partial \tau_i} > 0$ (for example, τ can be the price of k in a formal knowledge transfer or, alternatively, either keep the knowledge secret or make it publicly available). For simplicity, we assume firm i has no direct costs in setting τ.

The key building block of this model is that firm i can benefit from its own spillovers, by using external research as an input in the production process of its future inventions.

Given this set up and following Loury (1979) and Dasgupta and Stiglitz (1980), we consider the following probability firm i invents before time t :

$$F(t) = 1 - e^{-h(x_i, x_{-i})t} \tag{5.34}$$

Where $h(x_i, x_{-i})$ (also denoted by h_i for ease of notation) is the hazard rate function[45] of firm i, which is bounded between zero and one, x_i is the R&D expenditures of firm i with $\frac{\partial h_i}{\partial x_i} > 0$, $\frac{\partial^2 h_i}{\partial^2 x_i} \leq 0$ and $x_{-i} \equiv \sum\limits_{j \in S_{-i}} x_j$ with $\frac{\partial h_i}{\partial x_{-i}} > 0$. It is easy to show that firm i's innovation value is given in this case by

$$W_i = \frac{vh(x_i, x_{-i}) - c\,(x_i)}{a + r} \tag{5.35}$$

Where $a \equiv \sum\limits_{j \in S} h_j$, $h_j = h(x_j)\ \forall j \neq i$ is the hazard rate function of firm j, which depends only on firm j's R&D expenditures[46] that are denoted by x_j, $c\,(x_i)$ is the R&D costs of firm i with $\frac{dc(x_i)}{\partial x_i} > 0$ and r is the one period interest rate.

The probability that firm $j \in S_{-i}$ will perform a successful invention before time t is given by

$$F(t) = 1 - e^{-h(x_j)t} \tag{5.36}$$

In this case, firm $j \in S_{-i}$ innovation value can be expressed as

$$W_j = \frac{vh(x_j) - c\,(x_j)}{a + r} - \gamma\,(\tau_i) \tag{5.37}$$

Where, $c\,(x_j)$ is the R&D cost of firm j with $\frac{dc(x_i)}{\partial x_i} > 0$.

The effect of the spread of knowledge k on its value to firm i is ambiguous: on the one hand, the spread of this knowledge reduces the expected gains firm i receives, through increasing the probability that some other firm will be the first to invent the subsequent invention. On the other hand, the flow of the knowledge k inspires research of others that contributes to the research of firm i, which raises the probability it will make a discovery before its rivals do.

We consider a three stage game in which at the first stage firm i chooses its policy regarding external access to its private knowledge (τ_i), at the second stage $n - 1$ firms decide whether to enter the patent race (after the fixed access cost to the knowledge k has been determined) and at the third stage, the patent race takes place (in which, the n firms choose their optimal R&D investment strategy). We

[45] Which is the probability that firm i makes the discovery at each point in time, given it has not done so before.

[46] We assume that the hazard rate of firm j depends only on firm j's R&D since this model focuses on the ability to benefit from own knowledge flows. In this model the knowledge flows are only from invention k to the $n - 1$ firms that participate in the patent race.

solve the model using backward induction. For notational ease, we denote $\gamma(\tau_i)$ as γ in solving for the third and second stages of the game.

Third stage At the third stage, firms optimize their innovation efforts. We assume that firms are small in the sense they take the expected discovery date as given, or equivalently, take a as given. Hence, there is no strategic interaction in R&D. For $j \in S_{-i}$, the $n-1$ first-order conditions of maximizing equation (5.37) with respect to x_j are given by

$$v\frac{dh(x_j)}{dx_j} = \frac{dc(x_j)}{dx_j} \quad \text{for } j \in S_{-i} \tag{5.38}$$

Due to symmetry, denote by $\widehat{x}_j = \widehat{x}(v)$ the solution to (5.38) for $j \in S_{-i}$. By definition of x_{-i}, $\widetilde{x}_{-i} = (n-1)\widehat{x}(v)$ is the sub-game solution for the aggregate innovation efforts of firm i's rivals. Substituting $\widetilde{x}_{-i}$ into equation (5.35) and maximizing with respect to x_i, yields the following first order condition:

$$v\frac{\partial h(x_i,(n-1)\widehat{x}(v))}{\partial x_i} = \frac{dc(x_i)}{dx_i} \tag{5.39}$$

Let $\widetilde{x}_i = \widetilde{x}_i(v,n)$ solve equation (5.39).

Second stage In the second stage, firms make their entry decisions. If they decide to enter the patent race they incur a fixed cost of γ. Substituting $x_j = \widehat{x}(v)$ and $x_i = \widetilde{x}_i(v,n)$ into equation (5.37) and assuming free entry yields the following implicit solution for the number of firms that choose to participate in the patent race:

$$n = \frac{1}{h(\widehat{x}(v))}\left[\frac{vh(\widehat{x}(v)) - c(\widehat{x}(v))}{\gamma} - r - h(\widetilde{x}_i(v,n))\right] + 1 \tag{5.40}$$

Denote by $\widehat{n}$ the solution to equation (5.40) and substitute $\widehat{n}$ into the optimal R&D of firm i that was found in the third stage, $\widetilde{x}_i(v,n) = \widehat{x}_i(v,\widehat{n}) = \widehat{x}_i(v,\gamma,r)$. Substitute $\widehat{x}_i(v,\gamma,r)$ back into equation (5.40) to get

$$\widehat{n} = \frac{1}{h(\widehat{x}(v))}\left[\frac{vh(\widehat{x}(v)) - c(\widehat{x}(v))}{\gamma} - r - h(\widehat{x}_i(v,\gamma,r))\right] + 1 \tag{5.41}$$

Also, by the definition of a, it is given by

$$\widehat{a}\left(v,\gamma,r\right)=\left(\widehat{n}\left(v,\gamma,r\right)-1\right)h\left(\widehat{x}(v)\right)+h\left(\widehat{x}_i(v,\gamma,r)\right)=\frac{vh\left(\widehat{x}(v)\right)-c\left(\widehat{x}(v)\right)}{\gamma}-r \tag{5.42}$$

Further, substitute $\widehat{n}\left(v,\gamma,r\right)$ into $\widetilde{x}_{-i}$ to get $\widehat{x}_{-i}=\left(\widehat{n}\left(v,\gamma,r\right)-1\right)\widehat{x}(v)$. For notational ease, denote $\widehat{a}=\widehat{a}\left(v,\gamma,r\right)$, $\widehat{n}=\widehat{n}\left(v,\gamma,r\right)$ and $\widehat{x}_i=\widehat{x}_i(v,\gamma,r)$.

First stage Substituting equations (5.41) and (5.42) and $\widehat{x}_i(v,\gamma,r)$ into equation (5.35) yields

$$W_i=\frac{vh(\widehat{x}_i\left(v,\gamma(\tau),r\right),\widehat{x}_{-i}\left(v,\gamma(\tau),r\right))-c\left(\widehat{x}_i\left(v,\gamma(\tau),r\right)\right)}{\widehat{a}\left(v,\gamma(\tau),r\right)+r} \tag{5.43}$$

For ease of notation, denote $h(\widehat{x}_i\left(v,\gamma,r\right),\widehat{x}_{-i}\left(v,\gamma,r\right))=\widehat{h}_i$. As before, we assume firm i does not internalize its impact on the discovery date via its own hazard rate. Thus, by setting τ, firm i affects its own R&D (by changing n which is a negative function of γ), which affects the expected discovery date (firm i takes $\widehat{a}$ as given and not as a function of $\widehat{h}_i$). Nonetheless, firm i realizes its impact on the discovery data through affecting the number of firms that participate in the patent race, $\widehat{n}$. Thus, firm i maximizes equation (4.42) with respect to τ, which yields the following first order condition[47]:

$$\frac{\partial W_i}{\partial\tau}=\frac{d\gamma}{d\tau}\left[\frac{v\mu}{\left(\widehat{a}+r\right)}\frac{\partial\widehat{x}_{-i}}{\partial\gamma(\tau)}-\frac{\left(vh_i-c_i\right)}{\left(\widehat{a}+r\right)^2}\frac{\partial\widehat{a}}{\partial\gamma(\tau)}\right] \tag{5.44}$$

Where, $\theta\left(v,\tau,r\right)\equiv\frac{\partial\widehat{h}_i}{\partial\widehat{x}_{-i}}$, which is the effect of the optimal R&D expenditures of firm i's rivals on the hazard rate of firm i (which we link to its ability to reabsorb its spilled knowledge, or alternatively, exploit the technological opportunities it creates).

Focusing on specifications that ensure an interior solution, it must satisfy equating the first order condition to zero:

[47]After substituting $\widehat{x}_i$ and $\widehat{x}_{-i}$ into equation (5.39), the envelope theorem implies that $v\frac{\partial\widehat{h}_i}{\partial\widehat{x}_i}-\frac{dc}{dx_i}=0$. Thus, the chain role in differentiating equation (5.43) with respect to τ involves only the terms $\frac{\partial\widehat{h}_i}{\partial\widehat{x}_{-i}}$ and $\frac{\partial\widehat{a}(v,\gamma(\tau),r)}{\partial\widehat{x}_{-i}}$.

$$v\theta\widehat{x}(v)\frac{\partial\widehat{n}\left(v,\gamma(\tau),r\right)}{\partial\gamma(\tau)}=\frac{(vh_i-c_i)}{\widehat{a}+r}\frac{\partial\widehat{n}\left(v,\gamma(\tau),r\right)}{\partial\gamma(\tau)}\widehat{h}(v) \tag{5.45}$$

Rearranging equation (5.45) yields the following condition for the optimal $\widehat{\tau}=\widehat{\tau}_i(v,r)$:

$$\frac{\theta\left(v,\gamma(\widehat{\tau}),r\right)}{g\left(v\right)}=W_i\left(v,\gamma\left(\widehat{\tau}\right),r\right) \tag{5.46}$$

Where, $g\left(v\right)\equiv\frac{\widehat{h}(v)}{\widehat{x}(v)v}$.

The total flows of knowledge outwards from firm i is determined by the number of rival firms in the patent race, which is given by $n^*\left(v,\gamma(\widehat{\tau}),r\right)-1$. Equation (5.46) shows that the ability of firm i to benefit from the knowledge spillovers it creates has a positive effect of the value of its innovation.

Theoretical implications and empirical predictions The theoretical implications of this model are summarized in equation (5.46). The ability of firm i to benefit from its own knowledge flows is given by θ which is the effect of external research, that builds on the prior knowledge of firm i, on its hazard rate function. Equation (5.46) indicates a positive relation between the innovation value of firm i and its ability to technologically exploit its spilled knowledge.

The empirical implication of this model is that we should find a positive effect of the ability of the firm to build on its own spillovers on the private value of its knowledge, under the assumption that firms internalize and optimize the spread of their discoveries. Thus, this model is complementary for the model we have presented in section 3, which does not assume any strategic behaviour of firms.

Chapter 6

Endogenous Knowledge Flows and Industry Evolution: A Theory of the Dynamic Incentive to Diffuse Knowledge

We study the implications of allowing the firm to internalize the feedback it receives from the spillovers its inventions create and affect the diffusion of its knowledge to the evolution of industries. We relate the incentive of a firm in a main industry to diffuse its knowledge to a positive production externality, which is the result of its desire to stimulate the development of an ancillary industry that imposes a constraint on the growth possibilities of the main industry. The negative incentive to diffuse knowledge relates to the loss of market share associated with spreading valuable knowledge to rival firms. We demonstrate the importance of studying the endogenous and strategic nature of knowledge flows by simulating one of the most crucial phases in the industry life cycle, which the literature refers to as industry 'shakeout', merely by studying the dynamics of the incentive to spread knowledge. Finally, we broaden the analysis of the effect of competition on innovation by considering the negative impact competition may have on the incentive to diffuse knowledge. We show that stronger competition can discourage innovation by diminishing spillovers, as a result of a lower incentive of firms to share their knowledge.

6.1 Introduction

The study of knowledge has been in the heart of economic research in the last three decades, due to its remarkable ability to diffuse and benefit innovators that have not invested resources in its creation. The large interest in knowledge as an engine for economic performance, in both micro and macro fields, is related to its public good characteristics and to the existence of spillovers. Numerous attempts were made to identify spillovers and to quantify their effect[1]. However, in studying the positive externality associated with knowledge, the literature has assumed knowledge flows are exogenous, i.e., the diffusion of knowledge to the economy does not depend on the strategic behaviour of its inventor in shaping the way it spreads throughout the economy[2]. This strong assumption has no support in reality. On the contrary, firms have many methods that allow them to manage the flows of their inventions, such as patents, secrecy and informal and formal knowledge transfer (such as formal patent licensing and informal coordinated publications of recent developments)[3].

This paper studies the endogenous nature of spillovers, by arguing that the inventor of knowledge internalizes the return it captures on the flows of its discoveries and strategically optimizes them. In the empirical part of this thesis we have examined the return an inventor receives from the diffusion of its knowledge *via* inspiring the ideas of others, which may feed back into its future research in a sequential innovation framework.

Nevertheless, in this chapter we will focus on a different source of return the inventor receives from the diffusion of its knowledge, which is evoked from the product market. By focusing on this source of strategic behaviour in the diffusion of knowledge, we hope to illustrate an interesting picture that will highlight the importance of the strategic nature of knowledge flows for explaining the effect of spillovers on the evolution of industries. For this purpose, we develop a dy-

[1]For surveys see Griliches (1992), Mairesse (1995), Hall (1996) and Keller (2001).

[2]However, a different strand of literature has related to the endogenous nature of knowledge spillover (e.g., Cohen and Levinthal, 1989), through conditioning the ability of firms to benefit from external research on their attempt to absorb this research (which is referred to as *absorptive capacity*). However, knowledge flows are still exogenous in this framework.

[3]See Chesbrough (2003), or the introduction to chapter 5 for examples for the strategic behaviour of firms in managing their knowledge flows.

namic model of strategic interactions, which we solve using dynamic programming numerical methods.

We focus on the effect of the dynamic incentives of firms to diffuse their inventions on the evolution pattern of industries. In particular, we study the remarkable phenomena of *producers 'shakeout'*, which industries experience during their life cycle. Producers 'shakeout' is documented mainly in Gort and Klepper (1982), Klepper and Graddy (1980) and Utterback (1975, 1978)[4]. The large interest in identifying the triggers of producers 'shakeout' is related to the crucial role this 'shakeout' plays in shaping industry structure as it evolves from birth to maturity.

The literature incorporates two different approaches for explaining producers 'shakeout'. The first approach is discussed mainly in Utterback (1975, 1978), Utterback and Suarez (1993) and in Klepper and Graddy (1990). This approach relates producers 'shakeout' to an exogenous technological progress that changes the competition conditions in the industry, which, in turn, affects the survival hazard of firms. This event usually occurs after the completion of the first phase of the industry evolution trajectory, in which there is intense product innovation and high entry. Once the exogenous technical change occurs, the technological opportunities change and the firms with higher learning capabilities and enhanced scale economics (due to being larger producers) can better exploit these new opportunities and become dominant, while the others are forced out of the industry.

A similar approach is discussed in Jovanovic and MacDonald (1994) who study a partial equilibrium model with a radical exogenous technological change that allows massive cost reduction for firms that shift to the new technology and force out of the industry firms that continue producing in the old-fashioned way.

The second approach is introduced in Klepper (1996)[5] who suggests a model, in which a drastic innovation occurs endogenously as a result of R&D. Firms are able to invest in either product or process innovation, while their decision is based upon the return to each type of investments. By investing in process innovation,

[4]See also Klepper and Miller (1995), Klepper and Simons (1999) and Jovanovic and MacDonald (1994).

[5]See also Klepper and Simons (2000).

firms which are endowed with randomly allocated capabilities, can lower their cost of production. Thus, larger firms derive a higher return on process innovation than smaller firms. Further, firms can attract new consumers who are willing to pay more for the product by investing in product innovation and improving the quality of their brand. As the industry grows, the incentive to invest in process innovation rather in product innovation increases, since cost reduction can be applied over a higher production. There exists a production threshold, such that, after reaching it firms stop investing in product innovation and coordinate their innovative efforts only towards process R&D. The producers 'shakeout' occurs at this stage, when firms that have failed to reach this threshold are forced out of the industry.

In this chapter, we offer a third approach for explaining producers 'shakeout'. At the early stages of the industry life cycle, the incentive to diffuse knowledge is strong, due to a desire to expand the market by encouraging the developments of crucial ancillary products, which constraint the growth of the main industry. This generates a positive production externality, which we refer to as a *market expansion effect.* Strong spillovers (due to the desire of firms to diffuse knowledge) at the early stages of the industry life cycle allows entry of firms with low innovative capabilities, whose survival is conditioned on their being able to access external knowledge (i.e., exploit spillovers). As the industry matures and the ancillary products develop, the constraint that these products impose on the growth of the main industry relaxes, causing a reduction in the incentive to share knowledge, until reaching a point where firms find it optimal to prevent the flow of their inventions. At this stage in the industry life cycle, spillovers fall, triggering producers 'shakeout' that is characterized by a mass exit of low-capability firms that find it too hard to survive without enjoying larger spillovers.

In order to better empathize the importance of the endogenous nature of knowledge flows to the evolution of industries, it is useful to look at the early years of the US automobile industry and at the famous *Selden patent.* Selden was the first to invent the highway vehicle gasoline engine and applied for a patent in 1879. In that time, patents laws allowed for a large delay between the application date and the issue date of a patent. Selden exploited this law to delay the issue of his patent for

16 years after his initial application[6]. The deliberate delay in the patent issue was due to the fact that the automobile industry in the United States was not developed enough to allow capturing a substantial return on this discovery. Eventually, Selden was forced to sell his patent to a group of Wall-Street investors who used this patent as a monopoly power on the gasoline engine automobile industry.

The monopoly power this patent created led to the formation of the Association of Licensed Automobile Manufacturers (ALAM) in 1903. Entry into the US automobile was not possible in the absence of a license from the ALAM. The most famous producer who was not granted a license to enter the US automobile industry was Henry Ford. Although Ford did not believe in patents, he tried to get a license from the ALAM and was refused on the grounds of not having demonstrated sufficient ability for producing automobiles. Ford and others decided to fight the patent against the ALAM. The battle had dragged in courts for many years until 1911, when the Circuit Court of Appeals found that the Selden patent did not cover the new technology that was in possession at that time. This was the end of the ALAM and the beginning of the mass production era in the US automobile industry that put Ford as the leading manufacturer.

Thus, the Selden patent is an important example for the endogenous nature of knowledge flows and for the ability of firms to control the access of other firms to their inventions (in the Selden patent case this was done formally *via* granting a license). Avoiding studying the strategic behaviour of firms in managing their knowledge flows, will prevent us from illustrating a more complete and a more reliable picture of the evolution of knowledge-based industries, as the evolution pattern the US automobile experienced in its early development stage.

In addition to studying the effect of endogenous knowledge flows on the dynamics of industry structure, we aim to address the effect of competition on innovation. Previous studies in the literature have argued that there is a negative effect of competition on innovation[7], due to a reduction in the return to R&D as the degree of

[6]The patent was eventually granted in November, 5, 1895, and registered as a United States patent number 549160.

[7]E.g., Dasgupta and Stiglitz (1980).

competition increases. Alternatively, recent studies have argued that the effect of competition on innovation is not monotonic, but rather shaped as an inverted U[8].

In this paper, we offer an alternative analysis of the effect of competition on innovation, which also includes the effect of competition on the incentive to diffuse knowledge. Thus, as the degree of competition rises, firms become more reluctant to spread their discoveries, causing a reduction in spillovers that results in a reduction in the incentives to innovate. Hence, we argue that there exists another channel by which competition affects innovation, which is the effect of competition on the social return to innovation, *via* shaping the strategic component in the diffusion of knowledge.

Furthermore, we show that high innovation can be achieved as an equilibrium outcome in highly competitive industries, due to large spillovers when the incentive to diffuse knowledge is high. Nonetheless, high innovation cannot be supported as an equilibrium outcome in highly competitive industries, when the incentive to share knowledge is low.

In conclusion, this paper is a theoretical attempt to emphasize the importance of studying the strategic behaviour of firms in managing the flow of their knowledge. We will demonstrate the importance of the endogenous nature of knowledge flows by illustrating that one of the most important events in the industry life cycle, producers 'shakeout', can be explained merely on the basis of the dynamics of the incentive of firms to allow their knowledge to spill to others. Moreover, we will demonstrate that by investigating the incentives of firms to diffuse knowledge we can reassess and broaden the analysis of the effect of competition on innovation.

The rest of this chapter continues as following: section 2 provides a motivation for the theoretical model, section 3 presents the building blocks of the model, section 4 describes the dynamic game, section 5 presents the computational methodology, section 6 reports the findings and section 7 concludes.

[8] See Levin, Cohen and Mowary (1985) and Aghion, Bloom, Blundell, Griffith and Howitt (2002).

6.2 Motivation

The model we develop in this chapter allows firms to optimize the diffusion of their inventions. Based on their expected pay-offs, firms decide whether to make their discoveries available to their rivals or keep them to themselves. The dynamics of the incentives to share or protect knowledge and their effect on innovation are explored, as the industry evolves from birth to maturity.

In deciding whether to make its knowledge publicly available, the firm has to reconcile the following trade-off: by diffusing knowledge to its rivals, the firm loses the competitive advantage its knowledge generates. This encourages the firm to prevent the spread of its knowledge. Nevertheless, the firm can benefit from spreading its knowledge to its rivals. In this chapter, we link the benefits from spreading knowledge to a *market expansion effect*, which is the increase in the size of the market as a response to an increase in the aggregate production. This effect is the result of a positive production externality, such that by increasing the production of its rivals, the firm benefits from a higher demand for its product.

We model the source of this production externality in the following manner: in consuming a core product (e.g., an automobile), consumers must purchase an ancillary product (e.g., fuel). In order to increase the demand it faces, the firm can stimulate improvements in the ancillary product, which will raise the attractiveness of the core product in the eyes of the consumers. Improving the ancillary product is a costly process that can be made only by the ancillary firms that invest in R&D. This investment depends on the demand for the ancillary product, which defines the expected return on a successful R&D. Therefore, by increasing its production, the firm in the core industry also increases the aggregate demand for the ancillary product, which encourages the ancillary firms to invest in R&D. The improvement in the quality of the ancillary product increases the market for the core product, which yields the positive feedback firms receive from diffusing their knowledge.

In order to motivate this issue further, it would be useful to re-examine the early development of the US automobile industry. The evolution of this industry is characterized by a great influence on ancillary industries, whose developments were crucial for the continuing growth of the automobile industry. The main industries that were affected by automobiles production were steel, petroleum, tires and oil.

The steel industry had changed its course of production by investing in new machinery that allowed for the development of the products demanded by the automobile manufacturers (such as processing alloy steel). Similarly, the petroleum industry was revolutionized. Before 1900, only about one-tenth of the petroleum refined had been converted into gasoline. Gasoline was regarded as an undesirable waste product. This situation dramatically changed as the production of automobile started to rapidly rise. Furthermore, the rise in the demand for gasoline caused great increase in crude-oil production, so that total production rose from 60 million barrels in 1900 to 250 million in 1910. The production of tire and rubber had also been highly affected by the growth of the automobile industry. The high demand for tires encouraged firms in the tire industry to conduct intensive R&D to lower the production costs and to increase the quality of their product[9].

The development of the ancillary industries was crucial for the development of the automobile industry, since these ancillary products imposed a constraint on either the ability to produce automobiles (e.g., alloy steel) or the desire of the consumers to purchase them (e.g., fuel). In the model we present in this chapter, firms in a core industry internalize the constraint an ancillary product imposes on the demand they face, while they strategically aim to relax this constraint through shaping the spillovers their knowledge creates.

[9]See Klepper and Simons (2000) and Klepper (1996) for an analysis of the evolution of the US tire industry.

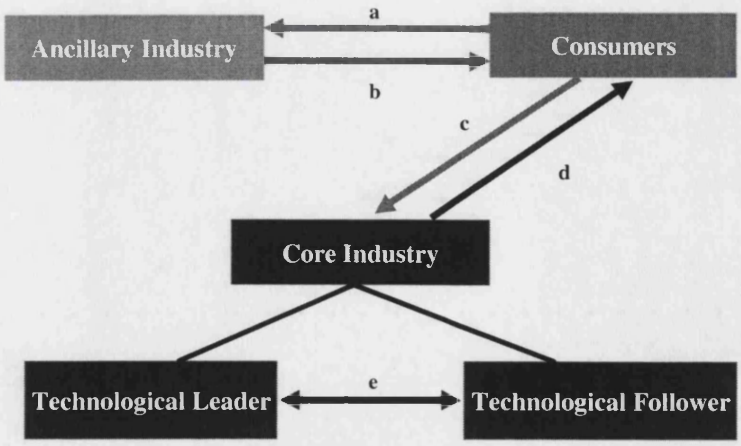

Figure 1: The interactions in the model

Figure 1: *Arrow a describes the effect of the consumers on the ancillary industry. The consumers buy the ancillary product whenever they decide to purchase the core product (e.g., assume the core product is an automobile and the ancillary product is fuel, thus, the consumer must purchase fuel when she decides to purchase an automobile). Arrow b describes the effect of the ancillary industry on the consumers through determining the quality of the ancillary product. Arrow c reflects the fact that consumers purchase the core product. Arrow d describes the effect of the core industry on the consumers, through determining the quality and the price of the core product. Arrow e represents the interaction between the two brands in the core industry. This interaction includes the static Cournot game of setting prices and quantities, and the dynamic game through R&D and knowledge diffusion strategies. The positive return to diffusing knowledge is governed by the fact that by encouraging the improvement of the quality of the other brand, the aggregate production of the core product increases. This increases the demand for the ancillary product, which stimulates its R&D. An increase in the quality of the ancillary product then raises the demand for the core product.*

Figure 1 illustrates the interactions among the players in the model. In consuming the core product, consumers must purchase the ancillary product as well, which is represented by arrows c and a. The ancillary firm affects the consumers by determining the quality of the ancillary product (for simplicity, we assume that the price of the ancillary product is given), which is represented by arrow b. Similarly, firms in the core industry can affect the consumers by determining the price and quality of the core product, which is represented by arrow d. We assume there are two brands in the core industry: a technological leader and a technological follower. The interaction in the core industry is taking place only between brands (thus, firms in the same brand are homogenous and do not interact with other firms in the same brand). The interaction within the core industry between the two brands includes product market competition and interaction in R&D and knowledge diffusion. Both firms decide upon their optimal level of R&D, however, firms in the technological leader brand also decide whether to share their knowledge with firms in the technological follower brand (for simplicity, we assume knowledge cannot flow from the technological follower to the technological leader). The interaction between the two brands is represented by arrow e.

The market expansion effect, which governs the positive incentives to transfer knowledge from the technological leader brand to the technological follower brand, is represented by arrows $d \rightarrow a$ and $b \rightarrow c$. Thus, the technological leader brand internalizes the fact that by increasing the quality of the technological follower brand, the consumers will raise their demand for the core product (arrow d) and, therefore, they will also raise their demand for the ancillary product, since they must purchase the ancillary product together with core product (arrow a). When the ancillary industry faces a surge in demand, its incentive to innovate increases. Thus, the quality of the ancillary product increases (arrow b), which raises the demand for the core product (arrow c).

If the ancillary product is of low quality, firms in the core industry will face strong incentive to encourage its development, since it imposes a strong constraint on the growth opportunities of the core industry. As the quality of the ancillary product increases, this constraint relaxes, implying less incentive to share knowledge. Strong spillovers at the early stages of the industry life cycle allows firms with low innovative capabilities to enter the technological follower brand. As the industry evolves, the incentive to diffuse knowledge weakens, until firms decide to prevent the flow of their knowledge, which eliminates spillovers. This triggers producers' 'shakeout' which is characterized by mass exit of firms whose survival was conditioned on their ability to rely on external research, which is no longer available.

Finally, our focus in this model is only on non-cooperative knowledge sharing between firms. Thus, we focus on an equilibrium in which firms are not allowed to collude in research or in production. Since we focus on the early stages of the life cycle of industries, we find it less likely that this strategic behaviour will take place. In future work, we plan to extend our framework to allow firms to formally affect the diffusion of their discoveries, such as forming research joint ventures, cross-licensing agreements and etc.

6.3 The model

We consider an infinite horizon interaction game between firms in a core industry for a differentiated product with two brands, a firm in an ancillary industry and consumers who purchase products from both industries. The main focus is on the dynamics of the incentive to diffuse knowledge and to invest in R&D in the core industry, which underpins its evolution pattern.

In this section, we introduce the building blocks of the model, which include firms and consumers primitives and the basic set-up of the dynamic game.

6.3.1 Building blocks

The consumers

There are M consumers in the economy that allocate their income between product C (the core product), product A (the ancillary product) and product Z (an outside product). Each consumer is assumed to purchase one unit of a unique brand of product C, which must be consumed with $\varphi(\tau)$ units of product A, where $\varphi'(\tau) < 0$ and τ is the efficiency level of using product A in the consumption of product C (e.g., consider product C as an automobile and product A as fuel, so that $\varphi(\tau)$ denotes the number of gallons consumed per mile, or alternatively, consider product C as the printers industry and product A as the tuner ancillary product, where $\varphi(\tau)$

denotes the number of papers printed, using one package of tuner). The consumer does not derive direct utility from purchasing the product A. Finally, the consumer uses the rest of her income on product Z. We disregard savings and consumers' preference dynamics, i.e., consumers maximize each period a static utility function under their intra-temporal budget constraint.

We consider a model with two brands of product C, denoted by l and f. We denote the two brands by $c \in \{l, f\}$. These brands differ in the quality of their h attributes. Let $q_c = (q_{c1}, ..., q_{ch})$ be brand c attributes' quality vector. Define $u_c(q_c) = u_c\left(u_{c1}(q_{c1}), ..., u_{ch}(q_{ch})\right)$ as the value the consumer places on each brand as a function of its attributes' quality, where, $u'_{cm}(q_{cm}) \geq 0, \forall m \in \{1, ..., h\}$. Further, let $\omega_c = \omega_c(\omega_{c1}, ..., \omega_{ch})$ be the vector of knowledge stock indices that is associated with the vector of attributes' quality, e.g., ω_{cm} denotes the level of knowledge needed to produce an attribute with a quality level m. Hence, we can rewrite consumers' utility from consuming brand c as $u_c\left(q_c(\omega_c)\right) = u_c\left(u_{c1}\left(q_{c1}(\omega_{c1})\right), ..., u_{ch}\left(q_{ch}(\omega_{ch})\right)\right)$, where, $q'_{cm}(\omega_{cm}) > 0$, $\forall\ m \in \{1, ..., h\}$. Thus, the utility of consuming product C can be simply described as $u_c(\omega_c) = u_c\left(u_{c1}(\omega_{c1}), ..., u_{ch}(\omega_{ch})\right)$ with $u'(\omega_{cm}) \geq 0$, $\forall$ $m \in \{1, ..., h\}$.

We have followed the literature on discrete choice[10] to characterize the maximization problem of the consumer by the following two stages: at the first stage, the consumer chooses the portion of her income which is devoted to product C and product Z, while at the second stage, she chooses the unique brand of product C. The consumer is assumed to maximize the following random utility function under her budget constraint:

$$\max_{Z,,c\in\{l,f\}} U_i = U\left(u_c(\omega_c), \varphi(\tau), Z\right) + \epsilon_i \quad ; \quad s.t. \quad p_c + \varphi(\tau)p_A + Z = Y \tag{6.1}$$

Where, ϵ_i is an independently and identically distributed random disturbance that represents the heterogeneity of consumers tastes for $i \in M$, $u(c)$ is the utility the consumer derives from consuming brand c (which depends on the quality of

[10]See McFadden (1981) and Small and Rosen (1981).

brand c), p_c is the price of brand c, p_A is the price of the ancillary product A, the outside product's price is normalized to unity and Y is the income. The consumption decision of product A is already embodied in the consumption decision of the core product C, which depends on $\varphi(\tau)$ (which is exogenous to the consumer). Since consumers maximize a random utility that depends on the distribution of consumers' tastes, the demand function is probabilistic.

The consumer is assumed to purchase one unit of product C, therefore, she spends the amount of $Z = Y-\ p_c\ -\varphi(\tau)p_A$ on the outside good. Substituting Z into equation (6.1) and assuming ϵ_i follows a type I extreme-value (or Weibull) distribution, utility maximization yields the following probability that brand c will be consumed:

$$\sigma_c = \frac{\exp(V_c)}{1+\exp(V_l)+\exp(V_f)} \tag{6.2}$$

Where, V_c is the deterministic component of the indirect utility function, which we assume to be linear in Y, p_c and $\varphi(\tau)P_A$. Thus, equation (6.2) becomes

$$\sigma_c = \frac{\exp\left(u(c)-p_c-\varphi(\tau)p_A\right)}{1+\sum\limits_{k=l,f}\exp(u(k)-p_k-\varphi(\tau)p_A)} \tag{6.3}$$

Hence, σ_c is the market share of brand c (with $\sigma_l+\sigma_f+\sigma_Z=1$, where σ_Z is the market share of the outside product Z).

6.3.2 The Core Industry

Two brands of product C are offered to consumers in the core industry. We assume the first brand is technological inferior to the second. Denote the technological leading brand by l and the technological inferior brand by f. The knowledge stock indices that are required for the production of each brand are given by the vector $\omega = \omega(\omega_l, \omega_f)$. Denote by n_l the number of firms that produce brand l and by n_f the number of firms that produce brand f. For simplicity, we impose symmetry among firms in the same brand and focus the analysis on inter-brand interaction. The symmetry assumption implies that firms in the same brand hold identical knowledge, so that ω does not depend on n_l and n_f.

Given this set-up, firms aim at maximizing their infinite discounted expected cash-flows. This maximization problem involves solving two steps; (1) maximizing the current period static profits and (2) computing the optimal expected discounted pay-offs using the inter-temporal strategies. We proceed by describing the behaviour of firms in each step.

Intra-temporal strategies

The intra-temporal strategies are those that aim at maximizing the profits of the firm in the current period. We characterize the static equilibrium in the product market as one that is achieved through a Nash-Cournot game between a single representative firm from each brand type. Caplin and Nalebuff (1991) show that in a market with a bounded set of active brands, no fixed costs of production, constant marginal costs equal to mc and firms choose prices to maximize profits, a unique Nash equilibrium exists and satisfies the following vector of first order conditions:

$$[-p_c - mc]\,\sigma_c\,[1 - \sigma_c] + \sigma_c = 0 \tag{6.4}$$

Where, σ_c is calculated from equation (6.3). The profits are then given by

$$\pi_c(\omega, \tau) = M\sigma_c(\omega, \tau)\,[p_c - mc] \tag{6.5}$$

Equation (6.5) is the current period pay-offs for each brand, given the knowledge stocks ω and τ.

Finally, in each period firms decide on whether to remain active or leave the industry. We assume there is free entry to each brand with fixed-costs that are proportional to the knowledge stock in that brand. Thus, the fixed-costs of production in every period are equal to $\kappa\omega_{tc}^2$, where, the index t represents the period of entry. The free-entry condition implies that the number of active firms in each brand in every period is given by

$$\widehat{n}_{tc} = \frac{\widehat{V}_{tc}}{\kappa\omega_{tc}^2} \tag{6.6}$$

Where, $\widehat{V}_{tc}$ is the post-entry value of brand c (net of fixed-costs) at period t.

Inter-temporal strategies

The inter-temporal strategies of firms include the decisions they have made at the current period, but will affect their value in the next period. These strategies are R&D investment (for both firms) and knowledge diffusion (which is relevant only for brand l, as described below). A firm can increase its knowledge stock by investing in a risky R&D, which is denoted by x. The future period knowledge stock evolves as following (we have omitted the brand index for convenience):

$$\omega_{t+1} = \omega_t + \zeta_t - \varrho_t \tag{6.7}$$

Where, ω_{t+1} is the knowledge stock next period, ζ_t is the R&D stochastic output that receives the value 1 with probability $P(\zeta_t = 1|x_t)$ and zero with probability $P(\zeta_t = 0|x_t)$, for $x_t \in R_+$, and ϱ_t is an exogenous aggregate shock that hit the core industry with probability δ. Thus, ϱ_t receives the value 1 with probability δ and zero with probability $1-\delta$. The evolution process of the knowledge stock ω is summarized as following:

$$\begin{aligned}
P(\omega_{t+1} &= \omega_t) = P(\zeta_t = 1|x_t)\delta + P(\zeta_t = 0|x_t)\,(1-\delta) \\
P(\omega_{t+1} &= \omega_t + 1) = P(\zeta_t = 1|x_t)\,(1-\delta) \\
P(\omega_{t+1} &= \omega_t - 1) = \ P(\zeta_t = 0|x_t)\delta
\end{aligned}$$

Where, the probability for a successful R&D is given by:

$$P(\zeta_t = 1|x_t) = \frac{\alpha x_t}{1+\alpha x_t} \tag{6.8}$$

Where, α represents the productivity of the innovation efforts of the firm. I assume α is constant and equals for both brands. In addition, brand l can affect the R&D investment in brand f by choosing to diffuse knowledge. Knowledge externalities are modelled as the effect of the knowledge of brand l on the R&D cost of brand f. This effect exists only if brand l allows its knowledge to spread to brand f. The R&D cost of brand l is denoted by γ_l, while brand f faces the following R&D cost, which depends on the knowledge stock of brand l and on the decision on whether to allow this knowledge to spread to brand f,

$$c_f = f\left(\gamma_f, \theta_l\omega_l\right) \tag{6.9}$$

Where, γ_f is a constant component of the innovation cost of brand f , with $\frac{\partial c_i}{\partial \gamma_i} > 0$, and $\theta_l\omega_l$ denotes knowledge externality, with $\frac{\partial c_f}{\partial(\theta_l\omega_l)} \leq 0$. θ_l is an indicator that receives the value 1 if brand l chooses to diffuse its knowledge and zero otherwise. Thus, $\frac{\partial c_f}{\partial(\theta_l\omega_l)} < 0$ if $\theta_l = 1$ and $\frac{\partial C_f}{\partial g(\theta_l\omega_l)} = 0$ if $\theta_l = 0$. The underlying assumption is that a firm can completely prevent its knowledge from drifting outside its boundaries. Although this is a strong assumption, the theoretical implications are robust for relaxing it, on the expense of further complicating the model[11].

6.3.3 The Ancillary Industry

The ancillary industry produces the product A which is consumed together with the product of the core industry, C. There is a single producer, denoted by subscript a. This producer is engaged in production and in R&D, which aims at advancing the ancillary knowledge stock, denoted by τ.

The future period knowledge stock evolves as following:

$$\tau_{t+1} = \tau_t + \zeta_{at} \tag{6.10}$$

Where, τ_{t+1} is the next period knowledge stock , ζ_{at} is the current period R&D stochastic output that receives the value 1 with probability $P(\zeta_t = 1|x_{at})$ and the value zero with probability $P(\zeta_t = 0|x_{at})$ for $x_{at} \in R_+$. For simplicity, we assume that the exogenous negative shock ϱ, does not directly affect the ancillary industry. Thus, the evolution process of the knowledge stock τ is given by

$$\tau_{t+1} = \begin{cases} \tau_t\,; & P(\zeta_t = 0|x_{at}) \\ \tau_t + 1; & P(\zeta_t = 1|x_{at}) \end{cases} \tag{6.11}$$

Where, the probability of a successful innovation is given, as in the core industry, by

[11] Nonetheless, the results will not be robust if we assume asymmetric information with regard to actual knowledge flows, i.e., if firm i believes it has a full control on its knowledge flows, where it does not fully control them. This relates to the idea discussed in Spence (1984).

$$P(\zeta_{at} = 1|x_{at}) = \frac{\alpha x_{at}}{1 + \alpha x_{at}} \tag{6.12}$$

Although the ancillary industry is governed by a single monopoly, we assume there is a constant threat of entry. In order to simplify the dynamics of the game, the price of the ancillary product remains constant over time. This allows for a clearer focus on the dynamics in the core industry, which is the main concern of this chapter.

Hence, we are interested in studying the effect of improving the quality of the ancillary good on the incentives to share knowledge in the core industry. If the ancillary price is allowed to shift with industry dynamics, identifying this desired effect would become more difficult. Therefore, despite being a monopoly, firm a cannot set the optimal monopolistic price, since it may collapse the entry barriers. Denote by p_a the highest price the incumbent can charge so as to support entry deterrence. The incumbent profits are then given by

$$\pi_a(\omega, \tau) = D(\omega, \tau)(P_a - mc_a) \tag{6.13}$$

Where, $D(\omega, \tau)$ is the demand facing firm a, which depends to the aggregate production in the core industry (e.g., the demand for fuel is a function of the number of automobiles produced and the fuel consumed per an automobile) and mc_a is the marginal cost of producing the ancillary product. The demand facing the ancillary industry is[12]

$$D(\omega, \tau) = M\left(\sigma_l\left(\omega, \tau\right) + \sigma_f\left(\omega, \tau\right)\right)\varphi(\tau) \tag{6.14}$$

The role of the ancillary industry in shaping the dynamics of the core industry relates to its effect on the incentive of brand l to share its knowledge with brand f. The ancillary firm invests in R&D in order to increase the demand for its product,

[12]Note the demand facing the ancillary firm can be either a positive or a negative function of τ. By raising the quality of the ancillary product, the demand for automobile increases and, therefore, the demand for the ancillary product increases as well. However, by raising τ, the number of units the consumers purchase of the ancillary product falls, when buying the core product. Thus, this causes a negative effect of raising τ on the demand facing the ancillary firm. We assume the former positive effect is stronger than the latter negative effect, implying that the R&D of the ancillary firm will always increase the expected demand it faces.

by encouraging the demand for the core industry (note that consumers do not derive a direct utility from consuming the product A). Thus, higher demand for automobiles encourages the ancillary R&D, since the expected return to this R&D rises with the demand for the ancillary product. Internalizing this effect, brand l can increase the demand for the ancillary product by spreading its knowledge to brand f. An improved ancillary product makes the core product more attractive to consumers and, therefore, raises the market share of the core product relative to the market share of the outside product Z.

6.4 The dynamic game

The dynamic game solves for the optimal R&D investment of brand l, brand f and the ancillary firm a, in addition to the knowledge diffusion decision of brand l. The model is too complex to be solved analytically, thus numerical methods for dynamic programming are used. We have adopted the framework developed by Ericson and Pakes (1995) and Pakes and McGuire (1994). This framework provides an algorithm (which we refer to as EP) to compute a Markov-Perfect Equilibrium (MPE), which we have adjusted in order address the ideas developed in this chapter.

Several papers extended the EP framework to account for changes in the static profit function, dynamic demand, mergers and multiple states per-firm. Fershtman and Pakes (2000) provide a theoretical analysis of a dynamic game with collusive prices that allows current price to depend on past prices. Benkard (2000) analyzes a model of learning by doing with a dynamic cost function. Markovich (1998) provides a theoretical analysis of a market with hardware-software connections, while Byzalov (2002) provides a model of the OPEC cartel with dynamic demand for oil commodities. Gowrisankaran and Town (1997) study profit and non-profit hospitals, and investigate the impact of health policy changes on the evolution of the hospital industry.

In this chapter, we focus on Markov strategies as defined by Maskin and Tirole (1988), which are analysed in a sub-game perfect equilibrium only as a function of the relevant state pay-offs (by this, the enormous multiplicity that arises in dynamic models of this type is eliminated), and in which players' expectations coincide with the actual distribution of the random variables in the model.

In particular, the strategies depend on the state space $\{\omega_l, \omega_f, \tau\}$. Knowledge diffusion is the strategy $\theta_l(\omega_l, \omega_f, \tau)$, R&D investment is the strategy $x_c(\omega_l, \omega_f, \tau)$, prices in the core industry is the strategy $p_c(\omega_l, \omega_f, \tau)$, entry is the strategy $\chi_c(\omega_l, \omega_f, \tau)$ and exit is the strategy $\psi_c(\omega_l, \omega_f, \tau)$. Finally, for firm a, the R&D investment is the strategy $x_a(\omega_l, \omega_f, \tau)$.

Firms maximize their discounted value conditional on expected industry structure. We focus on the dynamic interactions between firms in the core industry and between these firms and the ancillary industry. An outline of the dynamic game is as following:

- Firms in the core industry face a demand which is a function of their knowledge stock ω and the ancillary knowledge stock τ.

- The core industry realizes its ability to increase the aggregate demand for product C by raising the incentives of the ancillary industry to invest in R&D, in order to advance its knowledge stock τ. This will affect the consumers' income allocation in favour of product C rather than the outside product Z. The relation between core and ancillary industries creates a positive production externality in the core industry. Thus, by increasing its production, a firm in the core industry positively affects the demand facing the other firms in the core industry, via encouraging the improvement in the quality of the ancillary product. We refer to this externality as the *market expansion effect*, which creates the positive incentive for firms in brand l to share their knowledge with firms in brand f. Thus, although the diffusion of their knowledge erodes their market share, this effect can be offset by the positive production externality that stimulates the growth of the market. The exhaustion of the market expansion effect reduces the incentives to share knowledge, to a point where firms decide to prevent the spread of their inventions. This triggers the producers 'shakeout', which is in the focus of this research.

- The ancillary firm maximizes its expected discounted value by investing in R&D. The demand for the ancillary product depends on the aggregate production in the core industry (e.g., consider the automobile industry as industry C and the rubber industry as ancillary industry A. The demand for rubber depends on the number of automobiles produced in the core industry).

6.4.1 Sequence of events and information structure

Each period is a five-stage game, which is characterized by the following actions and events: at the beginning of the period, firms realize the current period states $\{\omega_l, \omega_f, \tau\}$. Further, the number of active firms in each brand is determined based on the free entry condition and the fixed-costs, as described in the previous section[13].

At the first stage, brand l decides whether to protect or diffuse its knowledge to brand f, denoted by $\theta_l(\omega_l, \omega_f, \tau)$, based on the expected pay-offs from each strategy. Following this decision, spillovers exist if $\theta_l(\omega_l, \omega_f, \tau) = 1$ and does not exist if $\theta_l(\omega_l, \omega_f, \tau) = 0$.

At the second stage, brand f determines its R&D (while the R&D cost is determined based on the knowledge diffusion decision of brand l from the previous stage).

Following this and prior to the third stage of the game, the realization of the R&D of brand f and the negative aggregate exogenous shock takes place. Thus, the knowledge stock of brand f in the next period is revealed (however, the knowledge stock will be adjusted only in the next period).

Based on these realizations, brand l chooses its level of R&D. Following this decision and before the forth stage of the game, a realization of the R&D of brand l takes place.

At the forth stage, the ancillary firm sets its R&D. Finally, in the fifth stage, product market competition between brand l and brand f takes place, where prices and quantities are determined in a Cournot game.

[13]We do not consider entry and exit as the first stage of the game, since it does not affect the solution methodology.

6.4.2 Defining the Equilibrium

We define the equilibrium using the value function approach (Starr and Ho 1969) as a Markov Perfect Equilibrium. The *MPE* is defined as the set of strategies

$$\begin{bmatrix} x_c(\omega_l, \omega_f, \tau), \theta_l(\omega_l, \omega_f, \tau), p_c(\omega_l, \omega_f, \tau), \\ \chi_c(\omega_l, \omega_f, \tau), \psi_c(\omega_l, \omega_f, \tau), x_a(\omega_l, \omega_f, \tau) \end{bmatrix}$$

and value functions $\{V_c(\omega_l, \omega_f, \tau), V_a(\omega_l, \omega_f, \tau)\}$. In equilibrium, the strategies of each player are optimal, given the value functions, and the value functions of the firms are equal to the actual continuation values when all firms follow their optimal strategies.

Solving for the MPE and defining the value functions

We solve the model in backward induction following the sequence of events that is described above. For each sub-game we define the relevant value function, which is maximized with respect to the relevant policies.

In the following presentation we denote the perfect-equilibrium of the game with $\hat{}$ and by $\tilde{}$ a sub-game equilibrium[14]. Further, we denote by ω the vector of knowledge stock of brands l and f in the current period, and by ω' the vector of knowledge stock of these brands in the following period.

Fifth stage At the last stage of the game the intra-temporal pay-offs are determined according to equations (6.3), (6.4) and (6.5). Denote by $\widehat{\pi}_c(\omega, \tau)$ and $\widehat{\pi}_a(\omega, \tau)$ the equilibrium profits of firms in the core industry and in the ancillary industry, respectively. Since, at this stage, firms maximize their current pay-offs, there is no associated value function.

Fourth stage At this stage, the ancillary firm already knows the next period knowledge stock states of brands l and f. Thus, the state space is given by (ω, ω', τ).

[14] A perfect equilibrium in this model is an optimal strategy that does not depend on the behavior of firms in the other stages of the game (thus, it is defined only as a function of the state variables and not as the control variables). A strategy which is a sub-game equilibrium depends on the behavior of firms in the previous stages of the game (the strategy is a function of both the state and control variables)

The value function of the ancillary firm is maximized with respect to its R&D spending, x_a, and is given by

$$V_a(\omega, \omega', \tau) = \max_{x_a} \left[\ \widehat{\pi}_a(\omega, \tau) - \gamma_a x_a + \beta \sum_{\tau'} V_a(\omega', \tau') P(\tau' | \tau, x_a) \ \right] \qquad (6.15)$$

Denote by $\widehat{x}_a(\omega, \omega', \tau)$ the optimal policy of the ancillary firms and by $\widehat{V}_a(\omega, \omega', \tau)$ its corresponding optimal value. Note that the information structure and sequence of events imply that at this stage, the future knowledge stocks of brand l and f are already revealed.

Third stage At the third stage, brand l determines its optimal R&D expenditures, after realizing the R&D output of brand f. Thus, the state space is given by $(\omega, \omega'_f, \tau)$.

$$V_l(\omega, \omega'_f, \tau) = \max_{x_l} \left[\begin{array}{c} \widehat{\pi}_l(\omega, \tau) - \gamma_l x_l + \\ \beta \sum_{\omega', \tau'} V_l(\omega', \tau') P(\omega'_l | \omega_l, x_l) P(\tau' | \tau, \widehat{x}_a(\omega, \omega', \tau)) \end{array} \right] \qquad (6.16)$$

Denote by $\widehat{x}_l(\omega, \omega'_f, \tau)$ the optimal R&D policy for brand l and by $\widehat{V}_l(\omega, \omega'_f, \tau)$ its corresponding optimal value. Note that at this stage, the future knowledge stock of brand f is already known, hence, the optimal policy and value are derived for every possible realization of brand f's R&D and the aggregate shock (where, for every possible realization, the necessary adjustments are made in the transition probabilities of brand l's knowledge stock[15]). Therefore, the value of brand l is a function of the future knowledge stock of brand f.

Second stage At the second stage, brand f chooses its optimal R&D based on expectations regarding the future knowledge stock of brand l and the ancillary firm. Thus, the relevant state space at this stage is (ω, τ). Further, the value function depends on the knowledge diffusion decision of brand l, which takes place at the first stage.

[15]More details are provided in the next section, where the computation algorithm is described.

$$V_f(\omega,\tau)=\max_{x_f}\left[\begin{array}{c}\pi_f(\omega,\tau)-c_f\left(\gamma_f,\theta_l\omega_l\right)x_f+\beta\sum_{\omega',\tau'}V_f(\omega',\tau')\\ P(\omega'_f|\omega_f,x_f,\theta_l\omega_l)P(\omega'_l|\omega_l,\widehat{x}_l(\omega,\omega'_f,\tau))P(\tau'|\tau,\widehat{x}_a(\omega,\omega',\tau))P(\varrho)\end{array}\right] \tag{6.17}$$

Denote by $\widetilde{x}_f(\omega,\tau;\theta_l)$ the optimal R&D policy for brand f and by $\widetilde{V}_f(\omega,\tau;\theta)$ the corresponding optimal value in the sub-game as a function of θ_l, which is to be determined at the first stage of the game. The optimal policy $\widetilde{x}_f(\omega,\tau,\theta_l)$ is the best response function of brand f's R&D to the knowledge diffusion decision of brand l.

First stage At the first stage, brand l decides whether to diffuse its knowledge to brand f. The decision rule is given as following:

Set $\theta=1$ iff

$$\sum_{\omega'_f}\widehat{V}_l(\omega,\omega'_f,\tau)P(\omega'_f|\omega_f,\widetilde{x}_f(\omega,\tau;\theta_l=1))>\sum_{\omega'_f}\widehat{V}_l(\omega,\omega'_f,\tau)P(\omega'_f|\omega_f,\widetilde{x}_f(\omega,\tau,\theta_l=0)) \tag{6.18}$$

And set $\theta=0$ otherwise. Brand l will decide to diffuse its knowledge if its expected value for setting $\theta=1$ (the lhs of inequality (6.18)) is greater than its expected value for setting $\theta=0$ (the rhs of (6.18)). The expectations are taken over brand f's next period knowledge stock. If an increase in brand f's knowledge stock is beneficial for brand l (due to the positive market expansion effect) it chooses to support the R&D of brand f. Nevertheless, in case increasing the knowledge of brand f is not desirable for brand l, it will discourage the innovation efforts of brand f by eliminating spillovers.

Finally, the number of firms in each brand is determined following equation (6.6).

6.5 Computation Methodology

Proof that an equilibrium exists for this model is straightforward and is essentially identical to the proof in Ericson and Pakes (1995). It is not possible to solve for the MPE of the model analytically. However, numerical methods can be used. Pakes and McGuire (1994,1997,2000) provide two algorithms that can be used to solve this model: the first is the asynchronous parallel Guass-Seidel value iteration algorithm and the second is the synchronous (stochastic) algorithm which is based on the artificial intelligence literature. We have used an augmented version of the Pakes-McGuire (1994) asynchronous algorithm, with extensions to asymmetric value functions and internalizing knowledge externalities.

The algorithm iterates in order to find a fixed-point solution to the dynamic programming described above. When the value function does not change very much point-wise between iterations, the algorithm is assumed to have converged. The algorithm is not guaranteed to be a contraction mapping, hence, a solution is not guaranteed. However, in practice, the algorithm has generally converged to an equilibrium for almost any given set of parameters, based on the sequence of events and information structure we impose. Although non-convergence does not necessarily imply that an equilibrium does not exist, convergence of the algorithm is sufficient to ensure the existence of an equilibrium for the given parameters set.

6.5.1 The State Space

Each state is defined as the tuple $\{\omega_l, \omega_f, \tau\}$. As in EP, we restrict the states ω_l and ω_f to integers from 0 to $\overline{\omega}$ and τ to integers from 0 to $\overline{\tau}$. The values of $\overline{\omega}$ and $\overline{\tau}$ have been chosen to ensure that the upper bound of the state space does not bind in equilibrium. Furthermore, we assume that the knowledge stock of brand f cannot exceed the knowledge stock of brand l. Thus, the size of the state space is $\frac{1}{2}(\overline{\omega}+1)^2 \times (\overline{\tau}+1)$.

The rest of this section discusses the iterative algorithm for computing the fixed-point solution of the dynamic programming problem. The reader who is not interested in these technicalities may comfortably proceed to the next section that presents the results.

6.5.2 The Algorithm for Computing the Fixed-Point

In this section, we describe the computation procedure used to derive the fixed-point solution of the model. As discussed in the previous section, each period is a sequence of five stages, which we solve in backward induction. In this section, we denote by ˆ a perfect equilibrium solution (which can differ from one iteration to the other) and by ˜, a sub-game perfect equilibrium, as in the previous section.

Fifth stage The algorithm begins with computing the static profit pay-offs according to equations (6.3), (6.4) and (6.5), as well as the profit of the ancillary industry according to equations (6.13) and (6.14) . The equilibrium profit matrices $\widehat{\pi}^c(\omega, \tau)$ and $\widehat{\pi}^a(\omega, \tau)$ are not part of the iterative procedure and are stored in memory at the beginning of every iteration.

Forth stage At the beginning of the forth stage, the algorithm stores the current period profits that were computed at the previous stage in memory. At this stage the ancillary firm maximizes equation (6.15) with respect to its R&D. The first-order condition with respect to x_a at iteration k for each point in the state set is given by

$$0 = -\gamma_a + \beta \sum_{\tau} V(\omega', \tau') P(\tau' | x_a) \tag{6.19}$$

After substituting for the expected pay-offs, the optimal ancillary R&D at iteration k for every point in the state set, denoted by $\widehat{x}_a^k(\omega, \omega', \tau)$, is

$$\widehat{x}_a^k = \frac{\alpha\gamma_a + \sqrt{a\alpha^3\beta\gamma_a - \alpha^3 b\beta\gamma_a}}{\alpha^2} \tag{6.20}$$

Where, a is the expected value of the firm in the presence of a successful innovation, whereas b is the expected value when the R&D project fails. Substituting $\widehat{x}_a^k$ into the value function yields the optimal firm value at iteration k, denoted by $\widehat{V}_a^k(\omega, \omega', \tau, \widehat{x}_a^k)$ and the optimal policy $\widehat{x}_a^k(\omega, \omega', \tau, \widehat{V}_a^k)$. Note that $\widehat{x}_a^k(\omega, \omega', \tau, \widehat{V}_a^k)$ is not a function of the R&D decisions of brands l and f, since the information structure assumes the realizations of the R&D in the core industry are already known at the stage the ancillary firm plays. This assumption allows to solve for the fixed-point solution of the ancillary firm before computing the R&D strategies of the core industry. The fixed-point solution for the ancillary firm is derived as following: at iteration $k+1$, substitute the matrix $\widehat{V}_a^k(\omega, \omega', \tau, \widehat{x}_a^k)$ for the *rhs* of equation (6.15) and repeat the procedure for finding the optimal R&D investment x_a^{k+1}. Continue iterating until $\widehat{V}_a^n(\omega, \omega', \tau, \widehat{x}_a^n) = \widehat{V}_a^{n+1}(\omega, \omega', \tau, \widehat{x}_a^{n+1})$. In this case the algorithm is assumed to have converged, where $\widehat{x}_a^n(\omega, \omega', \tau, \widehat{V}_a^n) \equiv \widehat{x}_a(\omega, \omega', \tau)$ and $\widehat{V}_a^n(\omega, \omega', \tau, \widehat{x}_a^n) \equiv \widehat{V}_a(\omega, \omega', \tau)$ are the fixed-point solutions for the optimal R&D and firm value, respectively. Since the future periods states are already known once firm a plays, this algorithm is a contraction mapping for this stage, i.e., a convergence for firm a is guaranteed.

Third stage At the beginning of the third stage, the algorithm stores the current period profits and the optimal R&D policy and value of the ancillary firm in memory. At this stage, brand l chooses its optimal R&D via maximizing equation (6.16). The first-order condition of maximizing equation (6.16) with respect to x_l at iteration k for every point in the state set is given by

$$0 = -\gamma_l + \beta \sum_{\omega_l', \tau'} V(\omega', \tau') P(\omega_l' | \omega_l, x_l) P(\tau' | \tau, \widehat{x}_a(\omega, \omega', \tau)) \tag{6.21}$$

The realizations of the R&D of brand f are already known at this stage, thus, the expectation term does not include the future knowledge stock of brand f. The computation of the optimal policy of brand l is performed for every possible realization of the R&D of brand f and the aggregate shock. In particular, the algorithm computes the optimal policy of brand l for ω_f, $\omega_f - 1$ and $\omega_f + 1$ (with the necessary adjustments in the transition probability matrix. E.g., for $\omega_f - 1$ it must be that the aggregate negative shock had hit the core industry and, therefore, $P(\omega_l' = \omega_l + 1 | \omega_l, x_l) = 0$, $\forall x_l \in R^+$). The future ancillary knowledge stock is unknown at this stage, therefore, expectations are formed based on the optimal strategy of firm a, which had been computed at the previous stage . The solution for brand l's R&D is given by

$$\widehat{x}_l^k = \frac{\alpha\gamma_l + \sqrt{a\alpha^3\beta\gamma_l - \alpha^3 b\beta\gamma_l}}{\alpha^2} \tag{6.22}$$

Where, a is the expected value of the firm in the presence of a successful innovation for each possible outcome of the ancillary R&D, whereas b is the expected value when the R&D project fails, again taking into account the expected change in the ancillary knowledge stock. Substituting $\widehat{x}_l^k$ into the value function yields the optimal value at iteration k, denoted by $\widehat{V}_l^k(\omega, \omega'_f, \tau, \widehat{x}_l^k)$ and the optimal policy rule $\widehat{x}_l^k(\omega, \omega'_f, \tau, V_f^k)$. Similarly to the ancillary firm, the fixed-point solution for this stage can be derived without solving for the second and first stages of the game. Thus, at iteration $k+1$, substitute the matrix $\widehat{V}_l^k(\omega, \omega'_f, \tau, \widehat{x}_l^k)$ for the value function in the rhs of equation (6.16) and repeat this procedure so as to find the optimal R&D investment $\widehat{x}_l^{k+1}$. Keep iterating until $\widehat{V}_l^n(\omega, \omega'_f, \tau, \widehat{x}_l^n) = \widehat{V}_l^{n+1}(\omega, \omega'_f, \tau, \widehat{x}_l^{n+1})$. Once this condition is satisfied, the algorithm is assumed to have converged, where $\widehat{x}_l^n(\omega, \omega'_f, \tau, \widehat{V}_l^n) \equiv \widehat{x}_l(\omega, \omega'_f, \tau)$ and $\widehat{V}_l^n(\omega, \omega'_f, \tau, \widehat{x}_l^n) \equiv \widehat{V}_l(\omega, \omega'_f, \tau)$ is the fixed-point solutions for the optimal R&D and firm value, respectively. This iterative procedure is not a contraction mapping for this stage and, therefore, convergence is not guaranteed.

Second stage At the beginning of the second stage, the algorithm holds in memory the static pay-offs, the optimal R&D strategy and value of the ancillary firm for all possible realization of the future period knowledge stocks of brands l and f, and the optimal R&D strategy and value of brand l for all possible realizations of brand f's future knowledge stock. At this stage, an iteration consists of two steps: first, find the best response function of brand f's R&D to the knowledge diffusion decision of brand l. Second, given this best response function, brand l determines its optimal knowledge diffusion decision at the first stage of the game. Maximizing equation (6.17) with respect to x_f yields the following first order condition:

$$\begin{aligned} 0 \;=\; & -c_f\left(\gamma_f, \theta_l \omega_l\right) + \beta \sum_{\omega', \tau'} V_f(\omega', \tau') P(\omega'_f | \omega_f, \widehat{x}_a(\omega, \omega', \tau)) \\ & P(\omega'_l | \omega_l, \widehat{x}_l(\omega, \omega'_f, \tau)) P(\tau' | \tau, \widehat{x}_a(\omega, \tau)) P(\varrho) \end{aligned} \tag{6.23}$$

Solving for the optimal $\widetilde{x}_f(\omega, \tau; \theta_l \omega_l)$ at iteration k yields:

$$\widetilde{x}_f(\omega,\tau;\theta_l) = \frac{\alpha c_f + \sqrt{a\alpha^3\beta c_f - \alpha^3 b\beta c_f}}{\alpha^2} \tag{6.24}$$

Where, a is the expected firm value in the presence of successful innovation for each possible outcome of the ancillary firm and the brand l's R&D output, while b is the expected value when the R&D project fails, again taking into account the expected change in the ancillary and brand f's knowledge stocks. In forming these expectations, substitute for the expected outcome of firm a the optimal strategy computed in stage four and for the optimal strategy of the brand l computed at stage three. Substituting $\widetilde{x}_f(\omega,\tau;\theta_l)$ into the value function yields the optimal firm value at iteration k, denoted by $\widetilde{V}_f^k(\omega,\tau,\widetilde{x}_f^k;\theta_l)$ and the optimal policy $\widetilde{x}_f^k(\omega,\tau,\widetilde{V}_f^k;\theta_l)$. At iteration $k+1$, substitute the matrix $\widetilde{V}_f^k(\omega,\tau,\widetilde{x}_f^k;\theta_l)$ for the value function in the *rhs* of equation (6.17) and repeat this procedure for finding the optimal R&D, $\widetilde{x}_f^{k+1}$. Keep iterating until $\widetilde{V}_f^n(\omega,\tau,\widetilde{x}_f^n;\theta_l) = \widetilde{V}_f^{n+1}(\omega,\tau,\widetilde{x}_f^{n+1};\theta_l)$. Once this condition is satisfied, the algorithm is assumed to have converged, where $\widetilde{x}_f^n(\omega,\tau,\widetilde{V}_f^n;\theta_l) \equiv \widetilde{x}_f(\omega,\tau;\theta_l)$ and $\widetilde{V}_f^n(\omega,\tau,\widetilde{x}_f^n;\theta_l) \equiv \widetilde{V}_f(\omega,\tau;\theta_l)$ is the fixed-point solutions for the optimal R&D and firm value, respectively, as a function of θ_l, which is determined at the first stage. The iterative procedure for this stage is not a contraction mapping and, therefore, convergence is not guaranteed.

First stage At the first stage of the game, brand l decides whether to diffuse its knowledge to brand f. At the beginning of this stage, the algorithm stores in memory the following matrices: the current period pay-offs, the optimal R&D and value of the ancillary firm for every possible realization of the future knowledge stock of brands l and f, the optimal R&D and value of brand l for every possible realization of brand f's future knowledge stock and the best response function of the R&D of brand f to the knowledge diffusion decision of brand l.

Brand l chooses to diffuse its knowledge, i.e., set $\theta_l = 1$, iff the following condition is satisfied:

$$\sum_{\omega'_f} \widehat{V}_l^k(\omega,\omega'_f,\tau)P(\omega'_f|\omega_f,\widetilde{x}_f^k(\omega_l,\tau;\theta_l=0)) > \sum_{\omega'_f} \widehat{V}_l^k(\omega,\omega'_f,\tau)P(\omega'_f|\omega_f,\widetilde{x}_f^k(\omega_l,\tau;\theta_l=0)) \tag{6.25}$$

Otherwise, set $\theta = 0$. Denote by $\widehat{\theta}_l^k\left(\omega, \tau; \widehat{x}_f^k(\omega_l, \tau; \widehat{\theta}_l^k)\right)$; the optimal knowledge diffusion decision at iteration k and $\widehat{x}_f^k(\omega_l, \tau; \widehat{\theta}_l^k)$ as the optimal R&D policy of brand f at iteration k. The corresponding value function of brand f at iteration k is $\widehat{V}_f^k(\omega, \tau; \widehat{x}_f^k(\omega, \tau; \widehat{\theta}_l^k))$.Keep iterating until $\widehat{V}_f^n(\omega, \tau; \widehat{x}_f^n(\omega, \tau; \widehat{\theta}_l^n)) = \widehat{V}_f^{n+1}(\omega, \tau; \widehat{x}_f^{n+1}(\omega, \tau; \widehat{\theta}_l^{n+1}))$ and $\widehat{\theta}_l^n\left(\omega, \tau; \widehat{x}_f^n\right) = \widehat{\theta}_l^{n+1}\left(\omega, \tau; \widehat{x}_f^{n+1}\right)$. Once this condition is satisfied, the algorithm is assumed to have converged. Define $\widehat{x}_f^n(\omega, \tau; \widehat{\theta}_l^n) \equiv \widehat{x}_f(\omega, \tau)$, $\widehat{V}_f^n(\omega, \tau; \widehat{x}_f^n(\omega, \tau; \widehat{\theta}_l^n)) \equiv \widehat{V}_f^n(\omega, \tau)$ and $\widehat{\theta}_l^n\left(\omega, \tau; \widehat{x}_f^n\right) = \widehat{\theta}_l\left(\omega, \tau\right)$ as the fixed-point solutions for the R&D and value of brand f and the knowledge diffusion decision for brand l, respectively.

This concludes the iterative procedure. Overall, we have found this game structure to be the least sensitive for choice of parameters. In most parameter sets er have experimented with, the algorithm has converged in approximately 200 iterations, after running for one hour on a 1G RAM computer with a 2.9G processor.

6.6 Findings

We consider the following specification for the model described above:

The market share of brand $c \in l, f$ is given by

$$\sigma_c = \frac{\exp\left(\psi\omega_c - p_c - \frac{\lambda}{\tau}\right)}{1 + \exp\left(\psi\omega_l - p_l - \frac{\lambda}{\tau}\right) + \exp\left(\psi\omega_f - p_f - \frac{\lambda}{\tau}\right)} \tag{6.26}$$

Where, $\varphi, \lambda > 0$. The parameter λ reflects the effect of the ancillary product quality on the demand for the core product. As λ increases, the development of the ancillary industry is more crucial for the growth of the core industry. Thus, we would expect to observe stronger incentives to share knowledge in order to encourage the development of the ancillary product as λ increases. In the appendix, we will present comparative statics regarding the effect of λ on the evolution pattern of the core industry.

In order to complete the specification of the model, the effect of spillovers on the R&D cost in brand f is given by

$$c_f\left(\gamma_f, \theta_l, \omega_l; \delta\right) = \frac{\gamma_f}{\left(1+\theta_l \omega_l\right)^{\delta}} \tag{6.27}$$

Where, γ_f is the R&D costs of brand f in the absence of spillovers. $\delta \geq 0$ denotes the effect of spillovers on the R&D costs of the brand f, thus, higher value of δ implies the spillovers of knowledge have a stronger effect on the R&D cost of brand f. Finally, the parameters set is given in the appendix.

6.6.1 Baseline findings

In this section we describe the baseline findings regarding knowledge diffusion and innovation in the core industry. We focus on the effect of spillovers on the value and R&D of brand f and present preliminary findings with respect to the probable impact of endogenously eliminating spillovers on the number of firms in the core industry.

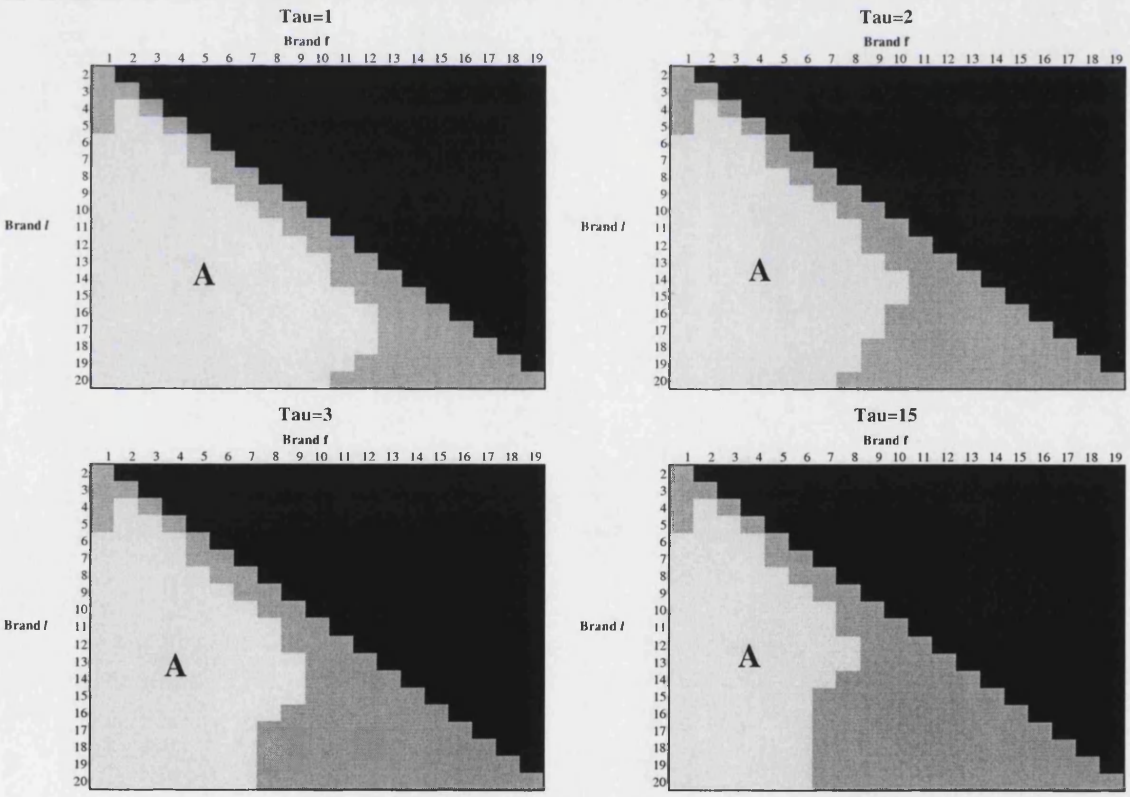

Figure 2: The area in the state space with endogenous knowledge flows

Figure 2: *Area A in the four diagrams above denotes the points in the state space, where brand l decides to diffuse its knowledge to brand f. The dynamics of this decision is given by the reduction in area A as the ancillary knowledge improves. Thus, the upper-left diagram plots the existence of knowledge flows when the ancillary knowledge stock is at its lowest level ($\tau = 1$). The upper-right diagram denotes the existence of knowledge flows when the ancillary knowledge stock is 2, the lower-left diagrams plots the flow of knowledge when the ancillary knowledge stock is 3 and, finally, the lower-right diagram plots the existence of knowledge flows where the ancillary industry is highly developed, with its knowledge stock equals 15. The main point to be inferred from these four diagrams is that as the ancillary knowledge becomes more advanced, the quality of the ancillary product becomes less a constraints on the potential expansion of the core industry and, therefore, the incentive to diffuse knowledge fall.*

Figure 2 plots the area in the state apace in which brand l finds it optimal to diffuse its knowledge to brand f. We plot the area in the state space with positive spillovers in equilibrium, under four different levels of ancillary knowledge stock. By raising the knowledge stock of the ancillary industry, we would expect to find lower incentives to share knowledge, since the market expansion effect weakens as the ancillary industry becomes more developed and therefore, constrains less the growth potential of the core industry.

The upper-left diagram shows the area in the state space that is associated with a decision to diffuse knowledge (the area A in the diagram), where the ancillary knowledge stock is in its lowest possible level ($\tau = 1$). In this case, the area A is very large (covers 71 percent of the state space), implying that the incentives to share knowledge are strong. Further, as brand f's knowledge stock becomes closer to that of brand l, we observe less knowledge sharing. This finding can be explained by the fact that as the level of competition becomes stronger (which is captures by the proximity of the knowledge stock of both brands), the desire to protect the market share is larger than the desire to expand the market.

The upper-right, lower-left and lower right diagrams plots the decision of brand l to share its knowledge with brand f, when the ancillary knowledge stock is 2, 3 and 15, respectively. The main finding derived from of these diagrams is that the shaded area reduces, as the ancillary knowledge stock increases (covers 50 percent of the state space when the ancillary knowledge stock equals 15). This relates to the fact that as the knowledge stock of the ancillary product rises, the potential additional increase in the market size of the core product, due to a further improvement in the quality of the ancillary product, reduces. Thus, the market expansion effect is exhausted as the ancillary knowledge stock improves, implying less incentives to share knowledge and less spillovers.

While figure 2 plots the dynamics of the incentives to share knowledge, figure 3 plots the effect of endogenous knowledge flows on the number of producers in brand f. For the purpose of identifying this effect, it is useful to look at the state space where brand f's knowledge stock equals 10 and the ancillary knowledge stock equals 1 and 2. From the upper-left and upper-right diagrams in figure 2 we know that brand l finds it optimal to share its knowledge with brand f when the ancillary knowledge stock is 1, for every possible level of brand l's knowledge stock. However, when the ancillary knowledge stock is 2, brand l finds it optimal to prevent its knowledge from spilling over to the brand f, as the knowledge stock of brand l exceeds 15. Thus, this shift in the knowledge diffusion strategy enables to identify and assess the effect of endogenous knowledge flows on brand f's number of producers.

Therefore, figure 3 plots the value and number of active firms in brand f when its knowledge stock of brand f is 10, as a function of the knowledge stock of brand l. As brand l's knowledge stock exceeds 15, it finds it optimal to prevent the spread of its knowledge to brand f. The effect of this decision is illustrated by the sharp drop in the value and number of active firms in brand f. Thus, endogenously eliminating spillovers triggers mass exist of producers in brand f.

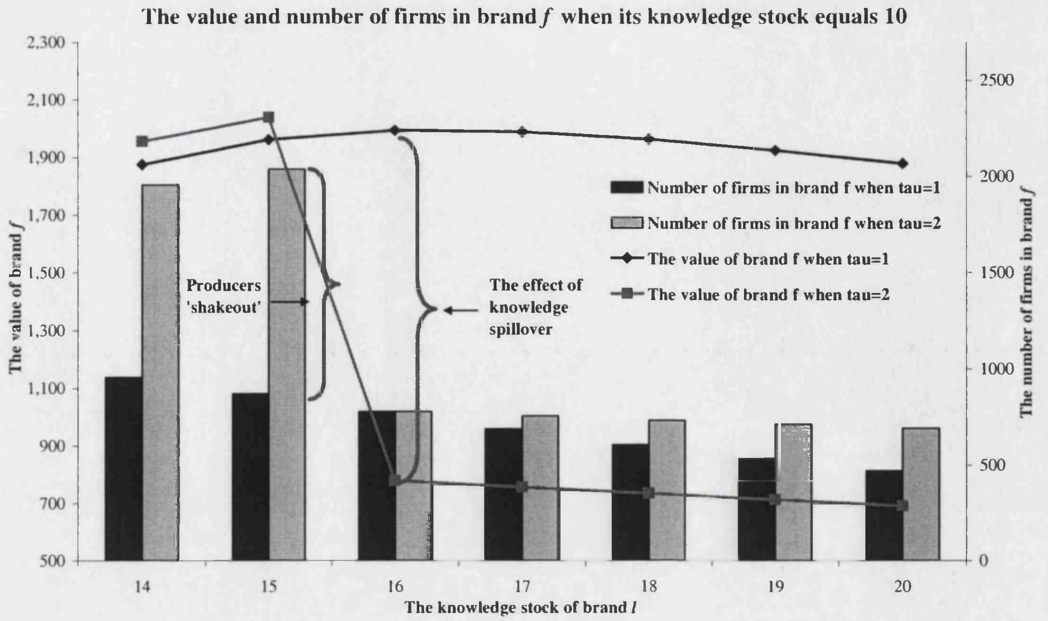

Figure 3: Endogenous knowledge flows and producers 'shakeout'

Figure 3: *This figure plots brand f 's value and number of active firms, when its knowledge stock equals 10, as a function of brand l 's knowledge stock. The line with the circle shapes represents brand f 's value when the ancillary knowledge stock equals 1 and the square shape represents brand f 's value when the ancillary knowledge stock equals 2. The dark bar graph (left) represents the number of firms in brand f when the ancillary knowledge stock equals 1 and the light bar graph (right) represents the number of firms in brand f when the ancillary knowledge stock equals 2. Once brand l 's knowledge stock exceeds 15, brand l finds it optimal to prevent its knowledge from spreading to brand f. This figure shows that the effect of this decision on the value and number of firms in brand f is large. Thus, producers 'shakeout' can be the result of endogenously reducing spillovers, which affects the survival of the lower capable firms.*

Figure 4 plots the R&D stock of brand f as a function of the knowledge stock of brand l, similarly to figure 3. A sharp drop in the innovation efforts of brand f is observed when the knowledge stock of brand l exceeds 15 and the ancillary knowledge stock is 2. We do not observe this drop when the ancillary knowledge stock is 1. This drop in innovation is the result of the decision to prevent knowledge flows. This decision takes place since as the ancillary product is of a higher quality, the advantage of further improving the quality of this product is overweighed by the costs of losing market share, due to giving up valuable knowledge that will improve the future market position of a strong rival brand[16].

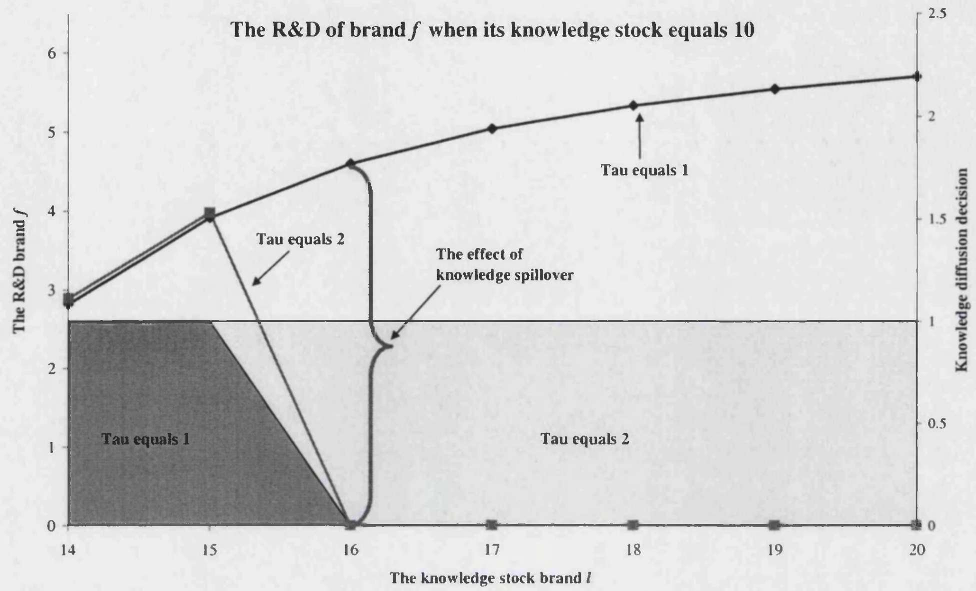

Figure 4: Endogenous knowledge flows and innovation

Figure 4: *This figure plots brand f's R&D, when its knowledge stock is 10, as a function of brand l knowledge stock. The line with the circular shapes represents brand f's R&D when the ancillary knowledge stock equals 1, whereas the square shape represents brand f's R&D when the ancillary knowledge stock equals 2. From figure 2, brand l finds it optimal to diffuse its knowledge to brand f for every level of its knowledge stock, when the ancillary knowledge stock is 1 and brand f's knowledge stock is 10. However, when the ancillary knowledge stock is 2 (thus, the ancillary industry is more developed) brand l finds it optimal to prevent the spread of its knowledge when its knowledge stock exceeds 15, thus, eliminating spillovers. The large drop in brand f's R&D when the knowledge stock of brand l exceeds 15 illustrates the importance of knowledge externalities to the innovative efforts of firms that benefit from these externalities.*

[16] The set of chosen parameters condition the innovation of brand f on the existence of knowledge spillovers. Thus, in the absence of knowledge spillovers, brand f finds it optimal not to innovate at all. The sharp drop in brand f's innovation is robust to choosing different parameter sets that allow for positive innovation also in the absence of knowledge spillovers.

6.6.2 Competition, endogenous knowledge flows and innovation

We test the hypothesis that the effect of competition on innovation relates to the endogenous nature of knowledge flows. A stronger competition can reduce the incentives to share knowledge, due to stronger risks of losing valuable market share, so that, stronger competition can discourage innovation by reducing spillovers. This negative effect differs from the Schumpeterian approach, since the effect I discuss in this section relates to the negative effect of competition on innovation indirectly, through reducing the incentives to diffuse knowledge.

Figure 6 illustrates this idea for an industry where the technology frontier is constant and equals 15 (the knowledge stock of brand l) and the ancillary knowledge stock receives the values of 1, 2 3 and 14. The line graph represents the R&D of brand f, while the area graph represents the decision whether to diffuse knowledge (which is 1 for knowledge diffusion or 0 for eliminating knowledge flows). The knowledge stock of brand f is given on the horizontal axis, while the degree of competition increases as brand f's knowledge stock gets closer to 15 (which is the knowledge stock of brand l).

Consider first the case that the ancillary knowledge stock equals 1. As the degree of competition increases, brand f's innovation changes in an inverted U shape. At the beginning it increases, until starting to fall before dropping to zero at the point where spillovers disappear. This inverted U relation is similar to that which was discussed in previous studies[17]. The fall in the innovation of the follower brand as it becomes closer to the technology frontier is consistent with the Schumpeterian approach in which the reward on becoming closer to the technology frontier falls as a function of the distance from this frontier. Nonetheless, when spillovers are endogenously eliminated as the 'cost' of sharing knowledge becomes too high, brand f's innovation drops to zero.

[17] See Levin, Cohen and Mowary (1985) and Aghion, Bloom, Blundell, Griffith and Howitt (2002).

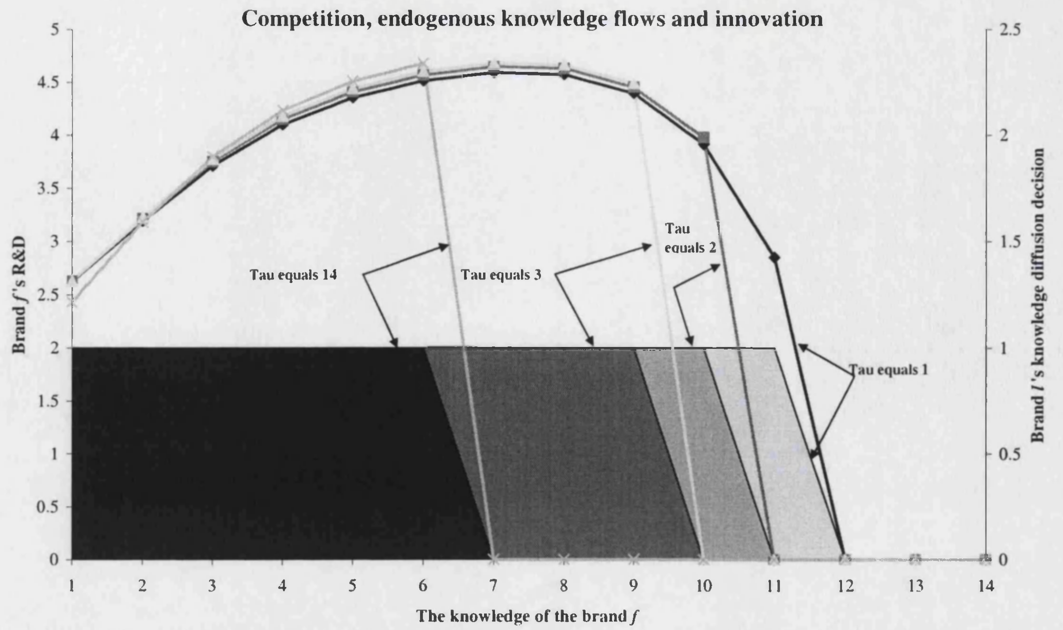

Figure 5: Competition, endogenous knowledge flows and innovation

Figure 5: *This figure plots the effect of competition on innovation. Brand l' knowledge stock is kept constant at 15 (which is the technology frontier in the core industry), where the degree of competition is defined as the proximity of brand f to this technology frontier (higher proximity corresponds to stronger competition). The equilibrium level of brand f 's R&D is plotted for different levels of ancillary knowledge stocks. The effect of competition on innovation takes the shape of an inverted U, until dropping to zero when spillovers are endogenously eliminated. However, we cannot infer a relation between competition and innovation without understanding the incentive to diffuse knowledge. High innovation can be supported as an equilibrium outcome in a competitive industry when the incentive to share knowledge is strong (e.g., when the ancillary knowledge stock equals 1). Nonetheless, high innovation cannot be supported as an equilibrium outcome in a competitive industry when the incentive to share knowledge is low.*

However, the inferred effect of competition on innovation is not as simple as that. As the ancillary knowledge increases, brand l decides to prevent the flow of its knowledge at a lower level of competition. Therefore, an equilibrium level of R&D can be supported in various industry structures, depending of the incentive of firms to diffuse knowledge (e.g., if the ancillary knowledge stock is 1, high innovation can be associated with high competition. However, if the ancillary knowledge stock is 14, high innovation cannot be sustained when competition is strong).

Therefore, the relation between market structure and innovation in a framework that allows firms to affect the spillovers their inventions create cannot be outlined without a complete consideration of the incentive to diffuse knowledge.

6.6.3 Simulation

Based on the numerical results described above, we simulate the evolution pattern of the core industry. The starting point is the state $(5, 1, 1)$, i.e., at period zero brand l's knowledge stock is 5 and the knowledge stocks of brand f and the ancillary industry is 1. We simulate the evolution trajectory of the core industry for 25 periods, repeated 100,000 times, where for each period we present the simulation mean.

Figure 4 plots the simulation results for the value of brand f and the percentage of draws with positive spillovers in equilibrium in every period. At the early stages of the industry life cycle, the incentive to share knowledge is high, due to a strong market expansion effect. Thus, the early periods in the industry evolution trajectories are characterized by intense spillovers. However, as the industry matures the incentive to diffuse knowledge is exhausted and brand l is reluctant to allow its knowledge to drift to brand f. At this stage (a decade after the industry was born), firms in brand f face a drastic increase in their innovation costs and, therefore, their market value drops.

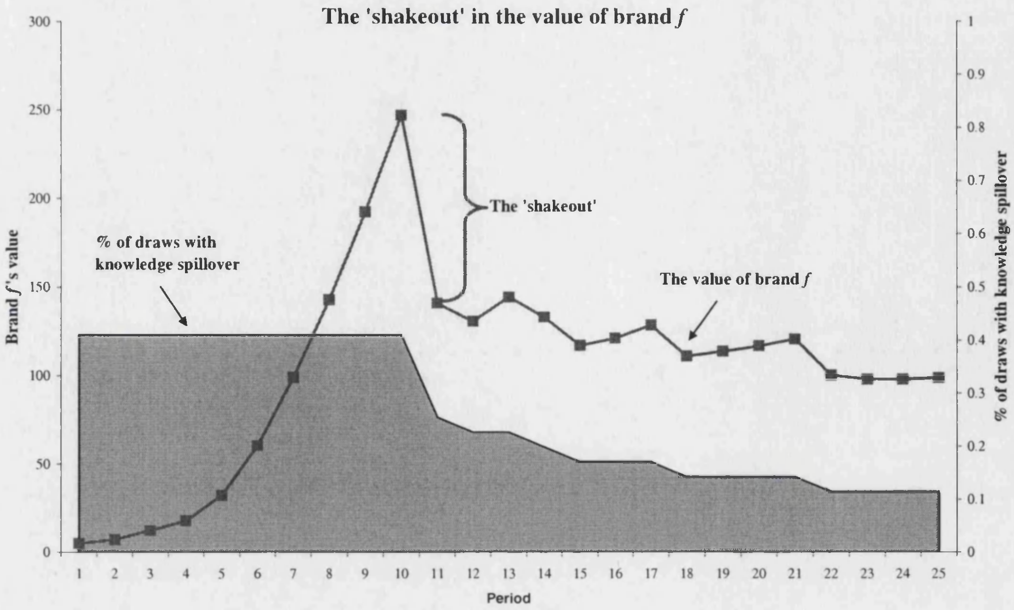

Figure 6: Endogenous knowledge flows and simulated brand f's value

Figure 6: *The area graph plots the percentage of periods in which brand l found it optimal to diffuse its knowledge to brand f. The line graph represents the corresponding value of brand f. A decade after the industry was born, the incentive to share knowledge disappears, due to exhausting the market expansion effect. The reduction in spillovers causes a hike in brand f's innovation cost and, therefore, a drop in its value.*

While figure 6 simulates the evolution of brand f's value, figure 7 simulates the evolution of the number of active firms in the core industry. The line graph represents the total number of firms in the core industry, where the dark (left) and light (right) bar graphs represent the number of firms in brand l and in brand f, respectively. The line graph shows that a 'shakeout' occurs in the number of active firms in the core industry, once spillovers disappear.

Decomposing the total number of firms into the number of firms in each brand yields the following pattern: at the early periods of the industry evolution path, most firms produce brand l, since its quality and associated market share are much larger than that of brand f. Since the ancillary knowledge stock is low at the early periods, production externality is strong, implying a strong incentive to share knowledge. The existence of spillovers enables brand f to develop its knowledge stock, which invokes a rise in the number of firms producing brand f. Nevertheless, the rising quality of the knowledge stock of brand l increases the fixed-costs of entering into the production of brand l more than it raises its value, therefore, the number of firms that can be simultaneously active in the production of brand l falls. As the industry reaches a certain threshold of development, the incentive to share knowledge disappears due to exhausting of the market expansion effect. At this stage, producers 'shakeout' occurs following a drop in the value of brand f (see figure 6). After the 'shakeout', the number of producers in brand l slightly rise and than stabilizes (the ratio of brand l's value and the fixed-costs of production remains relatively constant), where the number of producers in brand f continues to fall.

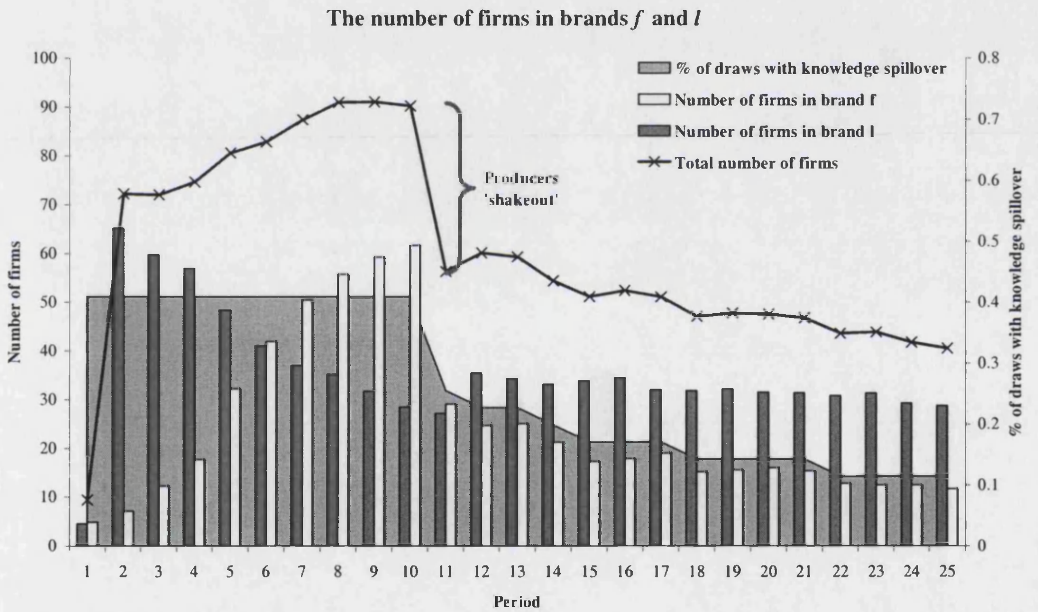

Figure 7: Endogenous knowledge flows and simulated producers 'shakeout'

Figure 7: *This figure plots the evolution of the number of active firms in the core industry. The line graph represents the total number of firms in the core industry, where the dark (left) and light (right) bar graphs represent the number of firms in brand l and in brand f, respectively. Producers 'shakeout' occurs as brand l finds it optimal to prevent its knowledge from spreading to brand f (this is reflected by the reduction in the percentage of draws with positive knowledge flows at period*

10). After the 'shakeout', the number of firms in brand f continues to fall, while the number of firms in brand l stabilizes (the rise in the value of brand l equals to the rise in the fixed-costs that are associated with more advanced knowledge stock).

Finally, we simulate the evolution pattern of an industry for two alternative levels of the parameter λ, which represents the importance of the ancillary industry to the growth of the core industry (higher λ implies a stronger market expansion effect, where lower λ implies a weaker market expansion effect). The simulation output is presented in the appendix.

The baseline value of the parameter λ is set to 1. Given this level, the mean percentage of draws with positive spillovers in the first 25 years of the industry evolution is 25 percent over the total cohort. When decomposing the cohort into pre and post producers 'shakeout' cohorts, this number rises to 41 percent in the pre-'shakeout' cohort (the first decade) and falls to 15 percent in the post-'shakeout' cohort.

We expect that a higher λ will result with stronger knowledge sharing. Thus, we raise λ to be equal to 1.5. Given this level, the mean percentage of draws with positive spillovers in the first 25 years of the industry evolution is 90 percent over the total cohort. When decomposing the cohort into pre and post producers 'shakeout' cohorts, this number rises to 100 percent in the pre-'shakeout' cohort (the first decade) and falls to 82 percent in the post-'shakeout' cohort. Thus, my prior regarding the intensity of knowledge sharing is supported.

Similarly, we expect that a lower λ will result with less knowledge sharing. Thus, we lower λ to be equal to 0.5. Given this level, the mean percentage of draws with positive spillovers in the first 25 years of the industry evolution is 24 percent over the total cohort. When decomposing the period into pre and post producers 'shakeout' cohorts, this number rises to 33 percent in the pre-'shakeout' cohort and falls to 17 percent in the post-'shakeout' cohort. Thus, our prior expectation regarding the intensity of knowledge sharing is supported in this case, as well (mainly due to lower knowledge sharing in the pre-shakeout cohort).

6.7 Summary and conclusions

This chapter investigates the role of the incentives of firms to diffuse their knowledge in shaping the evolution pattern of industries. In particular, we have aimed at exploring the 'shakeout' in the number of producers industries experience during their life cycle, based on a dynamic study of the incentives to spread knowledge.

Thus, we allow spillovers to depend on the strategic behaviour of firms, on whether to allow their rivals to benefit from their own inventions. We model the positive incentives to share knowledge as a positive production externality that relates to the desire to encourage the development of an ancillary product, which imposes a constraint on the growth of the main industry. We relate to this externality as a market expansion effect, which underpins the dynamics of spillovers. The negative incentive to diffuse knowledge relates to the loss of market share, due to potential improvement in the market position of rivals that benefit from this knowledge. Thus, the dynamics of the incentive to share knowledge consist of satisfying these two opposite forces. As the industry matures, the market expansion effect is exhausted, since the constraint the ancillary product has imposed on the development of the main industry relaxes as the quality of the ancillary product increases over time (until reaching a point where it is no longer optimal to diffuse knowledge). At this stage, spillovers are reduced, causing mass exit of firms that conditioned their survival on being able to exploit external knowledge.

The mechanism that generates the endogenous flow of knowledge is able to simulate producers 'shakeout', by studying the dynamics of the incentives to diffuse knowledge. Although we do not argue that endogenous knowledge flows are solely responsibly for the drastic change in industries structure, the fact that we can simulate this drastic change simply by looking at the incentive to diffuse knowledge demonstrates the importance of understanding the endogenous nature of knowledge flows in a framework that allows firms to internalize the feedback they receive from the spread of their knowledge and optimize it.

In order to further demonstrate the importance of the endogenous nature of knowledge, we offer an alternative approach for characterizing the effect of competition on innovation. As the degree of competition increases, it becomes more costly to share knowledge due to the loss of valuable market share to rivals that benefit from this knowledge. Thus, firms are more reluctant to share their knowledge as the degree of competition increases, causing a reduction in spillovers and therefore, a reduction in innovation. Following this approach, the effect of competition on innovation should be negative.

However, we also show that a simple relation between competition and innovation cannot be outlined without considering other factors that affect the incentive to share knowledge. High innovation can be achieved as an equilibrium outcome in a highly competitive industries, where the incentive to diffuse knowledge is high (as a result of a strong market expansion effect), due to large spillovers. On the contrary, high innovation cannot be supported as an equilibrium outcome in highly competitive industries, where the incentive to share knowledge is low (as a result a weak market expansion effect).

Therefore, this chapter demonstrates the importance of studying the strategic behaviour of firms in managing the flow of their knowledge. The theoretical implications of understanding the endogenous nature of knowledge flows are shown to be invaluable.

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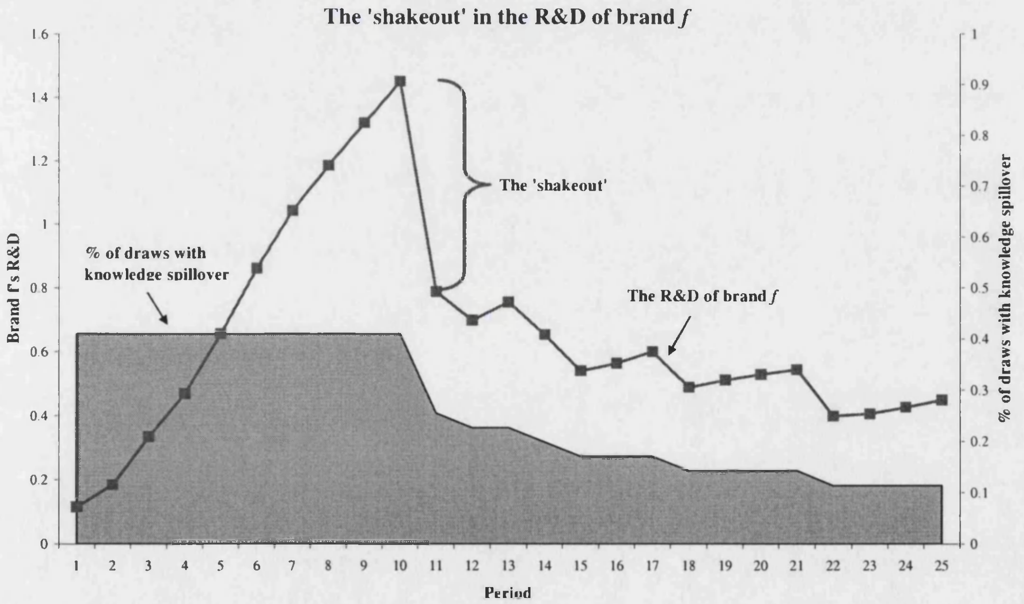
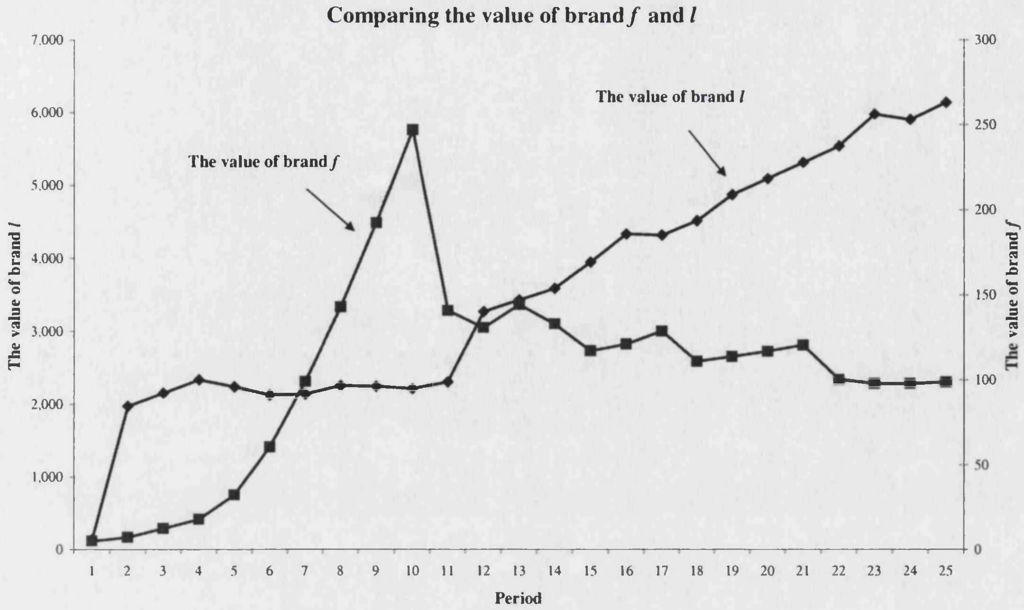
6.9 Appendix

The set of parameters values is as following:

Parameter	Value	Description
α	3	The productivity of R&D
β	0.925	The discount factor
γ_l	10	Brand l's R&D cost
γ_f	200	Brand f's R&D cost in the absence of knowledge flows
γ_a	5	The ancillary firm's R&D cost
λ	1	Reflects the market expansion effect
M	1000	Market size
δ	1.5	Reflects the effect of spillovers
ψ	0.1	A parameter in the utility function
κ	0.01	A parameter in the fixed-costs

6.9.1 Simulation results




Comparing the value of brand f and l
The value of brand l
The value of brand f
The value of brand l
The value of brand f
Period
0
1,000
2,000
3,000
4,000
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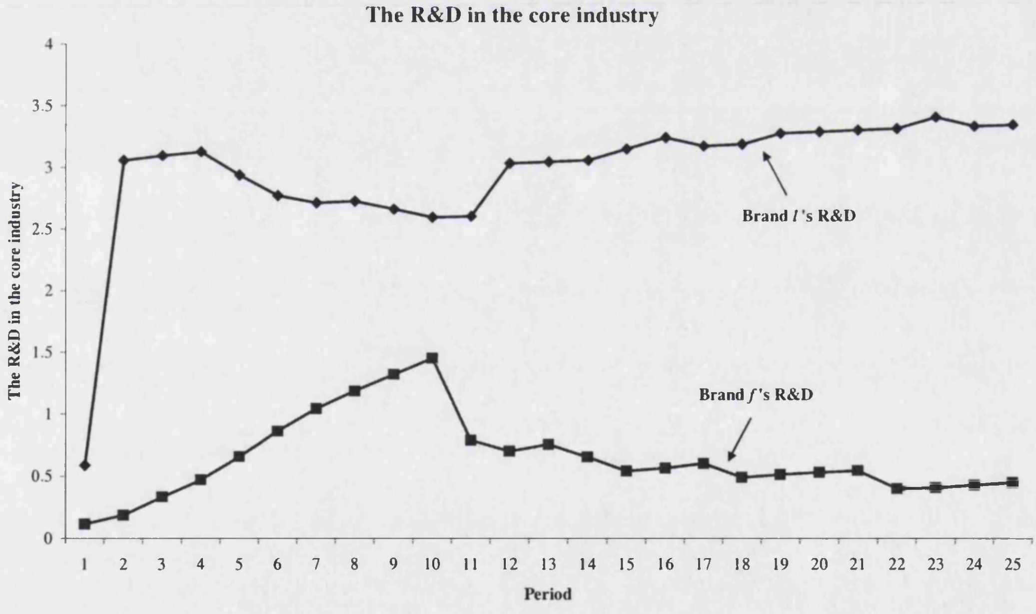
The R&D in the core industry
Brand l 's R&D
Brand f 's R&D
The R&D in the core industry
Period
0
0.5
1
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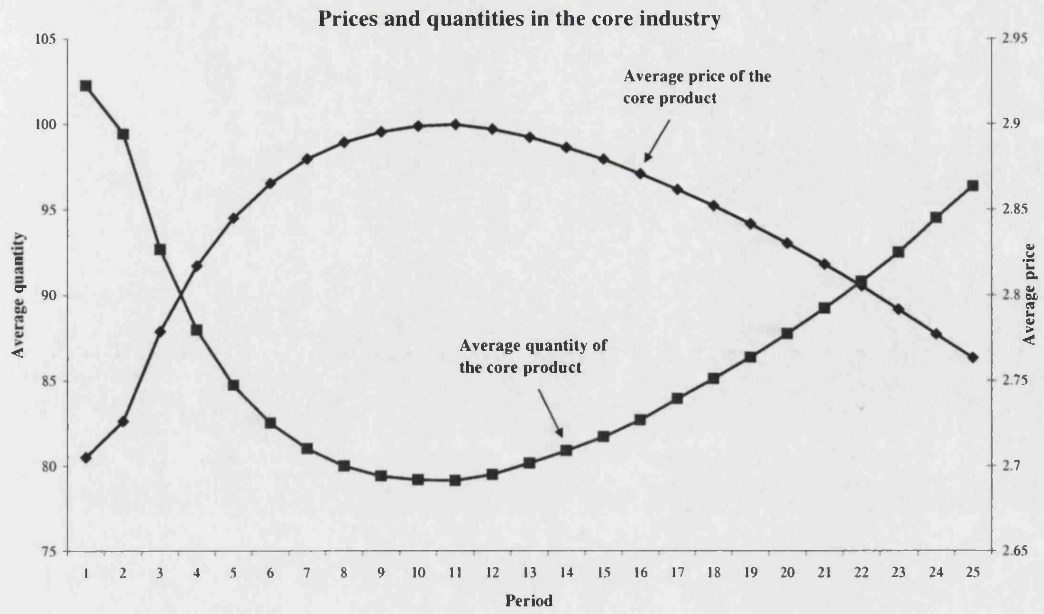
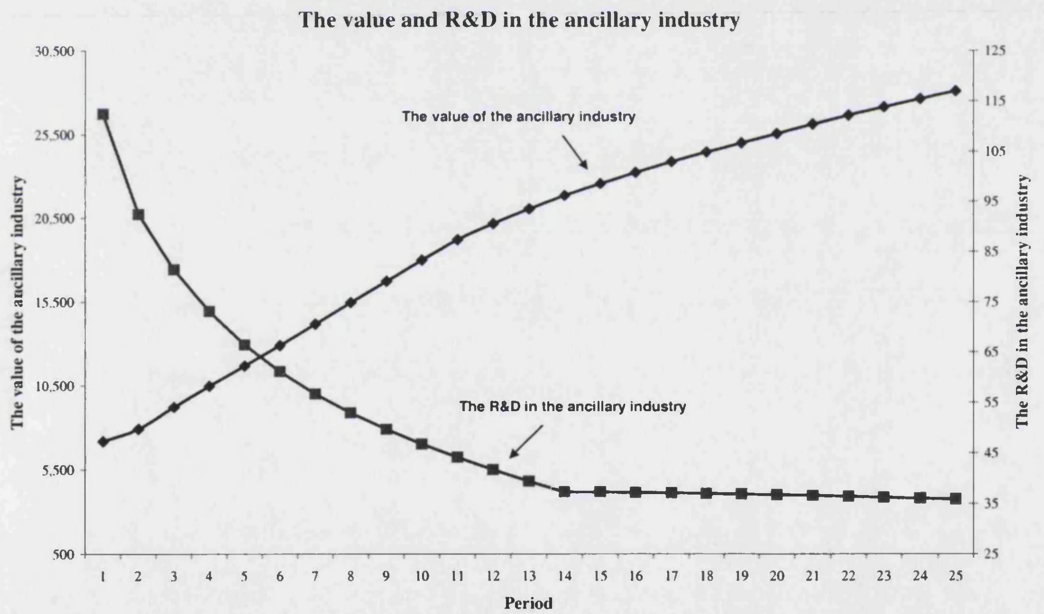
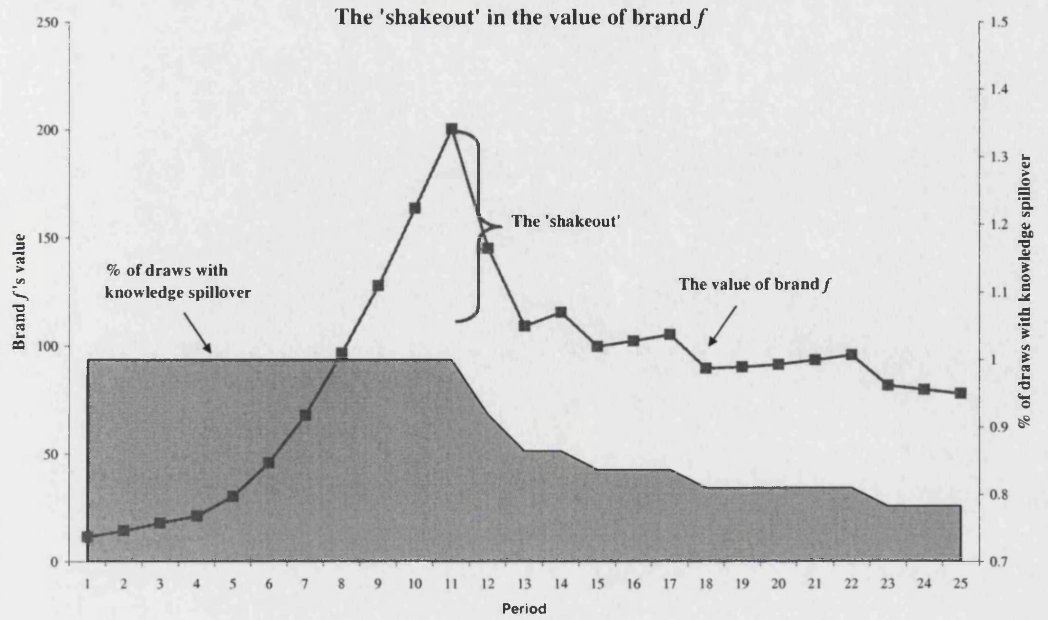
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

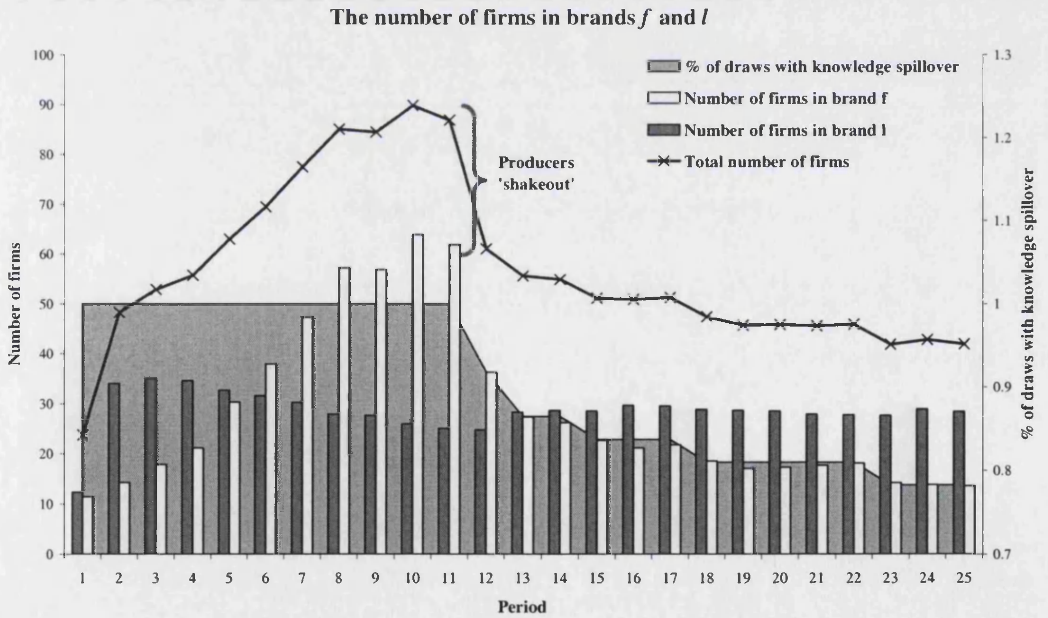


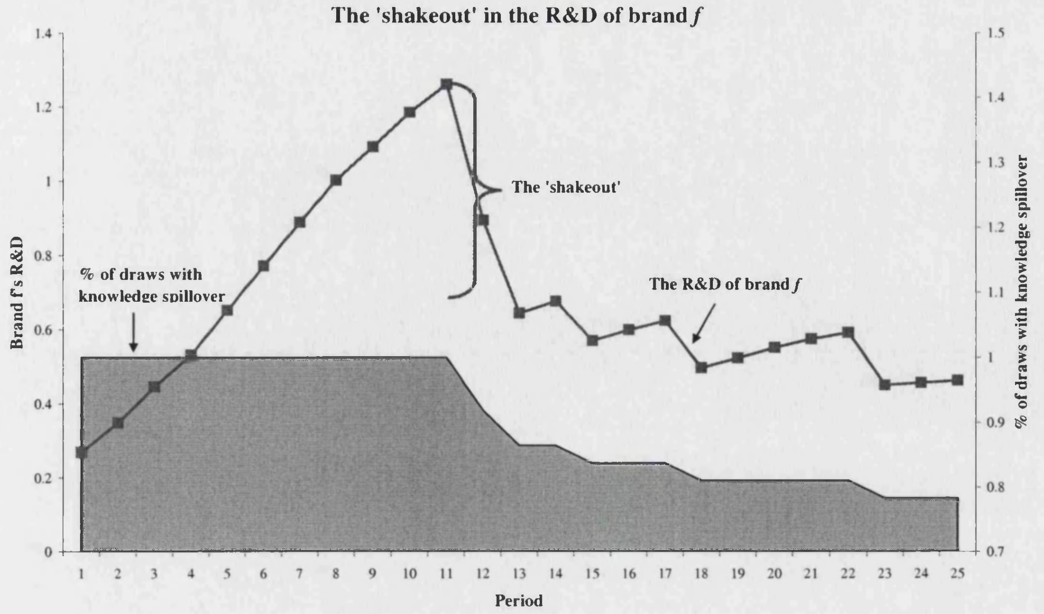


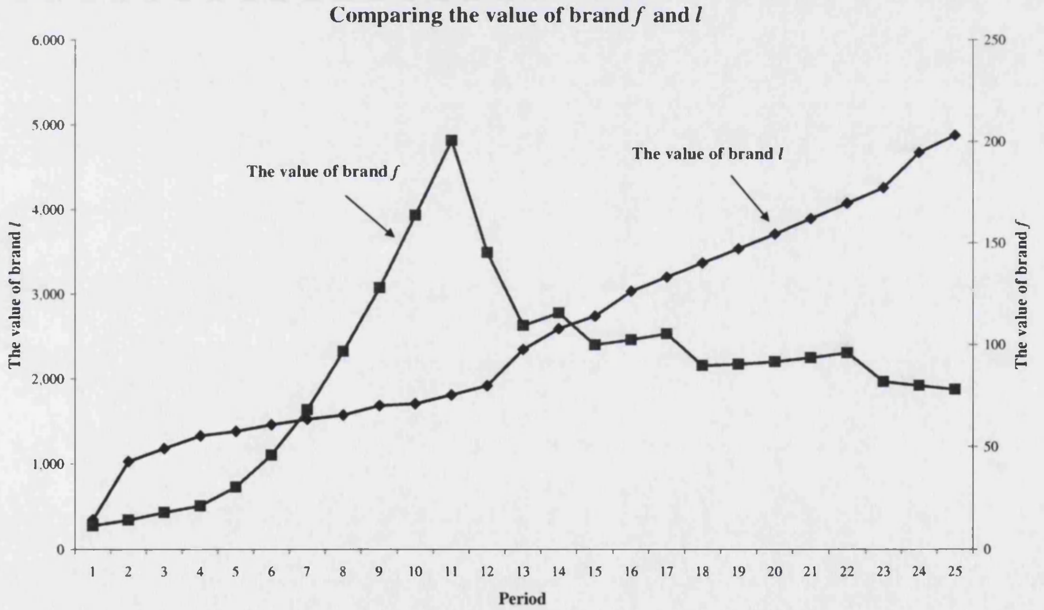
6.9.2 Comparative statics

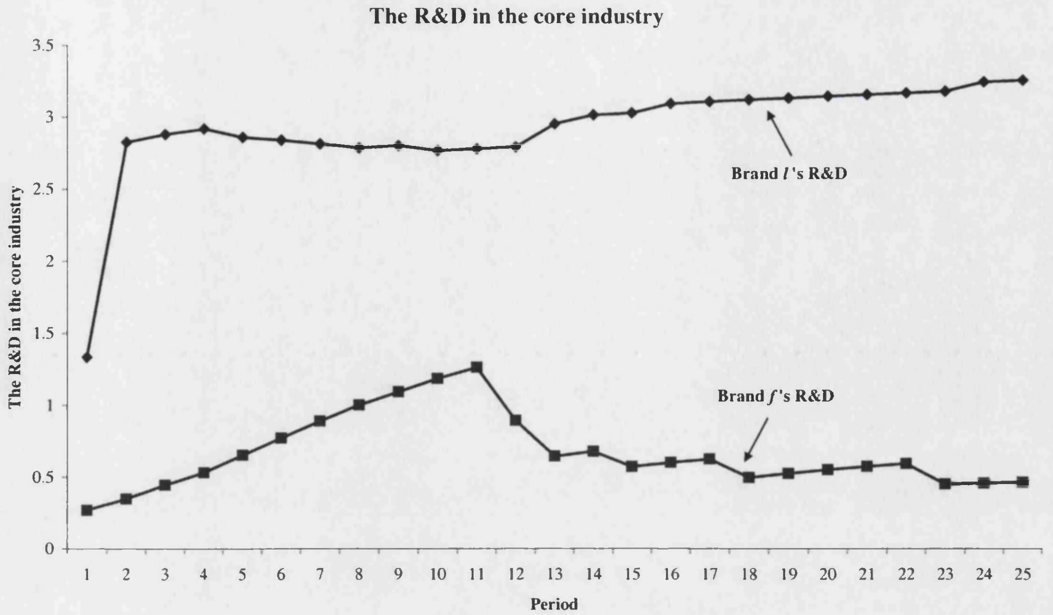
Increasing the market expansion effect (λ=1.5)

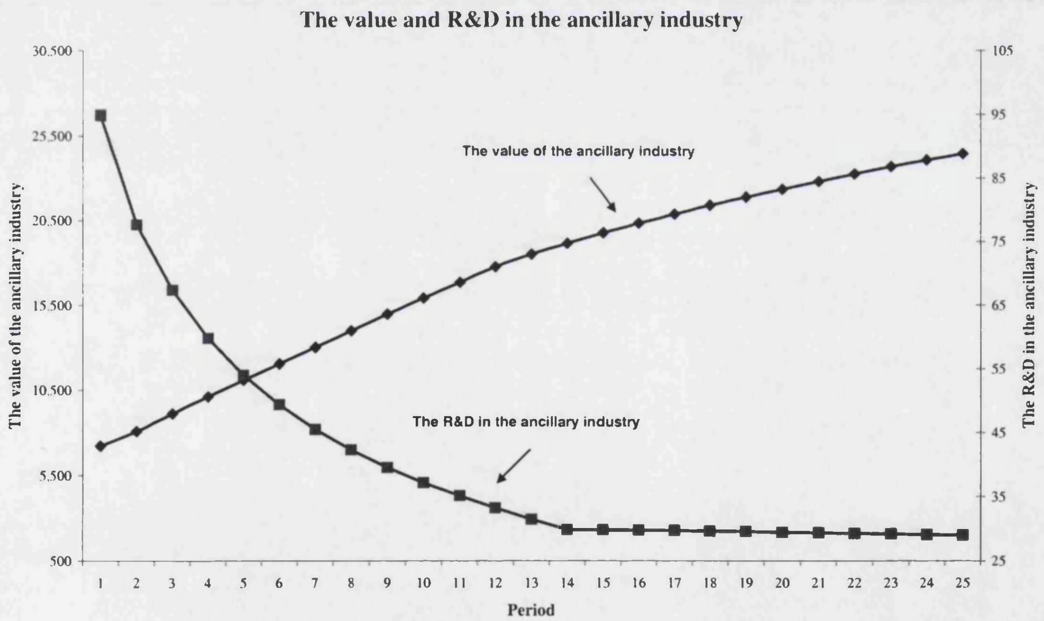

The 'shakeout' in the value of brand f
Brand f's value
% of draws with knowledge spillover
% of draws with
knowledge spillover
The 'shakeout'
The value of brand f
Period

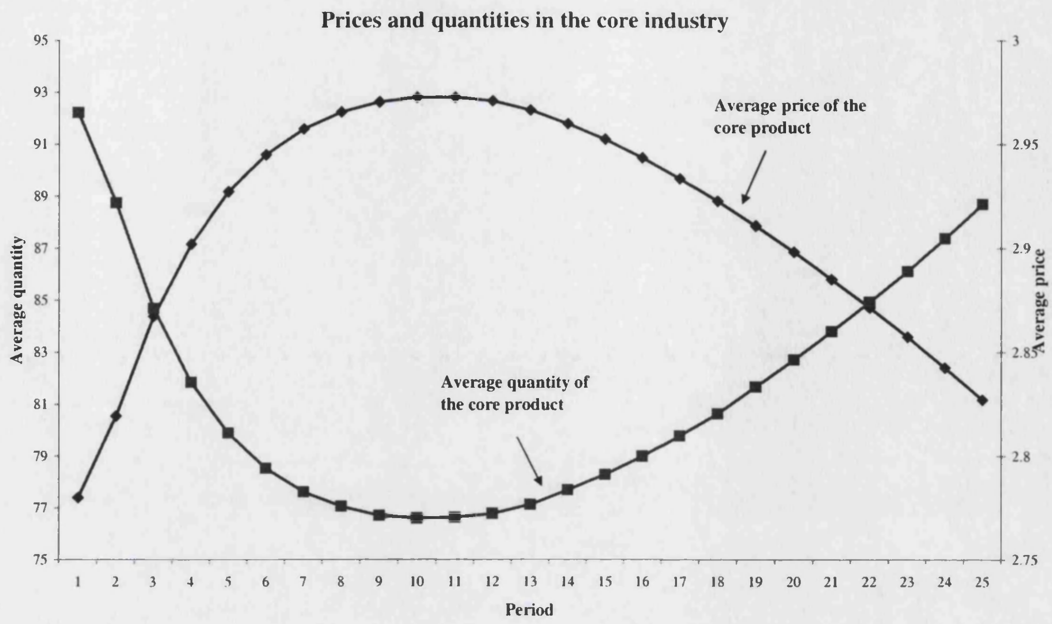

The number of firms in brands f and l
Number of firms
% of draws with knowledge spillover
% of draws with knowledge spillover
Number of firms in brand f
Number of firms in brand l
Total number of firms
Producers
'shakeout'
Period


The 'shakeout' in the R&D of brand f
The 'shakeout'
% of draws with knowledge spillover
The R&D of brand f
Brand f's R&D
% of draws with knowledge spillover
Period

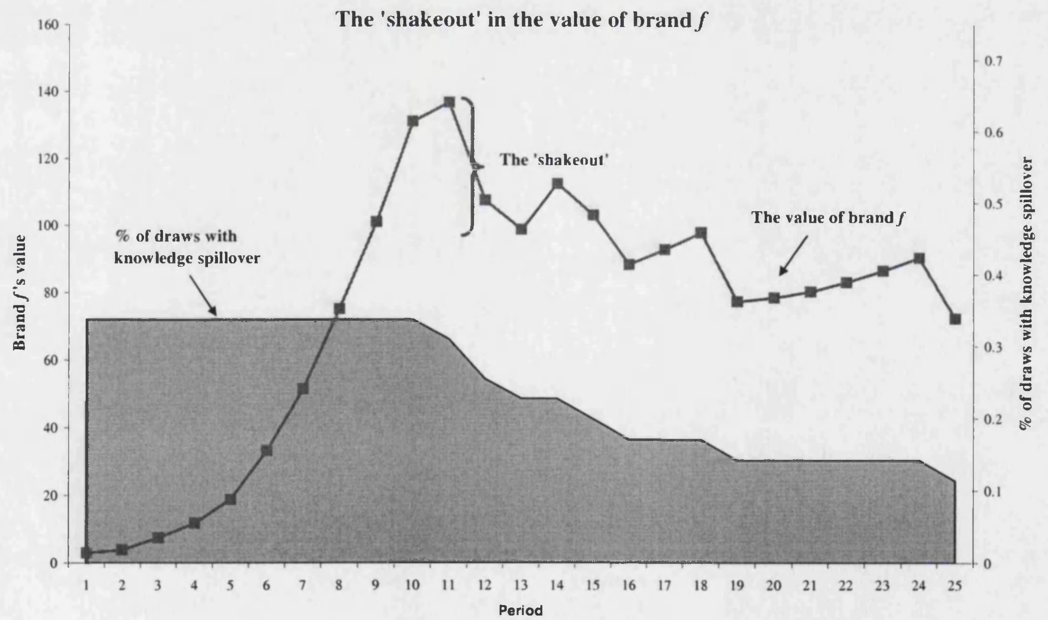

Comparing the value of brand f and l
The value of brand f
The value of brand l
The value of brand l
The value of brand f
Period

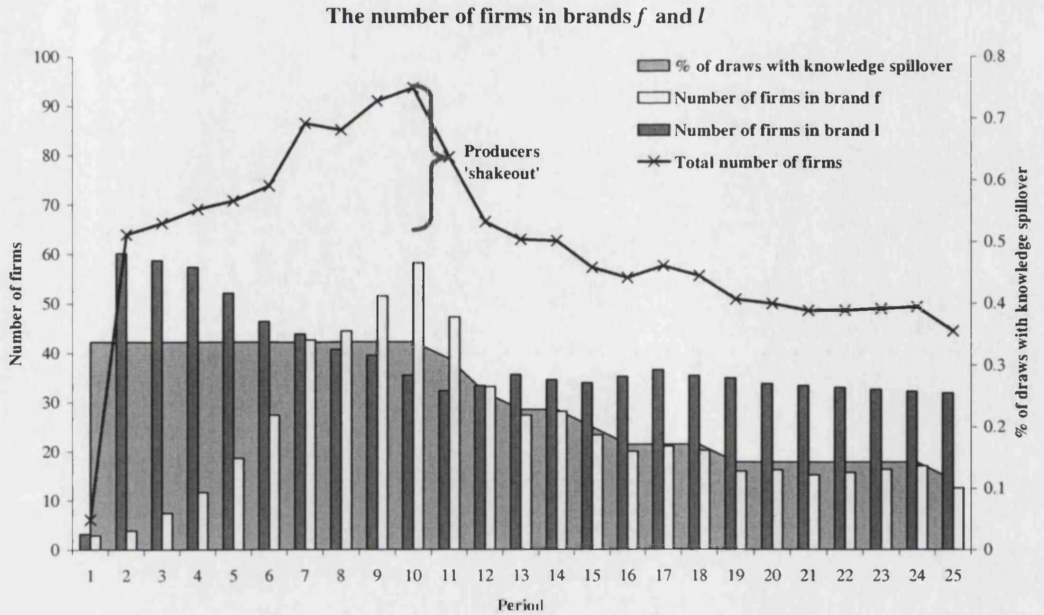

The R&D in the core industry
3.5
3
2.5
2
1.5
1
0.5
0
The R&D in the core industry
Brand *l*'s R&D
Brand *f*'s R&D
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Period

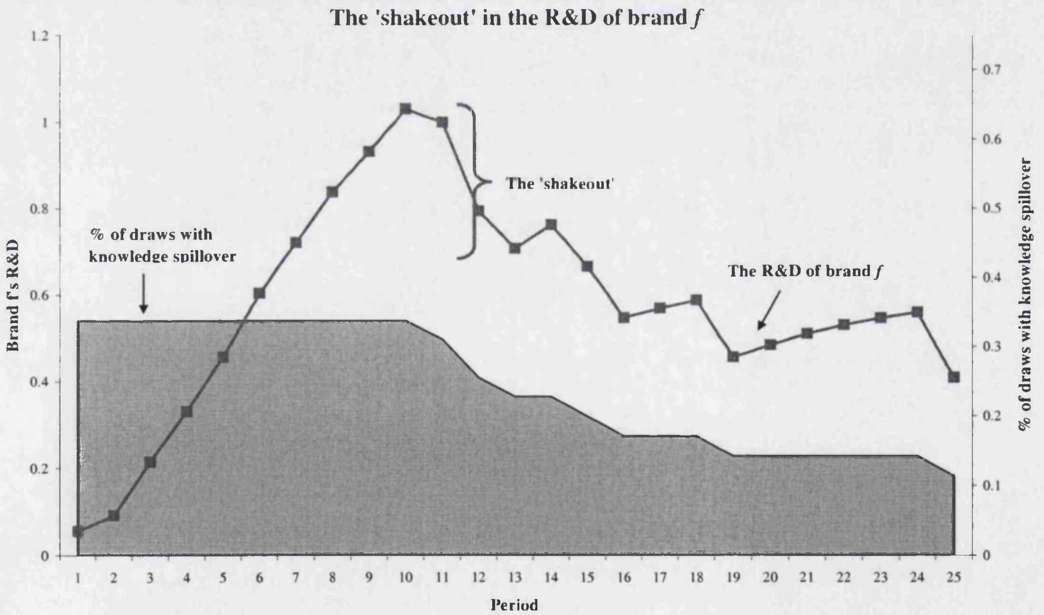

The value and R&D in the ancillary industry
30,500
25,500
20,500
15,500
10,500
5,500
500
The value of the ancillary industry
105
95
85
75
65
55
45
35
25
The R&D in the ancillary industry
The value of the ancillary industry
The R&D in the ancillary industry
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Period

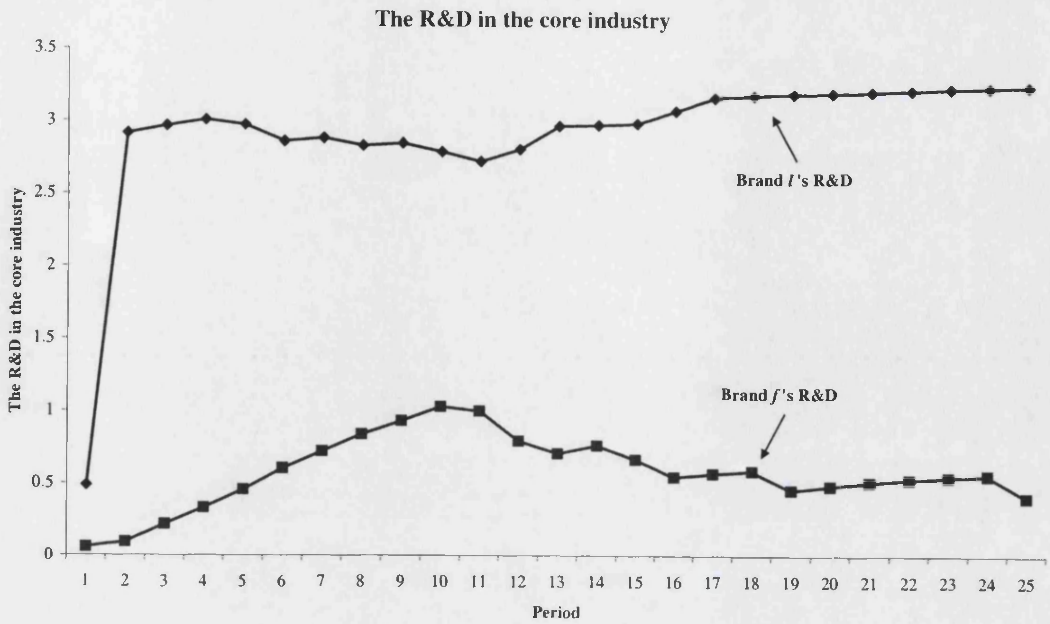


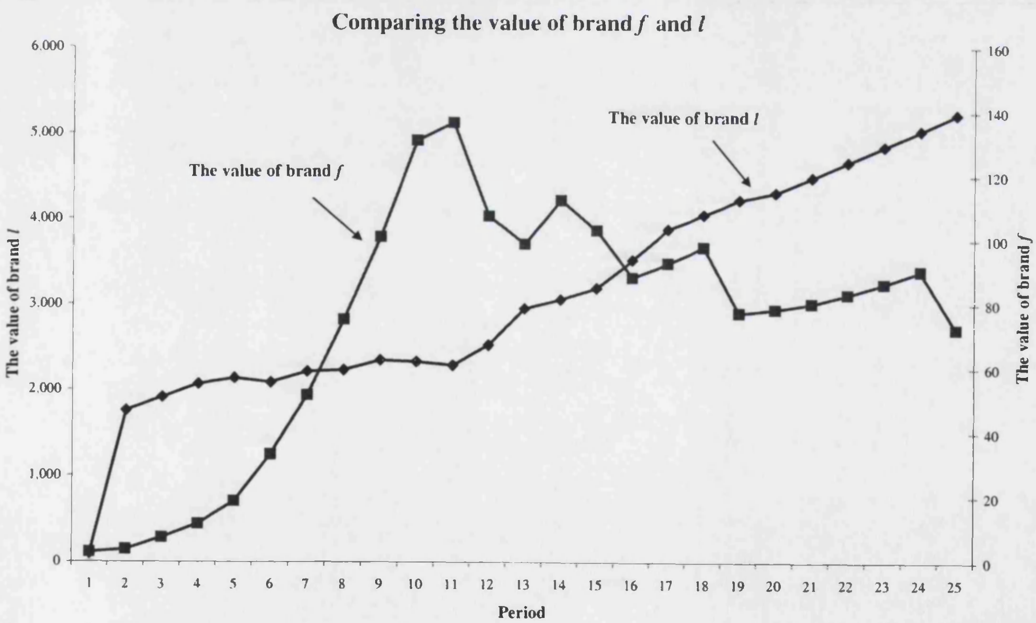
Decreasing the market expansion effect (λ=0.5)

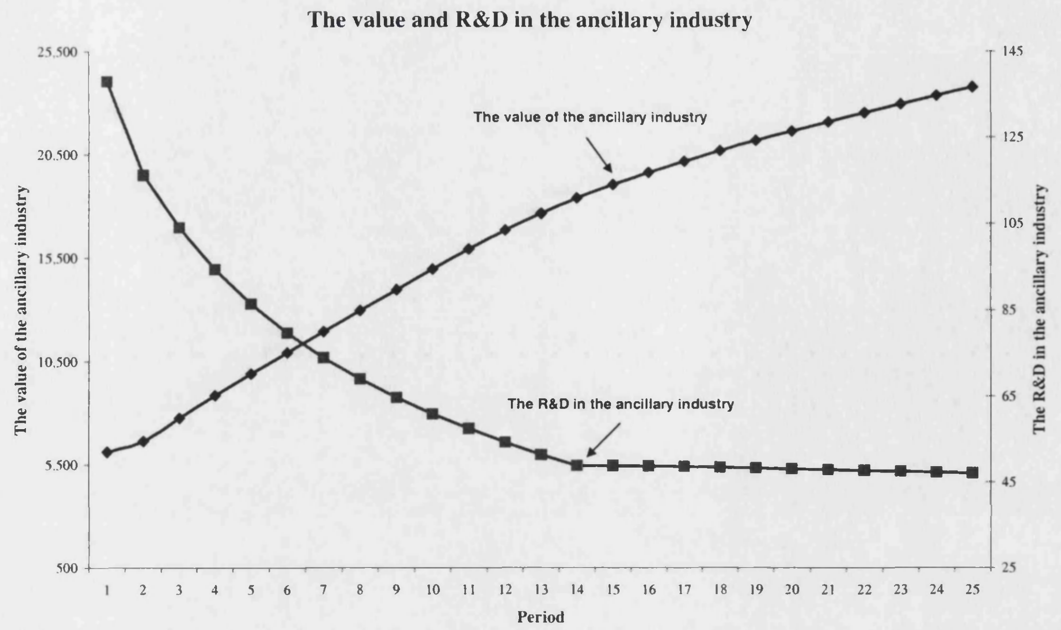



The number of firms in brands f and l
% of draws with knowledge spillover
Number of firms in brand f
Number of firms in brand l
Total number of firms
Producers 'shakeout'
Number of firms
% of draws with knowledge spillover
Period

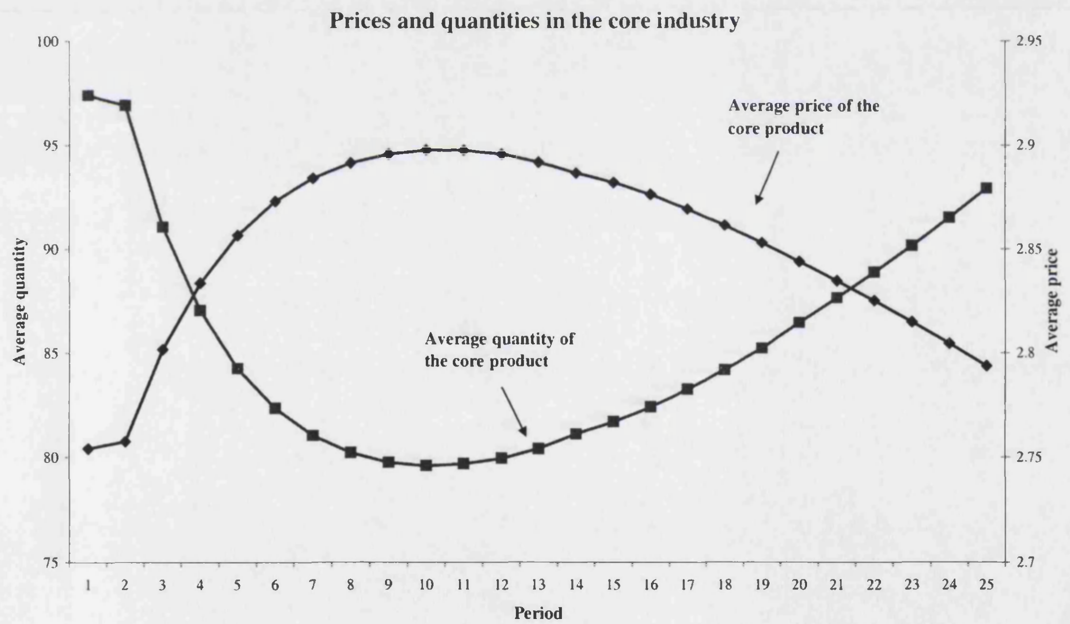

The 'shakeout' in the R&D of brand f
The 'shakeout'
% of draws with knowledge spillover
The R&D of brand f
Brand f's R&D
% of draws with knowledge spillover
Period


The R&D in the core industry
The R&D in the core industry
3.5
3
2.5
2
1.5
1
0.5
0
Brand l's R&D
Brand f's R&D
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Period


Comparing the value of brand f and l
The value of brand l
6.000
5.000
4.000
3.000
2.000
1.000
0
The value of brand f
160
140
120
100
80
60
40
20
0
The value of brand l
The value of brand f
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Period



The value and R&D in the ancillary industry
The value of the ancillary industry
The R&D in the ancillary industry
The value of the ancillary industry
The R&D in the ancillary industry
Period
25,500
20,500
15,500
10,500
5,500
500
145
125
105
85
65
45
25
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25



Prices and quantities in the core industry
Average price of the core product
Average quantity of the core product
Average quantity
Average price
Period
100
95
90
85
80
75
2.95
2.9
2.85
2.8
2.75
2.7
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

Figure 6-1:

6.9.3 Correlation of R&D and endogenous knowledge flows

We estimate the effect of the decision to diffuse knowledge and competition on the innovation on the artificial data we generate, just to show some statistical links between the main variables in our model.

We treat each point in the state set as an observation for firms' behaviour under different market structures (thus, an observation is defined over the tuple $\{\omega_l, \omega_f, \tau\}$). For each brand we estimate the following equation for the 3,800 observations (cells), which are included in the state space:

$$x_{ci} = \mu_0 + \mu_1 x_{-ci} + \mu_2 Diff_{li} + \mu_3 Com_i + \mu_4 DiffCom_i + \nu_i + \varepsilon_i \qquad (6.28)$$

Where, $c = l, f$, $Diff_l$ as an indicator that receives the value 1 if the brand l decides to diffuse its knowledge and zero otherwise, Com is a variable that measures the degree of competition in the core industry as the ratio between the sales of brand f and the sales of brand l (higher Com implies stronger competition). The variable $DiffCom$ is an interaction term between $Diff_l$ and Com, ν is a fixed-effect term that includes a complete set of dummies for the knowledge stocks of brand l, brand f and the ancillary industry.

Table 1

Competition, endogenous knowledge flows and innovation (sample: 3,800 observations)

	R&D of brand *f*	R&D of brand *f*	R&D of brand *l*	R&D of brand *l*
R&D of brand *l*	0.038 (0.009)	0.036 (0.007)		
R&D of brand *f*			0.044 (0.011)	0.131 (0.018)
Competition[a]	-1.622 (0.164)	1.317 (0.160)	6.701 (0.188)	6.672 (0.189)
[b]Diff		3.615 (0.172)		0.972 (0.114)
Competition x Diff		-1.453 (0.354)		-4.064 (0.203)
R^2	0.808	0.943	0.504	0.533

Robust standard errors are in brackets

All regressions include complete sets of dummies for the knowledge stock of brand *l*, the knowledge stock of brand *f* and the knowledge stock of the ancillary industry.

[a] Competition is defined as the ratio of the total sales of brand *l* and the total sales of brand *f*.

[b] Diff is the equilibrium outcomes of knowledge spillover. When Diff equals 1, brand *l* decide to diffuse its knowledge, thus, knowledge spillover exists, while Diff equals 0 when brand *l* decides to protect its knowledge, thus, there is no knowledge spillover.

The estimation results are summarized in table 1. Column 1 reports the estimation results for brand f without including the diffusion variable. The effect of x_l is positive and significant, implying that the R&D of both brands are strategic complements, i.e., brand f finds it optimal to increase its R&D as a response to an increase in the R&D of brand l. The effect of competition on the innovation efforts of brand f is negative, supporting the Schumpeterian hypothesis.

Column 2 reports the estimation results for brand f after including the diffusion variables linearly and interacted with competition. The effect of $Diff_l$ is positive and highly significant, implying that spillovers, which is endogenous in this model, play an important role in shaping the R&D of brand f, which directly benefits from it. The linear effect of competition on the innovation efforts of brand f becomes significantly positive, however, the interaction term of competition and knowledge diffusion is negative. This finding implies that the effect of competition on innovation is negative only through the effect of competition on the decisions of firms to diffuse their knowledge, since higher competition leads to less knowledge sharing, less spillovers and therefore, less innovation. Thus, after controlling for the effect of competition on the incentives to share knowledge, stronger neck-to-neck competition raises the innovation efforts of the laggard brand, which contradicts the Schumpeterian hypothesis.

Columns 3 and 4 report the results of estimating equation (6.28) for the innovation efforts of brand l. The findings are similar to those for brand f. Stronger competition encourages the incentives to innovate, however, when $\theta = 1$ (knowledge flow exists in equilibrium), stronger competition results with less incentives to innovate. This may be the result of reducing the incentives to share knowledge and therefore, not enabling to exploit the benefits of knowledge flows. Thus, brand l faces a reduction in the return it captures on its R&D, since it becomes too costly to share its knowledge with its rivals.