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### Innovation, profitability and growth in medium and high-tech manufacturing industries: Evidence from Italy

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For Peer Review

# Innovation, profitability and growth in medium and high-tech manufacturing industries: Evidence from Italy.

Claudio Cozza<sup>a</sup>, Franco Malerba<sup>b,d</sup>, Maria Luisa Mancusi<sup>b,d</sup>,  
Giulio Perani<sup>c</sup>, Andrea Vezzulli<sup>d</sup>

## Abstract

The main goal of this paper is to assess the impact of product innovation on the economic performance of firms operating in medium and high-tech industries. Using information from a large and unique dataset on Italian firms we estimate, by means of propensity scores matching methods, a positive and significant “innovation premium” both in terms of profitability and growth (in the short run) for those firms who introduced new innovative products. We also find that this innovation premium is particularly large for small firms and even more so when considering new established firms.

**JEL Codes:** L11, L25, O30

**Keywords:** innovation, profitability, growth, propensity score estimation

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## 1. Introduction

This paper aims at studying the impact of product innovation on the economic performance of firms (in terms of profitability and growth) using a large sample of Italian firms operating in Medium and High-Tech (M&HT) industries. We employ an original dataset which combines both data on firm's innovation activities coming from the Third Community Innovation Survey (CIS3) and economic performance indicators coming from the firm's accounting registers covering the period 1998-2003.

In the last two decades, firm-level analyses on the relationship between innovation and economic performance have flourished thanks to the growing availability of longitudinal micro data collecting not only financial and economic information, but also indicators of innovative activities carried out by firms. A large body of empirical literature has grown to test if and to what extent innovative firms perform better than non innovative ones in terms of different performance indicators, including profits and growth<sup>1</sup>. However, the empirical evidence on the the beneficial effects of innovation on firms' performance is still not conclusive, and deserves further exploration.

With reference to the relationship between innovation and profitability, previous studies (Geroski et al., 1993; Geroski et al., 1997) have found a positive, although modest direct effect, but a large indirect effect due to the relative insensitiveness of innovating firms to adverse macroeconomic shocks. This suggests that differences in profitability between innovative and non-innovative firms are likely to be due to the higher competencies of innovating firms, which allow them to face the challenges of the market better than non-innovating firms, rather than to a transitory change in the competitive position of the innovating firms.

With reference to growth, most of the empirical contributions aim to test the so-called Gibrat's law framework, according to which firm's size follows a random walk and firm's growth is driven by small idiosyncratic shocks. Hence, assuming that innovation is a driving force for growth, this framework would imply that it is a process that occurs randomly among firms (Geroski et al. 1993, Dosi et al., 1995).

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<sup>1</sup> There are a number of studies also studying the effects of innovation on productivity, (see, for example, Crepon et al., 1998), export (e.g. Wakelin, 1998) and survival (e.g. Audretsch, 1995; Cefis and Marsili, 2006).

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6 This assumption is far from being accepted in the economics of innovation literature,  
7 where instead innovation is viewed as a strategic and crucial activity and the decision for a  
8 firm to engage in innovation activities is driven by entrepreneurial market opportunities.  
9 In particular, according to Schumpeter's Mark I scenario (Malerba and Orsenigo, 1993),  
10 (product) innovation is mainly pursued by new entrants in order to gain new market  
11 shares for surviving longer and growing faster than competitors. This innovative pattern  
12 (Schumpeter mark I) characterizes a large population of innovators and is often present in  
13 medium and high-tech (M&HT) industries, particularly in countries such as Italy.  
14 However it has been found that also in Schumpeter mark II industries, which are  
15 characterized by cumulative advancements and large innovators, small and new firms do  
16 play some role, albeit at the fringe of the industry. The most successful companies indeed  
17 grow to become dominant players.

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19 From a methodological point of view, the driving force that pushes firms to engage  
20 innovation activities can be seen as a self-selection mechanism which makes the estimation  
21 of its economic impact trickier if confounding factors affecting this mechanism also affect  
22 the economic performance of the firms (e.g. managerial abilities, unobservable changes in  
23 the firm's operating environment or in the business cycle, etc.). We therefore use  
24 propensity score matching to "correct" the estimation of the treatment effect of  
25 innovation, controlling for the existence of such confounding factors.

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27 The paper is organized as follows. Section 2 briefly reviews the relevant literature on  
28 innovation and performance at the firm level. Section 3 describes the dataset employed in  
29 the analysis and explains in detail our definition of innovation and M&HT industries.  
30 Section 4 introduces our economic performance indicators and reports the corresponding  
31 main descriptive statistics in our sample. Section 5 describes the methodology adopted for  
32 estimating the firm's economic return to innovation and reports the main results. Finally,  
33 Section 6 draws some conclusions on the main findings and proposes future paths of  
34 research.  
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## 2. Related literature

Traditionally, scholars have followed two main approaches in studying how innovative activities may affect the profitability of firms. In the first one, innovations only have a transitory effect on firm's profitability by increasing its competitiveness in the short-run. The introduction of an innovative product gives to the firm a temporary monopoly power and allows it to exploit higher profits by increasing the firm's market share until other firms can imitate the innovation (Aghion and Howitt, 1992; Klepper, 1996).

A second approach stresses the assumption that innovations intrinsically "characterize" a firm by creating a structural difference between innovating and non-innovating firms. According to this point of view, each firm owns specific and cumulative technological competencies developed from the various learning processes experienced. These specific competencies enable the firm to better face changes in the market in order to survive or even to obtain persistent profits over time (Malerba and Orsenigo, 1993; Cohen and Levin, 1989; Dosi et al., 1995).

Previous empirical studies for United Kingdom (Smyth et al., 1972; Geroski, Machin and Van Reenen, 1993; Geroski, Van Reenen and Walters, 1997) have found positive, although modest, direct effects of innovations on profitability in the short run, and large indirect effects due to the relative insensitiveness of innovating firms to adverse macroeconomic shocks. This might suggest that innovating firms develop internal competencies and behavioral patterns that allow them to face the challenges of the market better than non-innovating firms (Cefis and Ciccarelli, 2005).

Economic theory also recognizes the key role of innovation in growth of firm sales (see for example Geroski, 1999). However, empirical studies have had difficulty in identifying any strong link between innovation and sales growth. This might be due to the existence of considerable lags between the time of discovery of a valuable innovation and its conversion into commercial success and to the uncertainty associated to every stage of the innovation process, with the overall outcome requiring success at each step of the process (Mansfield, 1977). It must however remain true that innovations do indeed pay off on average, otherwise firms would have no incentive to perform R&D in the first place.

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6 Geroski and Machin (1992) suggest that innovating firms (i.e. firms that produced at least  
7 one 'major' innovation) are both more profitable and grow faster than non-innovators, but  
8 the influence of specific innovations on sales growth are short-lived. Coad and Rao (2008)  
9 use a semi-parametric quantile regression approach and explore the influence of  
10 innovation at a range of points of the conditional growth rate distribution. Their results  
11 indicate that most firms don't grow very much, and that their growth can hardly be  
12 related to their attempts at innovation. Nevertheless, in contrast with a recent study by  
13 Almus (2002), Coad and Rao (2008) find that innovation is of critical importance for a  
14 handful of fast-growth firms. This emphasizes the inherent uncertainty in firm-level  
15 innovative activity and, once again, the potential relevant role of firm heterogeneity.

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17 The unsound empirical results from both strands of literature therefore suggest the need  
18 to control for the role of innovating firms' inherent characteristics and abilities in  
19 evaluating the returns to innovation, which is the main focus of our paper.

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21 We use a relatively new and original dataset to estimate the magnitude of the impact of  
22 innovativeness (measured with an indicator based on the firm's responses to the CIS  
23 questionnaire) on both profitability and growth by means of (propensity scores based)  
24 matching techniques, which have the advantage of not requiring the specification of a  
25 structural model relating innovation to firm's performance.

26  
27 We further concentrate on the relationship between innovation and employment growth.  
28 Our results are in line with those emerging from recent empirical studies concerned with  
29 such relationship. When the distinction is made between product and process innovation,  
30 the former is usually linked to employment creation, because the new products create new  
31 demand (although it is possible that they might replace existing products). Empirical  
32 results have mostly been in line with this interpretation (Van Reenen, 1997; Smolny,  
33 1998; Harrison et al., 2008). In particular, with reference to Italy, using survey data on an  
34 unbalanced panel of 9462 manufacturing firms, Hall et al (2008) find a positive  
35 contribution of product innovation on employment growth.

### 3. Data description

Our analysis is based on a novel and original dataset obtained combining data from two different sources: the third Italian Innovation Survey (1998-2000) and the accounting register data<sup>2</sup> of the observed firms for the years 1998-2003.

The third Community Innovation Survey (CIS3) has been carried out for Italy by the Italian National Institute of Statistics (ISTAT) on behalf of the Statistical Office of the European Communities (EUROSTAT) during 2002. The target population of the survey included all the enterprises with at least 10 employees operating in the manufacturing and service sectors during 2000. The sample of about 30,000 surveyed firms included all enterprises with more than 250 employees and a random sample of enterprises with less than 250 employees, stratified according to their industrial sector (2 digits NACE classification), their size class (number of employees: 10-19, 20-49, 50-249) and their region of residence (Nuts classification)<sup>3</sup>. The final sample of respondents to the survey includes 15512 Italian firms.

We merged data from the CIS3 survey with data from the accounting registers database using the firm's fiscal code, which uniquely identifies every firm operating in Italy. Firms included in the CIS3 survey with no accounting data matches have been dropped from the sample.

Since our interest focuses on M&HT industries, we restrict our sample only on the following manufacturing sectors (classified according to their NACE-ATECO 2 digits code), which show by far a higher share of innovating firms with respect to the other NACE-ATECO categories (see Table 1) and which are classified as either high or medium-high technology sectors according to the last version of the OECD classification by technology intensity (OECD, 2005)<sup>4</sup>:

24 - Manufacture of chemicals and chemical products;

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<sup>2</sup> As resulting by each firm's accounting register filed yearly at the Italian Chamber of Commerce.

<sup>3</sup> For more details on the survey's methodology see ISTAT (2004).

<sup>4</sup> Our list of sectors effectively almost totally overlaps with the list of OECD high and medium-high tech industries. We only exclude industry 35 (transport equipment) and include industry 25 (rubber and plastic products), which is classified by OECD as medium-low tech industry.

- 25 - Manufacture of rubber and plastic products;
- 29 - Manufacture of machinery and equipment n.e.c;
- 30\_72 – It encompasses sector 30 (Manufacture of office machinery and computers) and 72 (Computers and related activities);
- 31- Manufacture of electrical machinery and apparatus n.e.c;
- 32- Manufacture of radio, television and communication equipment and apparatus;
- 33 - Manufacture of medical, precision and optical instruments, watches and clocks;
- 34 - Manufacture of motor vehicles, trailers and semi-trailers.

Table1 reports the cross-sector distribution of the total number of firms in the CIS3 Survey, together with the percentage of firms within the sector having (a) any ongoing or completed innovation activity during the period 1998-2000 (*Innovators*), (b) any new (for the enterprise) or significantly improved product (*Product Innovators*), (c) any new or significantly improved production processes (including methods of supplying services and ways of delivering products)<sup>5</sup> (*Process Innovators*).

**Table 1. Distribution of Innovators across industries**

NACE-ATECO 2digit codes	N. of firms	% of Innovators with respect to the n. of firms within each sector		
		Innovators	Product Innovators	Process Innovators
<b>24</b>	523	63.29	52.00	42.26
<b>25</b>	498	45.58	34.14	34.14
<b>29</b>	697	64.28	54.95	39.74
<b>30</b>	85	65.88	57.65	24.71
<b>31</b>	466	49.36	42.49	32.62
<b>32</b>	250	58.40	50.00	42.00
<b>33</b>	323	64.40	58.20	41.80
<b>34</b>	289	52.60	44.29	35.99
<b>72</b>	411	52.31	43.80	33.09
<b>M&amp;HT industries</b>	<b>3542</b>	<b>56.83</b>	<b>47.80</b>	<b>37.30</b>
<b>Non M&amp;HT industries</b>	<b>11970</b>	<b>31.29</b>	<b>20.01</b>	<b>24.03</b>
<b>Total CIS3 sample</b>	<b>15512</b>	<b>37.12</b>	<b>26.35</b>	<b>27.06</b>

<sup>5</sup> For further details, see the Harmonized Questionnaire of the Third Community Innovation Survey – Eurostat.

The sample of M&HT industries encompasses 3542 firms (about 22.83% of the total CIS3 sample size), 56.83% of which are *Innovators* (versus 37.12% considering the whole CIS3 sample), 47.80% are *Product Innovators* (versus 26.35% considering the whole CIS3 sample) and 37.30% are *Process Innovators* (versus 27.06% considering the whole CIS3 sample), thus evidencing a higher intensity of innovation activities in the M&HT sub-sample with respect to the whole CIS3 sample.

Table 2 summarizes the further steps followed in cleaning the original M&HT sub-sample from the firms which did not match with accounting data for any year during the period 1998-2003 (i.e. unbalanced observations), from the potential outliers (i.e. firms with turnover greater than 2blns of euros in any year) and from potential split and merges of firms (i.e. firms with yearly sales or employment growth rates outside the range  $[-200\%, +200\%]$ ). We are then left with a final working M&HT sample of 1930 firms.

**Table 2. Panel Cleaning**

	Sample Size	Dropouts
Original M&HT sub-sample (unbalanced)	3542	
Balanced M&HT sub-sample (1998-2003)	2116	1426
Outliers dropped	2090	26
Splits and merges dropped	1988	102

Due to the relatively high number of observations dropped when moving from the unbalanced panel of firms to the balanced one, some concerns may arise for potential sample selection bias caused by panel attrition<sup>6</sup>. We check for the severity of this problem by comparing the distribution of firms' size for the dropped vs. retained observations.

<sup>6</sup> Unfortunately we have no precise information on the causes of attrition, whereas we are aware that it can occur for both entry and exit of firms during the period 1998-2003 as a consequence of different events such as post 1998 establishment, change in fiscal domicile or juridical form, fusion, merger, acquisition, inheritance and succession, bankruptcy.

Table 3 reports the main descriptive statistics of the total turnover and the number of employees for the firms included in the balanced panel (retained) and the dropped ones, using information on these variables as stated in the CIS3 survey for the year 2000. The dropped firms tend to be smaller on average than the ones included in the balanced panel, but the two distributions seems not to differ significantly according to the Mann-Whitney nonparametric test for the equality of distributions.

**Table 3. Size distribution of firms (year 2000): retained vs dropped firms**

	N. of obs.	Mean	Std. Dev.	Min.	Max.	Rank-Sum (Mann-Whitney) z-statistics (p-value)
Turnover dropped	1319	26324	70512	33	836908	H0: turnover(dropped)= turnover (retained) -1.613 (0.107)
Turnover retained	1988	29066	102404	45	1997563	
N. of employees dropped	1319	130.064	273.399	10	2895	H0: employees(dropped)= employees (retained) -0.926 (0.3546)
N. of employees retained	1988	138.549	408.676	10	8620	

The CIS3 survey also reports the same size indicators for the year 1998. Thus we can calculate the two-year growth rates for both turnover and number of employees and compare their distributions between dropped and retained firms as reported in Table 4.

**Table 4. Growth rate distribution (1998-2000): retained vs dropped firms**

	N. of obs.	Mean	Std. Dev.	Min.	Max.	Rank-Sum (Mann-Whitney) z-statistics (p-value)
Turnover growth dropped	1319	0.277	0.538	-0.999	3.907	H0: turn growth(dropped)= turn growth (retained) 1.243 (0.214)
Turnover growth retained	1988	0.227	0.415	-0.894	3.573	
Employees growth dropped	1319	0.134	0.360	-0.629	2.818	H0: emp growth(dropped)= emp growth (retained) 1.409 (0.159)
Employees growth retained	1988	0.105	0.404	-0.707	2.833	

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Once again, although the dropped firms declared in the CIS3 survey an average growth rate slightly higher than the retained ones, the Rank-Sum test still reject the null hypothesis of different distributions between the two groups of firms.

These results cannot be considered as definitive for rejecting the presence of further sample selection problems, but they represent a sort of “basis of trust” that justifies our next analysis only on the balanced panel of firms.

#### 4. Differences in profitability and growth between innovators and non-innovators in M&HT industries

In this section we analyze the economic performance of M&HT firms during the period 2000-2003, comparing (product) innovators (**InnPd**) and non-innovators (**No InnPd**) and further distinguishing among small, medium and large firms (according to their number of employees in 2000).

Economic performance will be here evaluated both in terms of profitability and growth. Two different index of profitability are computed: (a) **OPR** (Operating Profit Ratio), which is the ratio between operating profits (excluding any financial revenues) and sales; (b) **ROTA** (Return on Total Assets) which is the ratio between overall profits (including financial revenues), before taxes, and total assets.

Economic growth is measured as total turnover (**GRTurn**) and number of employees (**GREmp**) growth rates.

We focus on product innovators, i.e. those firms that declared in the CIS3 Survey to have introduced in the market new or significantly improved products during the period 1998-2000. The advantage in using this indicator of innovativeness, compared to other indicators such as patents or R&D expenses, relies on its availability even for small enterprises which often do not have enough resources to apply for a patent or to face the risk of engaging in important R&D projects.

Table 5 reports the distribution of product innovators according to firm's size measured by the number of employees in 2000. About 53% of the firms in our panel introduced at least one new or significantly improved product, but the percentage of product innovators increases significantly with firm size. This well known phenomenon has several motivations (high costs and high risks of new product development activities, liquidity constraints that are more binding for small firms, etc.), which we will focus on when analyzing the determinants of product innovation.

We first analyze the differences in profitability between innovators and non-innovators during the years 2000-2003 immediately following the CIS3 Survey reference period (1998-2000).

Table 5. Distribution of Product Innovators according to size (n. of employees)

Size	No Product Innovators (No InnPd)	Product Innovators (InnPd)	Total
<b>10-20</b>	333 61.33%	210 38.67%	543 100%
<b>21-50</b>	286 51.62%	268 48.38%	554 100%
<b>&gt;50</b>	309 34.68%	582 65.32%	891 100%
<b>Total</b>	928 46.68%	1,060 53.32%	1,988 100%

Pearson  $\chi^2(2) = 103.7862$  Pr = 0.000

Lik-ratio  $\chi^2(2) = 104.9261$  Pr = 0.000

Table 6 shows the distribution of the average OPR and ROTA indexes between innovators and non innovators across different size classes. The last column of the table shows that, on average and regardless of firm size, firms who successfully developed new products experienced a greater profitability in the following four years, compared to non-innovators. This difference tends to be more statistically significant when considering OPR than ROTA.

Focusing on size, we can see that the higher profitability of innovators with respect to non-innovators holds in particular for small-sized firms (21-50 employees), whereas for micro-sized firms (10-20 employees) this difference is weaker. The same difference is not significant for medium and large-sized firms (over 50 employees), suggesting that for such firms profitability may be driven by other forces than product innovation, (e.g. market dominance, cost saving innovation, etc.).

**Table 6. Average profitability (%) according to size and innovation activity (all firms)**

Year	Size									All		
	10-20			21-50			>50			InnP d	No InnP d	Diff.
	InnP d	No InnP d	Diff. .	InnP d	No InnP d	Diff.	InnP d	No InnP d	Dif f.			
<b>OPR 00_03</b>	5.7	4.42	1.28 *	6.21	4.41	1.8*	5.08	5.12	- 0.04	5.49	4.65	0.84* *
<b>ROTA 00_03</b>	5.96	5.27	0.69	6.6	5.23	1.37* *	5.31	5.23	0.08	5.76	5.24	0.52*
<b>N</b>	210	333		268	286		582	309		1060	928	

Statistically significant at 1%\*\*\*, 5%\*\*\*, 10%\* level (one-tail t-test)

00\_03 is the average profitability index during the 4 years period and N is the number of firms in each group.

In Table 7 we restrict our analysis to new entrants, i.e. those firms established between 1993 and 1998. For this sub-sample we find no overall significant differences in profitability between innovators and non-innovators, although micro and small sized innovative firms tend to show a higher profitability than non-innovative ones. On the other side, for medium and large sized firms we find a higher average profitability for non-innovators.

Profitability may be an incomplete indicator for firm's economic performance, especially for new firms, which may be more interested in increasing market shares or creating new market niches than maximizing profits in the short run. Such firms might even trade off profits with market shares if, for example, they lower prices in order to reach the minimum efficient operating scale.

Table 7. Average profitability (%) according to size and innovation activity (new entrants)

Year	Size									All		
	10-20			21-50			>50					
	InnP d	No InnP d	Diff	InnP d	No InnP d	Diff	InnP d	No InnP d	Diff	InnP d	No InnP d	Diff
OPR 00_03	5.02	4.25	0.77	5.12	4.82	0.3	3.16	5.62	- 2.46	4.27	4.64	- 0.37
ROTA 00_03	6.3	5.23	1.07	4.95	3.17	1.78 *	4.33	5.72	- 1.39	5.03	4.69	0.34
N	29	77		38	43		49	23		116	143	

Statistically significant at 1%\*\*\*, 5%\*\*\*, 10%\* level (one-tail t-test)

00\_03 is the average profitability index during the 4 years period and N is the number of firms in each group.

We do not have information on firms' market shares, but we measure firms' growth through total turnover (GRTurn) and number of employees (GREmp) growth rates. Table 8 summarizes the differences in growth rates between innovating and non-innovating firms. During the period 2000-2003 innovative firms experienced an average growth rate (both in term of total turnover and number of employees) which is almost two percentage points greater than non-innovative ones, especially for micro-sized firms.

Table 8. Average Growth Rate (%) according to size and innovation activity (all firms)

Year	Size									All		
	10-20			21-50			>50					
	InnP d	No InnP d	Diff.	InnP d	No InnP d	Diff	InnP d	No InnP d	Diff.	InnP d	No InnP d	Diff.
GRTurn00_03	3.25	1.12	2.13* *	3.77	2.8	0.97	3.97	2.72	1.25* *	3.78	2.17	1.61* **
GREmp00_03	1.42	-0.94	2.36* **	2.17	0.79	1.38 **	2.13	0.45	1.68* **	2	0.06	1.94* **
N	210	333		268	286		582	309		1060	928	

Statistically significant at 1%\*\*\*, 5%\*\*\*, 10%\* level (one-tail t-test)

Table 9. Average Growth Rate (%) according to size and innovation activity (new entrants)

Year	Size									All		
	10-20			21-50			>50			InnP d	No InnP d	Diff.
	InnP d	No InnP d	Diff.	InnP d	No InnP d	Dif f.	InnP d	No InnP d	Dif f.			
GRTurn00_03	7.81	2.04	5.77* *	6.36	4.87	1.49	4.89	7.66	- 2.77	6.1	3.91	2.19* *
GREmp00_03	4.23	0.34	3.89* *	5.49	4.37	1.12	2.64	4.45	- 1.81	3.98	2.2	1.78* *
N	29	77		38	43		49	23		116	143	

Statistically significant at 1%\*\*\*, 5%\*\*\*, 10%\* level (one-tail t-test)

These differences are more striking when considering newly established firms (see Table 9): micro-sized innovating firms experience an average growth rate more than three times larger than the growth rate of non-innovating firms.

These results seem to suggest that developing new products is a crucial activity for small and newly founded firms: product innovation enables them to expand their market shares more rapidly than their non-innovative competitors and strongly affects their ability to grow. By contrast, no similar evidence can be found for medium- and large-sized firms (i.e. firms with more than 50 employees in year 2000).

##### 5. Estimating the economic returns to innovation.

So far our analysis has been focused on differences in profitability and growth rates between innovators and non-innovators. Since our ultimate goal is not only to test the statistical significance of such differences but also to estimate the magnitude of the impact of innovation on profitability and growth we first need to analyze the reverse causality question: which are the main determinants of innovation activities? In particular we will try to analyze which firm's and industry's characteristics affect the probability to develop new or significantly improved products (**InnPd**). The resulting predicted probabilities can be interpreted as propensity scores, i.e. the conditional probabilities of receiving a

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6 treatment (i.e. to introduce product innovations) given pre-treatment characteristics  
7 (Rosembaum and Rubin, 1983; Imbens, 2000).  
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### 10 11 12 13 **5.1 Method**

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15 Propensity Score (PS) matching methods are widely known in evaluation problem  
16 literature to reduce the bias in the estimation of treatment effects with observational  
17 studies when traditional regression methods often are unreliable because of the non-  
18 random assignments of subjects to the treatment and control group which leads the  
19 estimation of the treatment effect to be biased for the existence of confounding factors. In  
20 our particular case these confounding factors can be viewed as unobserved (to the  
21 researcher) factors which may affect both the firm's economic performance and the firm's  
22 propensity to innovate (e.g. intrinsic managerial abilities, unobservable changes in the  
23 firm's operating environment or in the business cycle and so on). Propensity score  
24 matching is a way to "correct" the estimation of the treatment effects (TE) controlling for  
25 the existence of these confounding factors based on the idea that bias is reduced when the  
26 comparison of outcomes is performed using treated and control subjects (e.g. innovators  
27 and non-innovators) who are as similar as possible, by "summarizing" pre-treatment  
28 characteristics of each subject into the propensity score which makes the matching feasible  
29 when the n-dimensional vector of characteristics is large (Rosembaum and Rubin, 1983;  
30 Imbens, 2000; Becker and Ichino, 2002; Dehejia and Wahba, 2002).  
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34 This method, however, is not immune from drawbacks. The main criticisms arisen in the  
35 literature focus on the reliability of the estimated propensity scores. Smith and Todd (2005)  
36 have shown that TE estimation based on propensity score matching are highly sensitive  
37 to its specification (based on both the set of variables included in the scores and the  
38 particular sample used in the estimation). This potential limitation has recently driven  
39 the attention of many researchers to alternative algorithms of matching for TE estimation  
40 based on random recursive partitions of the observations and on coarsened levels of the  
41 covariates (Iacus and Porro 2009, Iacus et al. 2008).  
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In our case what we want to estimate is the average effect of the treatment on the treated (ATT) which is defined as:

$$\tau \equiv E\{\Delta_i\} \equiv E\{Y_{1i} - Y_{0i} \mid D_i = 1\} \equiv E\{Y_{1i} \mid D_i = 1\} - E\{Y_{0i} \mid D_i = 1\} \quad (4.1)$$

where  $Y_{1i}$  is the economic performance of firm  $i$  in case of innovation performed and  $Y_{0i}$  is the economic performance of the same firm in case of non-innovation performed.  $D = \{1, 0\}$  is an indicator of exposure to the treatment (1 = innovate, 0 = did not innovate).

Unfortunately only  $E\{Y_{1i} \mid D_i = 1\}$  and  $E\{Y_{0i} \mid D_i = 0\}$  are observed, whereas  $E\{Y_{0i} \mid D_i = 1\}$  and  $E\{Y_{1i} \mid D_i = 0\}$  are unobserved counterfactuals.

Note that in a randomized experimental setting this problem does not hold since  $E\{Y_{1i}, Y_{0i}\} \perp D_i$ .

The rationale behind matching estimator is to assume that such independence holds for within cells defined by a set of observed characteristics  $X$ :

$$E\{Y_{1i}, Y_{0i}\} \perp D_i \mid X \quad (4.2)$$

which is known in the literature as the conditional independence assumption (C.I.A.).

Rosenbaum and Rubin (1983) show that if C.I.A. holds, it also holds within cells defined by the values of the mono-dimensional variable  $p(X)$ , which is called propensity score, i.e. the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X) \equiv \Pr\{D = 1 \mid X\} = E\{D \mid X\} \quad (4.3)$$

Given this result the ATT can be estimated as follows:

$$\hat{\tau} \equiv E\{E[Y_{1i} \mid D_i = 1, p(X_i)] - E[Y_{0i} \mid D_i = 0, p(X_i)] \mid D_i = 1\} \quad (4.4)$$

Equation 4.4 implies two different conditions which must be satisfied in order to let  $\hat{\tau}$  an unbiased estimator of  $\tau$ :

- 1) Balancing of pre-treatment variables given the propensity score:

$$D \perp X \mid p(X) \quad (4.5)$$

- 2) Unconfoundedness given the propensity score:

$$Y_1 Y_0 \perp D \mid p(X) \quad (4.6)$$

## 5.2 Propensity score estimation.

In order to estimate  $p(X)$  we studied the role played by several firm's and industry's characteristics on the probability of introducing new products by running a logit regression with **InnPd** as dependent variable.

Table 10 provides a description of the variables employed in the analysis and Table 11 reports some descriptive statistics for these variables.

Our regressors include a number of potentially relevant firm's characteristics, including size, measured by the logarithm of the number of employees in 1998, and an indicator for newly established firms (**dumnew**), which will be interacted with most of our regressors in order to detect potential differences between old firms (incumbents) and new firms with respect to factors affecting the propensity to innovate. We further add the firm's share of turnover from export in 1998 (**tunr\_exp98**), in order to proxy for the degree of internationalization of the firm. We then include the firm's share of employees with university degree (**grad\_emp**) in 2000 (a measure of the stock of human capital intensity), and firm's total debt over total assets ratio (**debt\_assets98**) in 1998 (a measure of firm's financial leverage-exposure). Finally, we add further financial variables, such as firm's total liquidity over total assets ratio (**cf\_assets98**) in 1998, which is meant to capture the

firm's ability to generate cash flow for self financing R&D investments; the firm's stock of, respectively, physical (durable assets) and non-physical (immaterial durable assets excluded financial assets) capital over its total assets in 1998 (**cap\_assets98** and **capimm\_assets98**); a dummy variable which equal to 1 if the firm belongs to a mutual financing group of firms (**gp**)<sup>7</sup>.

Table 10 - Variable description

Variable	Description	Definition
<b>DEPENDENT VARIABLE</b>		
InnPd	The firm introduced new products (for the firm) during the period 1998-2000.	dummy: 0=no; 1=yes
<b>FIRM LEVEL REGRESSORS</b>		
Dumnew	Firm established during 1993-1998	dummy: 0=no; 1=yes
Gp	Firm belongs to a group.	dummy: 0=no; 1=yes
GRTurn1999	Firm's turnover growth rate in 1999	continuous
GREmp1999	Firm's employees growth rate in 1999	continuous
OPR1999	Firm's OPR in 1999	continuous
ROTA1999	Firm's ROTA in 1999	continuous
Lemp98	Firm's size = Log of the firm's number of employees in 1998	continuous
turn_exp98	Firm's share of turnover 1998 from export	continuous [0-1]
debt_assets98	Firm's total debts in 1998 / Total assets in 1998	continuous [0-1]
cf_assets98	Firm's available liquidity in 1998 / Total assets 1998	continuous [0-1]
grad_emp	Firm's share of employees with higher education in 2000	continuous [0-1]
Cap_assets98	Firm's stock of physical capital 1998 / Total assets 1998	continuous [0-1]
capimm_assets98	Firm's stock of non-physical capital 1998 / Total assets 1998	continuous [0-1]

In addition to the firm's characteristics we also include in each model a set of industry dummies (defined according to ATECO 2 digits level) to proxy for sector-specific unobserved characteristics (such as incoming spillovers, appropriability conditions, degree of concentration and so on), and the lagged performance indicator of interest (**OPR\_99**,

<sup>7</sup> The number of observations involved in this analysis is further reduced to 1499 firms (from the previous working sample of 1988 firms) due to the presence of missing values for some of the regressors listed in Tables 10-11.

ROTA<sub>99</sub>, GRTurn<sub>99</sub> and GREmp<sub>99</sub>), as a proxy for unobserved time-invariant firm's specific characteristics.

Table 12 reports the estimation output associated with the four different logit specifications adopted (each one includes a different lagged performance indicator as regressor) for estimating the propensity scores associated with each observation. Several regressors have been interacted with the **dumnew** dummy variable to check for possible different influences on the estimated propensity to innovate for new entrants with respect to incumbents<sup>8</sup>.

Table 11 - Descriptive statistics

Variables	No. of obs.	Mean	Std. Dev.	Min	Max
<b>DEPENDENT VARIABLE</b>					
InnPd	1499	0.573	0.495	0	1
<b>FIRM LEVEL REGRESSORS</b>					
Dumnew	1499	0.118	0.323	0	1
GRTurn1999	1499	-0.104	0.204	-1.029	1.072
GREmp1999	1499	0.055	0.156	-0.875	1.099
OPR1999	1499	0.069	0.099	-2.081	0.678
ROTA1999	1499	0.078	0.104	-0.824	0.692
lemp98	1499	4.021	1.229	2.303	9.727
turn_exp98	1499	0.246	0.287	0	1
cf_assets98	1499	0.066	0.093	0	0.736
grad_emp	1499	0.111	0.163	0	1
cap_assets98	1499	0.204	0.153	0	0.813
capimm_assets98	1499	0.027	0.052	0	0.588
debt_assets98	1499	0.630	0.186	0.064	1.073
Gp	1499	0.352	0.478	0	1

Before running the ATT estimation based on propensity score matching, we checked for the overall statistical significance of the estimated models, whether the balancing property condition was satisfied after partitioning the sample in 6 homogeneous blocks according to their value of the estimated propensity scores<sup>9</sup>, if the estimated  $p(X)$  spread on a

<sup>8</sup> We checked for the presence of multicollinearity amongst our regressors and no severe variance inflation factor emerged.

<sup>9</sup> Detailed output is available upon request.

reasonable wide common support and finally if the sign of each regressor is coherent in an economic sense. In particular, looking at the estimated coefficients in Table 12 we can see that firm size (**lemp98**) always exert a positive influence on the probability of introducing new innovative products, which is consistent with the previous preliminary findings of section 4.

**Table 12 - LOGIT estimation output of propensity scores. Dependent variable InnPd**

InnPd	Std.			Std.			Std.			Std.		
	Coef.	Err.	P>z									
Dumnew	-0.580*	0.311	0.062	-0.694**	0.317	0.028	-0.441	0.316	0.163	-0.722**	0.323	0.025
GRTurn1999	-0.894***	0.315	0.005									
dumnew*GRTurn1999	0.353	0.796	0.658									
GREmp1999				0.376	0.452	0.405						
dumnew*GREmp1999				-0.091	0.832	0.913						
OPR1998							1.157	0.707	0.102			
dumnew*OPR1998							-2.617	2.137	0.221			
ROTA1998										0.851	0.734	0.246
dumnew*ROTA1998										1.773	1.979	0.37
lemp98	0.293***	0.062	0	0.279***	0.063	0	0.288***	0.062	0	0.293***	0.062	0
turnexp98	0.858***	0.248	0.001	0.889***	0.249	0	0.898***	0.247	0	0.880***	0.247	0
dumnew*turnexp98	0.618	0.707	0.382	0.617	0.756	0.414	0.559	0.708	0.43	0.741	0.712	0.298
cf_assets98	-0.411	0.716	0.566	-0.701	0.678	0.302	-0.511	0.708	0.471	-0.520	0.713	0.466
dumnew*cf_assets98	0.278	1.745	0.874	1.544	1.819	0.396	0.569	1.738	0.743	0.124	1.804	0.945
grad_emp	1.807***	0.487	0	1.781***	0.491	0	1.867***	0.483	0	1.874***	0.483	0
dumnew*grad_emp	0.355	1.000	0.723	0.940	1.135	0.408	0.471	1.010	0.641	0.150	1.006	0.881
Cap_assets98	-0.395	0.396	0.319	-0.412	0.396	0.299	-0.247	0.394	0.532	-0.209	0.400	0.602
capimm_assets98	2.760**	1.271	0.03	2.393*	1.270	0.06	2.666**	1.268	0.036	2.853**	1.275	0.025
debito_assets98	0.262	0.327	0.424	0.242	0.301	0.423	0.418	0.340	0.218	0.499	0.357	0.162
Gp	0.249*	0.145	0.087	0.253*	0.147	0.085	0.268*	0.145	0.065	0.267	0.145	0.066
dumnew*gp	0.369	0.401	0.357	0.290	0.420	0.49	0.331	0.403	0.412	0.406	0.403	0.314
_cons	-1.649***	0.418	0	-1.477***	0.294	0	-1.787***	0.434	0	-1.867***	0.452	0
Log likelihood	-918.515			-935.712			-921.350			-942.800		
No. of observations	1499			1499			1499			1499		
Pseudo R <sup>2</sup>	0.1021			0.0950			0.0993			0.0922		

ATECO 2-digit level Industry dummy variables included

Statistically significant at 1%\*\*\*, 5%\*\*\*, 10%\* level

Also export intensity (**turnexp98**) positively affects the firm's propensity to innovate, consistently with the empirical literature focusing on innovation-export complementarity<sup>10</sup>. Finally our proxies for firm's human and knowledge capital (**grad\_emp** and **capimm\_assets98** respectively) positively correlate with the probability of introducing new innovative products.

### 5.3 ATT estimation.

Given the PS calculated as predictions of the logit models estimated in the previous section, we calculated the average treatment effects on the treated (ATT) for all the three performance indicators by using different matching methods: radius, kernel and stratification<sup>11</sup>.

The standard errors associated with the ATT estimates based on radius and stratification methods are computed analytically<sup>12</sup>, whereas for kernel matching we computed standard errors with bootstrap methods.

Table 13 reports the ATT estimated for each of the matching methods described above. The "treated" firms are those that introduced any new or significantly improved products (**InnPd**) whereas the "controls" are the non-innovative firms (**No InnPd**).

**Table 13 - ATT estimation (Treated=InnPd) all firms (mean 2000-2003).**

	Treated	Control	ATT (Y <sub>i</sub> =GRTurn)	ATT (Y <sub>i</sub> =GREmp)	ATT (Y <sub>i</sub> =OPR)	ATT (Y <sub>i</sub> =ROTA)
<b>Matching method:</b>						
Kernel	838	617	1.0**	1.8***	0.9**	0.8*
Radius	838	617	1.1**	1.9***	1.1*	0.8**
Stratification	838	617	1.1**	1.9***	0.8*	0.7*

Statistically significant at 1%\*\*\*, 5%\*\* , 10%\* level (one-tail t-test)

<sup>10</sup> See for instance Bernard and Jensen (1999), Hitt et al. (1997), Alvarez and Robertson (2004).

<sup>11</sup> See for instance Becker and Ichino (2002) for an extensive review of matching methods based on propensity scores estimation.

<sup>12</sup> See Becker and Ichino (2002) for the analytical formulas.

Our results confirm the findings of section 4: over the period 2000-2003, innovative firms show and higher economic performance with respect to non innovative ones. On average, during the period 2000-2003, the yearly growth rate premium for “product” innovating firms is estimated to be about +1.1% in term of turnover and about +1.9% in term of number of employees. Also the average profitability premium is estimated to be about +0.9% and +0.8% in term of OPR and ROTA respectively.

#### 5.4 New established firms

The previous findings do not hold when restricting our analysis only to new entrants. However, some interesting aspects emerge.

Looking at Table 14, ATT analysis estimates an average “negative premium” in terms of profitability for new innovating firms which ranges from -0.6% to -1.7% for OPR. On the other side, a positive innovation premium is estimated in terms of growth rates, which seems to be negligible when considering turnover but relevant (about +3%) when considering employment. These findings seem to support the hypothesis of strategic different behavior of new entrants firms in the M&HT industries with respect to incumbents, as described in Section 1. In particular, innovation seems more to be a crucial activity for achieving higher economic growth rates (in the short run) for entrants rather than for incumbents. Furthermore, the fact that growth rate premiums are more consistent when considering employment than turnover may be due to simultaneous price-cutting policies pursued by innovating firms. Unfortunately this is a hypothesis we cannot test, as we have no information on prices.

**Table 14 - ATT estimation (Treated=InnPd) new established firms (mean 2000-2003).**

	<b>Treated</b>	<b>Control</b>	ATT ( $Y_i = \text{GRTurn}$ )	ATT ( $Y_i = \text{GREmp}$ )	ATT ( $Y_i = \text{OPR}$ )	ATT ( $Y_i = \text{ROTA}$ )
<b>Matching method:</b>						
Kernel	82	78	0.9	2.9*	-1.5	-1.1
Radious	82	78	0.0	1.7	-0.6	0.6
Stratification	82	78	1.1	3.1*	-1.7*	-1.2

\* Statistically significant at 10% level (one-tail t-test)

## 6. Comments and conclusions.

The main purpose of this paper was to assess the impact of innovation on the economic performance at the micro (i.e. firm) level. We concentrate on one particular type of innovation activity - product innovation - and estimate its impact on firm's economic performance by using information coming from an original dataset, which combines data from the CIS3 Survey for Italy and the economic data of the surveyed firms from their balance sheets. One of the advantages in using this source of data was to have a representative sample also of the small (and new) firms, which are often underrepresented or even completely excluded from the analysis when other indicators for innovativeness (e.g. patents or R&D expenditures) are adopted. We specifically refer to firms that have introduced new or significantly improved products during the period 1998-2000. Since the definition of "new or significantly improved products" may change dramatically according to the sector of the firm's economic activity, we focused our analysis on Medium and High-Tech (M&HT) industries.

We have found significant differences between innovative and non-innovative firms both in terms of profitability and growth rates over the three-year period immediately following the CIS3 Survey reference period (i.e. over 2000-2003). In particular the differences in profitability are remarkable when considering micro and small sized firms, whereas they tend to disappear when considering medium and large firms. As such, these results are in line with the findings by Acs and Audretsch (1990) about the positive growth effect of industry relevant innovative effort on small firms.

In order to estimate the impact of innovative activities on the economic performance of the firms (i.e. the "innovation premium") we adopted a quasi-experimental design setting by using several matching methods based on propensity scores estimation. These methods do not require any structural (imposed) model (i.e. they are robust to model misspecification) when estimating the treatment effect.

Interesting results emerge when estimating the innovation premium only for the "new entrants" (i.e. those firms established during the period 1993-1998). In this case we

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6 estimated a negative innovation premium in terms of profitability and a positive and  
7 remarkable (about +3%) innovation premium in terms of employment growth rate.

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9 These convincing results can be related to the role of innovation in affecting the  
10 profitability and growth of firms in a context such as Italy. Innovation indeed represents  
11 an increase in profitability for small and medium size firms. However even without  
12 innovating, non-innovators still have a positive average profitability - and this is the case  
13 particularly for both small firms and new firms. Thus it seems that small and new firms in  
14 Italy do not need to innovate in order to be profitable. On the contrary, if an established  
15 small firm or a new very small firm wants to grow, it needs to innovate. In fact, for  
16 established small firms and for new very small firms innovation provides the trigger to  
17 move from a zero or very limited growth to a positive one.

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19 These results imply that small and new firms that want to continue to be profitable, do  
20 not have very high incentives to innovate, given the fact that innovation is associated with  
21 potentially high uncertainty in the discovery of new technologies and products, and that  
22 R&D investments are mostly sunk costs. This further explains why a large part of the  
23 Italian system, which is characterized by a significant presence of small and new firms,  
24 does not show an active innovation profile.

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26 Our results further imply that it is mostly those firms that want to grow - and therefore  
27 are willing to move to a less personal or family control to a more formalized and  
28 managerial structure – that have incentives to innovate. However, this group is a small  
29 part of the whole population in Italy  
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