Experience, innovation and productivity

Empirical evidence from Italy's slowdown

Francesco Daveri

Università di Parma,

Igier and CESifo

Maria Laura Parisi

Università di Brescia

Abstract

We investigate whether experience is good or bad for innovation and productivity in a sample of Italian manufacturing firms in the early 2000s. The findings differ depending on whether one looks at managerial or workers' experience. The effect of managerial experience - proxied by age - on firm performance appears to depend on the type of firm: in innovative firms the old age of managers and board members is bad for innovation and productivity, while costs and benefits of managerial old age appear to cancel out for non-innovative firms. As to workers, a high share of temporary – thus inexperienced - workers is instead unambiguously associated to low innovation and productivity.

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1. Introduction

1.1 The issue

Innovation is recognized to be one of the main drivers of productivity growth. It is thus no wonder that the study of its determinants has attracted considerable attention (Geroski, 2000; Comin and Hobijn, 2009). Extensive empirical evidence has documented that R&D enhances firm innovation and productivity by enabling product innovation (Griliches, 1992; van Pottelsberghe de la Potterie, 2008) as well as easing the adoption of technologies developed in other firms and countries (Griffith, Redding and van Reenen, 2004; Parisi, Schiantarelli and Sembenelli, 2006). The risky nature of innovation also makes it a typically hard-to-finance undertaking, and a number of scholars (Brown, Fazzari and Petersen, 2009; Geroski, van Reenen and Walters, 2002; Hall, Mairesse, Branstetter and Crépon, 1998) has investigated the enabling role of cash flows to avoid that liquidity constraints strangle yet undeveloped innovations in their infancy.

Less analyzed, and perhaps more controversial but not less relevant, is the question whether experience is associated with innovation and productivity. Does it pay for a firm to be endowed with the breadth and the novelty of ideas brought about by newcomers on the entrepreneurial and the workers' side? Or do innovation and productivity gains mostly originate from the competence of older – hence more experienced - workers and managers?

The answer to these questions is not obvious. As discussed by Jones (2010), the case list of how inexperienced entrepreneurs and workers managed to develop and bring brand new products and technologies to the market is long. It starts with an inexperienced Bill Gates leaving Harvard in 1975 to co-found Microsoft with his friend Paul Allen, and continues with Steve Jobs and Steve Wozniak, the young founders of Apple. More recently, Sergei Brin and Larry Page, the co-founders of Google, were bright but young and inexperienced Stanford PhD students when they started thinking about the number and the informational content and nature of the links underlying the functioning of the World Wide Web. Yet we can also think of radical innovations brought about by more experienced workers and entrepreneurs, in some cases by the same grown-up entrepreneurs that had revolutionized their industry already once. It is again Steve Jobs who has made a tremendous comeback with his i-Pod, i-Phone and i-Pad devices. So at times managers grow old, but their ability to innovate does not necessarily fade away.

Even among scientists and artists, there is widespread agreement that great innovations often come from the young and the inexperienced yet brilliant minds. Chicago economist David Galenson (2003, 2005, 2007) has documented how the life-cycle of artists may be distinctively of two types, of a conceptual and an experiential type, so that the young genius of Van Gogh and Picasso, of Melville and Welles can be matched with the experienced ability of Michelangelo and Rembrandt, Paul Cezanne and Alfred Hitchcock. The relation between age and fundamental innovations in arts and science seems not to be linear as well.

Apart from scientists, artists and managers, this set of issues also has deep implications for workers. The productivity of individual workers depends on a host of characteristics, such as education and skills, experience, motivation, intellectual and physical abilities. Some of these worker characteristics – notably the productive value of skills – may deteriorate with age. Verhaegen and Salthouse (1997) present a meta-analysis of 91 studies on how mental abilities develop over the individual life span. Based on these studies, they conclude that the cognitive abilities (reasoning, speed and episodic memory) decline significantly just before 50 years of age and more thereafter. Maximum levels are instead achieved in one's 20s and the 30s, independently of country and sex.

Altogether, whether the good or the bad effects of experience actually prevail in practice is largely an empirical matter that can be usefully investigated with company data.

1.2 Our idea

In this paper we take firm-level data for Italy in the early 2000s as a case study to learn about the role of managerial and workers' experience in spurring (or depressing) firm-level innovation and productivity gains. Italy in the early 2000s provides a fertile testing ground for this purpose. As shown in Table 1, since the second half of the 1990s a sharp productivity slowdown came about in the Italian economy, both in manufacturing and services. Yet the zeroing of productivity growth in manufacturing – hence in "the" leading sector of the Italian economy in the past decades - is particularly worrisome and has taken place smoothly throughout the period, though in a more pronounced fashion in 2001-03. Its prolonged nature suggests that Italy's productivity slowdown is not the consequence of unfortunate business cycle fluctuations. The slowdown is also particularly puzzling for it occurred at a time when brand new technologies and managerial techniques had become available out there "on the shelf" thanks to the ICT revolution following the introduction of the Internet.

Table 1. Growth of labor productivity in Italy, 1970-2003, main industry groups.

	1970-80	**1980-95**	**1995-03**	1995-00	2000-03
Economy	2.4	1.8	0.6	1.1	-0.2
Agriculture	3.1	4.3	2.7	5.2	-1.5
Manufacturing	2.8	3.0	0.2	1.0	-1.0
-- non-durables	2.7	3.1	0.3	0.7	-0.2
-- durables	2.9	2.7	0.0	1.7	-2.7
Construction	1.9	1.0	0.1	0.5	-0.5
Business sector services	1.8	1.1	0.1	0.5	-0.5

Source: Daveri and Jona-Lasinio, 2005

Why the slowdown, then? And why hasn't the technological revolution landed in Italy in the same fashion as in Northern Europe and other parts of the advanced world? Investigating the role of workers' and managerial experience may help answer these questions and at least partly explain Italy's slowdown in two ways. Firstly, productivity fell in the wake of the introduction of piecemeal labor market reforms which eased the entry of temporary (young thus inexperienced) workers in the Italian labor market. A few legislative changes effective since January 1997 gave full legal recognition to a host of contractual forms of part-time and temporary jobs, some of which had been in place even before though restricted to the unofficial labor market, while keeping job protection unchanged for permanent workers. As a result, the share of temporary workers in the total number of dependent workers - which had hovered around 9% of the total for years - steadily rose to 11.5 per cent between 1996 and 2001 (see Figure 1). In principle, temporary workers need not be inexperienced. Yet in this particular case they largely were, because the enacted piecewise reforms eased the entry of two categories of people previously left out of the official Italian labor market: the youngsters and the women.[1]

Robert Gordon and Ian Dew-Becker (2008) systematically analyzed the consequences of such partial labor market reforms for Europe at large, concluding that the process of labor market reform that occurred in many European countries in the second half of the 1990s did reverse the past tendencies towards job destruction but has been eventually detrimental to productivity growth. Simplifying their view to an extreme, if temporary job creation is allowed and labor demand does not shift outwards in parallel, labor supply shifts to the right along a given labor demand curve. No wonder that productivity declines as a result. In addition to this, as publicly recognized by many Italian entrepreneurs, the increased availability of inexperienced - thus relatively cheap - labor, has also discouraged firms' propensity to innovate. Entrepreneurs, in other words, found themselves confronted with the hard-to-resist temptation to adopt techniques intensively using part-time workers now abundantly available in the labor market instead of experimenting with (riskier) ICT-enabled innovations.

So much is for the workers' side. Yet experience may have affected Italy's productivity performance through another channel, the managerial one. The pace of adoption of ICT-related innovation has likely been hampered by the presence of old, thus very experienced but also conservative and powerful managers and board members, a reflection of the persisting lack of contestability of firm property rights in the Italian capital market. Bandiera, Guiso, Prat and Sadun (2008) have shown that only a fraction of firms – especially the non-family owned and multinationals - adopts a "performance-based" model, whereby managers are hired through business contacts and head-hunting activities, undergo regular assessment procedures and are rewarded, promoted and dismissed on the basis of their assessment results. Most firms, particularly the family-owned ones and those mainly active in the domestic market, follow instead a "fidelity

[1] The share of people aged 15-24 holding a temporary job went up from 18.7 in 1996 to 23.3 per cent in 2001. The same applied to women, whose share of those employed in temporary jobs reached 49.1 in 2001, up from 45.8 in 1996.

model" of managerial talent, hiring their managers based on personal or family contacts, which leaves formal assessment of performance in the background at best. The fidelity model selects and keeps in office old managers well connected to their shareholders, but only occasionally connected to market and technological developments. In short, the type of managerial model – based on performance or fidelity – is tightly associated with the quality, the conduct and the performance of managers as well as of the firm itself. Firms blessed with faithful managers are often at a disadvantage when faced with new technological opportunities with respect to foreign competitors less dependent on family-based modes of running a firm. This state of affairs has been increasingly perceived as a severe constraint for the Italian economy, particularly when it has been exposed to the chance of reaping the technological and organizational benefits brought about by the Internet revolution in other countries.

The full story may then be as follows. Labor market reform has channeled an inflow of relatively inexperienced workers into the Italian labor market. In parallel, the lack of financial market reform has instead kept the average age of those in charge of leading Italian companies unchanged, and this missing change (and "excess experience") may have lowered the propensity to innovate and the productivity performance of Italian firms at times of fast technical change. Gordon and Dew-Becker have not contrasted their ideas with micro data, while Bandiera, Guiso, Prat and Sadun have not looked at the interaction of labor market reform with the productivity and innovation counterpart of managerial practices. So there is room for comparing a streamlined version of the two views with company data. This is the main goal of our paper. More generally we believe that this combination of events and structural features is helpful for learning on the relation between experience, innovation and productivity.

1.3 Methods and main results

In our study we employ a firm-level data set to separately analyze the productivity counterpart of experience on both sides, the workers' and the managers' side. Within a two-stage formulation where the state of being innovative or non innovative for a firm is seen in the first stage as a function of some control variables such as R&D, cash flow and firm size - typically found to be significant in previous studies - as well as our measures of workers' and managerial experience. Experience variables are also allowed to enter the second stage estimation, where labor productivity growth is also correlated to the growth of capital per worker and other controls. This multi-stage framework is qualitatively similar to the one suggested by Crepon, Duguet and Mairesse (1998) and adopted in many other papers thereafter, including Huergo and Jaumandreu (2004), whose themes of analysis are particularly relevant for our paper.

Our preferred measure of experience on the workers' side is the average share of temporary workers in total employment. The increased presence of temporary workers in the Italian labor force has been a novelty of the late 1990s, and this is portrayed in our company data. We interpret this as a symptom of missing specific accumulation of human capital on the part of the firm. Our measure of experience on the manager side is the firm-averaged age of managers and board members. In doing so, we are confronted with (and we thus explicitly tackle) a few statistical hurdles, the main of which is the great deal of unobservable heterogeneity in firm performance that may result in reverse causation. The use of (long) differences for productivity growth - as opposed to the productivity levels employed e.g. in Hall, Lotti and Mairesse (2007) - allows us to lessen the simultaneity bias that would originate from regressing log levels of firm performance onto our variables of interest, such as managerial age or the share of temporary workers.

In common with previous studies, we find that both product and process innovations are positively related with productivity growth. Yet the evidence presented here indicates that innovation and productivity growth was particularly low in firms with disproportionately high shares of temporary workers. This result is robust to all changes of specifications. Declining productivity is also associated with managers' and board members' old age, although this correlation does not hold equally for all firms. Our estimates indicate that the old age of managers and board members is associated with lower productivity in innovative firms, while it is (weakly) associated with higher productivity in non-innovative firms. This non-negative correlation is consistent with common sense that suggests a more positive role of experience in firms with relatively standardized and stable business practices, while old age is likely more damaging for innovative firms that would be supposed to swiftly adopt new technologies as they become available.

Altogether, our results indicate that the partial correlation between workers' and managerial experience, innovation and productivity – subject to the caveats mentioned above - is a robust one.

1.4 Paper structure

This paper is structured as follows. In section 2, we discuss the paper's conceptual underpinnings and estimation strategy. In section 3 we describe the main features of our data set. In section 4 we present our main results and some extensions. Section 5 concludes.

2. Estimation

2.1 Conceptual framework

We study the relation between experience, innovation and productivity as a multi-step process, whereby experience contributes to the production of innovation, which in turn translates into firm's enhanced efficiency and productivity. This is reminiscent of the framework first suggested by Crepon, Duguet and Mairesse (1998) and many other papers since then. Our actual implementation differs from theirs, though.

We start from a Cobb-Douglas production function where real output is a function of capital, labor, intermediate inputs and (disembodied) efficiency. This allows us to differentially treat the substitutability of such inputs with respect to capital and labor without imposing separability between value added and intermediates. Within this framework, in each period t, labor productivity (in logs) for firm *i* at time *t* may be decomposed as follows:

$$\ln(Y_{i,t} / L_{it}) = \ln(A_{i,t}) + \beta_K \ln(K_{i,t} / L_{i,t}) + \beta_{IC} \ln(IC_{i,t} / L_{i,t}) + (\beta_K + \beta_{IC} + \beta_L - 1)\ln L_{i,t} \qquad (1)$$

where the log of total production per worker Y/L is a log-linear function of the capital labor ratio K/L, intermediate inputs per worker IC/L and the efficiency parameter A expressed in disembodied form. Equation (1) also includes a lnL term that allows us to test for the assumption of constant returns to scale. Under constant returns to scale, the coefficient of lnL in (1) should in fact be zero and the lnL term would then disappear. If scale returns are either decreasing or increasing then the coefficient would be respectively negative or positive. As shown below, we find that returns are decreasing for both innovative and non-innovative firms.

In turn, the efficiency parameter A is a function of time and innovation as follows:

$$\ln(A_{it}) = \lambda * t * INNOVATION + error \qquad (2)$$

The growth rate of the efficiency parameter is thus a linear function of INNOVATION. Under (1) and (2), the log difference (the growth rate) of labor productivity is a linear function of the growth rate of the capital-labor ratio, the growth of intermediate inputs per worker, the growth of labor and the innovation rate. In turn, INNOVATION is a linear function of a few variables including our proxies for experience, *i.e.* firm-averaged managerial age and the share of part-time temporary workers in each firm, and other determinants of the decision to innovate such as whether a firm undertakes R&D spending, the share of R&D workers in the total firm's labor force; and cash flows, plus an array of regional, size and industry dummies. Each of these variables affects (the log of) A through a separate parameter.

Leaving aside the other determinants of innovation for expositional purpose, INNOVATION may then be seen as a function of managerial experience and "business school" capital as follows:

$$\text{INNOVATION}_i = a\,\text{E}_i + b\,\text{S}_i + \text{OTHER VARIABLES} \qquad (3)$$

where E is experience and S is managerial capital formally accumulated going to business schools with S = T – E. The variable "E" is the number of years a manager has spent doing her job inside or outside the firm. The variable "S" is the managerial capital accumulated at the business school by the manager under the time constraint T=E+S, i.e. a manager either goes to the business school or learns on the job, so that the net effect of E on INNOVATION is positive or negative depending on whether $a>b$.

The intuition for (3) is simple. Traditional managerial techniques require on-the-job experience, while novel managerial techniques are those accumulated through off-the-job specific training or (business) schooling. This typically involves a trade-off, for a firm faces the decision to employ today a relatively experienced but old-fashioned manager or tomorrow a relatively inexperienced but well trained manager. It might also be that the marginal productivity of managerial experience and schooling is different across different categories of firms.

By the same token, we may think of the relation between workers' experience and innovation with the arrival of a new technology. The diffusion of a new technology is usually eased by the presence of firm- or technology-specific human capital E as well as by general human capital S. If a firm is endowed with a large share of temporary workers, this will presumably imply that the firm is endowed with lower firm-specific human capital E. This will in general result in lower adoption and innovation effort, unless the technology being introduced only requires general human capital (*i.e.* $a=0$ and $b>0$). Only in this particular case, the cost of having inexperienced workers around will be zero. Otherwise, however, having around a pool of inexperienced workers would be likely detrimental for innovation and productivity. Again, this may hold equally for all firms or not. We will systematically test whether a and b differ between innovative and non-innovative firms.

2.2 Empirical strategy

We empirically implement the logical framework described above in two stages. In the first stage, firms are all alike but they contemplate the choice of innovating or not. As documented in previous studies, they are more likely to become innovative if (i) they undertake R&D and (ii) they are endowed with enough cash-flows. Yet the choice of being innovative is also affected by other unmeasured time-invariant variables such as location, size and industry, all captured by fixed effects in our empirical analysis. In addition to these other determinants of innovation, the firm's propensity to innovate may also be affected by experience-related variables. The role of these variables has not been much investigated in previous studies on the determinants of innovation and is our main focus here. As long as being a temporary worker entails being a rather inexperienced worker (and we have discussed in the introduction that this was a plausible assumption in the Italian economy in the early 2000s), firms may innovate more if they do not employ too high a share of temporary workers. As far managerial experience is concerned, one may instead conjecture that a firm endowed with relatively young managers and board members is more likely to grab technological opportunities and adopt innovation. Then, once firms have selected themselves into innovative and non-innovative, we study the correlates of productivity which include experience, location, firm and size dummies but not R&D and cash flows. Namely, R&D and cash flows do affect productivity but only through their influence on innovation and the decision to be innovative or not. The exclusion of R&D and cash flows is thus our main identifying assumption.[2] This assumption will be tested for in the robustness checks section.

2.3 Competing specifications

We sought for the best empirical specification consistent with our data, starting from a baseline specification with no asymmetry between innovative and non-innovative firms. This benchmark specification is the following:

$$\begin{aligned}\Delta_2 \ln\left(\frac{Y}{L}\right)_{i,2001-03} &= \beta_K \Delta_2 \ln\left(\frac{K}{L}\right)_{i,2001-03} + \beta_{IC} \Delta_2 \ln\left(\frac{IC}{L}\right)_{i,2001-03} + \alpha_L \Delta_2 \ln L_{i,2001-03} + \beta + \\ &+ \gamma Age_{i,2001} + \mu\left(\frac{Temporary}{L}\right)_{i,2001} + \varepsilon_i \end{aligned} \tag{4}$$

The dependent variable in all specifications is the 2001-03 "long" growth rate of labor productivity for firm i calculated at time t = 2003, with respect to 2001. *Age* is calculated as the average age of the board members and managers when they were appointed. *Temporary/L* is the share of workers

[2] For a similar empirical modeling choice, see Mairesse, Mohnen and Kremp (2010).

in the firm operating on a temporary contract (full time + part time) in 2001. In the regressions we also control for twenty-one sector dummies,[3] four geographical macro areas,[4] size dummies for small, medium and large firms and a dummy for firm membership in a group. Size is measured following the European Commission definition: firms with less than 50 workers are "Small"; firms with more than 50 but less than or equal 250 workers are medium-sized; firms with more than 250 employees are "Large".

We define the parameter of the growth rate of firms employment as

$$\alpha_L = -(1 - \beta_K - \beta_{IC} - \beta_L) \tag{4'}$$

We test for constant returns to scale under the following null hypothesis:

$$H_0 : \alpha_L = 0$$
$$H_1 : \alpha_L < 0$$

The alternative hypothesis means that production is performed under decreasing returns to the three inputs.

Differencing the log levels of labor productivity, the capital-labor ratio and the intermediates ratio allows us to get rid of some of the unobserved heterogeneity between firms that represents the most obvious source of simultaneity bias.

As a second step in our empirical analysis, we run a Chow test of parameter instability on specification (4) to check whether there are significant asymmetries between innovative and non-innovative firms. We expect the parameters (β_K, β_{IC}, γ,μ) to differ between innovative and non innovative firms. Innovative firms had introduced a product or process innovation (or both) in the three-year period considered by the survey (2001-2003). "Non-innovative firms" are those firms declaring not to have introduced any innovations during the period of observation. This test is at first carried out without allowing for endogenous regime switching.

[3] The sector breakdown is based on the Ateco2007 classification of Italy's industries, in turn equivalent to the NACE rev.2 European code.

[4] Macro areas are defined by the Italian National Institute of Statistics (ISTAT) which groups Italian regions into 4 areas: North West (Lombardy, Piedmont, Liguria), North East (Veneto, Trentino Alto Adige, Friuli Venezia Giulia, Emilia Romagna), Centre (Lazio, Umbria, Marche, Tuscany), South and Islands (Campania, Apulia, Abruzzo, Molise, Basilicata, Calabria, Sicily, Sardinia).

We perform the intended test by comparing the estimates of equation (4) for the two subgroups (unconstrained model) and for the entire sample (constrained model). The null hypothesis is that the constrained model is valid. The p-values of the F-test are reported in Table 4 and refer to the three innovation modes, depending on whether the group discriminant refers to whether the firm undertakes either product or process innovations, product innovation only, or process innovation only. The Chow tests always reject the null hypothesis, thus indicating that the partial correlation between age and the share of temporary workers, on one side, and the dependent variable, on the other, differs across the two groups of firms.

Consistently with the test results, we concentrate on our second specification which allows the parameters of the experience variables to vary across groups, in accordance to equation (5). The logs of the per worker variables are denoted by small letters: $y_{it} = \ln \frac{Y_{it}}{L_{it}}$, $k_{it} = \ln \frac{K_{it}}{L_{it}}$, $ic_{it} = \ln \frac{IC_{it}}{L_{it}}$, $l_{it} = \ln L_{it}$, while $share_{it-2} = \frac{Temporary_{it-2}}{L_{it-2}}$:

$$\begin{aligned} \Delta_2 y_{it} &= \beta_K D_1 \Delta_2 k_{it} + \beta_{IC} D_1 \Delta_2 ic_{it} + \beta_K D_2 \Delta_2 k_{it} + \beta_{IC} D_2 \Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \\ &+ \beta_1 D_1 + \beta_2 D_2 + \gamma_1 D_1 Age_i + \gamma_2 D_2 Age_i + \mu_1 D_1 share_{it-2} + \mu_2 D_2 share_{it-2} + \varepsilon_{it} \end{aligned} \tag{5}$$

The dummies D_1 and D_2 identify the two groups of firms ($D_1 = 1$ if the firm is innovative and $D_2=1$ if it is non innovative). The constant D_2 will be omitted in the regression because of collinearity. Notice that the innovation dummy captures the impact of technological progress on labor productivity as in a standard Cobb-Douglas production function approach.

In Table 4 we also report the Wald tests (and the relative p-values) of parameter instability for each parameter, when the null hypothesis is:

$$H_0 : \begin{cases} \beta_{K,1} = \beta_{K,2} \\ \beta_{IC,1} = \beta_{IC,2} \\ \gamma_1 = \gamma_2 \\ \mu_1 = \mu_2 \end{cases}$$

In our third empirical specification we consider the formation of the groups as endogenous. The idea is that firms introduce innovations because they are more productive, young or intensive at investing into R&D activities or innovative capital, or maybe because they have more cash flows. As previously discussed, the age profile of the board members and/or the share of temporary workers might be correlated to the innovativeness of the firms as well.

This third specification for labor productivity growth can be thought of as a standard case of switching regression model with endogenous switching (as explained in Maddala, 1983, and his successive applications). We want to consistently estimate the parameters in two regimes: whether firms are innovative (regime j = 1) or non innovative (regime j = 2) over the period of observation. The new model specification is the following:

$$\begin{cases} \Delta_2 y_{it} = \beta_{K,1}\Delta_2 k_{it} + \beta_{IC,1}\Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \beta_1 + \gamma_1 Age_i + \mu_1 share_{it-2} + \varepsilon_{1it} \ \text{ if innovative} \\ \Delta_2 y_{it} = \beta_{K,2}\Delta_2 k_{it} + \beta_{IC,2}\Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \beta_2 + \gamma_2 Age_i + \mu_2 share_{it-2} + \varepsilon_{2it} \ \text{ if noninnovative} \end{cases} \tag{6}$$

The marginal distribution of the error terms ε_{jit} j=1,2 can be assumed normal with zero mean and constant variance σ_j^2. We shall modify this strong assumption in the robustness estimations. The conditional means of the error terms are instead different from zero, according to:

$$\begin{aligned} &\mathrm{E}(\varepsilon_{1it} \mid \text{innovative}) \neq 0 \\ &\mathrm{E}(\varepsilon_{2it} \mid \text{non innovative}) \neq 0 \end{aligned} \tag{6'}$$

This is because a criterion function determines whether a firm belongs to regime 1 or 2, as in equation (7):[5]

$$\begin{cases} D_1 = 1 \ \text{ if } \delta' \mathrm{Z_{it}} + \omega_{it} > 0 \\ \quad D_1 = 0 \quad \text{otherwise} \end{cases} \tag{7}$$

[5] $\mathrm{D}_1 = 0 \Leftrightarrow D_2 = 1$, meaning that, if a firm has not introduced an innovation in 2001-2003, it is non innovative by definition.

The criterion function depends on the Zs, namely variables correlated with the decision of introducing innovations, such as R&D expenditure at the beginning of the sample period and the other determinants of innovation, including age and the share of temporary workers.

To estimate the parameters *δ'* we observe that the expected value $E(D_1)=P(D_1=1)=P(\delta' Z_{it}+\omega_{it}>0)$ is the probability of being an innovative firm. If the error term ω_{it} is assumed with $E(\omega_{it}) = 0$ and $V(\omega_{it}) = 1$ the (first stage) estimation method applied is the probit maximum likelihood.

While equation (6) is usually estimated separately for the two regimes, whose idiosyncratic errors are correlated with ω_{it}, according to the covariance matrix:

$$Var\begin{bmatrix}\varepsilon_1 \\ \varepsilon_2 \\ \omega\end{bmatrix} = \begin{bmatrix}\sigma_1^2 & 0 & \sigma_{\varepsilon_1\omega} \\ 0 & \sigma_2^2 & \sigma_{\varepsilon_2\omega} \\ \sigma_{\varepsilon_1\omega} & \sigma_{\varepsilon_2\omega} & 1\end{bmatrix}$$

in this case we need to introduce corrections for the error conditional mean as in (8) and (8'):

$$\mathrm{E}(\varepsilon_{1it} \mid D_1 = 1) = \mathrm{E}(\sigma_{\varepsilon_1\omega}\omega_{it} \mid \delta' Z_{it} + \omega_{it} > 0) = -\sigma_{\varepsilon_1\omega}\frac{\phi(\delta' Z_{it})}{\Phi(\delta' Z_{it})} \tag{8}$$

$$\mathrm{E}(\varepsilon_{2it} \mid D_2 = 1) = \mathrm{E}(\sigma_{\varepsilon_2\omega}\omega_{it} \mid \delta' Z_{it} + \omega_{it} \le 0) = \sigma_{\varepsilon_2\omega}\frac{\phi(\delta' Z_{it})}{1-\Phi(\delta' Z_{it})} \tag{8'}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are, respectively, the standard normal density and cumulative distribution functions. To calculate (8) and (8') notice that we used the conditional distribution of ε given ω. This is normal with mean $E(\varepsilon_{jit} \mid \omega_{it}) = \sigma_{\varepsilon j\omega}\omega_{it}$ and variance $V(\varepsilon_{jit} \mid \omega_{it}) = \sigma_j^2-\sigma^2_{\varepsilon j\omega}$.

Given (6)-(8'), our specification becomes:

$$\begin{cases}\Delta_2 y_{it} = \beta_{K,1}\Delta_2 k_{it} + \beta_{IC,1}\Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \beta_1 + \gamma_1 Age_i + \mu_1 share_{it-2} - \sigma_{\varepsilon_1\omega}\dfrac{\phi(\delta Z_{it})}{\Phi(\delta Z_{it})} + \mathrm{u}_{1it} & \text{if } \mathrm{D}_1 = 1 \\ \Delta_2 y_{it} = \beta_{K,2}\Delta_2 k_{it} + \beta_{IC,2}\Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \beta_2 + \gamma_2 Age_i + \mu_2 share_{it-2} + \sigma_{\varepsilon_1\omega}\dfrac{\phi(\delta Z_{it})}{1-\Phi(\delta Z_{it})} + \mathrm{u}_{2it} & \text{if } \mathrm{D}_1 = 0\end{cases} \tag{9}$$

This system of equations can be estimated consistently with OLS (second stage) after substituting the estimate of δ'Z in the correction terms (derived from first stage probit estimation).[6]

[6] Building on Maddala (1983) we could simplify equation (9) simultaneously, adding the correction term, i.e. the sum of (8) + (8'), for the whole sample:

Clearly, if none of the parameters varies across groups, equation (9) reduces to its original formulation expressed in (4):

$$\Delta_2 y_{it} = \beta_K \Delta_2 k_{it} + \beta_{IC} \Delta_2 ic_{it} + \alpha_L \Delta_2 l_{it} + \beta + \gamma Age_i + \mu share_{it-2} + \varepsilon_{it}$$

This is the constrained equation (constraint being equal parameters in all groups) used in the former Chow test. Leaving aside the potential endogeneity of the capital-labor ratio and the intermediate consumption per worker, the problem of endogenous group formation in this latter case disappears altogether.

As to the potential endogeneity of the capital stock, we assume that capital accumulation depends on past investment intensities and initial levels of capital/labor ratio, conditional on size, sector and group of the firm, whether or not it has introduced innovations, and on firm age. We also instrument intermediates' intensity. The instruments for the intermediates per worker are the same as for the capital stock except that the initial levels of the capital-labor ratio are replaced by the IC/L ratio. Because of this, we will use 2SLS-IV method for the equation systems (9) and (9') at the second stage as well, where both the growth rate of the capital-labor ratio and intermediates per worker are instrumented.

$$\mathrm{E}\left(\Delta_2 y_{it}\right) = \mathrm{E}\left(\Delta_2 y_{it} \middle| D_1 = 1\right) * P(D_1 = 1) + \mathrm{E}\left(\Delta_2 y_{it} \middle| D_1 = 0\right) * P(D_1 = 0)$$

$$= \alpha_L \Delta_2 l_{it} + \left\{ \beta_{K,1} \Delta_2 k_{it} + \beta_{IC,1} \Delta_2 ic_{it} + \beta_1 + \gamma_1 Age_i + \mu_1 share_{it-2} - \sigma_{\varepsilon_1 \omega} \frac{\phi(\delta' Z_{it})}{\Phi(\delta' Z_{it})} \right\} \Phi(\delta' Z_{it}) +$$

$$+ \left\{ \beta_{K,2} \Delta_2 k_{it} + \beta_{IC,2} \Delta_2 ic_{it} + \beta_2 + \gamma_2 Age_i + \mu_2 share_{it-2} + \sigma_{\varepsilon_2 \omega} \frac{\phi(\delta' Z_{it})}{1 - \Phi(\delta' Z_{it})} \right\} \left[1 - \Phi(\delta' Z_{it})\right]$$

Rearranging terms, we would obtain an estimable specification which allows to perform Wald tests of parameters instability. When the coefficients of the interactions are equal to zero, this procedure is a convenient way to impose cross-equation restrictions on the two-regime specification:

$$\Delta_2 y_{it} = \alpha_L \Delta_2 l_{it} + \beta_{K,2} \Delta_2 k_{it} + \beta_{IC,2} \Delta_2 ic_{it} + \beta_2 + \gamma_2 Age_i + \mu_2 share_{it-2} + (\beta_{K,1} - \beta_{K,2}) \Delta_2 k_{it} \Phi(\hat{\delta}' Z_{it}) +$$

$$+ (\beta_{IC,1} - \beta_{IC,2}) \Delta_2 ic_{it} \Phi(\hat{\delta}' Z_{it}) + (\beta_1 - \beta_2) \Phi(\hat{\delta}' Z_{it}) + (\gamma_1 - \gamma_2) Age_i \Phi(\hat{\delta}' Z_{it}) + (\mu_1 - \mu_2) share_{it-2} \Phi(\hat{\delta}' Z_{it}) +$$

$$+ \phi(\hat{\delta}' Z_{it})(\sigma_{\varepsilon_2 \omega} - \sigma_{\varepsilon_1 \omega}) + \xi_{it}$$

where ξ_{it} has a standard normal distribution.

3. Data

We collected balance sheet data for a representative sample of Italian manufacturing firms and their board characteristics in the period 2001-2003 from two sources of data. Information about employment characteristics, innovation activity and R&D investment at the firm level come from the IXth Survey on Manufacturing Firms by the Italian bank Capitalia-Unicredit.

This survey has been run in 2004 through questionnaires distributed to 4177 firms. The questionnaires inquire about location, legal form, group, sales, investments, R&D investments, innovation activity, exports, labor force characteristics, financial status and incentives, balance sheets. Most of the quantitative information relates to the previous three years since the time of the survey, separately. Some qualitative answers, instead, are related to the whole three-year period, i.e. innovation activity.

Information about balance sheets and age of the board members come instead from the AIDA database. AIDA is managed by Bureau Van Dijk. It collects balance sheets, proprietary shares, firm characteristics and board characteristics on about 250000 Italian firms. We are using data for firms with at least €800.000 of gross sales.

AIDA is updated every week but maintains balance sheet data for the previous years as well. Thus we extracted balance sheet items over the 2001-2003 spanning to check and correct for inconsistencies between the two sources. Our chosen sub-period - the years between 2001 and 2003 - happens to be a period during which Italy's productivity shortfall has been particularly severe.

While we can extract balance sheet data from AIDA in the years of interest to match the two sources, the database just registers the most recent information as to board composition. Therefore the information on board members of existing firms used here dates back to December 31, 2007, the day of data extraction. We know the year of nomination but not the duration of his or her service. In other words, we take the board composition as of December 31, 2007 as if it were the same as in 2001-2003. In any case, if people appear in AIDA in December 2007, this means that he/she was already working in the firm. For each member with available data, we calculate his/her age at the time of the nomination within the board, as well as the age in 2001, 2002 and 2003. For each firm we have calculated an average age of the board. We excluded from the dataset those firms whose board name appeared to be another company, not a physical person. We also excluded those firms whose board members' appointment appears to have occurred before their declared birth dates. Firms in the Capitalia-Unicredit dataset (with information relative to the 2001-2003 period) also present in 2007 to match AIDA information are 3562 (that is 85.3% of the sample). Firm-individual observations are 21081. We first test for potential sample selection of these firms, in terms of age, size, location and sector of production (younger, bigger or particular sectors could have a higher survival rate, higher productivity or innovation capacity). The discussion of the potential selection bias is placed in Appendix B. In any case, the data need a cleaning procedure because of inconsistencies between birth dates and appointment dates of the individual board members, implausible firm age, non-individual board members, missing values. Only 7977 (about 40% of total observations) distributed in 1042 firms contain sensible information on birth and service dates and other variables, which finally becomes our longitudinal or "quasi"-panel dataset with firms as units and board members as the longitudinal dimension, in the years 2001-2003.

In Table 2 and 3 we present summary statistics, respectively, for the entire sample and for the sub-samples of innovative and non-innovative firms. The data in Table 3 are more closely related to the empirical exercise undertaken in the next section and therefore we go through the preliminary evidence offered by the data presented in such a table.

The definition of "innovativeness" used to classify firms in Table 3 is the least restrictive one, but results do not change much even if we look at more restrictive classifications such as the one that defines as innovative only those firms which have undertaken a product innovation in the previous three years or those which have undertaken a process innovation over the same period of time. In any case, irrespective of the precise definition of innovation, a relative large fraction of the firms in the sample appears to be innovative. This is a well known feature of the Unicredit/Capitalia data set and has partly to do with the way in which the question is posed in the questionnaire. Defining innovative a firm that has undertaken at least one innovation in the previous three years is not a very restrictive criterion and it is thus no wonder that a relatively large fraction of firms turns out to be innovative. Apart from this, Table 3 shows that in 2001-03 innovative firms experienced faster labor productivity growth than non innovative firms for about two full percentage points. This may have been because they have accumulated capital per worker at a faster rate (+19.1% against +13.5%). But it might also be because they are more typically part of a group - a feature found to be associated with faster growth in the previous studies – and/or because they are more involved in R&D activities than non-innovative firms. Yet innovative firms also present a lower share of temporary workers and a relatively younger managerial age in 2001, which appears to be consistent both with the Gordon-Dew Becker idea that too little workers' experience may hamper growth as well as with Bandiera-Guiso-Prat-Sadun idea that "too much" managerial experience may be bad for innovation and productivity. Altogether, the evidence brought forward from these summary statistics looks encouraging and is subjected to rigorous multivariate empirical scrutiny in section 4.

Table 2. Descriptive statistics of the main variables of interest.

Fixed characteristics[°,b]	Firms	Yes	No		
Product	1042	51.1	48.9		
Process	1042	55.2	44.8		
Either Product or Process	1042	73.7	26.3		
R&D spending (yes/no)	1042	63.3	36.7		
Group	1042	49.3	50.7		
High-tech	1042	33.2	66.8		
Variables of interest		Mean	St.D.	Min	Max
Production per worker[€]	1042	311.67	268.42	16.54	2384.78
$\Delta_2$log(Production/L)[b]	1042	2.11	30.45	-294.86	293.71
Capital Stock per worker[€]	1042	64.45	67.63	0.193	652.99
$\Delta_2$log(Capital Stock/L)[b]	1042	17.60	42.03	-365.23	348.57
Total Workers[a] (L)	1042	208.7	559.5	6	12199
Temporary Workers Rate[a,b]	1042	4.21	12.43	0	100
R&D Workers[a]	1020	7.47	34.08	0	755
R&D investment per worker[€,a]	563	3.14	5.44	0	77.672
R&D intensity (Production)[a,b]	563	1.64	3.83	0	57.6
Investment intensity (Production)[a,b]	1042	3.86	5.18	0	34.4
Cash flow per worker[€,a]	1042	23.089	37.769	-86.603	736.728
Average Board age (years)	1042	49.6	6.45	20	77
Age of the firm[a] (years)	1033	26.9	20.0	0	172

note: Dummy variables statistics are expressed in fraction. [a] measured in 2001. ° referred to 2001-2003 period, [b] in percentage points, [€] in thousands euro.

Table 3. Sample characteristics by type of firms.

	INNOVATIVE	NON INNOVATIVE
$\Delta_2$log(Production/L)$_{2003}$	2.62 (29.5)	0.68 (32.9)
$\Delta_2$log(Capital Stock/L)$_{2003}$	19.1 (43.1)	13.5 (38.5)
Temporary Workers Share$_{2001}$	3.98 (11.8)	4.87 (14.1)
Average Board Age (years)	49.4 (12.4)	50.4 (12.6)
Part of a group	51.1	45.9
Undertake R&D activity	73.7	34.3
Share of R&D workers$_{2001}$	9.5 (39.4)	1.8 (6.2)
Cash flow/L$_{2001}$ (euro)	22916 (39106)	23579 (33804)
Number of firms	768 (73.7%)	274 (26.3%)

Note: Shares are measured in percentage points unless explicitly stated. Standard deviations in parentheses. Non innovative firms are those firms that did not introduce any type of innovations.

4. Results

This section presents our estimation results. In section 4.1, we show the results obtained under the assumption that the firms exogenously happen to be innovative or not. In section 4.2 we study the case of firms taking some decisions that increase or decrease their chance of being innovative or not, thereby making group formation endogenous.

4.1 Exogenous group formation

If the decision to innovate (and hence group formation) is taken for granted, equation (5) can be estimated through OLS.

Table 4 shows the OLS coefficients and robust standard errors of the estimates of labor productivity growth rates (two-year rates) on our variables of interest, interacted with the group dummies. Column (1) and (2) refer to firms which have introduced any - hence either product or process - innovation. Column (3) and (4) refer to firms which have introduced product innovation only and column (5) and (6) refer to firms having introduced process innovation only. All the regressions include standard control variables such as size, geographical areas, industry dummies, as well as the dummy that takes a value of one for firms belonging to a group and a value of zero for those not belonging to any group, which, in previous work (see for instance Parisi, Schiantarelli and Sembenelli, 2006) has been shown to be a statistically significant correlate of firms' productivity performance.

Table 4. OLS Estimates of labor productivity growth rates (in percentage points)

$\Delta_2 \ln \frac{Y_{it}}{L_{it}}$	Innovation = Any		Innovation = Product		Innovation = Process	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
$\alpha_{K,1}$	0.038***	0.009	0.049***	0.010	0.045***	0.010
$\alpha_{IC,1}$	0.177***	0.008	0.185***	0.010	0.224***	0.010
Innovation	38.202***	6.404	7.982	5.372	32.935***	5.419
Age_1	-0.419***	0.062	-0.334***	0.077	-0.522***	0.071
Temporary $share_1$	-0.124***	0.031	-0.099***	0.037	-0.115***	0.035
$\alpha_{K,2}$	-0.065***	0.014	-0.028***	0.011	-0.047***	0.011
$\alpha_{IC,2}$	0.186***	0.016	0.175***	0.010	0.128***	0.010
Age_2	0.331***	0.112	-0.160**	0.076	0.150*	0.083
Temporary $share_2$	-0.155***	0.040	-0.188***	0.033	-0.170***	0.034
α_L	-0.358***	0.010	-0.349***	0.011	-0.335***	0.0103
Large	-1.647	1.026	-1.204	1.028	-0.615	1.015
Medium	-5.730***	0.785	-5.578***	0.783	-5.073***	0.777
Group	2.894***	0.624	2.926***	0.626	2.468***	0.620
Constant	-19.79**	9.072	8.974	7.809	-11.903	8.199
Industry dummies	yes		yes		yes	
Region dummies	yes		yes		yes	
WALD TESTS						
$\beta_{K,1} = \beta_{K,2}$	[0.00]		[0.00]		[0.00]	
$\beta_{IC,1} = \beta_{IC,2}$	[0.594]		[0.490]		[0.00]	
$Age_1=Age_2$	[0.00]		[0.105]		[0.00]	
$Share_1=Share_2$	[0.542]		[0.073]		[0.259]	
CHOW TEST	[0.00]		[0.00]		[0.00]	
CRS TEST	[0.00]		[0.00]		[0.00]	
R^2	0.372		0.368		0.380	
N	7427		7427		7427	

Note: * 10%, ** 5%, * 1% level of significance, p-values in brackets. Size, areas, industry and group dummies are included in all regressions. Variables with subscript 1 are related to the innovative firms while those with subscript 2 are related to the non innovative firms. α_L is the coefficient of $\Delta_2 \ln L$, α_K is the coefficient of $\Delta_2 \ln(K/L)$, α_{IC} is the coefficient of $\Delta_2 \ln(IC/L)$. Output Y is measured as total production.**

The innovation dummy coefficient is statistically significant at the 1% level, with a slightly higher point-wise estimate for firms introducing any innovation (38.2) than for those introducing process innovation only (32.9). This points to a significant drift ranging between .3 and .4 percentage points for productivity growth for the Italian innovative firms, even in the slowdown years considered. The drift is instead not significant for those firms that have introduced a product innovation.

Starting from control variables, it turns out that, for all types of firms, the coefficient of employment is strongly significant and negative. This implies that returns to scale are decreasing in our sample of firms. We retain the formulation inclusive of the growth of employment as our preferred formulation. The main results of the paper do not change with a constant returns to scale specification, though.

As to the capital-labor and the intermediates-labor ratios, results are as expected for the innovative firms, hence both positive and statistically significant. Yet the small size of the point-wise estimate for capital is likely at least partly the result of the multicollinearity between capital and the other inputs, namely intermediates and employment. This problem is even more apparent in the equations for the non-innovative firms, where the capital coefficient takes an implausibly negative and significant sign, while the coefficient of intermediates is positive and significant as expected. In the constant returns to scale formulation whose results we are not reporting here this problem is much less severe but is present as well. Given that our main purpose here is to net out as much as possible the influence of overall factor accumulation and use from the growth labor productivity, we report the less restrictive decreasing returns to scale formulation.

As previously discussed, our main variables of interest are the proxies of experience on the manager and the worker side. For the group of innovative firms, irrespectively of how innovation is defined, the estimate of the managerial age coefficient is negative and statistically significant – an indication that a high value of our proxy for experience is harmful for productivity for this category of firms. The point-wise estimates indicate that an increase in the average age of the board members of one year translates into lower productivity growth of some 0.33-0.52 percentage points. The effect is instead zero or even positive for the firms that belong to the non-innovative group: being endowed with a younger board of governance on average does not hamper (and may actually spur) the growth of productivity for the non-innovative firms. Interestingly, as one considers the average relation between managerial age and productivity in the entire sample, the semi-elasticity of age is not significantly different from zero. In order to capture the partial correlation of age and productivity growth it is thus crucial to distinguish between innovative and non-innovative firms.

On the workers' side, the estimated coefficient for the share of temporary workers is instead statistically significant and equally negative both for the innovative and the non-innovative group, with point-wise estimates ranging between negative .10 and.15 for the innovative and between negative .15 and .20 for the non innovative firms. The Wald test for parameter equality in this case rejects the hypothesis of coefficient equality, except (weakly) for those firms introducing product innovation whereby a p-value of .07 is calculated.

In a nutshell, a firm endowed with a high share of temporary workers always exhibits lower productivity growth. But this effect is on average stronger for the group of non innovative firms.

Table 4 reports p-values of the Wald tests of parameter instability for the H_0 hypotheses:

$$H_0 : \begin{cases} \beta_{K,1} = \beta_{K,2} \\ \beta_{IC,1} = \beta_{IC,2} \\ \gamma_1 = \gamma_2 \\ \mu_1 = \mu_2 \end{cases}$$

The test for age and the capital-labor ratio coefficients rejects the null of equal parameters (p-value of the test is equal to zero). In general, the three Wald tests reveal that the constrained model should be rejected. This is why we run the endogenous regime switching regressions whose results are reported in the next section.

4.2 Endogenous innovation decision

Firms are unlikely to be born innovative or non-innovative. They may be of either type depending on the amount of money they spend in R&D, on the amount of cash flows they are endowed with and – possibly - of the stock of experience of their workers and managers. If we can measure their effort in "innovation investment", we can estimate the probability of whether they are innovative firms. If the state of being innovative or not is no longer a state of nature, then this circumstance should be taken into account in estimating the relation between experience, innovation and productivity.

Table 5 and 6 show the results from the two-stage method of estimation of the parameters in (7) and (9'), which take into account the endogenous formation of the two groups.

Table 5. Probit Maximum Likelihood for Innovation dummies (first stage).

Probit ML	Innovation		Product		Process	
	Coeff	Robust Std. Err.	Coeff	Robust Std. Err.	Coeff	Robust Std. Err.
R&D: yes	0.687***	.0431	0.811***	.041	0.329***	.039
R&D workers$_{t-1}$	0.250***	.0221	0.316***	.018	0.118***	.016
Cash flow$_{t-2}$	0.0017***	.0006	0.0006	.0004	0.0015***	.0004
Large	0.260***	.0594	0.211***	.056	0.250***	.053
Medium	0.297***	.0424	0.138***	.042	0.254***	.039
Temporary workers	-0.003	.0014	0.0006	.0014	-0.0019	.0013
Age of board members	-0.012***	.0031	-0.008***	.0029	-0.017***	.0027
Constant	0.439***	.1576	-0.552***	.149	0.465***	.141
Pseudo-R^2	0.153		0.2014		0.047	
N	7773		7773		7773	

Table 5 shows the estimates of the first stage, namely the decision to innovate. The probit estimations of Table 5 are used as a first stage in the switching regression with endogenous switching described by equation (7). As for previous tables, the results in column (1) and (2) refer to any innovation, the results in column (3) and (4) are for product innovation and those in column (5) and (6) refer to process innovation. These latter regressions are useful to understand the importance of the different instruments in determining innovation decisions. The given set of instruments predicts much better the probability to undertake a product innovation than a process innovation. Moreover, engaging in R&D activity and hiring R&D workers has a much stronger effect on the probability of undertaking product innovation than on the one of process innovation. In contrast, per-worker current cash flow seems to be an important pre-condition for introducing process innovations. Both large and medium-sized firms plausibly appear to be more often innovative that small firms.

As to our main variables of interest, the share of temporary workers does not appear to significantly affect the decision to innovate, while the average age of board members does it and negatively already at this first stage.

Table 6 shows the estimates of the second stage of the switching regression. We present results from an OLS specification of the Maddala method as in equation (9') and a 2SLS-IV method to take into account the endogeneity of the growth rate of the capital stock and of the intermediates per worker.[7] The instruments used to predict the growth rate of the capital stock are the initial level of the capital/labor ratio, the age of the firm, the investment intensity, all measured at the beginning of the sample period, as well as size, area, sector and group dummies. The intermediates' instruments are the same except that the initial period variables obviously refer to intermediates instead of capital.

Table 6 indicates that estimates differ a great deal across categories of firms but not across estimation method. The OLS and 2SLS coefficients are in fact very similar for both innovative and non-innovative firms. It should also be noticed that the switching regression correction is only positive and significant for the innovative firms.

As to the overall goodness of fit, the estimated regressions for the innovative firms tend to exhibit a much larger R^2 than in the case of non-innovative firms (some .50 in the former case vis-à-vis .20 in the latter case). The Sargan tests for over-identifying restrictions cannot reject the hypothesis of

[7] We run similar regressions of the equations derived in Note 8, which allows to test for parameters equality between the two regimes. The results confirm the presence of significant differences in the estimates of the coefficients, in particular as far as age and the rate of temporary workers are concerned, between the two regimes. The table with these other regressions are available upon requests.

instrument validity only at the 10% level, with a p-value of .10 for the innovative and .87 for the non-innovative firms.

Table 6. Second stage results for system (9'), OLS and 2SLS.

Dependent	OLS		2SLS			OLS		2SLS	
$\Delta_2 \ln \frac{Y_{it}}{L_{it}}$	**Coeff**	**Robust St.E.**	**Coeff**	**Robust St.E.**		**Coeff**	**Robust St.E.**	**Coeff**	**Robust St.E.**
	Innovative firms					**Non Innovative firms**			
$\alpha_{K,1}$ (Δlnk)	0.042^{***}	0.015	0.053^{**}	0.022	$\alpha_{K,2}$	0.011	0.022	0.039	0.025
$\alpha_{IC,1}$ (Δlnic)	0.177^{***}	0.020	0.107^{***}	0.033	$\alpha_{IC,2}$	0.270^{***}	0.031	0.167^{**}	0.069
$\alpha_{L,1}$ (**ΔlnL**)	-0.354^{***}	0.028	-0.385^{***}	0.033	$\alpha_{L,2}$	-0.202^{***}	0.056	-0.206^{***}	0.058
β_1 (constant)	33.80^{***}	3.469	32.23^{***}	3.284	β_2	-24.37^{***}	8.062	-18.48^{**}	8.705
γ_1 (age)	-0.384^{***}	0.048	-0.390^{***}	0.048	γ_2	0.349^{***}	0.133	0.275^{*}	0.147
μ_1 (temporary workers)	-0.139^{***}	0.021	-0.130^{***}	0.023	μ_2	-0.281^{**}	0.124	-0.262^{**}	0.125
$-\sigma_{\varepsilon 1 \omega}$	-6.106^{***}	1.498	-3.941^{***}	1.450	$\sigma_{\varepsilon 2 \omega}$	-3.884	3.155	-4.094	3.116
R^2	0.488		0.479		R^2	0.194		0.183	
Sargan test			4.688 [0.10]					0.275 [0.871]	
N	5419		5381		**N**	1828		1828	

Note. All regressions include size, sector, area and group dummies. The first stage refers to column 1 and 2 of Table 5. The 2SLS method instruments the growth rate of the capital stock per worker (k) and intermediate consumption per worker (ic) with the lagged K/L in levels, lagged investment intensity, lagged IC/L and age of the firm.

Again replicating the same pattern of results as in Table 4, the intermediates' coefficients are well determined in both cases while the estimates for the capital-labor ratio are well measured for innovative firms and are instead not significantly different from zero for the non-innovative firms.

Our main focus lies in the experience-related variables. The impact of mean age of the board members on productivity growth is negative and statistically significant ($\gamma_{1,OLS}$ = -0.38, $\gamma_{1,2SLS}$ = -

0.39) for innovative firms and positive and significant in the OLS case ($\gamma_{2,OLS}$= .35) and positive but only weakly significant for the 2SLS estimate ($\gamma_{2,2SLS}$ = .27) for the non-innovative firms. Hence the statistical significance essentially stays there and the point-wise estimates are in the same ballpark (a bit lower for the innovative firms) as the OLS results previously shown in Table 4.

The impact of the share of temporary workers does not also differ significantly across estimation methods but they differ in significance across categories of firms. The share of temporary workers affects negatively productivity growth at the second stage for innovative firms (with coefficients of negative .13, thus very similar to those found in Table 4), and it is instead twice as much in absolute value for the non innovative firms. In Table 4, the estimated coefficients for the two categories of firms were instead rather similar.

4.3 Extensions

We implement four main robustness checks.[8] Firstly we check the validity of our identifying assumption that R&D and cash flow affects productivity growth only through the decision to innovate or not. The results for these experiments are shown in Table 7 (Columns "1R: OLS" and "1R: 2SLS"). Consistently with our assumptions, R&D-related variables (either a dummy indicating whether firms engaged into R&D, or the intensity of investments or R&D per worker) are not significant in the second stage for innovative firms. Some firms, which never introduced an innovation in the period (our non-innovative ones), have invested resources into R&D activity, and plausibly this has increased productivity directly. What was the objective of this R&D and how it turned out to be productive can be a matter of discussion. Caution should be paid to the measure of R&D investments which is missing for many firms, included those that have answered to be R&D

[8] Given the sizeable amount of robustness regressions, and for brevity sake, we summarize the results for innovative firms only in one table, when the two-stage switching specification is considered. We will just comment where possible the results for non innovative firms as well.

active in the questionnaire.[9] For this reason, in our preferred two-stage regressions we use the information given by the variable dummy "R&D active = 1 or 0" because basically all firms have answered to that question.[10]

The results are more clear-cut for cash flows, instead. The coefficient of the cash flows is not significant for both types of firms.[11] The coefficients of our variables of interest remain pretty much similar to our preferred results of Table 6, however. We conclude that our identifying restriction assumptions are overall appropriate.

Secondly, we want to check whether our results are partly driven by the exclusion of some relevant variables, potentially important for productivity growth and correlated to our variables of interest. One possibility is that firms employing a bigger share of skilled workers grow faster and tend to employ temporary employees to a lesser extent while also being run by younger managers. Indeed once the share of workers with tertiary education is appended to our regressions, this variable turns out weakly significant with a positive sign, as expected, but only under 2SLS method (columns "2R: OLS" and "2R: 2SLS" of Table 7). Also in this case the estimated coefficients of our variables of interest do not change dramatically.

Thirdly, in our main regressions we use an extensive measure of who is a manager in the firm. Yet not all managers and board members are equally likely to contribute and take decisions on such matters as innovation activities. A more restrictive definition of managers and board members does not change our results, although it does make our sample much smaller. We replicate the estimates of equation (4) for the sub-sample of managers who are supposed to take decisions within the board. We select those firms whose board contains competence-specific managers, who are

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[9] So we must assume strong hypotheses on the investments levels of those firms, to be able to use R&D per worker as a regressor. Coefficients estimates could become biased.

[10] If we use the R&D dummy at the second stage, the relationship between R&D and Labor Productivity growth is weakly positive for non-innovative and not significant or negative for innovative firms.

[11] Three firms registered an implausibly high cash flow (more than 100% of the value of production) and had been excluded from this check, leaving us with 1039 total firms.

supposed to influence the decision to introduce innovations in the firm, eventually. [COLUMNS "3R: OLS" AND "3R: 2SLS" ARE TO BE ADDED TO TABLE 7]

Table 7. Four robustness checks at second stage for innovative firms.

$\Delta_2 \ln \frac{Y_{it}}{L_{it}}$	**1R: OLS**	**1R: 2SLS**	**1R: OLS**	**1R: 2SLS**	**2R: OLS**	**2R: 2SLS**
$\alpha_{K,1}$ (Δlnk)	0.050^{***}	0.042^{*}	0.050^{***}	0.044^{**}	0.044^{***}	0.049^{**}
$\alpha_{IC,1}$ (Δlnic)	0.166^{***}	0.132^{***}	0.167^{***}	0.129^{***}	0.176^{***}	0.108^{***}
$\alpha_{L,1}$ (ΔlnL)	-0.362^{***}	-0.386^{***}	-0.360^{***}	-0.384^{***}	-0.354^{***}	-0.387^{***}
β_1 (constant)	30.224^{***}	29.043^{***}	30.131^{***}	29.477^{***}	33.264^{***}	31.713^{***}
γ_1 (age)	-0.392^{***}	-0.402^{***}	-0.396^{***}	-0.400^{***}	-0.391^{***}	-0.398^{***}
μ_1 (temporary workers)	-0.135^{***}	-0.133^{***}	-0.138^{***}	-0.135^{***}	-0.141^{***}	-0.133^{***}
$-\sigma_{\varepsilon 1\omega}$	-5.637^{*}	-3.490	-5.290^{***}	-4.113^{***}	-4.712^{***}	-2.595^{*}
$\ln(R\&D/L)_{2001}$	0.047	0.153				
CF intensity_{2001}			1.518	0.832		
Hired graduates_{2001}					0.030	0.034^{*}
R^2	0.517	0.515	0.517	0.514	0.488	0.479
Sargan test		[0.085]		[0.084]		[0.083]
N	5366	5366	5366	5366	5381	5381

Fourthly and last, we implement the Maximum Likelihood Endogenous Switching model which allows us to obtain consistent, and efficient, estimates. Unlike the two-stage method, ML does not need to estimate the conditional expectation of the growth rate of LP, with the Heckman correction term included.[12] Although maximizing the likelihood for this problem is quite cumbersome, we apply the method suggested by Lokshin and Sajaia (2004) and their algorithm. We estimate the equation system (9') first by including the growth rate of the capital stock as it is (analogously to the OLS method in Table 6), second by substituting the variable with its predicted value obtained

[12] Moreover, the two-stage method implies that 2nd stage residuals may suffer from heteroskedasticity. OLS should then be replaced by Weighted OLS method. We follow the standard procedure and use OLS. However, it is known that by iterating the 2-stage estimation procedure, the coefficients estimates would converge to ML estimates.

through a first-stage regression with instruments (analogously to the 2SLS method used in Table 6). The results of the ML Endogenous Switching Model are shown in Table 8 below.

The results for innovative firms largely confirm those of Table 6. The estimated share of the capital stock is low and imprecise when the capital stock is predicted (even negative for the non innovative). This means that we are not dealing with the potential endogeneity of the capital stock and IC correctly, and this is why at the moment our preferred estimates are those of Table 6. The parameters for mean age are estimated to be equal to -0.39 (the same as OLS and 2SLS). The temporary worker share coefficient is roughly equal to -0.13 both in ML and ML predicted. The value of ρ_1 lower than zero means that the correlation between the residuals of the second-stage equation and the selection equation is negative.

Our estimates also indicate that the impact of average board age for non innovative firms is zero or positive. This result is the same as that of Table 6, where the 2SLS coefficient is weakly positive.

The impact of the share of temporary workers is instead negative and significant ($\mu_{2,ML} \cong \mu_{2,MLpred} =$ -0.23). Finally, the correlation between selecting the regime and the second-stage equation is zero. The Wald test of independence across the equations (8) and (8') rejects the null of independence. Together with the positive and statistically significant Mills ratios, this means that the error correction-switching method is appropriate.

Table 8. Second stage results for system (9'), Maximum Likelihood efficient method.

Dependent	ML		ML (predict $\hat{k}$)			ML		ML (predict $\hat{k}$)	
$\Delta_2 \ln \frac{Y_{it}}{L_{it}}$	**Coeff**	**Robust St. E.**	**Coeff**	**Robust Std. Err.**		**Coeff**	**Robust St. E.**	**Coeff**	**Robust St. E.**
	Innovative firms					**Non Innovative firms**			
$\alpha_{K,1}$	0.039^{***}	0.015	0.0248	0.0218	$\alpha_{K,2}$	-0.076^{**}	0.020	-0.079^{***}	0.029
$\alpha_{IC,1}$	0.174^{***}	0.019	0.183^{***}	0.019	$\alpha_{IC,2}$	0.247^{***}	0.027	0.228^{***}	0.028
$\alpha_{L,1}$	-0.359^{***}	0.028	-0.376^{***}	0.026	$\alpha_{L,2}$	-0.253^{***}	0.056	-0.221^{***}	0.054
β_1	17.00^{***}	3.343	18.17^{***}	3.381	β_2	-29.14	8.47	-27.13^{***}	8.27
γ_1	-0.389^{***}	0.047	-0.390^{***}	0.048	γ_2	0.279^{**}	0.131	0.214	0.134
μ_1	-0.129^{***}	0.021	-0.138^{***}	0.022	μ_2	-0.216^{*}	0.122	-0.238^{**}	0.118
σ_1	22.058^{***}	0.044	22.11^{***}	0.048	σ_2	28.91^{***}	0.077	28.99^{***}	0.071
ρ_1	-0.147^{***}	0.054	-0.150^{***}	0.056	ρ_2	0.060	0.078	0.050	0.074
Mills ratio	0.444^{*}	0.302				1.383^{***}	0.537		
Condition	**Exogenous K**		**Endogenous K**						
Wald $\chi^2(1)$	7.84 [0.005]		7.51 [0.006]						
P(Inno)	0.735	0.194	0.736	0.193					
N	7247		7247						

Note. All regressions include size, area and sector dummies. Columns 3 and 4 show ML with predicted value of the growth rate of capital stock for innovative firms. Columns 7 and 8 replicate ML with predicted value for the non innovative cluster. Wald Chi-square test is testing for the independence of the residuals in system (8). P(Inno) is the predicted probability of being in the innovative regime in the first stage.

5. Conclusions

In this paper we exploited data from a sample of some eight thousands innovative and non-innovative firm-observations to describe the pattern of correlation between experience, innovation and productivity growth during the recent period of serious productivity slowdown in the Italian economy. Our results seem to indicate that both workers' and managerial experience matter for productivity growth.

As to managerial age, definite patterns of correlation are present once the whole sample is split into innovative and non-innovative clusters. Age, in particular – a measure of overall experience – in the labor market appears to be (positively correlated or) uncorrelated with productivity growth in non-innovative firms, while it is robustly negatively correlated with productivity growth in the sample of innovative firms. Results are also strongly statistically significant for our other variable of interest: the share of temporary workers is in most cases negatively correlated with productivity growth. This result seems to differ across groups in absolute value, being more important for non innovative firms.

The cross-sectional statistical analysis of long-differences based on firm-averaged data is not problem-free. A big issue is potential reverse causation. The statistical relations we intend to analyze posit that (say) age is the independent variable and productivity the dependent variable. But cross-section data as such (be they observed at a given point in time or averaged over time) may only indicate correlation, not causation. Therefore, if the estimated coefficient linking age and productivity is negative, this may not indicate that the firms where aged managers are employed are less productive. Rather, the negative correlation may simply signal that older managers tend to stay longer in less productive and older firms, featuring outdated machines and methods of production, probably because they managed to put in place successful "relations", while new, innovative and high-productivity plants may be more often matched to young and brilliant managers. If this is the case, we would be wrongly interpreting what causes what, attributing to age a causal influence on plant productivity, which may go the other way around. This is why we implement our 2SLS specification. Our expectation is that by choosing predetermined instruments, which also include age of the firm, we are lessening the simultaneity problems.

Surely, a lot of unobserved heterogeneity in plant productivity is still there in the data even if we have augmented the list of productivity determinants with dummies and other control variables. Yet the problem of interpreting the statistical results from cross-sectional estimates arises if and only if the unobserved (therefore unmeasured) firm variables are correlated with the included explanatory variables. For example, if managerial ability – a typically unobserved firm variable – were unrelated to the age of managers, then leaving it out of the empirical analysis would not be a major problem. This may or may not be the case though. If managerial ability is not observed and therefore omitted from the analysis but it turns out to be correlated with some included variable such as the age of managers, its effect may be picked up by the negative estimated relation between high-age managers and productivity. We would be misperceiving the effect of managerial ability on productivity as if it were the causal effect of age on productivity. To tackle this problem, we control for a few dummy variables that capture some, though presumably not all, of the unobserved determinants of firm productivity.

Finally, we looked at how some worker and manager characteristics may correlate with innovation and productivity. A long tradition of studies – the most recent of which is Lachenmaier and Rottmann (2011) - has lent considerable attention on the study of the reverse chain of causation, namely the labor market implications of product and process innovation. An interesting area of future research might be in the joint study of these effects to achieve a better understanding of the determinants and the consequences of innovation.

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Appendix

We control for sample selection that could actually come up when Capitalia-Unicredit IX survey data are matched with AIDA balance sheet of firms present in 2007. Not all Capitalia firms exist in AIDA register. Nonetheless, we manage to retain almost 86% of the Capitalia sample. Therefore, we check in what type of characteristics do firms in-sample and out-of-sample differ.

Figure A 1. In and Out Sample distribution of Capitalia firms by size

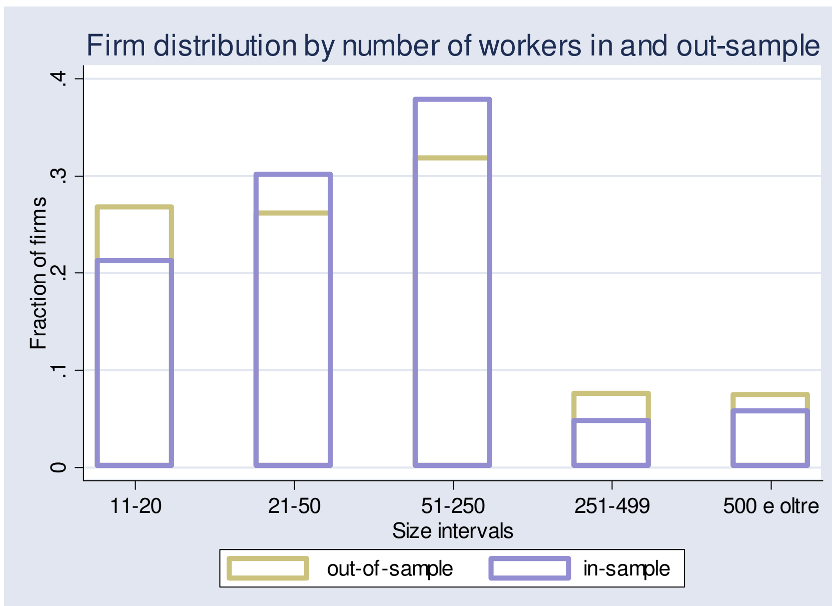


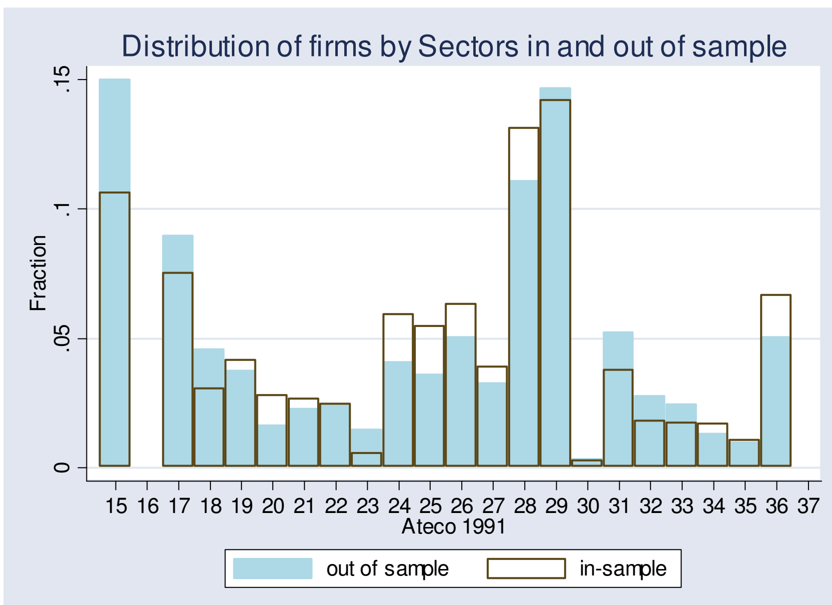
Figure A1 shows the distribution by class of workers of the firms falling in and out of our final panel. The panel tends to maintain medium size firms mainly (87%), while keeping around 79% of the medium-large and large firms. As far as the very small firms, our panel keeps 82% of them. Formally, the test for independence hypothesis rejects the null (Pearson chi-square(4) = 25.7455, p-value = 0.000) meaning that being in or out of sample depends in a certain way on firm size.

We lose 15.6% of firms located in North-West part of Italy (Lombardia, Piemonte, Liguria, Valle d'Aosta), 13.9% of the firms located in the North-East (Trentino A.A., Veneto, Friuli V.G., Emilia Romagna), 13.5% of the firms located in the Centre (Toscana, Umbria, Marche, Lazio) and 15.8% of the firms located in the South. The Pearson chi-square(4) = 3.4150 with p-value = 0.491 says that there is statistical independence between the regional distribution and being in or out of sample.

Traditional sectors with lower Ateco 1991 code, i.e. Food and Beverages, Textiles, Clothes, Tobacco, tend to be underrepresented with respect to the original Capitalia sample, as we can see from Figure A2. In any case if we consider High-Tech versus the others, there is an independent distribution of frequencies in and out of sample (Pearson chi-square(1) test = 0.3952 with p-value=0.530).

We then run a two-sample t test with equal variances to test for equality of average firm age between the two groups (in-sample, out-sample). The results highlight that firms outside the sample are on average 3 years older, and the difference in means is statistically significant.

Figure A 2. Distribution of firms by Ateco 1991 classification, in and out-sample



Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Out sample	570	31.87	.938	22.41	30.03	33.72
In sample	3469	28.87	.325	19.16	28.24	29.51
Combined	4039	29.29	.309	19.67	28.69	29.90
diff		3.00	.887		1.259	4.742

Degrees of freedom: 4037

Ho: mean(out) - mean(in) = diff = 0

Ha: diff < 0	Ha: diff ≠ 0	Ha: diff > 0
t = 3.3795	t = 3.3795	t = 3.3795
P < t = 0.9996	P > |t| = 0.0007	P > t = 0.0004

Finally, we run an association tests to check for independence between being an innovative firm and being in or out of sample, to evaluate whether less innovative firms are those kicked out of the final panel. The Pearson chi-square tests are listed for different types of innovation activity:

R&D expenditures in 2001-2003 (yes/no)	Pearson chi-square(1) = 3.52 p-value = 0.061
Introducing product innovations (yes/no)	Pearson chi-square(1) = 7.194 p-value = 0.007
Introducing process innovations (yes/no)	Pearson chi-square(1) = 2.189 p-value = 0.139
Introducing both process and product innovations (yes/no)	Pearson chi-square(1) = 2.249 p-value = 0.134

We reject the hypothesis of independence for R&D expenditure and product innovation only. That means that firms investing into R&D and introducing product innovations have a (slightly) higher probability to survive. We cannot reject the null for process innovations or both kinds of innovations, instead. Introducing process innovations or not provide a firm equal probability to remain in our sample.

Appendix B

Figure 1.B: The gradually rising share of temporary employment after 1996

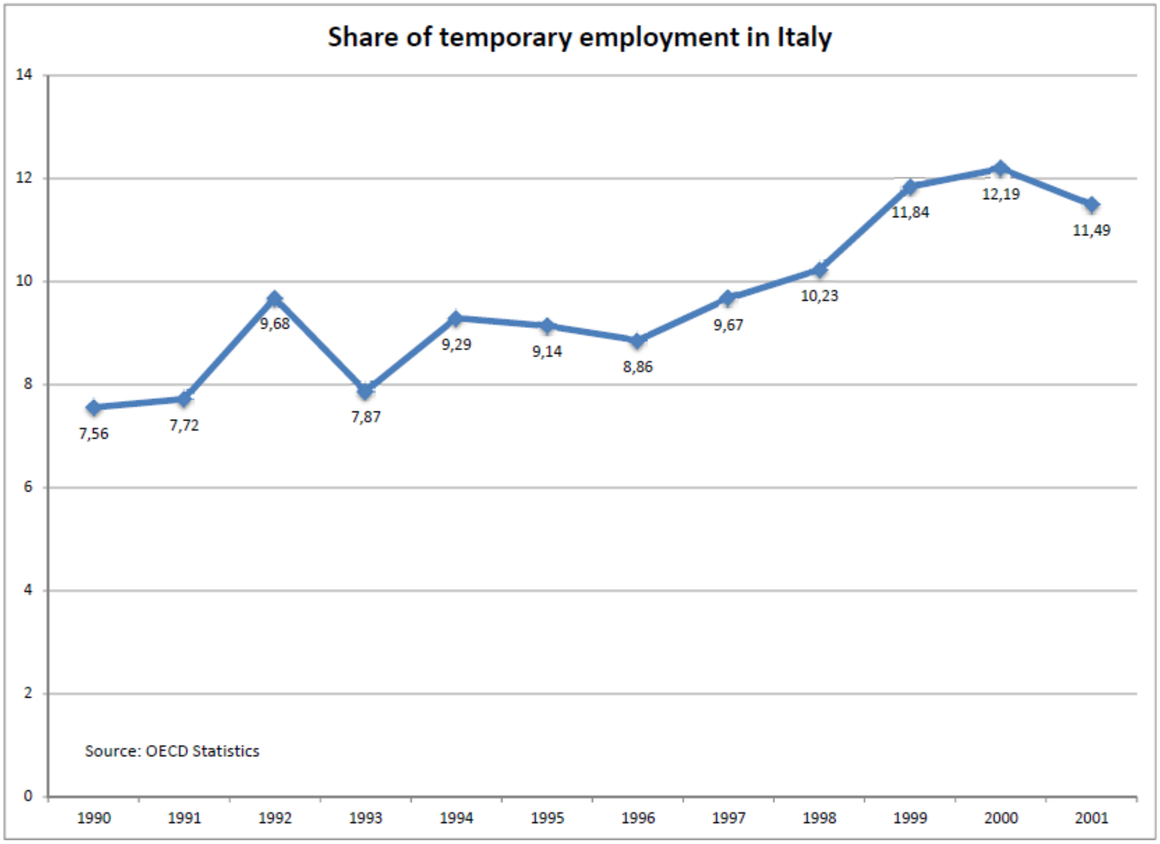


Table 1 B. Firm productivity growth by control variables.

controls	N	Mean productivity growth	% Innovative
Large	178	4.05%	82.6%
Medium	658	0.38%	75.4%
Small	206	5.96%	60.6%
part of a group	514	3.34%	75.7%
independent	528	0.92%	71.8%
Centre	160	-0.29%	79.4%
North West	376	3.12%	74.7%
North East	354	-0.14%	71.5%
South	152	7.37%	70.4%
High-tech	346	0.06%	35.6%