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CREATIVE DESTRUCTION AND THE INNOVATIVE CORE: IS INNOVATION PERSISTENT AT THE FIRM LEVEL?

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Creative Destruction and the Innovative Core: Is Innovation Persistent at the Firm Level?

An empirical examination from CIS data comparing the propensity score and regression methods[*]

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Abstract

At the macroeconomic level, the persistence of technological change allows sustainable growth. But do innovations come from the same set of firms or from a continuous renewal of innovators? On this point, the assumptions underlying the endogenous growth models differ and innovation persistence at the macroeconomic level can be supported by different firm-level behavioral assumptions. The aim of this article is threefold. Firstly, we evaluate the degree of innovation persistence at the firm level and try to solve the paradox between the theoretical predictions of innovation models and the conclusions of previous empirical studies. Secondly, we uncover the factors underpinning the innovation persistence by testing the theoretical explanations that have been proposed in the literature. Lastly, we examine the robustness of the standard econometric methods used in innovation economics. We show that the innovation persistence at the firm level is strong and that the determinants of this persistence depend on the size of the firm.

Keywords: Community Innovation Surveys, Creative destruction, Innovation, Learning-by-doing, Matching, Persistence, Propensity score, Research and development.

JEL Classification: C14, O31, O32.

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1. Introduction

Innovation is a primary source of economic growth. But do innovations come from the same set of firms or from a continuous renewal of innovators? On this point, the assumptions underlying the endogenous growth models are different. While Romer (1990) suggests a strong persistence of innovators, Aghion and Howitt (1992) take the opposite view and develop a neo-Schumpeterian model in which the process of creative destruction leads to a perpetual renewal of innovators.[3] More recently, Aghion, Harris and Vickers (1997), Stein (1997), Encaoua and Ulph (2000) and Aghion, Harris, Howitt and Vickers (2001) have shown that a rich number of individual patterns of innovation persistence are in fact possible. Hence, innovation persistence at the macroeconomic level can be supported by different firm-level behavioral assumptions. What is the empirical relevance of these different microeconomic foundations?

This question relates to two central problems in economic theory. In the first place, the frequency with which firms introduce innovations plays a central role in the analysis of technical progress and economic growth (Romer, 1990; Aghion and Howitt, 1998). In the second place, understanding whether innovation is persistent or not at the firm level constitutes an important piece of evidence for finding and improving current theories of industrial dynamics, where some forms of dynamic increasing returns play a major role in determining degrees of concentration, the evolution of market shares and their stability over time (Baldwin and Scott, 1987; Geroski, 1989).

Despite of the theoretical importance of this topic, only few empirical works have examined the issue of innovation persistence at the firm-level data (Crépon and Duguet, 1997; Geroski, Van Reenen and Walters, 1997; Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001). Roughly, these works conclude either that there is a small degree of innovation persistence, or that innovation is persistent in a small number of firms only. Hence, as long as the majority of innovators would be involved in *a creative destruction process*, there would still remain *an innovative core*. However, several considerations led us to investigate the robustness of this conclusion.

First, the conclusions of previous empirical studies seem to contradict the theoretical predictions of existing innovation models. Indeed, these models generally predict a rather pronounced innovation persistence at the firm level. This paper explores this apparent paradox and shows that it is invalid. It originates from the way innovation is measured in the previous

[3] This difference of assumptions can be seen by comparing the innovation value equations of these models.

studies that use patent data or "major" innovations data.[4] By definition, these data tend to underestimate the number of innovative firms and therefore the persistence of innovation. For the patent data, the main problem is that a patent involves both to innovate and to be *the first* to innovate. This means that patent data can measure the persistence of innovative leadership rather than the persistence of innovation. In the same way, the "major innovations" data involve some kind of leadership as well. Consequently, the evaluation of innovation persistence requires separating innovation from its commercial performance and from the intellectual protection strategies of the firms. In this article, we use detailed data coming from the Community Innovation Surveys (CIS) that provide information that satisfy these conditions.

The second motivation of this paper is to illuminate the factors underpinning the innovation persistence by testing the theoretical explanations of the different models that exist. The previous studies do not allow for the identification of the theoretical model that generates the data. Indeed, some data limitations prevent them from testing some theoretical propositions. This paper identifies the theoretical models that are compatible with the empirical regularities. We fulfilled this objective by bringing together, for the first time, the different streams of innovation surveys.

Lastly we examine the robustness of the standard econometric methods. Ideally, we would like to measure the difference between, on the one hand, the innovative performance a firm makes today knowing that the firm has innovated in the past and, on the other hand, the innovative performance the same firm *would have done* if it had not innovated in the past.[5] There is no way to observe these two quantities at the same time for any firm.[6] The standard econometric methods assume that the non-observable outcomes can be obtained from a regression model, which could be invalid. In this article, in order to solve this problem, we use the propensity score approach introduced by Rubin (1974), Rosenbaum and Rubin (1983) and developed by Heckman, Ichimura and Todd (1997) and use non-parametric methods of estimation (Härdle, 1990).

Several important findings emerge from our research. First, we find a significant persistence of innovation. Second, we find that different factors are at the origin of this persistence. More

[4] In the applied literature, "major" innovations refer to innovations that have met a large commercial success

[5] We evaluate the importance of innovation persistence of a firm through the impact of its past innovations on its current innovation. On the other hand, Geroski et al. (1997) apprehend the extent of innovation persistence of a firm by the number of consecutive years during which it obtains a patent or a major innovation. We discuss the differences between these two approaches below.

interestingly, our results suggest that the factors that induce innovation persistence depend on the characteristics of the firms, especially on their size. Learning-by-doing effects in the production of innovations appear to play a major role on innovation persistence in the small firms. In the largest firms, this effect vanishes and the persistence of innovation originates from the persistence of the formal research and development investments. Lastly, we find that the standard regression methods provide correct results on average but conceal an interesting composition effect.

The article starts with a short review of the literature that lays the theoretical foundations of our econometric model. In particular, we highlight the theoretical predictions about innovation persistence of the different innovation models. Then we summarize the empirical results from previous studies. In the section 3, we describe the data on which the study is based. Section 4 discusses some estimation issues and sets out the estimation methods. Section 5 outlines the empirical results and briefly discusses their implications. Section 6 concludes the paper.

2. Theoretical framework and previous empirical studies

2.1. *The theoretical framework*

Different types of models, which lead to different empirical predictions, can explain the persistence of innovation at the firm level. The *linear model* of innovation establishes a simple relationship between the research and development (R&D) expenditures of a firm and its innovations. The firms that can support the sunk costs of R&D make inventions that lead to product or process innovations (Cohen and Klepper, 1996). In this model the successive innovations originate from the continuity of R&D expenditures and are not directly connected between them. According to this vision of the innovative process, innovation is persistent only if R&D is.

This model implies that, on average, there should be no innovation difference between firms once controlled for R&D expenditures. Hence, it is possible to test this model by regressing a measure of innovation on a measure of past innovation and a measure of R&D. The issue is then

[6] Either the firm innovated and we cannot observe what it would have done if it had not innovated, or the firm did not innovate and we cannot observe what it would have done if it had innovated.

whether there is an additional effect of past innovation on present innovation.[7] If R&D and past innovation are both significant, other models should be investigated.

A second stream of the literature underlines the importance of the *financial constraints* related to the R&D activities (Nelson and Winter, 1982). Giving the difficulty of funding the R&D activities, the commercial success of past innovations helps to fund the current innovative activities: successful innovative firms make profits that can be allocated to future R&D investments. This problem of funding appears when the financial markets are imperfect. A firm that reached a commercial success in the past has more chance to innovate in the future merely because it reinvests its benefits in its research projects. Hence, "success breeds success": a past innovation that met commercial success becomes a necessary condition to finance the future research projects.

Empirically, one way to test this model is to control for the differences of financial constraints between the firms before examining the relation between past and current innovations. This control can be made with a variable of size.[8] If this model is valid, past innovation should not be significant once the firm-level differences of size and R&D expenditures have been controlled for. If past innovation is significant, other determinants of innovation persistence must be considered.

A third stream of literature emphasizes *the strategic considerations* in the innovation decision. A seminal article by Arrow (1962) suggested that firms in competitive markets have significantly greater incentive to invest in innovation than do firms in markets characterized by a significant degree of monopoly power. Gilbert and Newberry (1982) showed that if there is free entry to the industry, Arrow's result does not hold. If there is no uncertainty on the innovation process (auction model) and if the innovation is non-drastic, the incumbents firms with monopoly power will rationally preempt potential entrant investment in innovation in order to continue to profit from the extension of existing market power to a new generation of technology. But Reinganum (1983) re-established Arrow's result by showing that under conditions of uncertainty, incumbent monopolists will rationally invest less in innovation than entrants will, for fear of cannibalizing

[7] Once the R&D differences are controlled for, the impact of past innovation on current innovation reflects the innovation persistence that is not explained by R&D.

[8] Recent work by Himmelberg and Petersen (1994) demonstrates that, at least among small and medium-sized firms in high-technology industries, financial constraints play a major role in determining whether firms pursue innovation. Using a broader sample of firms, Hall (1992) similarly concludes that liquidity constraints are an important determinant of R&D expenditures. On the relationship between size and liquidity constraints, see also Audretsch and Elston (2002).

the stream of rents from their existing products.[9] In these models the successive innovations are not directly connected but two firms with different market shares will not have the same incentives to remain innovative.

Empirically, it is thus necessary to control for these strategic incentives differences. This control can be made with a variable of market share.[10] However, after controlling for these effects, past innovation can remain significant, which leads us to learning-by-doing.

A last stream of literature relies on the idea that innovations result from an accumulation of specific competencies (Rosenberg, 1976). More precisely, this literature considers that the innovative abilities that a firm develops when it invests in research projects do not necessarily depreciate rapidly over time. Therefore, the same knowledge or know-how may be applied to develop several innovations at successive times.[11] The competencies related to innovation do not only refer to the scientific knowledge available to the firm but also to an informal know-how in the production of innovations. According to that view, firms benefit from dynamic increasing returns in the form of *learning-by-doing or learning-to-learn* in the production of innovations (henceforth, learning-by-doing effects), which leads to a strong innovation persistence at the firm level.[12]

Empirically, a simple way to test this hypothesis is to examine whether past innovations still have an effect on present innovation, once R&D, market power and size have been controlled for. According to this third model, past innovation should remain significant.[13] This conclusion differs from the ones of the previous models.

Finally, even if these models do not explain the persistence of innovation in the same way, most of them suggest that we should observe a significant degree of persistence.[14] According to the first model, a weak persistence would mean that firms do not invest in R&D continuously. But, empirically, it is widely observed that there are large differences in R&D efforts across firms

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[9] This result comes from the fact that an innovative monopoly replaces its own product so that it only earns the difference between its two innovative profits, while the incumbent earns a monopoly profit.

[10] Henderson (1993) used the same type of variable to control for strategic effects.

[11] It is particularly true when the innovations are cumulative. See Scotchmer (1999) for a discussion of the concept of cumulative innovations.

[12] There are many possible sources of dynamic increasing returns in the production of innovations. For instance, Cohen and Levinthal (1989) emphasize the necessity to develop internal capacities in order to profit from external opportunities. Chandler (1990) highlights the importance of such effects in the production of innovations.

[13] The inter-industry differences of technological opportunities and demand-push must also be controlled for.

[14] The model with strategic considerations is less clear on this point.

and that these differences in R&D effort are persistent over time.[15] Only a part of the firms performs R&D but these firms generally invest in R&D activities continuously.

According to the second model, a weak innovation persistence would imply either that the capital markets would not be able to fund the innovation projects, or that firms would not reinvest their profits from past innovations in their current research projects. These two implications are unlikely. On the one hand, the financial markets have increased the funds available for the innovation projects considerably and many public policies supporting innovation exist in OECD countries (Hall and Van Reenen, 2000). If there remains a funding problem, it is unlikely that it is so large that innovation would stop being persistent. On the other hand, it is equally unlikely that firms do not reinvest their profits from past innovations in their current research projects, giving the importance of innovation for their competitiveness. In some industries, competition principally centers on innovation (Encaoua and Hollander, 2002). When a firm reinvests its profits in innovation projects, it has more chance to create or maintain its market power.

According to the last model, a weak innovation persistence would imply that learning-by-doing effects in the production of innovations are not important. Some recent empirical analyses suggest the contrary. Kim (1997) showed the central role played by the development of internal innovative know-how in Samsung's technological successes in the semi-conductors industry. Henderson and Cockburn (1996) and Nightingale (2000) studied the pharmaceutical industry. The first ones show that the firms of this industry have profited from significant scope economies in the production of new drugs. Nightingale (2000) finds that the pharmaceutical firms have succeeded in lowering the production costs of new drugs by adopting new experimentation methods and organizational changes. Klette (1996) provides also some empirical evidence of the importance of scope economies in knowledge production for Norwegian manufacturing.

If we combine these models, we should expect a significant degree of innovation persistence. But, until now, previous studies rather conclude that the innovation persistence at the firm level is weak. We think that this paradox is largely due to the kind of data that was available to measure innovation.

[15] See for instance Hall, Griliches and Hausman (1986).

2.2. *The previous empirical results*

The issue of innovation persistence at the firm level has recently been studied by Geroski, Van Reenen and Walters (1997). The authors use two different measures of innovation: annual patent data and annual major innovations data. The extent of innovation persistence of a firm is defined as the number of consecutive years during which it has a recorded innovative output (see below). The authors do not account for innovation inputs differences (like R&D expenditures) but for size differences in the explanation of major innovations. They conclude *"it is very hard to find any evidence at all that innovative activity can be self-sustaining over anything other than very short periods of time"*. Three explanations related to the measurement of innovation could explain this result.[16]

The first point is that there is a strong difference between a patent and an innovation (Griliches, 1990). The most important difference for this study is that a patent implies *leadership* in innovation.[17] Indeed, an innovative firm needs to be the first to apply for a patent in order to be properly registered in the data set. Patent data do not only measure innovation but also the fact that a firm won an innovation race. Hence, a sample including firms that win the innovation race from time to time would show up a weak persistence of innovation, even if these firms innovate all the time. The second point is that leadership itself could be poorly measured by patent data. This problem is linked to the intellectual property strategy of the firms. Firms can have an obvious interest in avoiding patenting an intermediate innovation in order to conceal the knowledge that could be used by their competitors.[18] There is a strong empirical evidence of this kind of behavior (Levin et al., 1987, and Cohen et al., 1997, on American data; Duguet and Kabla, 1998, on French data).[19] Lastly, the firms tend to patent more their product innovations

[16] The data available for measuring the persistence of innovation can also explain the weakness of the persistence that has been found. Indeed, this data source requires that a firm obtains a patent or a major innovation every year in order to be identified as a persistent innovator. Moreover, it is difficult to make a decision on which frequency to use (every two years, three years etc.). Finally, the differences between low-tech and high-tech industries could also lead to retain at least two different frequencies. CIS data measure the innovation persistence in a less restrictive manner.

[17] For a theoretical analysis of the persistence of leadership, see Gruber (1992) or Denicolo (2001).

[18] Moreover, patents underestimate the innovation of small-sized firms that use less patents than large firms. See Acs and Audretsch (1988).

[19] Duguet and Kabla (1988) show that on average only a third of the innovations are patented because of the information disclosure implied by the patent documents. Moreover, after controlling for the propensity to patent, R&D investments, market share and industry of the firm, the determinants "will to avoid litigation" and "technology negotiations" remain strongly significant in the explanation of the number of patent applications. Hence, strategic aspects are omnipresent in the patent numbers, which precludes from using it as a mere innovation indicator. This strategic dimension of patents is more and more present in the firms' decisions to patent their innovations (Encaoua and Hollander, 2001).

than their process innovations (Arundel and Kabla, 1998). The patent data are thus biased in favor of product innovations. Hence it is unlikely that the persistence of innovation can be fully measured with these data.[20]

The second type of data used in Geroski, Van Reenen and Walters (1997) concerns innovations that met a commercial success. Here, the data avoid the biases associated to the patenting strategy of the firms but there remains one limitation. Since this definition involves a commercial success, the firms considered as innovative are likely to be either innovation leaders or commercial leaders. In the latter case, the data measure the ranking of the firms on the market, that is their ability to adapt the available innovations to consumers' tastes.

The work of Crépon and Duguet (1997) is equally related to the issue of innovation persistence. They use a panel of R&D performers operating in France and they also use patent data to measure innovation.[21] They estimate a dynamic count data model that links the current number of patents to both the previous year number of patents and the amount invested in R&D. They also add an individual fixed effect that can represent differences in size, of technological opportunities and of the firm's propensity to patent. Contrary to Geroski et al. (1997), they find that innovation persistence is strong among R&D performers since the effect of lagged patents on the current number of patents is significantly positive. At first glance, the results of Crépon and Duguet (1997) seem to contradict the results of Geroski et al. (1997). However, the study of Malerba and Orsenigo (1999) suggests that these two works are in fact complementary.

The descriptive statistics study by Malerba and Orsenigo (1999) examined the issue of persistence by using patent data of six countries over the period 1978-1991.[22] They conclude that a large fraction of innovators is casual. Nevertheless, there would still remain a stable group of innovators that apply for a large share of patenting. The results of this study are confirmed by Cefis and Orsenigo (2001) who find that both "great-innovators" and non-innovators have a high probability of staying in the same innovative state. Then, there would be a strong persistence of innovation in a core of firms.

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[20] Needless to say that patent data remain irreplaceable for other purposes, like the measurement of spillovers through citations or the identification of the technology classes.

[21] R&D performers are defined according to the Frascatti criterion (at least one research working full time on R&D).

[22] The six countries are : France, Germany, Italy, Japan, the U.K. and the U.S.A. Their patent data are available for different periods: 1978-1982, 1982-1985, 1986-1988 and 1988-1991.

Globally, two interesting elements emerge from these studies. On the one hand, the weakness of persistence degree, found in several empirical studies, suggests that the theoretical predictions would be applicable only to a restricted group of firms. On the other hand, few empirical studies have paid attention to the *determinants* of innovation persistence, so that we do not know how to weight the empirical relevance of the different theoretical models.

In order to determine which of the previous theoretical models is relevant, one should take into account the whole list of explanatory variables included in a regression, since the degree of significance found for each determinant obviously depends on all the explanatory variables included in the analysis. Current innovation must be explained by past innovation, research, market power, size and industry effects so that a significant effect of past innovation on current innovation can be interpreted as a learning-by-doing effect. Crépon and Duguet (1997) take into account these different variables (through R&D and a fixed effect) but their sample is limited to the significant R&D performers only. Moreover, they use patent data so that the robustness of their results needs to be examined on different data sources. Our objective is thus to use a different measure of innovation and to develop a model in which it is possible to identify the determinants of innovation persistence with a more representative sample of firms.

3. The data

The data used in this paper allow for the separation of leadership, either commercial or innovative, from innovation itself. They come from the recent Community Innovation Surveys (CIS) that provide information about the implementation of innovation at the firm level, without any reference to their commercial success or their patenting status.[23]

The data come from five data sets, including three about innovation. The first data set is the Innovation Survey "*L'Innovation Technologique dans l'Industrie*" conducted by the SESSI that was performed in order to prepare all the other innovation surveys in France. It was conducted in 1991 and provides information about the period 1986-1990. In order to identify innovation persistence, we also use two Community Innovation Surveys (henceforth CIS). The CIS1, conducted in 1993, provides information about the period 1990-1992, while the CIS2, conducted in 1997, gives information about the period 1994-1996.

[23] Moreover, these surveys have been conducted in many European countries so that international comparisons are now possible.

The remaining data sets provide accounting information. First, the annual industry census 1985 (in French, "*Enquête Annuelle d'Entreprises*") provides data about the main line of business and sales at the firm level.[24] Second, the annual line-of-business data on domestic sales 1985 (in French, "*Enquête Annuelle d'Entreprises par Fractions*") gives information on sales of firms in each line of business where they operate. This allows computing a domestic market share that takes into account the fact that some firms are diversified. The market power variable is then a weighted average of the different market shares of a firm.[25]

The merger of these data sets provides a sample of 621 firms operating in manufacturing and covers the period 1986-1996.[26] Year 1993 is missing since no innovation survey covers this year.[27]

Table 1 provides the percentage of innovators by industry. These percentages are not directly comparable since the first survey spans 5 years, while the two other innovation surveys 3 years. Hence the first survey gives the highest innovation figures. The maximum is reached in equipment goods (including cars) and the minimum in consumer goods. The two following surveys (CIS1 and CIS2) provide lower figures as expected. Nevertheless, the three innovation surveys give comparable results in the sense that the order between industries is maintained.

Globally, the first survey reports 78% of innovators and the following ones 61% of innovators. These figures seem high but there are two reasons for it: they cover a three-year period or a five-year period and the definition of innovation includes new products and new processes as well as innovations of different heights.[28] Since these data do not refer to the market performance of the firms or to their patenting strategy, we should be able to evaluate better the persistence of innovation. The advantage of this innovation definition is that it allows for

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[24] EAE is the « Enquête Annuelle d'Entreprises » (the industry census). It is compulsory for all firms above 20 employees.

[25] This measure is presented in detail in Crepon, Duguet and Kabla (1996).

[26] Notice that we imposed the presence of firms in each innovation survey and in the 1985 E.A.E. survey. We thus examine the innovation persistence conditional to the existence of the firms in 1985 and to their survival up to 1997. The integration of entry and exit issues of innovative firms in our analysis would require another data we do not posses. Nevertheless, the impact of new entrants on the date at which the incumbents decide to innovate is taken into account. Moreover, the role of new innovative firms, in particular of start-ups, could be relatively minor in France. In a recent study, Arora et al. (2000) show that in Europe 90% of research projects in biotechnological sectors are due to large installed firms, whereas in United States more than 50% of the research projects are accompanied by the creation of a new firm. Chesbrough (1999) finds similar results in the semi-conductors industry.

[27] Without market share data, the sample size increases up to 808 firms. We have conducted our study on this data set a well and present it in appendix. Our basic conclusions are not altered by this data change.

[28] The definition used in the innovation surveys includes the five following types of innovation : (1) significant improvement of an already existing product; (2) introduction of a product that is new both for the firm and for the market; (3) introduction of a product that is new for the firm but not for the market; (4) significant improvement of an already existing production process and (5) process breakthrough. Notice that the full decomposition is available in the first survey only.

measuring innovation in a firm that persistently innovates but in a different manner over time, for instance by introducing a new product and then by improving on the production process. The case studies confirm the view of the innovative process according to which the persistence originates from the diversity of innovative behaviors (Kim, 1997).

-Insert Table 1-

The innovation surveys also include information about the inputs that have been used to innovate. The 1991 innovation survey distinguishes formal R&D according to the Frascatti criterion and the informal R&D identified as "technical studies". The answers are provided on a four-point scale ("none", "weak", "moderate" and "strong"). The figures are reported in Table 1. Over 1986-1990, about two thirds of the innovative firms declare to have conducted moderate or strong informal R&D, 43% have conducted strong formal R&D and 28% have conducted no research at all. The CIS1 does not allow for the separation of the formal R&D from the informal one. The only available data aggregate both definitions. We have grouped the weak and moderate levels to obtain a four-point scale. It appears that a third of the firms have conducted very strong formal or informal R&D, a figure that is close to the one obtained in the previous survey for informal R&D.

Table 1 equally presents some descriptive statistics on the size of the firms measured by their sales in 1985 and on the degree of technological opportunities in their activity.[29] The advantage of measuring the size of the firms by sales rather than employment is that it is less sensitive to the differences in the capital-labor ratio (Cohen and Levin, 1989; Kleinknecht ed., 1996). The degree of technological opportunities does not come from an industry classification but is available at the firm level in the first innovation survey that provides information about the degree of innovation of a firm's line of business (four levels are distinguished: "none", "weak", "moderate" and "strong"). Based on previous works, we define the "low-tech" activities as "none" or "weak", and the "high-tech" as "moderate" or "strong". This variable has proved to be useful in previous econometric studies in French manufacturing where it revealed significant differences of performances that were not attributable to the firm-level innovation.[30] We see that the innovators

[29] The Sales and market share are lagged (1985) in order to avoid simultaneity.

[30] This variable could indirectly measure a spillover potential available to the firm. See Barlet et al. (1998).

generally have a larger size than the non-innovators and operate in lines-of-business where the technological opportunities are higher.

4. Methodology

Let y_i denote the current innovative performance of firm i and T_i denote his past innovation.[31] Each firm has two different innovative performances depending on whether it innovated in the past ($T_i = 1$) or not ($T_i = 0$). We denote them $y_i(1)$ and $y_i(0)$. The effect of past innovation on the whole population, called *the average causal effect* in the statistical literature, is defined as $c = \mathrm{E}[y_i(1) - y_i(0)]$. If it was possible to observe the performances of each firm in both states 0 and 1, the average effect of past innovation could be estimated by the difference of the corresponding sample averages. Since such data are not available, one needs to construct a *counterfactual* artificially, that is an estimation of $y_i(1)$ for the firms that did not innovate in the past and an estimation of $y_i(0)$ for the firms that innovated. The most widespread method is to use a parametric model $y(.)$ that explains the performance y_i by past innovation T_i and the characteristics of the firm (denoted X_i): $y_i = y(T_i, X_i)$. The counterfactuals are simply obtained by $y_i(0) = y(0, X_i)$ and $y_i(1) = y(1, X_i)$.

When the performances are binary variables (e.g., to innovate or not), the evaluation can be obtained from a probit model, that explains the probability to innovate today by past innovation and the characteristics of the firm (size, market power, industry, R&D expenditures etc.). It is given by:

$$y(T_i, X_i) = \Phi[X_i\beta + \gamma T_i],$$

where Φ is the cumulative distribution function of the standard normal distribution. The average effect of past innovation is therefore estimated by:

$$\hat{c} = \frac{1}{N}\sum_{i=1}^{N}\{\hat{y}(1, X_i) - \hat{y}(0, X_i)\} = \frac{1}{N}\sum_{i=1}^{N}\{\Phi(X_i\hat{\beta} + \hat{\gamma}) - \Phi(X_i\hat{\beta})\},$$

[31] The current innovative performances also correspond to a binary variable.

where $\hat{\beta}$ and $\hat{\gamma}$ denotes the maximum likelihood estimates from the probit model and N is the number of firms in the sample.[32]

One of the main limitations of the probit method is that it assumes that there is always a *perfect counterfactual* given by the parametric model, that is it assumes there can exist a firm that did not innovate in the past and that has *exactly* the same characteristics than the firm that innovated (or more precisely the same $X_i\beta$). Therefore this method could be invalidated when innovative firms have different characteristics X_i from the non-innovative firms. The basic argument why the firms are not comparable may simply be that innovative firms do more R&D or have a size that differs from the size of non-innovative firms.[33] In this case, it is possible that the probit method provides inconsistent estimates of the effect of past innovations.

With the Rubin method, the counterfactuals are not obtained from a parametric model, but from the *actual* data. This methodology was first proposed by Rubin (1974, 1977) and developed by Rosenbaum and Rubin (1983) as well as Heckman, Ichimura and Todd (1997) among others. The intuition is a follows. If we had an experimental sample, a direct comparison of the percentage of innovation between the two sets of firms, defined by T_i, would provide a consistent estimate of c.[34] This is because the performances difference of averages between past innovative and non-innovative firms could only come from past innovation and the empirical average would be a consistent estimator of the expected causal effect. But past innovation is not allocated at random between firms so that a generalization of this method is needed. Rubin (1974) showed that it is possible to evaluate the effect c if the following condition if fulfilled:

$$\left(y_i(0), y_i(1)\right) \perp T_i \middle| X_i \qquad \textit{(H-1)}$$

where $\perp$ denotes statistical independence. This implies that one can evaluate the counterfactuals by:

$$\mathrm{E}(y_i(1)|X_i, T_i = 0) = \mathrm{E}(y_i(1)|X_i, T_i = 1) = \mathrm{E}(y_i(1)|X_i)$$

$$\mathrm{E}(y_i(0)|X_i, T_i = 1) = \mathrm{E}(y_i(0)|X_i, T_i = 0) = \mathrm{E}(y_i(0)|X_i)$$

The only practical problem with this method is that it implies to match firms on large number of variables X_i. Fortunately, Rosenbaum and Rubin (1983) have shown that this

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[32] The same computation can be done for any binary explanatory variable. It is thus possible to compare the importance of past innovation with the importance of other explanative variables, especially with R&D.

[33] For evidence, see Cohen and Levin (1989) and Kleinknecht ed. (1996) on European data.

condition can be simplified to conditional independence on the one-dimensional *propensity score* defined as $\Pr(T_i = 1|X_i)$. This selection probability conveys the following useful intuition. Suppose that we have a group of firms with the same probability to have innovated in the past. Inside this group, there are firms that innovated in the past and firms that did not. Hence, the allocation of past innovation between these firms can be considered as random. The comparison of the average performances *inside* homogeneous probability groups is therefore relevant. More precisely, Rosenbaum and Rubin (1983) have shown that:

$$(y_i(0), y_i(1)) \perp T_i|X_i \Rightarrow (y_i(0), y_i(1)) \perp T_i|\Pr(T_i = 1|X_i).$$

In practice, the propensity score is replaced by its estimate. Following the literature on discriminant analysis, the propensity score can be estimated by a probit or a logit model, with X_i as explanatory variables (see Maddala, 1983).[35] But the propensity score may also depend on a firm-level fixed effect, which represents any time-invariant factors that influence the innovative performances of the firms.[36] For instance, this effect may represent firms that have research teams with more successful researchers. We denote this fixed effect by α_i. The identification condition becomes:

$$(y_i(0), y_i(1)) \perp T_i|(X_i, \alpha_i) \Rightarrow (y_i(0), y_i(1)) \perp T_i|\Pr(T_i = 1|X_i, \alpha_i).$$

The fixed effect raises an issue because it is unobservable. There are two ways to deal with this problem. The first method is to estimate a fixed-effect logit model on panel data and to use the predicted probability to match firms. But, unfortunately, this is not possible with the Community Innovation Surveys for the two following reasons:

1. In the fixed effect logit model, the estimation proceeds by the conditional maximum likelihood method, where the conditioning variable is the number of times that a firm innovates (i.e., the sum of the innovation dummies). This implies that two kinds of events must be excluded from the regression (Hsiao, 1986). First, one should exclude the firms that have always innovated and, secondly, one should exclude the firms that have never innovated. The reason why the always-innovators are excluded by this method is that the

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[34] In this literature, T_i is called the treatment and the firms that innovated in the past the Treated.

[35] Notice that this is not the same as the parametric model. In the Rubin approach, the treatment is explained by a probit model and the outcome of the treatment remains *non-parametric*. In the parametric model, there is no matching and the outcome is given explained by a probit model.

[36] Taking into account an individual fixed effect implies that the selection equally comes from unobservable variables. See Heckman et al. (1998) on this issue.

conditional probability to innovate knowing that one has always innovated is equal to one, so that it does not contribute to the conditional likelihood (i.e., provides no relevant information for the estimation). The reason why never-innovators are excluded is that the conditional probability to innovate knowing one has never innovated is equal to zero. Hence *the higher the persistence of innovation is, the less there will be firms available for the fixed-effect logit regression*. And we have a majority of such firms.

2. In a logit model with a fixed effect and two years of data, one needs to do a regression on the difference of the explanative variables (Hsiao, 1986). Unfortunately the definition of research inputs changes over time. In the first survey, formal and informal R&D are separated and the firms answer on a four-point scale ("Not important", "Weakly important", "Moderately important", "Strongly important"). In the second survey, formal and informal R&D are grouped together and firms answer on a 5 points scale (0,1,2,3,4). Hence, there is no way to take the difference.

Therefore, the applied researcher has no other choice than to use another method. The second method is to find out observable variables that are strongly correlated to the fixed effects so that the permanent differences between firms can be controlled for. Thus, we need variables that, for example, give information on the competencies of the research team of a firm. The most obvious set of variables is the past innovative history of the firm. If a firm has a successful research team, its innovation history should score better than the one of another firm.

The first innovation survey is especially useful for this purpose since it provides information on the innovation history of the firms over the five years period 1986-1990. The long length of inquiry of this data set is an advantage when trying to control for individual effects. Firms that did not innovate over five years may not have successful research teams, while firms that innovated at least once in five years may have more competent research teams. Another time-persistent variable available in this survey is the degree of technological opportunities of firm's line-of-business. We denote these two variables by Z_i. Replacing the fixed effect formulation by its observable counterpart, we use the following condition:

$$(y_i(0), y_i(1)) \perp T_i | W_i \Rightarrow (y_i(0), y_i(1)) \perp T_i | \Pr(T_i = 1 | W_i)$$

where $W_i = (X_i, Z_i)$. We perform the matching on the corresponding estimated propensity score.

Whichever the method used, the first precaution to take is to check that the supports of the propensity score have a sufficient overlap between the two groups of firms (i.e. treated and non-treated firms) (Dehejia and Wahba, 1998). Some firms can be excluded from the sample because there exists no relevant counterfactual. It is therefore not possible to evaluate a causal effect for these latter firms. It is an important difference with the probit method which uses all the observations.

Our simplest evaluation of the causal effect is based on the construction of several probability classes.[37] This method allows to compute the effect of past innovation by regression and to compute heteroskedasticity-robust standard errors in a simple way. However, the matching is not perfect. In order to fix this problem, we have grouped observations into strata defined on the estimated propensity score so that the covariates within each stratum are balanced, following Rosenbaum and Rubin (1983) and Dehejia and Wahba (1998).[38] Once the probability classes are constructed, we compute the average difference of performance *inside each propensity score class* by the following regression:

$$y_i = a + c\,T_i + u_i,$$

where u is a disturbance. The OLS estimator simply gives the difference of the means between the past innovators and the other firms: $\hat{c} = \bar{y}_1 - \bar{y}_0$. A second evaluation is based on an extension of the previous regression:[39]

$$y_i = a + bm_i + T_i\left(c + dm_i\right) + v_i,$$

where $m_i = W_i\hat{\delta}$ is the score obtained from the (selection) probit model, $\hat{\delta}$ the corresponding maximum likelihood estimate and v a disturbance.[40] Here, the effect of past innovation depends on the characteristics of the firm through the score. When the score m_i is centered, the average causal effect is still given by the coefficient of the treatment since we have:

$$\mathrm{E}\left(y_i(1) - y_i(0)\right) = \mathrm{E}\left(c + dm_i\right) = c.$$

The previous estimator provides valid inference for the whole population of firms, but we are also interested in the causal effect on the treated. The difference between the two quantities is

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37 An imperfect matching allows keeping more firms in the sample but implies the necessity to test for homogeneity inside the classes. On the problems associated to matching, see Heckman et al. (1998).

38 For this reason, we test the equality of the means of the covariantes. Since most of these covariates are dummies, this is equivalent to test the equality of their distributions.

39 See Crépon and Iung (1999) for a formal justification.

40 The propensity score is strictly increasing with m_i so that it could be used to match firm as well. The reason why we take this score instead of the propensity score is that it is a linear function of the variables, so that we get a standard-looking regression.

that the causal effect can be different for each firm so that there is no reason *a priori* why the effect of the treatment should be the same among the treated and the non-treated. More precisely, we evaluate $c_1 = \mathrm{E}(c_i | T_i = 1)$. Here, the identifying assumption is less demanding:

$$y_i(0) \perp T_i | W_i \Rightarrow y_i(0) \perp T_i | \Pr(T_i = 1 | W_i)$$

The simplest way to evaluate this quantity is to use the Nadaraya-Watson (non-parametric) estimator (Härdle, 1990). For each treated firm, we compute the difference between its performance and a local weighted average of the performances of its non-treated neighbors, where the weights decrease with the difference of the propensity score. The kernel estimator of E[$y_i(0)$ | T=1] is defined as:

$$\hat{E}[y_i(0) | T = 1] = \sum_{j \in I_0} \omega_j \times y_j \text{ where } i \in I_0 \text{ and } \omega_j = \frac{K[(p_i - p_j)/h]}{\sum_{j \in I_1} K[(p_i - p_j)/h]}$$

where p_i is the propensity score of the treated firm *i*, p_j the propensity score of the non-treated firm *j*, *K(x)* is a gaussian kernel, *h* the window and I_0 the set of firms that have not innovated in the past.[41]

The average causal effect of the treated is obtained by:

$$\hat{c}_1 = \frac{1}{N_1} \sum_{i \in I_1} \{ y_i(1) - \hat{E}[y_i(0) | T = 1] \}, \; N_1 = \mathrm{card}(I_1)$$

This estimator is asymptotically normal and its variance can be obtained by the bootstrap, with 100 simulations (Efron and Tibshirani, 1983).[42]

5. The results

We begin by presenting results obtained with the probit models (Table 2). This provides a first evaluation of the degree of innovation persistence (model 1) as well as the determinants of this persistence (model 2). We then assess the robustness of these results by using the Rubin method and implemented different estimation methods. The first one, the estimation method by class, led us to construct three classes (Table 3) and allows determining the causal effect on the

[41] In order to make this estimation we took a Silverman window. For more information about this non-parametric method, see Härdle (1990).

[42] The propensity score is re-estimated for each simulation. The estimation was performed under SAS-IML.

whole sample *(c)*. The second one, the Kernel method, does not impose to construct classes but can be applied on the whole sample as well as the sample of each class. This estimator allows to evaluate the causal effect on the treated *(c_1)*. Table 4 presents results obtained from Rubin model, while table 5 explores the characteristics of firms in each class.

5.1. *The probit models*

Table 2 presents the results of the probit models. Two different sets of explanatory variables are examined. The aim of model 1 is to evaluate the degree of innovation persistence, so that the current innovation (1994-96) is explained by lagged innovations, industry dummies and a firm-level dummy indicating whether the firm belongs to a high-tech activity. We controlled for industries differences because we want to evaluate the firm-level persistence of innovation. The model 2 includes past innovations, past research activities, the average market share and size as explanative variables. It is only this last model that allows us to identify precisely the determinants of the innovation persistence.

We find a strong persistence of innovation at the firm level. In model 1, all the lagged innovation variables are significant. A firm that innovated in the past thus has a stronger probability to innovate today: the fact that a firm innovated between 1986 and 1990 (resp. 1990 and 1992) increases its propensity to innovate currently of + 23% (resp. + 27%). Indeed both past innovations are significant, which suggests that the process is cumulative: each time a firm innovates, it increases its innovative advantage. However, the coefficients of past innovations decrease with the lag length. This means that the advantage of previously innovating firms decays progressively over time. Lastly, this result also suggests the existence of a strong entry barrier to innovation: it appears particularly difficult for a firm to innovate if it has never innovated.

These findings are robust to the introduction of industrial and technological opportunities dummies, so that the past innovation variables reflect neither differences between industries nor differences between low-tech and high-tech activities. The industry of equipment goods (including car industry) appears more innovative than the industry of consumer goods, which is coherent with previous studies (Cohen et Levin, 1989). On the other hand, the high-tech dummy is not significant.

This first model allows us to conclude to the likely existence of an innovative core of firms that innovate persistently and whose advantage decays relatively slowly over time since innovations that have been made 10 years before still have a significant effect.

- Insert Table 2-

After having controlled for research, size and market power differences (model 2), lagged innovations remain significant but with a lower impact (average effect of + 12% for innovation 1986-1990 and + 16% for innovation 1990-1992). This result suggests that firms that innovated in the past benefit from advantages that do not come only from formal research activities but equally from more informal activities. The learning-by-doing effects in the production of innovations thus play a significant role to explain the persistence of innovation. The relevance of the model with learning-by-doing is thus confirmed.

While past innovations remain significant, formal research over the period 1986-1990 and the size variables are significant as well. It means that a good part of the persistence found in model 1 comes from R&D and financial constraints. The linear model and the model with financial constraints are thus partly validated. On the other hand, the market power variable is not significant.[43]

Nevertheless, only the strongest level of formal research 1986-1990 is significant. This result indicates that R&D activity leads to a durable advantage to innovate only if a firm has conducted strong formal R&D.

Another interesting result is that while formal R&D over 1986-1990 is significant on innovation over 1994-1996, informal R&D is not. This suggests that informal knowledge would have a higher depreciation rate than formal knowledge. One explanation is that formal R&D can be more easily codified and transmitted to the new researchers or engineers or simply that the knowledge generated by formal R&D is relevant for a wider scope of applications than the knowledge generated by informal research.

The research variables over the period 1990-92 are not significant, which is relatively surprising. It is likely that the aggregation of formal and informal research leads to lose information. For the previous period (1986-1990), we saw indeed that the results can be very different between formal research and informal research. The question is then the following: if we were able to distinguish between formal and informal research over 1990-1992, would the coefficient of past innovation 1990-1992 have been changed following to the significance of formal research over 1990-1992? Certainly given sufficient variability in the data but this variable

[43] Therefore, we have performed the estimations on the 808 firms sample. The results, provided in appendix, are basically unaltered.

should remain significant. This is what our results suggest since both past innovation 1986-1990 and formal research 1986-1990 are significant.

Table 2 also presents the average effects of all significant variables in each model on the whole sample and on the sample of the past-innovators. In the model 2, the average effects allow to compare the relative importance of research and past innovations for current innovation. Whichever sample is considered, we find the interesting result that the achievement of a past innovation would be more important than formal research itself. Indeed, on the whole sample for instance, we find that a firm that has innovated over 1986-1990 has on average a 12% higher probability to innovate in 1994-1996, once controlled for all the other determinants of innovation. The ones that innovated over 1990-1992 have on average a 16% higher probability to innovate in 1994-1996. These figures are twice as high as the impact of the strongest level of formal research and development over 1986-1990 (+ 8%).

These different results suggest strong innovation persistence at the firm level. The determinants of this persistence refer not only to research activities but also to advantage due to the size of firms. Firms that were engaged in research activity over 1986-1990 or that innovated over the same period still benefit from advantages to innovate a few years later. This result challenges the standard assumption of memoryless patent races, which is often at the basis of the neo-schumpeterian endogenous growth models.

5.2. The Rubin model and the evaluation of the causal effect

The estimation of the causal effect is based on the first-step estimate of the probability to have innovated in the past (1990-92).[44] After that the *propensity score* has been estimated, it is possible to match firms in several ways. The first one consists in constructing probability classes in which there are firms that innovated in the past and firms that did not innovate. Then, in each probability class, the causal effect is evaluated, i.e. the specific effect of past innovation on current innovation. The second matching method is the Nadaraya-Watson kernel estimator.

The estimate of the probability to have innovated over 1990-92, i.e. of the propensity score, is equivalent to choosing a set of conditioning variables. We have retained size, industry dummies, high tech dummy, past research activities (1986-90) and innovation 1986-90 as

[44] The results of this estimation are reported in appendix.

explanatory variables.[45] For each firm, we get an estimated probability to have been treated and construct probability classes (or perform matching) according to this estimated *propensity score.*

The construction of probability classes requires several steps. First, we determine the common support of the propensity score of treated and non-treated firms (see figure 1). This first step leads us to exclude from the sample all the firms for which no suitable *counterfactual* exists. Indeed, for the excluded firms, it is not possible to evaluate the causal effect. Therefore, the comparison between past innovative and past non-innovative firms can only be made for a part of the sample (see Tables 3 and A.2). The probit model does not allow to correct for this potential source of bias.

- Insert Figure 1 -

In a second step, we check that the conditioning variables are well balanced between the treated and the non-treated firms inside each class. We performed a test for the statistical significance of differences in the distribution of observable variables (see Table 3). These two steps lead to three probability classes: 15-50%, 50-79% and 79-93%.

- Insert Table 3-

We distinguish two types of evaluation: first, we compute the difference of the average probabilities to innovate inside each probability class (Table 4: regression 1). Secondly, we run a regression of the current innovation dummy on the score, past innovation and the cross product of the two latter variables (Table 4: regression 2).[46] The purpose of the latter regression is to allow for firm-level variation of the causal effect.

Table 4 presents the results of these first estimations (Table 4: regressions 1 and 2). We find some important differences between probability classes: the causal effect is significant for the lowest probability class, around 28%, and vanishes in the two last classes.

[45] The innovation 1986-90 is used in order to correct a possible individual correlated effect. This estimate relies on a probit model. Also notice that the market share is not significant and has therefore been excluded from the regression.

[46] We have centered the score before to take the cross products so that the average causal effect is given directly by the coefficient of past innovation.

- Insert Table 4-

The class 1 corresponds to small-sized firms that do not invest in R&D activities (see Table 5). In these firms, the causal effect is the strongest. This does not mean that the persistence of innovation is the strongest in this class but that the learning-by doing effects play an essential role in these firms. The existence of such effects leads to a strong innovation persistence in this group since firms that innovated in the past increase their probability to innovate again of around 28%.

- Insert Table 5-

On the other hand, there is no significant causal effect in the classes 2 and 3. This result does not mean that the innovation is not persistent within these firms. This class includes firms with a larger size and more R&D. Here, the information contained in the variable of past innovation corresponds to the one related to the size and research activities of the firms. Our result means that the innovation persistence of these firms is due to their research activities and to their access to finance. These results confirm the ones of the probit model. Moreover, the averages' difference is close to the different estimators, so that we do not find evidence of a severe selection bias.

These results contrast with those of Cefis and Orsenigo (2001) that find persistence only for firms with more than 200 employees. This work shows that, even among small firms without research activity, there is innovation persistence: these are always the same firms that tend to innovate.

The causal effect on the three classes can be obtained simply by computing the average of the causal effects of the different classes. We find a global causal effect around 15%, which is very close to the results obtained with the probit model.

In Table 4, the Nadaraya-Watson kernel estimates are equally presented for each class and for the whole sample. However, these estimates correspond to the causal effect on the treated. These last estimates are similar to the ones obtained from the probability classes' method. Thus, as for the probit models, we find a causal effect on treated very close to the one on treated and non-treated.

The origin of innovation persistence thus depends on the size of the firm. Consequently, the relevance of the different theoretical models depends on the characteristics of the firms. In the largest firms, the linear model applies whereas in the smallest firms, the relevant model includes learning-by-doing effects. This last conclusion is close to the results of Kleinknecht (1987) and emphasizes the inadequacy of R&D data to evaluate the innovative competencies in the small-sized firms.

All the estimation methods we used lead to an average causal effect of past innovation on the whole sample around 15%.[47] Consequently, the learning-by-doing effects play an essential role in the persistence of innovation. This result is very close to the result of the probit model but this last model does not allow for differences between small and large firms.

6. Conclusion

This paper shows that the paradox between the theoretical predictions and the empirical results on innovation persistence at the firm level is only apparent and principally comes from the nature of data used until now. Indeed, our results based on the Innovation Surveys contrast with the results of previous studies on patent data and seem more in accordance with the theoretical literature.

Our first major finding is that the innovation persistence is strong. Indeed, using a data set that combines, for the first time, three Innovation Surveys, we show that, *ceteris paribus,* a firm that already innovated in the past has a stronger probability to innovate today (around +15%). This persistence has several origins: persistence of research activities, easier access to funding or learning-by-doing effects.

Our second major finding is that the origin of the persistence depends on the size of the firm. Whereas the *learning-by-doing* model seems to play a major role in the small-sized firms, its validity decreases with the size of the firms. In the largest firms, the linear model is relevant, since we do not find any significant direct effect of past innovation on current innovation. The innovation persistence is due to the formal research of these firms. Consequently, the relevance of the innovation models depends on the size of the firm, so that the *learning-by-doing* model and the linear model are not conflicting but complementary.

Finally, our results suggest the following functioning of innovation: the importance of learning-by-doing decreases with the formalization of research and development activities. Clearly, the last class includes mostly firms with the highest formal R&D budgets, so that the persistence of innovation for these firms comes from the persistence of research. In order to evaluate the degree of innovation persistence at the firm level, both effects must be accounted for. The fact to omit the *learning-by-doing effect* leads to underestimate the innovation persistence, in particular in small-sized firms.

One direction may prove particularly fruitful for further research. It would be particularly interesting to pursue the analysis of the dynamic incentives of firms to innovate by distinguishing their technological position. More precisely, it would consist in examining whether a technological leader is more or less enticed to innovate more often than a technological laggard. This extension would connect this work with previous empirical papers since the patent data measure the technological leadership of a firm.

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[47] For the large sample of 808 firms, this effect is higher, around 20%. The reason is that the inclusion of the annual line-of-business data to compute market power leads us to eliminate rather small-sized firms with few research activities in which learning-by-doing effects are present.

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Table 1: Sample Statistics

Survey	Innovation 1991	CIS1 (1993)	CIS2 (1997)
Period	5 years (86-90)	3 years (90-92)	3 years (94-96)
% of innovators			
Consumer goods (160 firms)	64	47	49
Car industry (29 firms)	96	79	86
Other equipment goods (137 firms)	87	82	78
Intermediate goods (295 firms)	81	61	61
Sample total (621 firms)	*78*	*63*	*63*
Innovation inputs (% of firms):			
Formal research and development			
- none / weak / moderate / strong	28/ 12 / 17 / 43	×	×
Informal research			
- none / weak / moderate / strong	13 / 17 / 33 / 37	×	×
Formal or informal R&D			
- none / weak or moderate / strong / very strong	×	10 / 17 / 40 / 33	×
Other variables:			
Sales 1985 – Millions of Euros (Averages)*			
- Innovative firms / Non-innovative firms	21.7 / 3.2	25.0 / 5.4	26.0 / 3.6
High technological opportunities (% of firms)			
- Innovative firms / Non-innovative firms	71.1 / 8.2	70.6 / 35.6	67.8 / 40.1

* Official conversion rate: 1 Euro = 6.55957 FRF.

Note: Sample of 621 French manufacturing firms of 20 employees or more resulting from the fusion of the three consecutive innovation surveys and of the 1985 E.A.E. surveys. Information on research activities is available only for firms that innovated during the period considered. In regressions, we set the research variables of the firms that have not innovated to 0. The 1997 innovation survey equally questions firms on their research activities but only for the year 1996 so that this information cannot be used in our model.

Table 2 – The probit models and the average effects

Left-hand variable: implementation of a product or a process innovation between 1994 and 1996. Maximum likelihood estimates of the probit model (standard errors between parentheses). *: significant at 1%, **: significant at 5%.

Variables	Model 1	Average effect[a]		Model 2	Model 2	Average effect[a]	
		Whole sample	Sample of treated		*(significant variables)*	Whole sample	Sample of treated
- Intercept	-0.81* (0.14)	×	×	-3.63* (1.35)	-5.15* (0.68)	×	×
- Innovation 86-90	0.51* (0.16)	0.23	0.22	0.15 (0.22)	0.38** (0.15)	0.12	0.11
- Innovation 90-92	0.74* (0.12)	0.27	0.27	0.49** (0.23)	0.51* (0.13)	0.16	0.15
- Industry[b]							
- Car industry	0.71**(0.32)	0.17	0.14	0.53 (0.34)	×	×	×
- Other equipment goods	0.46* (0.17)	0.20	0.18	0.48* (0.18)	0.37**(0.15)	0.10	0.09
- Intermediate goods	0.16 (0.13)	×	×	0.16 (0.14)	×	×	×
- High tech dummy	0.21 (0.13)	×	×	0.04 (0.14)	×	×	×
- Formal R&D 86-90[c]							
- weak	×	×	×	0.31 (0.22)	×	×	×
- moderate	×	×	×	0.20 (0.20)	×	×	×
- strong	×	×	×	0.38** (0.19)	0.27** (0.14)	0.08	0.07
- Informal R&D 86-90							
- weak	×	×	×	0.28 (0.23)	×	×	×
- moderate	×	×	×	0.02 (0.21)	×	×	×
- strong	×	×	×	0.10 (0.21)	×	×	×
-Formal or informal R&D 90-92							
- weak	×	×	×	-0.18 (0.28)	×	×	×
- moderate	×	×	×	-0.02 (0.26)	×	×	×
- strong	×	×	×	0.12 (0.27)	×	×	×
- ln(market power)	×			0.06 (0.05)	×		
- ln(Sales)	×	×	×	0.18* (0.06)	0.25* (0.04)	×	×
Log-likelihood	-344.19	×	×	-310.99	-316.77	×	×
% correct predictions	73.3%	×	×	81.7%	80.7%	×	×

Note: Sample of 621 French manufacturing firms of 20 employees or more resulting from the fusion of the three consecutive innovation surveys and of the 1985 E.A.E. surveys.

[a] The average effects are computed only for the significant binary variables of the regression.

[b] The consumer goods industry is the industry of reference.

[c] For research activities, the reference is the modality none.

Table 3: Comparison of the treated with the non-treated in each probability class

p-values	Attribute*	Class 1	Class 2	Class 3
Propensity score classes		**15-50**	**50-79**	**79-93**
Sales (logarithm)	Yes	0.08	0.08	0.32
Market share (logarithm)	No	0.82	0.33	0.96
Innovation 1991 (dummy)	Yes	0.12	0.19	Perfect matching
Formal R&D weak	Yes	0.26	0.56	0.09
Formal R&D moderate	Yes	0.96	0.94	0.93
Formal R&D Strong	Yes	Perfect matching	0.39	0.59
Informal R&D weak	No	0.75	0.96	0.87
Informal R&D moderate	No	0.31	0.92	0.40
Informal R&D Strong	Yes	0.74	0.15	0.93
Equipment goods	No	0.58	0.15	0.59
Cars	Yes	0.60	0.25	0.10
Consumer goods	No	0.51	0.36	0.98
High-tech dummy	No	0.63	0.46	0.01
Number of firms in the common support	548 out of 621	182	183	183

* "Yes" indicates a variable that is significant at the 10% level in the *probit* regression that explains the treatment (i.e, in the propensity score)

Note: Sample of 621 French manufacturing firms of 20 employees or more resulting from the merger of the three consecutive innovation surveys and of the 1985 E.A.E. surveys.

Table 4: Effect of innovation 1990-92 on innovation 1994-96

Standard errors between parentheses. The standard errors of the kernel estimators were computed by the *bootstrap* with 100 simulations. OLS standard errors are reported for the regression methods. ** Significant at the 5% level.

Propensity score classes	Class 1 15-50	Class 2 50-79	Class 3 79-93	Sample* 15-93
Averages' difference	0.30** (0.07)	0.08 (0.08)	0.12 (0.07)	0.17** (0.04)
Matching by class on the whole sample: regression with the propensity score (*c*)	0.27** (0.07)	0.06 (0.08)	0.10 (0.07)	0.15** (0.04)
Matching by class on the whole sample: regression with the cross products (*c*)	0.28** (0.08)	0.08 (0.08)	0.10 (0.07)	0.15** (0.04)
Kernel matching estimator on the treated (c_1)	0.30** (0.08)	0.08 (0.08)	0.12 (0.10)	0.14** (0.05)

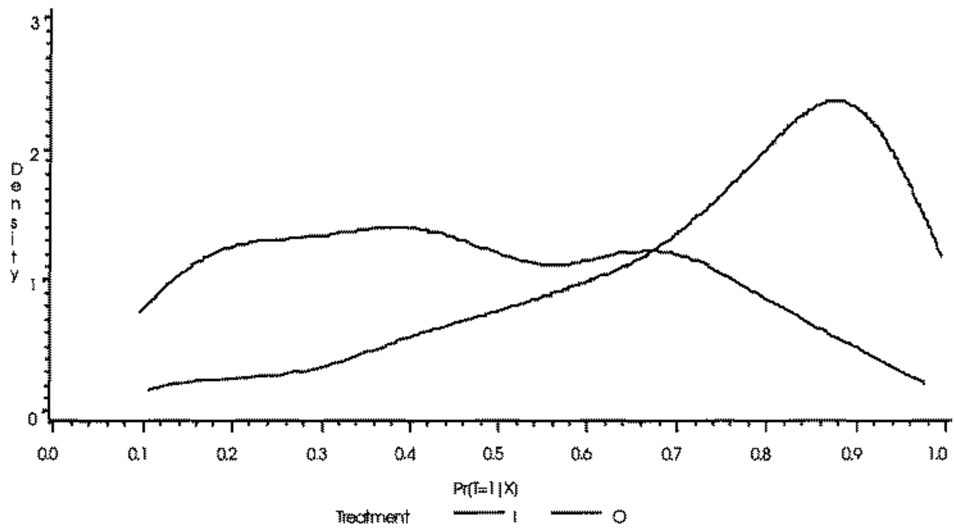
* Optimal asymptotic least squares are used to compute the average effect on the sample for the regression methods.

Table 5: Average characteristics by probability class

Propensity score classes	Class 1 15-50	Class 2 50-79	Class 3 79-93
Sales logarithm (std error)	17.7 (0.09)	18.9 (0.10)	20.3 (0.09)
Market share log. (std error)	-5.65 (0.11)	-4.72 (0.12)	-3.51 (0.11)
Average sales in millions €	19.6	58.1	192.1
Average market share in %	1.1	2.9	7.7
Percentages :			
Innovation 1991	41.7	96.2	All
Formal R&D weak	4.4	21.9	4.9
Formal R&D moderate	1.6	19.7	22.4
Formal R&D Strong	None	19.7	69.9
Informal R&D weak	12.6	20.8	12.6
Informal R&D moderate	10.4	31.1	38.3
Informal R&D Strong	6.0	31.1	41.5
Equipment goods	1.1	7.1	5.5
Cars	6.6	13.7	29.0
Consumer goods	53.2	57.9	45.9
High-tech dummy	22.0	63.4	82.0
Number of treated firms (%)	58 (32%)	121 (66%)	157 (86%)
Number of firms in the common support	182	183	183

Figure 1: Distributions of the propensity score among treated and non-treated firms

(Parzen-Rosenblat kernel density estimator with a gaussian kernel and a Silverman window)



Appendix I : Estimation of the propensity score

Table A.1: Propensity Score

Left-hand variable : implementation of a product or a process innovation between 1990 and 1992. Maximum likelihood estimates of the probit model (standard errors between parentheses). * : significant at 1%. ** : significant at 5%.

Variables	Probit model	Significant variables
- Intercept	-4.79* (1.35)	-4.45* (0.67)
- Innovation 86-90	0.24 (0.22)	0.63* (0.16)
- Industry[b]		
- Car industry	0.17 (0.31)	×
- Other equip. goods	0.71* (0.18)	0.60*(0.15)
- Intermediate goods	0.22 (0.14)	×
- High tech dummy	0.21 (0.14)	0.27** (0.13)
- Formal R&D 86-90[c]		
- weak	0.24 (0.21)	×
- moderate	0.29 (0.20)	×
- strong	0.51* (0.18)	0.40* (0.15)
- Informal R&D 86-90		
- weak	0.20 (0.22)	×
- moderate	0.35 (0.21)	×
- strong	0.45** (0.21)	×
- ln(market share)	-0.03 (0.06)	×
- ln(Sales)	0.21* (0.06)	0.21* (0.04)

Note: Sample of 621 French manufacturing firms of 20 employees or more resulting from the merger of the three consecutive innovation surveys and of the 1985 E.A.E. surveys.

Appendix II : Estimation on the Large Sample

Since market share is not significant in the analysis the Appendix I regression, it is possible to make evaluate the effect of past innovation on the larger sample of 808 firms. The following tables show that our results are unaltered by this change.

Table A.2: Average characteristics by probability class (Large Sample)

	Class 1	Class 2	Class 3
Propensity score classes	**16-43**	**43-76**	**76-92**
Sales logarithm (std error)	17.5 (0.08)	18.5 (0.09)	20.0 (0.09)
Average sales in millions €	13.7	44.6	162.7
Percentages :			
Innovation 1991	39.1	90.0	All
Formal R&D weak	0.4	18.3	10.0
Formal R&D moderate	1.7	16.9	25.2
Formal R&D Strong	0.4	16.5	62.2
Informal R&D weak	9.6	20.9	15.2
Informal R&D moderate	5.2	27.8	39.1
Informal R&D Strong	3.9	29.1	40.9
Equipment goods	1.3	4.3	6.1
Cars	8.3	14.8	26.1
Consumer goods	53.0	55.2	48.7
High-tech dummy	17.4	60.9	85.2
Number of treated firms (%)	65 (28%)	141 (61%)	194 (84%)
Number of firms in the common support	230	230	230

* "Yes" indicates a variable that is significant at the 10% level in the *probit* regression that explains the treatment (i.e., in the propensity score).

Note: Sample of 808 French manufacturing firms of 20 employees or more resulting from the merger of the three consecutive innovation surveys and of the 1985 E.A.E. surveys.

Table A.3: Comparison of the treated with the non-treated in each probability class (Large sample)

p-values	Attribute*	Class 1	Class 2	Class 3
Propensity score classes		**16-43**	**43-76**	**76-92**
Sales (logarithm)	Yes	0.04	0.48	0.82
Innovation 1991 (dummy)	No	0.44	0.06	Perfect matching
Formal R&D weak	Yes	0.53	0.26	0.04
Formal R&D moderate	Yes	0.33	0.74	0.97
Formal R&D Strong	Yes	0.53	0.33	0.37
Informal R&D weak	Yes	0.70	0.64	0.81
Informal R&D moderate	Yes	0.09	0.20	0.44
Informal R&D Strong	Yes	0.73	0.04	0.40
Equipment goods	No	0.85	0.22	0.54
Cars	Yes	0.07	0.41	0.33
Consumer goods	No	0.46	0.82	0.85
High-tech dummy	Yes	0.30	0.44	0.06
Number of firms in the common support	690 out of 808	230	230	230

* "Yes" indicates a variable that is significant at the 10% level in the *probit* regression that explains the treatment.

Table A.4: Effect of innovation 1990-92 on innovation 1994-96 (Large sample)

Standard errors between parentheses. The standard errors of the kernel estimators were computed by the *bootstrap* with 100 simulations. OLS standard errors are reported for the regression methods. ** Significant at the 5% level.

	Class 1 16-43	Class 2 43-76	Class 3 76-92	Sample* 16-92
Averages' difference	0.38** (0.06)	0.10 (0.07)	0.10 (0.07)	0.21** (0.04)
Regression with the propensity score (*c*)	0.37** (0.06)	0.09 (0.07)	0.09 (0.07)	0.20** (0.04)
Regression with the cross products (*c*)	0.38** (0.07)	0.09 (0.07)	0.10 (0.07)	0.19** (0.04)
Kernel matching estimator on the treated (c_1)	0.32** (0.08)	0.08 (0.07)	0.11 (0.10)	0.14** (0.05)

* Optimal asymptotic least squares are used to compute the average effect on the sample for the three regression methods.

Appendix III : Supplementary information on the data

The innovation surveys

The first innovation survey in France, namely *"l'innovation technologique dans l'industrie"*, was conducted in 1991. The firms were asked to report retrospectively over the 1985-1990 period. Hence, the choice of the respondent was an important issue. Here intervenes the SESSI (Industrial Statistics Bureau of the Ministry of Industry) which is responsible of the Industry Census and of all innovation surveys in France (and more surveys). The basic organization is as follows: inside SESSI the same person always works with the same set of firms. A part of his (or her) job is to find the right interlocutor inside the firm. On each questionnaire appear the name and the phone number of the SESSI correspondent inside the firm. Here the correspondent (which is an employee of the firm) has to send the questionnaire to "a person responsible of innovation, development, strategy issues or to the boss himself" (literal translation). The name of the respondent, that can be different from the name of the correspondent, and its phone number, have to be systematically reported on the questionnaire. The respondent has a SESSI phone number he (or she) can use to have explanations on how to reply to the survey. The census file is used for the mailing that prints automatically the name of the correspondents on the questionnaire itself etc. In other words, this survey has been conducted by an administration that has for main purpose to collect data among industrial firms.

The survey was presented as an appendix to the Industry Census, which is compulsory. While the Census was compulsory, the appendix was not, but it *was not indicated* on the questionnaire so that the firms could have believed that it was compulsory. This is likely to be the case since the response rate to the innovation survey is the same as the one of the industry census (85% for compulsory surveys in France). The possibility of a response bias is systematically studied by the specialists of SESSI, for all the surveys. They compute the response rate after the "first wave" of the survey for each size class and each industry in order to detect abnormal response rates (e.g., below 85%). When the questionnaire does not come back, they can launch a second wave.

Last but not least, all French firms have a compulsory national identification number that is called the SIREN code. The use of this code is compulsory for all the relationship that a firm has with the administration (including taxes). Its main advantage is that it allows for matching all the surveys without loss for identification reasons.

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