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Explaining Growth Differences across Firms: The Interplay between Innovation and Management Practices

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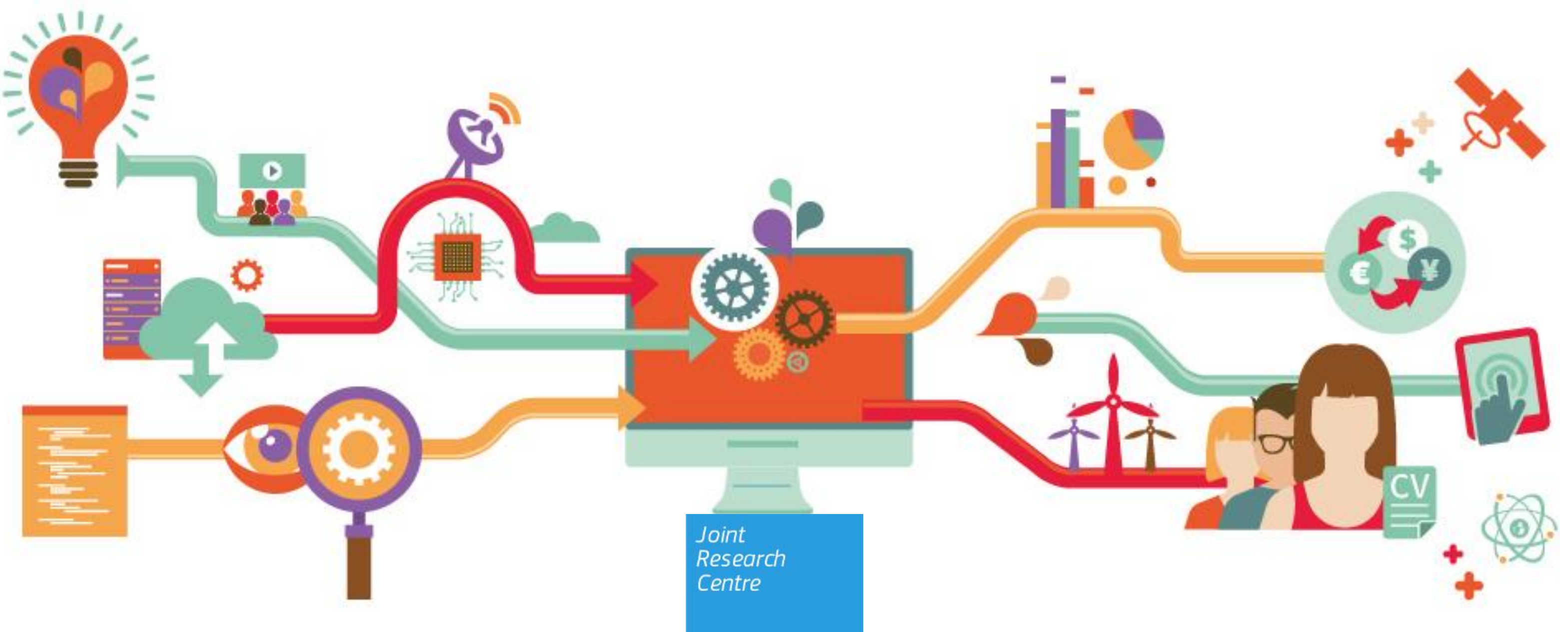

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Explaining Growth Differences across Firms: The Interplay between Innovation and Management Practices*

Livio Romano †

Abstract

This paper provides first empirical evidence of the joint effects that innovation strategies and human resource management practices exert on firm growth. By exploiting unique information from a large sample of Italian manufacturing companies in the very recent years, it shows that investing in technology and implementing performance-based pay policies are both positively associated with a significant turnover, employment and labor productivity growth premium. However, their joint adoption does not necessarily sum the two effects. In particular, performance-based rewards boost growth of non-innovators and of firms pursuing relatively simple innovation strategies, centered around the acquisition of embodied technology. For firms strongly relying on R&D as an additional lever for product and process upgrading, the estimated effect of having in place monetary incentive mechanisms is null or even negative.

Keywords: Heterogeneity, Innovation, Management Practices, Firm Growth

JEL classification: L20, M21, O30

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1 Introduction

There is widespread international evidence of persistent differences in the performance of firms even within the same sector of activity, region of establishment and class size. The causes underlying such heterogeneity are manifold, often sourced within the boundaries of the firms themselves. Among such "internal" causes, the different strategic choices concerning technological innovation and managerial practices play a crucial role (Syverson 2011). The idea of a positive relation between innovation and economic performance has a long tradition in economics, dating back to Schumpeter (1934, 1943). It has become an essential ingredient in macro-models of endogenous growth (Romer 1990; Aghion and Howitt 1992; Grossman and Helpman 1991; Jones 1995) as well as in micro-models aimed at explaining industry evolution with heterogeneous firms, both in neo-classical frameworks (Jovanovic 1982; Hopenhayn 1992; Erikson and Pakes 1995) and in evolutionary ones (Penrose 1959; Nelson and Winter 1982; Dosi et al. 1995). The interest of scholars in the link between performance and management practices, in their different typologies, is much more recent at least in economics, building momentum after the seminal contributions of Bloom and Van Reenen (2007),Bloom et al. (2012); their general conclusion is that there exists a set of good managerial practices whose implementation is conducive of higher firm performance (Bloom et al. 2010, 2013, 2016).

However, so far the impact of the adoption of different innovation strategies and that of different managerial practices have been typically analyzed in isolation, despite the fact that from a theoretical point of view we can expect (at least some of) the management choices to affect the managers' investment horizon, the risk bearded by workers, the alignment of individual with corporate incentives, the flows of information within and outside the boundaries of the organization and the accumulation of knowledge, all factors that, ultimately, should impact firm innovative and economic performance (Cohen and Levinthal 1990; Roberts 2004; Laursen and Foss 2003). A major explanation for that has to do with the difficulty in collecting detailed information on both technological and organizational characteristics for the same firm. For instance, in one of the most comprehensive surveys on technological innovation, the Community Innovation Survey (CIS henceforth), organizational change is defined according to a limited set of broad categories which group together managerial practices of different nature; this allows to empirically approach the multifaceted nature of innovation and highlight the strategic role played by non-technological changes within the firm (see, for instance, Evangelista and Vezzani 2010, 2011), but it inhibits an identification of the relevant organizational drivers/constrains to firm performance.

Partial exceptions are the exploratory analysis of Kremp and Mairesse (2004) using a large sample of French manufacturing firms and focusing on knowledge management, and the recent empirical contribution by Bartz et al. (2016), covering some emerging economies and focusing on operations, strategic and human resource management. Although in the two above mentioned works the positive contributions to firm productivity of technological innovation and of "good" management practices are analyzed jointly, it is still unclear whether the channels through which the two strategic choices exert their effects are complement, substitute or independent. Moreover, both papers focus on a single input of the innovation process, namely R&D effort, whilst the literature has extensively documented in the last two decades at least that innovation is a learning process which involves multiple inputs whose diverse combinations give rise to different strategies and, ultimately, to different outcomes of the innovation process (see Smith 2004 and Mairesse and Mohen 2010, among others). Indeed, for many firms, especially small and medium sized enterprises operating in technologically mature industries, investing in non-R&D activities is the main channel for fueling competitiveness and growth (Moncada-Paternò-Castello and Cincera 2012).

Given this premise, the scope of this paper is twofold: to complement the scant empirical evidence on the relationship between technological innovation strategies and management practices, focusing in particular on those applied to human resources, and their impact on firm growth; and to study such relationship taking properly into account the complexity of the innovation process, which includes, but is not confined to, R&D investments. To do so, a unique dataset built by the Italian Statistical Office in agreement with the Economic Research Department of Confindustria and covering the Italian industrial system in the very recent years has been used.

The first step of the analysis has been the identification of different profiles of product and/or process innovators, combining factor and cluster analyses to the many variables describing inputs of the technological innovation strategies pursued in the years 2010-2012. The result has been the classification of each innovating firm in the sample according to the degree of complexity of the technological innovation process: high, medium, low. Only firms pursuing innovation strategies of high complexity invest significant resources in both (almost entirely in-house) R&D and in the acquisition of technology embedded in new machinery, equipment and software. For firms undertaking innovation strategies of medium or low complexity, instead, the latter investment channel represent a disproportionately larger weight of the total innovation expenditure and R&D efforts play a much minor role. The complexity of the innovation strategy is positively correlated with the complexity of the innovation outcome: the ability to introduce products new to the market, a measure of innovation radicality, is at its highest/lowest in those firms pursuing the most/least sophisticated strategies, also taking into account a whole set of confounding factors.

The analysis also reveals that firms having invested in technological innovation during the 2010-2012 period have outperformed non-innovators in the subsequent triennium in terms of turnover, employment and labor productivity growth. However there is no evidence of large differential growth premia related to degree of complexity of the innovation strategies implemented. In particular, the economic return of choosing a sophisticated approach to innovation is not statistically different from the return of choosing simpler alternatives.

A first plausible explanation is that the benefits from investing in R&D - the key feature of firms pursuing high complex innovation strategies - are deferred in time, thus not yet visible after three years, while (at least part of) the benefits from investing in the renewal of the stock of physical capital - a common feature of the different types of innovators - are grabbed much earlier by the firms, thus are already visible in the data under scrutiny[1]. This is fully consistent with the difficulty encountered in most of the empirical literature to identify a strong link between innovation and growth when the explanatory variable in represented precisely by R&D or by R&D-related patent activities (Coad 2009 for a review; Coad et al. 2016 for a notable exception), ignoring the impact exerted by other innovation inputs.

A second explanation, in line with previous arguments set forth by Roberts (2004) and Manso (2011), and evidence from lab experiments brought about by Ederer and Manso (2013), is that the economic return from investing in R&D and other science-related activities is weakened by the contemporary adoption of performance-based pay schemes for the remuneration of workers. The reason is that science-based "*innovation is the result of learning through the exploration of untested approaches that are likely to fail. Because of that, the optimal incentive scheme that motivates exploration is fundamentally different from standard pay-for-performance schemes used to motivate effort*" (Manso 2011: 1851). Consistently with that, the analysis shows that pay-for-performance schemes are systematically associated with positive firm revenue, employment and productivity growth, but also that this positive association does not hold true for firms pursuing innovation strategies of high complexity. In particular, only for these firms the magnitude and (negative) sign of the interaction term suggest that the effect on economic performance of having in place pay-for-performance policies is null or even negative.

Thus, the analysis performed in this paper confirms the existence of potential

[1] The investment in new machineries as a channel for technological upgrading has a long tradition in the Italian industrialization history, as extensively documented by Barbiellini et al. (2011).

detrimental effects that standard incentive-pay schemes may have on performance (Bloom and Van Reenen 2011 for a review), but it also provides first evidence of the heterogeneous impact of such managerial practice among different types of firms.

The rest of the paper is organized as follows: section 2 describes the data; section 3 presents the methodology used to identify the different groups of innovators and the results of its implementation; section 4 describes the different human resource management practices surveyed and how they are correlated with the different groups of innovators previously identified; section 5 investigates the relations between the different choices concerning technological innovation and managerial practices and firm economic performance; section 6 concludes.

2 Data

The dataset used in the analysis mixes quantitative and qualitative information in order to reconstruct a comprehensive image of the manufacturing basis in Italy in the very recent years. In particular, three official sources of information have been merged: the 7th wave of the Italian CIS, covering the years 2010-2012; the 9th industry and services Census, having 2011 as the reference year; the FRAME-SBS statistical register for the years 2012 and 2015.

There is not perfect overlap among the different data sources, because the statistical coverage of the Census is the total population of firms with at least 20 employees and only a (very large) sample of firms of smaller size, while the CIS survey includes sampled firms with 10 employees or more. This implies that full information is available for around 78% out of the 4,070 manufacturing firms recorded in the Italian CIS survey. For each data source, Table 1 shows the type of information used in the analysis.

Information collected from the CIS includes not only innovation strategies (inputs and outputs) but also structural statistics on sector of activity, employment and revenues levels, the Italian headquarters' region, the belonging to an enterprise group, the geographical extent of the market and the share of workers with tertiary degree. From the Census, information regarding firm governance, the adoption of different human resources management practices, the presence of foreign direct investments (FDIs) and the principal sources of finance are recovered. Finally, the statistical register FRAME-SBS provides data on age, employment, revenue, and wage levels.

Table 1: *Variables used in the analysis*

Variable	*Type*
Community Innovation Survey (2010-2012)	
Sector of activity	Categorical
Employment	Continuous
Turnover	Continuous
Region of headquarters	Categorical
Being part of a enterprise group	Dummy
Geographical extent of the market (national, EU, extra-EU)	Dummy
Types of innovations	Dummy
Innovation investment channels	Dummy
Innovation expenditures	Dummy
Introduction of products new to the market	Dummy
Sources of informations used to innovate	Likert scale
Formal cooperation for innovation	Dummy
Public financial support for innovation	Dummy
Methods of protections of the innovation	Likert scale
Share of workers with tertiary degree	Ordinal
Organizational innovation	Dummy
Marketing innovation	Dummy
Census (2011)	
Family control of the firm	Dummy
Professional management of the firm	Dummy
Human resources management practices	Dummy
Principal sources of finance	Dummy
FDI	Dummy
FRAME-SBS statistical register (2012 and 2015)	
Age	Continuous
Turnover	Continuous
Employment	Continuous
Labor costs	Continuous

3 Identifying the profiles of innovators

The identification of the different profiles of product and/or process innovators has followed a two-stages methodology widely used in the literature, which consists of first estimating latent variables from a factor analysis applied to their answers to different sections of the CIS questionnaire, and then applying a clustering algorithm to the latent variables (see Leiponen and Drejer 2007, Frenz and Lambert 2009, Srholec and Verspagen 2012 as examples). The logic is as follows: studying the correlations across CIS variables, the factor analysis identifies which of them form coherent subsets (factors); these are then interpreted, using inductive reasoning, as possible ingredients of an innovation strategy; the clustering algorithm applied to these factors allows to split the sample of firms according to the degree of similarity/dissimilarity of the mix of ingredients of their innovation strategies, seeing which are common to all groups, and which are group-specific; finally, such clusters, using again inductive reasoning, are given an economic interpretation.

All the CIS variables considered in the factor analysis are either binary indicators, referring to the different innovation investment channels, the existence of formal cooperation agreements for innovation and of public sources of funding to support innovation, or Likert scale variables, measuring the importance of different sources of information used to innovate, and of the different methods of protection of the innovations. The nature of the variables suggests using a polychoric correlation matrix in the factoring procedure. Extraction method used is principal-component. Results have been interpreted after the application of oblimin oblique rotation (see Srholec and Verspagen 2012 for a extensive discussion of the motivation underpinning these technical choices).

Table 2 reports for each factor with eigenvalue greater than 1 the coefficients of correlation between the corresponding latent variable identified by the estimate and the CIS original variables. The economic interpretation of these factors, their "label", is derived by the reading of such correlations (named factor loadings), that is by looking at which set of variables have a high correlation with the same factor.

In particular, the table includes seven factors: three mainly related to the different nature of the investment activities, two to the sources of information, two to the ways firms protect their innovation. The factor labeled as "Science" is highly correlated with investments in R&D, both intra- and extra-muros, with information useful for innovation coming from universities and public research centers, with formal cooperation agreements signed for innovation purposes, and with public financial support for innovation. The factor labeled "Embedded technology" loads high with the acquisition of machinery, equipment and software, and with information coming from firm's suppliers. The factor labeled as "Other intangibles" captures the other channels of innovation: training, marketing and design. Another dimension identified by the factor analysis puts together information from clients, both public and private, from competitors and other firms in the same industry, which has been labeled as "Market information". The factor labeled as "Non-market information" is highly correlated with information from conferences, fairs, scientific journals and employers' associations. Among the different ways of protecting technological innovations, the analysis clearly identifies one factor strongly associated with "Formal methods", that is patents, design registration, copyright, trademarks, and another factor connected with the remaining "Informal methods", that is lead time advantages, complexity of design and secrecy.

Table 2: *Factor analysis on the innovation activites of Italian manufacturing firms*

CIS variables:	Factors: (1) Science	(2) Embedded technology	(3) Other intangibles	(4) Market information	(5) Non-market infomation	(6) Formal protection	(7) Informal protection
Intra-muros R&D	**0.58**	-0.40	0.18	0.02	-0.08	0.01	0.31
Entra-muros R&D	**0.74**	0.09	0.18	-0.08	-0.07	0.01	0.00
Acquisition of machinery, equipment, software	0.03	**0.84**	0.12	-0.04	-0.12	0.04	0.03
Acquisition of other external knowledge	0.22	0.29	0.49	0.01	-0.08	0.16	-0.19
Training	0.11	0.30	**0.71**	-0.02	0.08	-0.04	0.05
Markeking	0.01	0.01	**0.76**	-0.06	0.22	0.06	0.04
Design	-0.03	-0.17	**0.77**	0.15	-0.03	0.10	-0.03
Public support to innovation	**0.59**	0.07	0.06	-0.02	0.03	-0.11	0.01
Information from							
within the firm	0.47	-0.08	0.00	0.08	-0.17	0.19	0.23
suppliers	-0.07	**0.57**	-0.11	0.22	0.17	-0.14	0.22
private clients	0.00	0.00	0.03	**0.86**	-0.07	-0.07	0.13
universities	**0.76**	-0.05	-0.10	0.07	0.27	0.09	-0.12
public research institutes	**0.58**	0.07	-0.09	0.05	0.38	0.21	-0.14
public clients	0.18	0.05	-0.07	**0.54**	0.15	0.30	-0.35
competitors	-0.05	0.01	0.07	**0.67**	0.18	0.06	-0.03
consultants and private labs	0.33	0.22	-0.08	-0.10	0.47	0.02	-0.01
conferences, fairs	-0.13	-0.10	0.22	0.09	**0.75**	0.03	0.07
scientific journals	0.10	-0.07	0.07	0.09	**0.75**	-0.06	0.11
employers' associations	0.07	0.08	0.00	0.02	**0.66**	0.05	0.01
Cooperation agreements	**0.75**	0.05	0.11	0.12	-0.08	-0.10	0.18
Patents for industrial invention	0.18	-0.07	0.06	0.04	-0.10	**0.76**	0.11
Patents for utility model	-0.05	0.03	0.05	0.05	-0.04	**0.88**	0.00
Design registration	-0.06	-0.02	0.05	-0.05	0.02	**0.89**	0.04
Copyright	-0.04	0.02	-0.01	0.06	0.03	**0.88**	-0.01
Trademarks	0.01	0.04	-0.01	-0.10	0.13	**0.61**	0.35
Lead time advantages	0.09	0.00	0.08	0.04	0.06	0.22	**0.68**
Complexity of goods or services	0.00	0.07	0.00	0.11	0.09	0.13	**0.76**
Secrecy	0.13	0.04	-0.06	0.01	0.08	0.42	**0.55**
Proportion of variance explained	0.09	0.04	0.06	0.04	0.07	0.31	0.05

Only factors with eigenvalues greater than 1 have been considered. Factor analysis on the matrix of polychoric correlations, using principal component factors, and oblimin oblique rotation method. Unweighted data. Factor loadings greater than 0.5 in bold.

The k-median clustering procedure applied to these seven principal factors has lead to the identification of three groups of innovators in the Italian manufacturing, whose characterization is reported in Table 3[2]. The choice of the number of clusters, which is defined a priori and does not result from the clustering algorithm, has been made with the goal of balancing the need to give a description of the heterogeneity in the innovation processes prevailing in Italy as detailed as possible against the need to have group sizes large enough to make robust statistical inference on the determinants of firm growth.

Data show that the different groups of firms are characterized by different degrees of complexity of the innovation strategies pursued. The first column of Table 3 refers to the so-called "High Complexity" innovators (**HCIs** henceforth), firms that beside investing in the renewal of their machineries and equipments (which account, on average, for 33,3% of the total expenditures in technological innovation) exert significant efforts in almost entirely in-house R&D activities (51,1% on average). Moreover, they make use of many different sources of information useful for innovation, both internal and external to the firm, and protect their innovations with formal and (especially) informal methods.

Columns two and three of Table 3 refer to firms labeled as "Medium Complexity" and "Low-Complexity" innovators respectively (**MCIs** and **LCIs** henceforth). These firms attach a disproportionately larger weight to investments in the renewal of their physical capital in comparison to those in R&D: on average, 55,3% against 31,3% of the total expenditures in innovation for MCIs, 57,9% against 25,6% for LCIs. Moreover, they use only a limited number of sources of information useful for innovation (higher for MCIs as compared to LCIs), while formal and informal methods of protections of innovations are typically absent.

For three out of four HCIs the technological innovation effort is accompanied also by organizational innovation and for two out of three of them by marketing innovation; both figures are significantly lower for MCIs and LCIs. The three groups of firms differ in terms of the stock of human capital detained: the average value of the categorical variable capturing the share of workers with tertiary degree is 3.5 for HCIs, while it is below 3 for both MCIs and LCIs. The value of 4 corresponds to a share between 10% to 24%, thus implying that even within firms that undertake complex innovation strategies the stock of human capital is relatively low. Finally, HCIs are, on average, double the size of MCIs and LCIs.

Some common features emerge from the analysis: all the three groups of innovators place a lot of value on information coming from suppliers, which is consistent

[2]The k-median has been preferred to the k-mean because it is less sensitive to outliers and provide stable results when the clustering procedure is repeated.

Table 3: *Results of the cluster analysis. Mean values*

	HCIs	MCIs	LCIs	Non innovators
Factors:				
Science	0.75	0.44	0.37	-
Embedded technology	0.97	0.92	0.94	-
Other intangibles	0.26	0.17	0.10	-
Information from the market	1.56	1.76	0.36	-
Information from outside the market	1.50	1.39	0.57	-
Formal methods of protection	0.88	0.01	0.10	-
Informal methods of protection	2.42	0.49	0.70	-
Selected CIS variables				
Intra-muros R&D expenditure in 2012 (% of turnover)	1.96	0.86	0.81	-
Extra-muros R&D expenditure in 2012 (% of turnover)	0.37	0.26	0.15	-
M&E expenditure in 2012 (% of turnover)	1.51	1.98	2.17	-
Total innovation expenditure in 2012 (% of turnover)	4.56	3.58	3.75	-
Importance of (scale from 0 to 3):				
Information from within the firm or own group	2.02	1.01	1.02	-
Information from suppliers	1.95	1.87	1.57	-
Information from universities	0.98	0.70	0.31	-
Information from public research centers	0.75	0.50	0.16	-
Information from private clients	1.61	1.75	0.30	-
Information from competitors	1.26	1.37	0.31	-
Using patents	1.28	0.20	0.29	-
Using trademarks	1.55	0.24	0.41	-
Using lead-time advantage on competitors	2.19	0.33	0.48	-
Using complexity of design	2.04	0.32	0.42	-
Organizational innovation (share of cluster's firms)	0.77	0.55	0.52	0.15
Marketing innovation (share of cluster's firms)	0.68	0.50	0.47	0.17
Workers with tertiary degree in 2012 (scale from 1 to 7)*	3.50	2.79	2.64	2.12
Log(employees in 2010)	4.99	4.12	3.86	3.42
N° of observations	965	635	706	1764

*: 1=0%, 2=1-4%, 3=5-9%, 4=10-24%, 5=25-49%, 6=50-75%, 7=75-100%. K-median clustering. Mean values for each variable in each cluster. Unweighted data. HCIs: High-complexity innovators; MCIs: Medium-complexity innovators; LCIs: Low-complexity innovators.

with the high relevance attached to their investments in machinery, equipment and software; on the other hand, they consider information from universities and public research centers as almost irrelevant for their innovation strategies.

By looking at the sectoral distribution of the different profiles of innovators, it emerges that HCIs are more frequent in high- and some medium-high tech sectors. In particular, in the electronic, optical and medical equipment industry they constitute almost half of the total number of firms, and they are a large share also of the chemical, the pharmaceutical and the electrical machinery enterprises. However, they play a significant role also in the textile and in the manufacturing n.e.c industries, which are typically associated with technological maturity. Overall, the HCIs are estimated to represent almost 13% of the Italian total population of manufac-

Table 4: *Type of innovators and innovative performance*

Dep. variable: Introduction of products new to the market in 2012	(1)	(2)
HCIs	0.207***	0.100***
	(0.026)	(0.028)
LCIs	-0.095***	-0.077**
	(0.026)	(0.029)
Constant	0.436***	0.526
	(0.020)	(1.316)
Control variables	No	Yes
N° of observations	2013	2013

Note: Linear probability model used to estimate the dependent variable. The reference group is represented by Medium-Complexity Innovators. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Control variables are: sector of activity at 2 digit, class size, macro-region of establishment of the national headquarters, being part of a enterprise group, age of the firm, geographic extent of the market (national, European, international), having introduced in the same years organizational and/or marketing innovations, whether the firms is family controlled and whether it is managed by professionals, and the share of workers with tertiary degree. HCIs: dummy for High-Complexity Innovators; LCIs: dummy for Low-Complexity Innovators.

turing firms with 10 employees or more, MCIs the 14%, LCIs the 19%, while the remaining 54% have not been product or process innovators in the years 2010-2012.

The different profiles of innovators are associated with varying innovative performance, measured as the likelihood of having introduced at the end of 2012 products new to the market[3]. In particular, Table 4 shows the estimates of a linear probability model without and with control variables. Control variables are: sector of activity at 2 digit, class size, macro-region of establishment of the national headquarters, being part of a enterprise group, age of the firm, geographic extent of the market (national, European, international), having introduced in the same years organizational and/or marketing innovations, whether the firm is family controlled and managed by professionals CEOs, and the share of workers with tertiary degree[4].

Results clearly show that the innovative performance is positively correlated with the complexity of the innovation strategy implemented. As such, they offer a direct testing of the goodness of the clustering procedure in isolating conceptually

[3]The CIS survey distinguishes between products new only to the firms or new also to the market. The more stringent definition of innovation has been preferred in order to isolate breakthrough discoveries, which are the natural outcome of R&D activities.

[4]Because we use information from the Census regarding family control and management, the number of observations lowers compared to the original sample of innovating firms from the CIS survey. However, results are virtually the same when analysis is repeated on the larger sample, excluding the two Census variables.

meaningful groups of firms. Compared to MCIs, HCIs are estimated to have a 20.7 p.p. higher probability of generating radical product innovations, while LCIs have a 9.5 p.p. lower probability. After controlling for the set of observable characteristics listed above, the differences among the groups lower but remain highly significant both in economic and statistical terms: +10.0 p.p. for HCIs as compared to MCIs, -7.7 p.p. for LCIs.

These figures are fully consistent with the complementarity hypothesis between internal research efforts and the other inputs of the innovation process in boosting innovative performance, tested by Cassiman and Veugelers (2006) and Catozzella and Vivarelli (2014). They are also in line with the idea set forth by Jensen et al. (2007) that strategies combining science-based and learning and experienced-based modes on innovation yield better outcomes than those relying predominantly on only one of them.

4 Human resource management practices

The 2011 Census has surveyed nine different human resource management practices (HRMPs henceforth), which can be conceptualized, according to Gibbons and Henderson (2013), in three groups: "High-powered incentives", "Skill development" and "Communication and local problem solving". The first group comprises individual performance pay schemes, collective performance pay schemes and promotions. The second group comprises job rotation and job enlargement. The third group comprises delegation, teamwork associated with a simplification of the organizational hierarchy, employee empowerment and quality circles.

As shown in Table 5, at least one managerial practice is each group has been used by a relevant share of the surveyed firms. In particular, the three most frequently adopted practices are respectively employee empowerment (used in 2011 by 47,1% of the firms in the sample), job enlargement (38,2%) and individual performance pay (35,7%); the remaining practices, with the exception of collective performance pay, which was chosen by more than 25% of firms in the sample, play a residual role if any.

The vast majority of firms has adopted at least one managerial practice. However, it is rare to find firms adopting a plurality of managerial practices: the median is two and in the top decile number raises to three. The combinations of single managerial practices actually used are manifold, as suggested by the low frequencies associated with each of them: the three most represented couples are the combination of job enlargement and employee empowerment (chosen by 19.4% of firms in the sample for which information is available), individual and collective performance

Table 5: *Rate of adoption of Human Resource Management Practices*

High-powered incentives	Individual performance pay	36.4%
	Collective performance pay	28.0%
	Promotions	16.4%
Skill development	Job enlargement	38.1%
	Job rotation	19.3%
Communication and local problem solving	Employee empowerment	47.0%
	Delegation	11,8%
	Teamwork with a simplified hierarchy	7.9%
	Quality circles	2.9%

Note: Unweighted data.

pay (12.7%), individual performance pay and employee empowerment (10.7%). This evidence is in line with the low HR management score registered by the Italian manufacturing firms according to the analysis of Bloom and Van Reenen (2011).

Firms pursuing product or process innovation strategies typically adopt a larger number of managerial practices as compared to not innovating firms. As shown in Table 6, column (1), HCIs have adopted more than 2 practices with a probability that is 20 p.p. higher than that of non innovators (baseline); for MCIs and LCIs the magnitude is "only" 10 p.p. higher. Part of this difference is explained by the average size of the firm, which differs significantly across groups. In fact, as shown in column (2) which controls for size, sector of activity, macro-region of establishment of the headquarters and governance structure of the firm, larger firms tend to implement more managerial practices at once, and size is also positively correlated with the complexity of the innovation strategy pursued, with non innovators being typically smaller than the three cluster of innovators (see again Table 3, last row).

Moreover, by looking separately at the rates of adoption of the principal managerial practices, columns (3) to (10), it emerges a positive difference between innovators and non innovators for the class of "high-powered incentives" - both pay for individual and for group performance schemes - increasing in the complexity of the innovation strategy pursued, and, to a lesser extent, for the employee empowerment policies, while no statistical significant difference is observed for the policies targeting job enlargement.

From the same columns it can be noticed that the larger the firm the more frequent, *ceteris paribus*, the adoption of monetary incentives schemes, but, at the same time, the lower the rate of adoption of employee empowerment policies. In other words, larger firms tend to remain highly hierarchical as compared to small sized organizations.

Finally, by looking at the variables capturing the governance structure of the firm, it emerges that, *ceteris paribus*, professional managers tend to implement incentive pay schemes with a higher frequency than family-managed firms, but they are also associated with a lower recourse to employee empowerment policies. The variable capturing the family ownership of the firm, instead, is negatively associated with pay for group performance schemes and positively associated with job enlargement ones.

All in all, the descriptive analysis shown in Table 6 suggests that in the Italian industrial landscape there is no evidence of a widespread adoption of "high performance working systems", which presupposes the combination of complementary managerial practices with the objective of boosting firm performance (Ramsay et al. 2000). Even among larger firms, the use of multiple managerial levers to motivate workers seem, to a large extent, confined to monetary incentive schemes.

Table 6: *Types of innovators and HRMPs*

	Dependent variable: Dummy for the use of:									
	More than 2 managerial practices		*Pay for individual performance*		*Pay for group performance*		*Job enlargement*		*Employee empowerement*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HCIs	0.216***	0.107***	0.271***	0.067***	0.259***	0.084***	-0.007	0.028	-0.025	0.058**
	(0.020)	(0.023)	(0.013)	(0.023)	(0.019)	(0.021)	(0.021)	(0.024)	(0.022)	(0.024)
MCIs	0.103***	0.055**	0.122***	0.053**	0.122***	0.038*	-0.032	-0.018	-0.002	0.034
	(0.023)	(0.024)	(0.025)	(0.025)	(0.023)	(0.021)	(0.026)	(0.026)	(0.026)	(0.027)
LCIs	0.101***	0.074***	0.049**	0.002	0.094***	0.042**	0.027	0.041	0.028	0.055**
	(0.023)	(0.023)	(0.023)	(0.022)	(0.021)	(0.021))	(0.025)	(0.025)	(0.025)	(0.026)
Family Ownership		-0.017		-0.013		-0.053***		0.045**		0.008
		(0.017)		(0.017)		(0.015)		(0.018)		(0.018)
Professional management		0.026		0.109***		0.106***		-0.027		-0.061**
		(0.023)		(0.023)		(0.023)		(0.023)		(0.023)
Size: 50-249 employees		0.047**		0.063**		0.156***		-0.013		-0.093***
		(0.020)		(0.018)		(0.016)		(0.021)		(0.021)
Size: 250-999 employees		0.201***		0.287***		0.318***		-0.056**		-0.178***
		(0.028)		(0.026)		(0.024)		(0.026)		(0.023)
Size: 1000+ employees		0.331***		0.393***		0.400***		-0.057		-0.229***
		(0.047)		(0.042)		(0.044)		(0.046)		(0.045)
Constant	0.219***	0.173***	0.271***	0.217***	0.172***	0.110***	0.384***	0.390***	0.473***	0.506***
	(0.012)	(0.337)	(0.013)	(0.032)	(0.014)	(0.029)	(0.014)	(0.037)	(0.014)	(0.037)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N° of observations	3153	3153	3153	3153	3153	3153	3153	3153	3153	3153

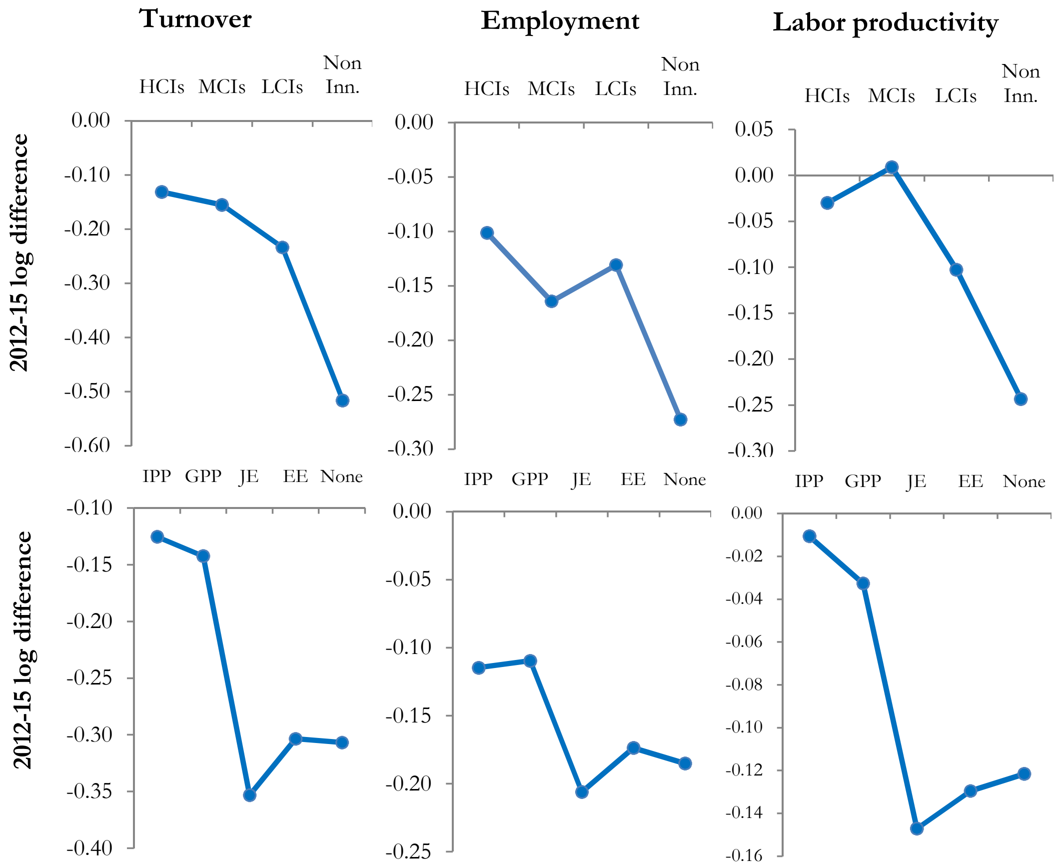
Note: Linear probability model used to estimate the dependent variable. The reference group is represented by non innovators. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Other control variables are: sector of activity at 2 digit, macro-region of establishment of the national headquarters. HCIs: dummy for High-Complexity Innovators; MCIs: dummy for Medium-Complexity Innovators; LCIs: dummy for Low-Complexity Innovators.

5 Innovation, HRMPs and firm growth

5.1 Descriptive analysis

In order to shed first light on the relations between the technological innovation strategies and the human resource managerial practices on the one side, and the economic performance of the firms on the other side, Figure 2 plots the average growth rate between 2012 and 2015 of turnover, employment and labor productivity (turnover per employed worker) associated with each group of innovating firms and with each of the four mostly adopted HRMPs previously identified[5].

Figure 1: *Unconditional means of firm growth by innovation strategy and HRMP*



HCIs: High-Complexity Innovators; MCIs: Medium-Complexity Innovators; LCIs: Low-Complexity Innovators; Non Inn.: Non innovators; IPP: Individual Performance Pay; GPP: Group Performance Pay; JE: Job Enlargement; EE: Employee Empowerment.

[5]Turnover and productivity are measured at current prices. The growth rate is proxied by the log difference.

The graphical inspection shows that firms having invested in new product or process technologies between 2010 and 2012 have outperformed non innovators in the subsequent triennium despite an overall decline in the revenue and employment levels induced by the economic crisis. In terms of revenues: -16.6% against -51,6%; in terms of employment: -12.6% against -24.4%; in terms of labor productivity: -4.1% against -24.4%.

There is also some evidence of differential growth premia associated with the different complexities of the innovation strategy implemented: HCIs are characterized by the highest growth rates of both revenues (-13.1%) and employment (-3.0%), while LCIs by the lowest (-23.3% and -10.3% respectively). However, the magnitude of such differential premia are of a lower order than the gains from investing in technology *per se*: the least complex innovation strategies account on their own for two thirds or more of the positive performance differences associated with HCIs: around 73% in terms of revenues, 88% in terms of employment, and 66% in terms of labor productivity.

Looking at the performance dynamics associated with the different HRMPs, there is a striking difference between the resilience recorded by firms having implemented monetary incentive-based policies and the significant shrinkage recorded by firms with employee empowerment and job enlargement policies in places, which have performed, at best, similarly to firms not having implemented any of the four HRMPs. Individual and group performance pay polices, in particular, are associated with the highest growth rates of revenues (-12.5% and -14.3% respectively), employment (-11.5% and -11.0%), and productivity (-1.1% and -3.3%).

5.2 Econometric analysis

The observed unconditional log variations are very likely to reflect not only the effects of the innovation strategies and of the different HRMPs *per se* but also those exerted by structural characteristics of the firms and by other strategic choices put in place in the same years. In order to (imperfectly) isolate the impact of the innovation strategies and of HRMPs on firm growth, the following regression model has been estimated:

$$\Delta_t logY_i = \alpha + \sum_{j=1,2,3} \beta_{0,j} IS_{j,i} + \beta_1 HRMP_i + \sum_{j=1,2,3} \beta_{1,j} IS_{j,i} \times HRMP_i + \mathbf{\Gamma} \times \mathbf{X}_i + \epsilon_i \quad (1)$$

where $\Delta_t logY_i$ measures the growth rate between 2012 and 2015 of the economic outcome variable of firm i, $IS_{j,i}$ refers to the different groups of innovators, $HRMP_i$ is a dummy capturing either the adoption of performance-based pay schemes, or of job enlargement policies or of employee empowerment policies, and $\mathbf{X}_i$ are control variables capturing non-innovation and non-human resource management related strategic differences among the firms. In particular, the regression model has been estimated including a whole set of potential confounding factors: age, sector of activity at 2 digit, macro-region of establishment of the national headquarters, family ownership and management, belonging to a group, geographical extent of the market, existence of foreign direct investments, choice of the principal sources of investment finance (cashflow, equity, bank lending), share of workers with tertiary degree, average salary and adoption of marketing and organizational innovations. The log level of Y measured in 2012 is also included as a control.

The interaction terms between the dummies identifying groups of innovators and those refereed to managerial practices are meant to capture the extent to which the two strategic choices are complement, substitute or independent channels for firm growth. The baseline is represented by firms not investing in technological innovation nor having in place performance-based pay schemes, job enlargement, employee empowerment policies, depending on model specification. Results are shown in Table 7.

The econometric analysis confirms the graphical inspection. There is evidence of a growth premium which is positively associated with both the decision to invest in technological innovation and to implement performance-based pay schemes, and absence of significant differential growth premia among different types of innovators, especially for HCIs. For instance, in comparison to firms not investing in innovation nor using monetary incentives, the turnover growth associated with investing in HC innovation strategies has been, ceteris paribus, 27.3 percentage points higher, very close to the figures associated with investing in MC strategies (29.2) and in LC strategies (23.3), and also to the growth premium (23.5) associated with having in place performance pay renumeration schemes (column 1, upper part). Job enlargement and employee empowerment policies, instead, are not found to directly impact on the economic performance of the firms.

Table 7 also shows that while, taken individually, both investing in HC innovation strategies and using performance pay schemes are associated with a significant positive differential growth relative to the baseline, their joint adoption does not sum the two coefficients but even results in a net effect which is below that associated with HCIs alone[6]. This result holds true regardless of the outcome variable considered. For instance, estimate of the turnover growth premium is 49.1 percentage points

[6]However, the Wald test on the joint significance of the beta estimates cannot reject the hypothesis that the net effect of using performance pay schemes is just null. Results are available upon request.

Table 7: *Economic impact of innovation strategies and HRMPs*

	Dependent variable: 2012-2015 log difference of:					
	Turnover		*Employment*		Labor productivity	
	(1)	(2)	(3)	(4)	(7)	(8)
HCIs	.273**	.491**	.112***	.196***	.143*	.289**
MCIs	.292***	.307*	.060	.028	.220***	.264**
LCIs	.233**	.194	.096**	.123**	.143	.087
Performance based pay	.235***	.333**	.088***	.131**	.141***	.206*
HCIs × Performance based pay		-.381**		-.147**		-.256*
MCIs × Performance based pay		-.064		.043		-.107
LCIs × Performance based pay		.058		-.065		.097
HCIs	.293***	.199	.101**	.062	.139	.081
MCIs	.305***	.278**	.065	.119	.222***	.246**
LCIs	.245**	.205	.119***	.103	.125	.123
Job enlargement	-.082	-.180	-.049*	-.104*	-.039	-.072
HCIs × Job enlargement		.244		.095**		.150
MCIs × Job enlargement		.070		.021		-.072
LCIs × Job enlargement		.105		.060		.008
HCIs	.292***	.286**	.118***	.106**	.139	.151
MCIs	.308***	.285**	.066	.106**	.223***	.150
LCIs	.244**	.118	.099**	.027	.124	.088
Employee empowerment	-.022	.078	.008	-.012	-.013	-.042
HCIs × Employee empowerment		.011		.026		-.029
MCIs × Employee empowerment		.049		-.084		.156
LCIs × Employee empowerment		.255		.145		.074
N° of observations	3049		3049		3049	

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include controls for: age, sector of activity at 2 digit, macro-region of establishment of the national headquarters, family ownership and management, belonging to a group, geographical extent of the market, existence of foreign direct investments, choice of the principal sources of financing (cashflow, equity, bank lending), share of workers with tertiary degree, average salary, and contemporary adoption of marketing or organizational innovations, 2012 log levels of the dependent variable. Turnover and labor productivity growth measured in nominal terms. HCIs: dummy for High-Complexity Innovators; MCIs: dummy for Medium-Complexity Innovators; LCIs: dummy for Low-Complexity Innovators.

for HCIs not using monetary incentives schemes while it is 33.3 percentage points for non-innovators using monetary incentives schemes; however, the estimate for HCIs using monetary incentives schemes is “only” 44.3 percentage points (column 2, upper part).

For MCIs and LCIs, instead, estimates of the interaction terms are never statistically significantly different from zero, beside the fact that their individual effects, depending on model specification, are estimated to be positive. Thus, the analysis suggests that the benefit from using pay-for-performance schemes is null or even negative in firms choosing to invest in innovation strategies of high complexity. The same attenuation effect is not found in firms pursuing relatively less complex innovation strategies, for which pay-for-performance practices seem to act an independent channel for fueling growth.

5.3 Robustness checks

Due to the large number of variables used to control for possible confounding factors, the econometric model in equation (1) has been specified considering the principal HRMPs one at a time. However, in order to exclude that the estimated effects of having in place pay-for-performance practices are somehow driven by the contemporary adoption of job enlargement and/or employee empowerment policies, a less parsimonious model, which includes the three mostly used HRMPs and their interactions with the different groups of innovators, has been used as a robustness check. Results, not reported for reasons of space but available upon request, are qualitatively the same as those reported in the previous paragraph, reassuring about the general claim already stated.

Moreover, the analysis thus far has looked at the relation between the mix of innovation inputs, used to define the degree of complexity of the innovation strategy, and the subsequent performance of the firm, without taking explicitly into account the knowledge production process (Pakes and Griliches 1980) relating the former to the latter. In other words, we do not know whether the growth premium associated with HCIs, MCIs and LCIs is driven by product innovations, process innovations or by a mix of the two. To take innovation output explicitly into account, for each innovation strategy three dummy variables have been identified accordingly, as reported in Table 8.

Table 8: *Input and output of innovative activities*

Class of innovators	Innovation outcome	% in each class
	Product innovation only	15.2
HCIs	Process innovation only	11.0
	Both product and process innovation	71.3
	Product innovation only	21.7
MCIs	Process innovation only	26.0
	Both product and process innovation	46.0
	Product innovation only	21.2
LCIs	Process innovation only	36.0
	Both product and process innovation	37.3

HCIs: High-complexity innovators; MCIs: Medium-complexity innovators; LCIs: Low-complexity innovators. Unweighted data.

There exists a positive association between the increasing complexity of the innovation strategy pursued and the scope of the change brought about. In 71.3% of the cases, HCIs have been able to introduce a combination of product and process innovations, against 46.0% for MCIs and 37.3% for LCIs.

To understand which type of innovation has driven the observed growth of the firms, equation (1) has been re-estimated, replacing each dummy capturing the level of complexity of the innovation strategies with the corresponding innovation outcome dummies, capturing only product, only process, product and process innovations respectively[7]. The analysis focuses on the possible interaction between the different innovation outcomes and the existence of pay-for-performance schemes already in place. Results are shown in Table 9.

Table 9: *Economic impact of innovation outcomes and HRMPs*

Dependent variable: 2012-2015 log difference of:	Turnover	Employment	Labor productivity
	(1)	(2)	(3)
Performance based pay	.324**	.123**	.200**
Product Innovation only$_{HCIs}$	.339*	.018	.307**
Process Innovation only$_{HCIs}$	.746***	.289***	.454***
Product and Process Innovation$_{HCIs}$	.475***	.228***	.236*
Product Innovation only$_{HCIs}$ × Performance based pay	-.115	.043	-.155
Process Innovation only$_{HCIs}$ × Performance based pay	-.507***	-.163	-.372**
Product and Process Innovation$_{HCIs}$ × Performance based pay	-.408**	-.180**	-.248
Product Innovation only$_{MCIs}$	-.031	-.229	.172
Process Innovation only$_{MCIs}$	.271	.020	.272*
Product and Process Innovation$_{MCIs}$	.492**	.170**	.285
Product Innovation only$_{MCIs}$ × Performance based pay	.253	.272	.005
Process Innovation only$_{MCIs}$ × Performance based pay	-.082	.004	.129
Product and Process Innovation$_{MCIs}$ × Performance based pay	-.223	-.050	-.146
Product Innovation only$_{LCIs}$	.200	.097	.133
Process Innovation only$_{LCIs}$	-.147	.094	-.230
Product and Process Innovation$_{LCIs}$	.454***	.170**	.290**
Product Innovation only$_{LCIs}$ × Performance based pay	.107	-.150	.144
Process Innovation only$_{LCIs}$ × Performance based pay	.315	-.046	.365
Product and Process Innovation$_{LCIs}$ × Performance based pay	-.148	-.023	-.120
N° of observations	3049	3049	3049

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include controls for: age, sector of activity at 2 digit, macro-region of establishment of the national headquarters, family ownership and management, belonging to a group, geographical extent of the market, existence of foreign direct investments, choice of the principal sources of financing (cashflow, equity, bank lending), share of workers with tertiary degree, average salary, and contemporary adoption of marketing or organizational innovations, 2012 log levels of the dependent variable. Turnover and labor productivity growth measured in nominal terms. HCIs: High-Complexity Innovators; MCIs: Medium-Complexity Innovators; LCIs: Low-Complexity Innovators.

The general claim of section 5.2 is robust to this alternative specification of the model. In particular, it is confirmed that technological innovation and pay-for-

[7]This strategy can be interpreted as an alternative way to measure the quality of product and process innovations when trying to identify a link between innovation output and growth. See Cucculelli and Ermini (2012) for a detailed discussion on this issue and for further references.

performance schemes for the remuneration of workers are two different channels for fueling firm growth; and, that, in general, the benefit arising from their contemporary use sums the two individual effects only when firms pursue relatively simple innovation strategies but not the more complex ones.

Further insights can be gained from Table 9. First, the innovation outcomes of HCIs yield more often to firm growth than those resulting from less sophisticated innovation strategies, regardless of the variable used to measure growth. For instance, by looking at turnover (column 1), it emerges that product and process innovations are associated with ex-post growth of HCIs both singularly and jointly, while these same innovations are conducive of higher growth for MCIs and LCIs only when realized jointly.

Second, in line with the general conclusions of Lachenmaier and Rottmann (2011), Harrison et al. (2014) and Hall et al. (2008), there is not supporting evidence, at the firm level, to the hypothesis of a job-destroying net effect induced by the implementation of process innovation; quite the opposite, process innovation is found to have had, in many cases, a net positive impact of firm employment growth for the different groups of innovators, implying that its direct negative effect have been more than offset by compensation mechanisms (Vivarelli 2014).

Finally, the (joint) impact of technological innovation and managerial practices on firm growth have been analyzed netting out possible sectoral specificities. However, one may wonder to what extent the observed results vary across industries, as it cannot be excluded *a priori* that sectoral patterns of technical change (Pavitt 1984) affect the economic return of the different innovation strategies and of the HRMPs implemented. Indeed, it can be expected that the return from investing in R&D is maximum in sectors where innovation is primarily the result of scientific research activity, while choosing performance-related pay schemes for the remuneration of workers should benefit more those firms operating in industries where technological change takes place smoothly, so that it is easier to identify performance targets and induce workers' commitment towards those targets.

To answer this question more formally, manufacturing industries have been classified, according to a revised Pavitt taxonomy applied to the 2 digit Nace Rev. 2 classification (Bogliacino and Pianta 2010), into the well-known "Science-based", "Specialized-suppliers", "Scale intensive" and "Supplier dominated" classes. Then, the baseline regression model of equation (1) has been re-estimated for each subgroup of industries, using pay-for-performance schemes as the relevant HRMP. Results are shown in Table 10.

The analysis reveals, in line with expectations, that within the class of "Science-based" industries the economic performance of HCIs is significantly better as com-

Table 10: *Economic impact of innovation strategies and HRMPs by industry*

Dependent variable: 2012-2015 log difference of:	Turnover	Employment	Labor productivity
	(1)	(2)	(3)
Science-based industries (N=325)			
HCIs	.577**	.355**	.245**
MCIs	.342	.119	.228**
LCIs	.284	-.042	.309**
Performance based pay	.312	.241	.111
HCIs × Performance based pay	-.678**	-.407*	-.272*
MCIs × Performance based pay	-.307	-.138	-.174
LCIs × Performance based pay	-.334	-.081	-.252
Specialized-suppliers industries (N=633)			
HCIs	-.057	.069	-.089
MCIs	-.229	-.162	-.060
LCIs	.082	.086	.033
Performance based pay	-.074	-.009	-.060
HCIs × Performance based pay	.108	-.010	.092
MCIs × Performance based pay	.351	.301	.081
LCIs × Performance based pay	-.199	-.082	-.123
Scale intensive industries (N=759)			
HCIs	.400***	.217*	.179*
MCIs	0.290	.060	.238**
LCIs	.426***	.267**	.149*
Performance based pay	.422***	.210**	.204***
HCIs × Performance based pay	-.332***	-.117	-.189*
MCIs × Performance based pay	-.353	-.028	-.325**
LCIs × Performance based pay	-.381***	-.172	-.190*
Supplier dominated industries (N=1296)			
HCIs	.197	.101	.085
MCIs	.022	.021	.012
LCIs	.116	.092	.028
Performance based pay	.170	.097	.077
HCIs × Performance based pay	-.109	-.078	-.037
MCIs × Performance based pay	.032	-.037	.046
LCIs × Performance based pay	-.023	-.067	.046

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include controls for: : age, sector of activity at 2 digit, macro-region of establishment of the national headquarters, family ownership and management, belonging to a group, geographical extent of the market, existence of foreign direct investments, choice of the principal sources of financing (cashflow, equity, bank lending), share of workers with tertiary degree, average salary, and contemporary adoption of marketing or organizational innovations, 2012 log levels of the dependent variable. Turnover and labor productivity growth measured in nominal terms. HCIs: dummy for High-Complexity Innovators; MCIs: dummy for Medium-Complexity Innovators; LCIs: dummy for Low-Complexity Innovators. Sectors grouped according to Pavitt taxonomy revised by Bogliacino and Pianta (2010).

pared to MCIs and LCIs: they have been the only group of innovators able to systematically outperform non innovating firms in terms of turnover (57.7 p.p. difference) and employment growth (35.5 p.p.). Performance-based pay schemes are not found to directly impact on firm growth in these sectors (the coefficient is never statistically significant), except when they are used by HCIs, in which case the interaction is negative, resulting in a net reduction in firm growth.

The "Scale intensive" class is the other group of industries where innovation and managerial practices exert a significant impact. HCIs but also LCIs and, to a less extent, MCIs are associated with a positive growth premium as compared to non innovating firms, whatever the variable used to measure growth. In particular, the beta estimates are very similar among the different groups of innovators, which suggests that, at least in the three-years period under scrutiny, the benefits from investing in technological upgrading of the physical capital stock - a common feature of the different groups of innovators - tend to overcome those associated with R&D and other science-related activities.

Again, in line with expectations, such industries, for which efficiency gains are a primary source of competitive advantage, are also the ones where pay-for-performance schemes are systematically associated with higher firm growth (including labor productivity growth). However, this result is true only for non innovating firms: the interaction between incentive-pay and innovation is, once again, negative (although the coefficient is not always statistically significant) and the net effect for innovating firms of using monetary incentive mechanisms is null[8]. The novelty, in comparison to what has been documented so far, is that such strategic "interference" does not affect only HCIs but also LCIs and MCIs.

In the classes of "Specialized-suppliers" and "Supplier dominated" industries, no correlation between firm growth and innovation and/or incentive-based schemes has been detected. In the former group, the strategic variables that are systematically correlated with positive firm growth are: introduction of organizational innovation, family ownership, professional management, and use of cash flow as principal source of financing. In the latter group, instead, only one variable has some predictive power in the econometric model: the strong reliance on bank credit as source of business financing which is negatively associated with firm growth[9].

[8]The Wald test on the joint significance of the beta estimates cannot reject the hypothesis that the net effect of using performance pay schemes is just null for the different specifications of the outcome variable. Results are available upon request.

[9]The beta estimates of these variables have not been included in Table 10 for reasons of space, but are available upon request.

6 Conclusions

The core of the paper has been the investigation of how the choices concerning investments in technological innovation and management of the human resources interact with each other in affecting firm growth, thus contributing "from inside the firm" to the observed performance heterogeneity within the Italian production system. The results confirm the existence of potential detrimental effects that pay-for-performance schemes may have on performance but they also add to the existing literature evidence that such distortions are contingent upon the complexity of the innovation strategy pursued by the firm.

When firm objective is to maximize efficiency in delivering on the existing production plan, then the adoption of pay-for-performance policies seems to be a viable solution to induce higher workers' effort which translates into higher productivity and firm growth (as suggested by the many examples surveyed by Lazear and Oyer 2013). This applies, according to the analysis presented in this paper, not only to non innovating firms but also to most of the firms pursuing relatively simple technological innovation strategies, centered around the renewal of the stock of machineries and equipments. However, when firms need to balance the incentive to exploit the mastered technological paradigm with that of exploring unknown technological opportunities (March 1991) through science-based activities which are, by their very nature, subject to substantial ex-ante uncertainty and ex-post failure, then explicit performance rewards offer weak incentives to meet the goals pursued by the organization and may even destroy firm value. This is true, first and foremost, in industries whose main sources of technology upgrading are R&D activities.

Results also show that the other managerial practices commonly discussed in the human resource management literature, and in particular job enlargement and employee empowerment policies, are not found on their own to exert significant direct effects, at least in the medium-short term, on firm growth.

These results have strong implications for the efficient strategic management of the firm, as they highlight that, in order to sustain growth, it is crucial to ensure over time consistency between the human resource management practices adopted and the technological trajectory undertaken (in line with Baron and Kreps 1999). However, this is by no means an automatic or simple task, as organizational inertia often causes firms to rely on established routines which prove to be inadequate in coping with environmental changes (Kaplan and Henderson 2005; Gibbons and Henderson 2013).

References

Aghion P., Howitt P. (1992), A Model of Growth Through Creative Destruction, Econometrica 60 (2), 323-351.

Barbiellini Amidei F., Cantwell J., Spadavecchia A. (2011), Innovation and Foreign Technology in Italy, 1861-2011, Quaderni di Storia Economica n. 7.

Baron J.N., Kreps D.M. (1999), Consistent Human Resource Practices, California Management Review 41(3), 29-53.

Bartz W., Mohen P., Schweiger H. (2016), The Role of Innovation and Management Practices in Determining Firm Productivity in Developing Countries, EBRD Working Paper n. 188.

Bloom N., Van Reenen J. (2007), Measuring and Explaining Management Practices Across Firms and Countries, The Quarterly Journal of Economics 122 (4), 1351-1408.

Bloom N., Van Reenen J. (2011), Human Resource Management and Productivity, in D. Card, O. Ashenfelter (eds.), Handbook of Labor Economics, Vol. 4, Part B, 1697?1767, Amsterdam, North Holland.

Bloom N., Genakos C., Martin R., Sadun R. (2010), Modern Management: Good for the Environment or Just Hot Air?, The Economic Journal 120 (544), 551?572.

Bloom N., Genakos C., Sadun R., Van Reenen J. (2012), Management Practices across Firms and Countries, Academy of Management Perspectives 26 (1), 12?33.

Bloom N., Eifert B., Mahajan A., McKenzie D., Roberts J. (2013), Does Management Matter? Evidence from India, The Quarterly Journal of Economics 128 (1), 1-51.

Bloom N., Sadun R., Van Reenen J. (2016), Management as a Technology?, NBER Working Paper n. 22327.

Bogliacino F., Pianta M. (2010), Innovation and Employment. An Investigation using Revised Pavitt Classes, Research Policy, 39(6), 799-809.

Cassiman B., Veugelers R. (2006), In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition, Management Science 52 (1), 68-82.

Catozzella A., Vivarelli M. (2014), The Catalysing Role of In-House R&D in Fostering Complementarity Among innovating Inputs, Industry and Innovation 21 (4), 179?196.

Coad A. (2009), The Growth of Firms. A Survey of Theories and Empirical Evidences, Cheltenham and Northampton, Edward Elgar.

Coad A., Segarra A., Teruel M. (2016), Innovation and firm growth: Does firm age play a role?, Research Policy, 45 (2), 387-400.

Cohen W.M., Levinthal D.A. (1990), Absorptive Capacity: A New Perspective on Learning and Innovation, Administrative Science Quarterly 35(1), 128-152.

Cucculelli M., Ermini B. (2012), New Product Introduction and Product Tenure: What effects on Firm Growth? Research Policy 41(5), 808-821.

Dosi, G., Marsili, O., Orsenigo, L. and Salvatore, R. (1995), Learning, Market Selection and the Evolution of Industrial Structures, Small Business Economics 7(6), 411-36.

Frenz M., Lambert R. (2009), Exploring Non-technological and Mixed Modes of Innovation Across Countries, in OECD (ed.), Innovation in Firms: A Microeconomic Perspective, Ch. 2, 69-110, Paris, OECD Publishing.

Ederer F., Manso G. (2013), Is Pay for Performance Detrimental to Innovation?, Management Science 59 (7), 1496-1513.

Ericson R., Pakes A. (1995), Markov-Perfect Industry Dynamics: A Framework for Empirical Work, The Review of Economic Studies 62(1), 53-82.

Evangelista R., Vezzani A. (2011), The Impact of Technological and Organizational Innovations on Employment in European Firms, Industrial and Corporate Change 21(4): 871-899.

Evangelista R., Vezzani A. (2010), The Economic Impact of Technological and Organizational Innovations. A Firm-Level Analysis, Research Policy 39(10): 1253-1263.

Gibbons R., Henderson R. (2013), What Do Managers Do? Exploring Persistent Performance Differences among Seemingly Similar Enterprises, in R. Gibbons, J. Roberts (eds.), The Handbook of Organizational Economics, Ch. 17, 680-731, Princeton and Oxford, Princeton University Press.

Grossman G., Helpman E., (1991), Innovation and Growth in the Global Economy, Cambridge, MIT Press.

Hall B.H., Lotti f., Mairesse j. (2008), Employment, Innovation and Productivity: Evidence from Italian Microdata, Industrial and Corporate Change 17(4), 813-839.

Harrison R., Jaumandreu J., Mairesse J., Peters B. (2014), Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries, International Journal of Industrial Organization 35, 29-43.

Hopenhayn H.A. (1992), Entry, Exit, and Firm Dynamics in Long Run Equilibrium, Econometrica 60(5), 1127-1150.

Jensen M.B., Johnson B., Lorenz E., Lundvall B.A. (2007), Forms of knowledge and modes of innovation, Research Policy 36(5), 680-693.

Jones C.I. (1995), R&D-Based Models of Economic Growth, The Journal of Political Economy 103(4), 759-784.

Jovanovic B. (1982), Selection and the Evolution of Industry, Econometrica 50(3), 649-670.

Kaplan S., Henderson R.(2005), Inertia and Incentives: Bridging Organizational Economics and Organizational Theory, Organization Science 16 (5), 509-521.

Kremp E., Mairesse J. (2004), Knowledge Management, Innovation, and Productivity: A Firm Level Exploration Based on French Manufacturing CIS3 Data, NBER Working Paper n. 10237.

Lachenmaier S., Rottmann H. (2011), Effects of innovation on employment: A dynamic panel analysis, International Journal of Industrial Organization 29(2), 210-220.

Laursen K., Foss N.J. (2003), New Human Resource Management Practices, Complementarities and the Impact on Innovation Performance, Cambridge Journal of Economics 27(2), 243-263.

Lazear E.P. Oyer P. (2013), Personnel Economics, in R. Gibbons, J. Roberts (eds.), The Handbook of Organizational Economics, Ch. 12, Princeton and Oxford, Princeton University Press.

Leiponen A., Drejer I. (2007), What Exactly Are Technological Regimes?: Intra-industry Heterogeneity in the Organization of Innovation Activities, Research Policy 36 (8), 1221-1238.

Mairesse J., Mohen P. (2010), Using Innovation Surveys for Econometric Analysis, NBER Working Paper n. 15857.

Manso G. (2011), Motivating Innovation, The Journal of Finance 66 (5), 1823?1860.

March J. (1991), Exploration and Exploitation in Organizational Learning, Organization Science 2(1), 71-87.

Moncada-Paternò-Castello P., Cincera M. (2012), Enterprises' Growth Potential in the European Union: Implications for Research and Innovation Policy, The IUP Journal of Entrepreneurship Development IX(4), 7-40.

Nelson R.R., Winter S.G. (1982), An Evolutionary Theory of Economic Change, Cambridge and London, The Belknap Press of Harvard University Press.

Pakes A., Griliches Z. (1980), Patents and R and D at the Firm Level: A First Report, Economics Letter 5(4), 377-381.

Pavitt K. (1984), Patterns of Technical Change: Towards a Taxonomy and a Theory, Research Policy, 13(6), 343-374.

Penrose E.T. (1959), The Theory of the Growth of the Firm, Oxford, Basil Blackwell.

Ramsay H., Scholarios D., Harley B. (2000), Employees and High-Performance Work Systems: Testing inside the Black Box, British Journal of Industrial Relations 38(4), 501?531.

Roberts J. (2004), The Modern Firm. Organizational Design for Performance and Growth, New York, Oxford University Press.

Romer P.M. (1990), Endogenous Technological Change, Journal of Political Economy, 1990 98(5),S71-S102.

Schumpeter J.A. (1934), The Theory of Economic Development: An Inquiry Into Profits, Capital, Credit, Interest, and the Business Cycle, New Brunswick and London, Transaction Publishers.

Schumpeter J.A. (1943), Capitalism, Socialism and Democracy, London, Allen and Unwin.

Smith K. (2004), Measuring innovation, in J. Fagerberg and D.C. Mowery (eds.), The Oxford Handbook of Innovation, Ch. 6, Oxford, Oxford University Press.

Syverson C. (2011), What Determines Productivity?, Journal of Economic Literature 40(2), 326-365.

Srholec M., Verspagen B. (2012), The Voyage of the Beagle into Innovation: Explorations on Heterogeneity, Selection and Sectors, Industrial and Corporate Change 21(5), 1221-1253.

Vivarelli M. (2014), Innovation, Employment, and Skills in Advanced and Developing Countries: A Survey of the Economic Literature, Journal of Economic Issues 48(1), 123-154.

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