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Experience, Innovation and Productivity. Empirical Evidence from Italy's Slowdown

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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. These results also hold when we allow for endogenous regime switching.

JEL classification: M54, O31, D24
Keywords: Productivity, innovation, experience, Italy

Experience, Innovation and Productivity.
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Outline

1. Introduction

Does it pay for a firm to be endowed with the breadth and the novelty of ideas brought about by young entrepreneurs and workers?[1] Or do innovation and productivity gains mostly originate from the competence of senior – hence more experienced – people? In this paper we take up these issues and use firm-level data for Italy in the early 2000s as a case study, to learn about the role of both managerial and workers' experience in affecting firm-level innovation and productivity.

Italy in the early 2000s was a fertile ground in this respect. Since the second half of the 1990s, in the midst of the Internet-led revolution, a sharp productivity slowdown came about in the Italian economy, both in manufacturing and service industries. Yet the zeroing of productivity growth in manufacturing – "the" leading sector of the Italian economy in the past decades – became particularly pronounced in 2001-03, the time frame of our analysis.

Experience may have contributed to the productivity slowdown in Italy's manufacturing both on the workers' and the managerial side. On the side of workers, in 1996 a few legislative changes gave full legal recognition to a host of contractual forms of part-time and temporary jobs, not allowed before. As a result, by 2001, the share of temporary workers in Italy's dependent workforce had gone up to 11.5 per cent, i.e. 2.5 percentage points higher than in 1996. In principle, temporary workers need not be inexperienced, but this time they largely were. As shown in Figure 1, the share of young – thus with little work experience – temporary workers was three times higher and growing compared to the share of prime aged workers. These developments may

[1] We are very thankful to the ILR Review Editor and two referees for their helpful comments on a previous draft.

bear a relation with productivity developments. The entry of relatively inexperienced workers in the labor market likely lowered labor productivity, both directly by reducing the capital-labor ratio and indirectly, making it easier for entrepreneurs to employ cheap work instead of experimenting riskier ICT-enabled innovation.[2]

Experience affected innovation and productivity in the Italian economy on the managerial side as well. The pace of adoption of Internet-related innovation has been hampered by the unusually high presence of very experienced but possibly conservative managers and board members. This was a reflection of the persisting lack of contestability of firm property rights in the Italian capital market. Many Italian firms are family owned and follow a "fidelity model" of managerial conduct and selection, rather than a "performance-based" model. This has consequences for innovation and productivity. Faithful but conservative senior managers make family firms less inclined to innovate and raise productivity, with respect to their competitors following the performance-based managerial model, typical of the Anglo-Saxon world. This became an important shortcoming for Italian firms when the new technological opportunities brought about by the Internet revolution appeared.

In this paper, we test whether the firm variation in workers' and managerial experience is related to Italy's productivity slowdown. We use the firm's share of temporary workers as a proxy for worker experience, and managerial age as a proxy for managerial experience. The innovative capacity of the firms is captured through a

[2] Gordon and Dew-Becker (2008) made a similar point for European countries at large, showing that the labor market reforms that occurred in many European countries in the second half of the 1990s has been eventually detrimental to productivity growth.

questionnaire statement where firms report whether they introduced either product or process innovations or both. Our empirical setting is based on a two-stage model where the firm's propensity to innovate is, in the first stage, a function of control variables such as R&D investment, cash flow, firm age and size – found to be significant in previous studies – as well as our measures of workers' and managers' experience. Experience variables also enter the second stage, where the correlation between the firm's growth rate of labor productivity and the growth of capital per worker and other inputs is investigated.

2. Background discussion

Innovation and productivity are known to depend on R&D and cash flow. 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). Cash flows have been found instrumental to avoid that liquidity constraints strangle yet undeveloped innovations in their infancy (Brown, Fazzari and Petersen, 2009; Geroski, van Reenen and Walters, 2002; Hall, Mairesse, Branstetter and Crépon, 1998).

The question whether experience is associated to innovation and productivity is more controversial. As discussed by Jones (2010), the case list of inexperienced entrepreneurs inventing brand new products and technologies started with Bill Gates leaving Harvard in 1975 to co-found Microsoft with Paul Allen, and continued with Steve Jobs and Steve Wozniak, the young founders of Apple. More recently, Sergei Brin and Larry Page, the cofounders of Google, were bright but young and inexperienced Stanford PhD students. Yet one can also think of radical innovations brought about by experienced entrepreneurs, in some cases by the same grown-up entrepreneurs who changed their industry already once. Indeed, Steve Jobs 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 fade away.[3]

The productivity of workers is also known to depend on experience as well as on other traits, such as education, skills, motivation, intellectual and physical abilities. Using a meta-analysis of 91 studies on how mental abilities develop over the individual life span, Verhaegen and Salthouse (1997) concluded that cognitive abilities (reasoning, speed and episodic memory) decline significantly just before 50 years of age and more so thereafter, with maximum cognitive levels being achieved in one's 20s and 30s, independently of country and sex.[4] These effects are magnified or lessened by workplace and management practices, and involvement programs, as shown by Black and Lynch (2001). While they concentrated on organizational innovations and human capital investment, their finding of a negative correlation between labor productivity and the share of workers employed for less than a year is consistent with the topic we discuss here.

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[3] Galenson (2003, 2005) documented how the life-cycle of artists may be of two types, of a conceptual and an experiential type, so that the young genius of Van Gogh and Picasso, Melville and Welles can be matched with the experienced ability of Michelangelo, Rembrandt, Cezanne and Hitchcock. The relation between age and fundamental innovations seems non-linear in arts as well.

[4] Kanazawa (2003) found that this curve shape also applies to jazz musicians, painters and authors. Castellucci, Padula and Pica (2011) confirmed this for Formula One drivers.

When evaluating the relation between firm performance and managerial experience, the latter has been conceptualized and measured in many ways, interacted with demographic or manager personality traits, mainly with the aim of analyzing CEO performance, board composition, capital structure or financial performance. A strand of papers spurred from the so-called "Upper Echelons perspective" (Hambrick and Mason, 1984). This literature – mostly based on survey data about top manager leadership and practices – deemed age, educational experience and background heterogeneity as important observables of individual "psychological construct", directly affecting firm performance (including product innovation).[5] Overall, managerial experience is often measured as a set of personal capabilities like intellectual power, leadership, behavior and psychological traits of individual managers, as well as their practices.

More recently, Bloom and Van Reenen (2010) provided

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[5] This literature – reviewed by Carpenter, Geletkanyc and Sanders (2004) and Elenkov and Manev (2005) – investigated how the top management of different countries affects innovation. Given innovations, the influence of leadership and socio-cultural values on innovation is evaluated. In the same vein, from a meta-analysis of several papers, Deutsch (2005) found that the relationship between board composition and firms' "crucial" decisions is ambiguous. Among the "crucial" decisions, Deutsch included R&D expenditure, which managers tend to postpone in favor of more rewarding short-run financial performance, but he also related board members' independence to R&D. Dalton, Daily, Ellstrand and Johnson (1998) found no relation between board composition, board leadership and financial – rather than innovative – performance, at least with 1990s data. The role of managerial and psychological barriers in slowing down technology adoption and firms' market performance have been instead confirmed by Kitchell (1997), Bertrand and Schoar (2003) and Malmendier and Tate (2009), using more recent data.

evidence that persistent productivity differences at the firm or country level reflect variations in management practices. Interestingly for our purpose, their study showed that labor market rigidities and the presence of managerial incentives are negatively correlated across countries. Italy, in particular, featured an intermediate level of labor market rigidity and a rather low score on management incentives (lower than the score of Germany, France and the US). The importance of managerial incentives was further emphasized in other studies using Italian data, such as Bandiera, Guiso, Prat and Sadun (2010), Lippi and Schivardi (2013) and Caggese (2012). These studies showed that Italy's family firms are often organized in accordance with the fidelity-model principles, not along performance-based lines. So they tend to have lower productivity and worse firm performance.

3. Conceptual framework

We start from a Cobb-Douglas production function where real output is a function of capital, labor, intermediate inputs and (disembodied) efficiency. Within this framework, in each period t, labor productivity (in logs) for firm *i* at time *t* may be decomposed as follows:

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

where total production per worker *Y/L* is a log-linear function of capital per worker *K/L*, intermediate inputs per worker *IC/L* and the efficiency parameter *A*, expressed in disembodied form. Equation (1) also includes a separate term in *L* which allows us to test for the assumption of constant returns to scale. Under constant returns to scale, the coefficient of *ln(L)* would in fact be zero and the latter term would disappear from (1). With decreasing (increasing) returns to scale, the coefficient would instead be significantly negative (positive).

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

$$(2) \qquad \ln(A_{it}) = \lambda t \Omega_i + \eta_i + \varepsilon_{it}$$

where Ω is an indicator of whether the firm has introduced an innovation, η is a firm-specific unobserved effect and ε is a white noise disturbance term capturing residual technology shocks. Under (1) and (2), the log difference (the growth rate) of labor productivity is a linear function of the growth of the capital-labor ratio, the intermediate inputs per worker, the labor input, the propensity to innovate and technology shocks, while firm-specific unobserved effects are washed out. The propensity to innovate Ω is determined by the variables previously discussed in the innovation literature as well as the experience variables we care about. Among the standard innovation determinants we include the firm propensity to undertake R&D, the share of R&D workers in total firm's labor force, cash flow, firm age, plus an array of regional, size and industry dummies. We also include a dummy for family firms so as to test whether family firms – particularly common in Italy – have a special tendency to innovate less. Each of these variables affects *A* through a separate parameter. Among the experience determinants, we include firm-averaged managerial age – a proxy for managerial experience – and the share of temporary workers – a proxy for workers' experience. To account for the ambiguous effect of experience on innovation, the relation between these two is specified as follows:

(3) $$\Omega_i = aE_i + bX_i + \kappa_i$$

where E is experience capital, X is "openness to innovation" and κ indicates other measured and unmeasured innovation-enhancing variables. As documented in the social psychology studies mentioned in the background discussion, X is presumably higher when young than when old. It is the X factor that makes younger minds prone to innovate. Yet, as previously discussed, other psychology studies indicate that the passage of time and the accumulated experience may still prove valuable for innovativeness. Daveri and Maliranta (2007) found that the value of experience may depend on such circumstances as whether an industry or a firm operates with a cutting edge or a traditional technology. In traditional industries an experienced but old-fashioned manager may well be an asset, while a high-tech firm may prefer to be endowed with relatively inexperienced but high-tech-familiar young managers. Altogether, from equation (3), the number of years a manager has spent doing her job inside or outside the firm may positively or negatively affect Ω, for the passage of time positively affects E and negatively X. Hence, the marginal effect of experience on Ω may be positive or negative depending on whether $a>b$. In the empirical section, we will test whether a and b differ between innovative and non-innovative firms and show that this is indeed the case.

Notice that our description of the relation between experience, innovation and productivity embodies an important implicit assumption, namely that Italian firms take their decisions to innovate and raise productivity holding their production and workforce structure as given. This assumption is mainly motivated by Italy's "Statuto dei Lavoratori", a piece of labor market legislation in place since the early 1970s that involves specific "social" obligations onto firms above the 15-employee threshold.

Available evidence (Garibaldi, Pacelli and Borgarello (2004) and Schivardi and Torrini, 2008) indicates that, also as a result of this legislation, Italy's firms have often started and remained comparatively small, with very limited status switches or fundamental reorganization throughout.

4. Data

We collected balance sheet data and statements of account for a representative sample of Italian manufacturing firms and their board characteristics in 2001-2003 from two sources. Information about employment characteristics, innovation activity and R&D investment come from the IXth Survey on Manufacturing Firms by the Italian bank Capitalia-Unicredit. This survey was run in 2004 through questionnaires distributed to 4177 firms. Those form a representative sample of Italian manufacturing firms, selected with a stratified method (see Appendix B). The questionnaires inquire about location, legal form, group, sales, investments, R&D investments, innovation activity, exports, labor force characteristics, financial status and incentives. Most of the quantitative information relates to the previous three years since the time of the survey, separately. Innovation activity, instead, refers to the entire three-year period.

The pieces of information about balance sheets, income account and age of the board members originate from the AIDA database (managed by Bureau Van Dijk). It collects balance sheets, financial accounts, proprietary shares, firm characteristics and board characteristics on about 250.000 Italian firms with at least €800.000 gross sales.

AIDA is updated every week but maintains balance sheet data for the previous years as well. Thus we extracted firm items over 2001-2003 to check and correct for inconsistencies between the two sources. During the years between 2001 and 2003 Italy's productivity shortfall had been particularly severe, being thus a good case in point for the analysis. To obtain predetermined instruments for IV estimations, we also retrieved and employed data on total value of production, total assets, shareholders funds, raw materials, intermediates and services, number of workers, variations of inventories and materials, in 1999 and 2000. While the match between the two sources was quite easy, we could not do the same for board composition. The information on board members of existing firms used here dates back to December 31, 2007. We know the year of appointment but not the duration of members' service. Therefore we considered the board composition information available from AIDA at the end of 2007 as if it were the same in 2001. We ran a few random checks on boards stability, using the website of Guida Monaci, a useful source for Italy's firm-level data maintained since 1870.[6] Then we calculated the age of each member at the time of the appointment (until 2002) within the board and, for each firm, the average age of the board. We excluded from the dataset the – very few – firms whose board names appeared to be a company instead of a physical person. We also excluded those firms whose board members' appointment appeared to be anomalous. The matching procedure between the two sources left us with 3562 firms – some 85 per cent of the Capitalia-Unicredit sample – and 21081 firm-individual observations. We tested for potential sample selection of these firms in the first place, in terms of age,

[6] The stability of board composition over time is not exclusive of Italy. Bloom and van Reenen (2010) presents evidence that board composition tends to stay constant over long spells of time in other countries as well.

size, location and sector of production.[7] In the end, our quasi-panel data set consists of 7977 observations (thus about 40 per cent of the potential), originating from 1042 firms each with an average of 7.7 managers.[8]

In Table 1 and 2 we present summary statistics for the entire sample and for the sub-samples of innovative and non-innovative firms, respectively. A firm is deemed “innovative” if it introduced either a product or a process innovation in 2001-03.[9] Labeling “innovative” a firm that introduced at least one innovation in the previous three years is indeed a mild criterion. It is thus no wonder that some three-fourths of the firms in the sample are reported to be innovative. Nonetheless results would not change much when employing more restrictive definitions of innovativeness. The high share of innovative firms is a well-known feature of the Capitalia/ Unicredit data set, already identified in previous studies.

Table 2 shows that in 2001-03 innovative firms experienced faster labor productivity growth than non-innovative firms for about two full percentage points. They accumulated capital per worker at a faster rate (+19.1 against +13.5 per cent). They were more typically part of a group – a feature associated with faster growth in previous studies – or they were more involved in R&D activities than non-innovative firms. Yet innovative firms also presented a

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[7] Younger, bigger or particular sectors could have a higher survival rate, higher productivity or innovation capacity. The discussion of the potential selection bias is in Appendix A.

[8] We describe the geographical and size distribution of our sample and the distribution of board size in Appendix B.

[9] In the questionnaire, the definition of Product Innovation is: “the introduction of at least a new or significantly improved product”. Process Innovation: “the adoption of at least one new or significantly improved production process”. As explained in the Data section, these definitions are in line with the Oslo Manual.

lower share of temporary workers and a relatively younger managerial age. This is consistent both with the idea that too many inexperienced workers may hamper growth, as well as with the Bandiera-Guiso-Prat-Sadun idea that "too much" managerial experience may be bad for innovation and productivity. Altogether, the evidence from these summary statistics looks encouraging and is subjected to rigorous multivariate empirical scrutiny in the next section.

5. Empirical specification

5.1. *Three empirical hurdles*

To implement the model described by equation (1)-(3) we faced three main hurdles.

The first hurdle is a standard issue arising when estimating a production function: inputs are endogenously chosen by firms and therefore they cannot be uncorrelated with the productivity shifter A. The zero covariance between the error term and the regressors is, however, a necessary condition for obtaining unbiased estimates when running an ordinary least squares regression. Hence to achieve unbiased estimates we will need to instrument the inputs on the right hand side.

A second problem arises when interpreting the coefficient linking age and productivity. A negative coefficient may either indicate that senior managers "cause" productivity to grow less in the firms where they are employed, or that senior managers tend to stay longer in less productive firms, where they have successfully established "relations". Less productive firms may be endowed with outdated machines and methods of production as well as "outdated" managers, while innovative and high-productivity start-up plants may be more often matched to young and brilliant managers. If this were the case, we would be wrongly interpreting what causes what, attributing to age a causal influence on plant productivity growth which may go the other way around. By using, among others, the level of capital and intermediates per worker in earlier years compared to our period of analysis as instruments, we expect to be able to partially capture this reverse causation effect and strengthen our interpretation that it is age that drives productivity developments and not the opposite.

The third problem stems from the fact that firms are not born innovative or non-innovative. Rather, innovativeness is the consequence of purposeful activity which is more likely to materialize if a firm has specific characteristics. We then worked with a two-step framework qualitatively similar to Crepon, Duguet and Mairesse (1998) and Huergo and Jaumandreu (2004), whose themes of analysis are particularly relevant for our paper. However, we extended those approaches and applied the endogenous-switching regression analysis to allow for the fact that innovation activity is not given, but stems from firms' choice. In the first step, firms evaluate 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 have enough cash-flow, in addition to other time-invariant factors such as location, size, industry, ownership, which are all captured by fixed effects. Moreover, the firm's propensity to innovate may also be affected by experience-related variables – our main object of interest in this paper. As long as a temporary worker is also inexperienced, the availability of a large pool of temporary workers may stifle the firm's incentives to innovate. As to managerial experience, the relation may go in either way as we have previously discussed.

In the second step we study the correlates of productivity, including experience variables. As in

Mairesse, Mohnen and Kemp (2010), we initially maintained that R&D and cash flow affect productivity only through their influence on the decision to be innovative. The exclusion of R&D and cash flow from the second stage is admittedly restrictive, however: both variables may well affect the quality and quantity of innovation and thus productivity at the second stage. Whether R&D and cash flow should belong to both stages or just to the first one is testable. We do it in the Robustness check section.

5.2. *Empirical strategy*

We start from a baseline equation with no asymmetry between innovative and non-innovative firms. Denoting log-per-capita variables by small letters as $y_{it}=ln(Y_{it}/L_{it})$, $k_{it}=ln(K_{it}/L_{it})$, $ic_{it}=ln(IC_{it}/L_{it})$, $tshare_{it-2}=T_{it-2}/L_{it-2}$, where T is the number of workers on a temporary contract (full time and part time), the production function can be written as equation (4):[10]

(4)

$$\Delta_2 y_{i2003}=d+\beta_K\Delta_2 k_{i2003}+\beta_{IC}\Delta_2 ic_{i2003}+\alpha_L\Delta_2 l_{i2003}+\gamma Age_i+\mu\cdot tshare_{i,2001}+\Delta_2\varepsilon_{i2003}$$

The dependent variable $\Delta_2\, y$ and the independent variables $\Delta_2\, k$, $\Delta_2\, ic$ and $\Delta_2\, l$ are "long" growth rates for firm i calculated between 2003 and 2001. *Age* is calculated as the average age of the firm board members and managers when they were appointed, while *tshare* is calculated at an initial time, *i.e.* in 2001. In the regressions we also control for

[10] From (2) and (3), $\ln A_{it} = \lambda t\Omega_i + \eta_i + \varepsilon_{it}$ implies $\Delta_2 \ln A_{it} = \lambda\Omega_i + \Delta_2\varepsilon_{it} = \lambda(aE_i + bX_i + \kappa) + \Delta_2\varepsilon_{it}$. The vector $\lambda a = [\gamma, \mu]$ corresponds to the parameters in (4).

sector, geographical and firm size dummies[11] as well as for group membership. The parameter α_L (the negative of one minus the sum of the input coefficients K, IC and L) is a synthetic measure of returns to scale. We test for constant returns to scale under the null hypothesis that $\alpha_L=0$. The alternative hypothesis $\alpha_L<0$ is that production is performed under decreasing returns to the three inputs K, L, IC.

The total number of usable observations is 7977, as previously mentioned, belonging to a quasi-panel of 1042 firms, each with 7.7 board members on average. Yet board size greatly differs across firms (see the skewed distribution in Table B2, Appendix B) so, in order to balance size contribution to shape the average board age, our estimates are weighted with board size.[12]

Equation (4) is the result of long differencing (1)-(3). Long-differencing allows us to get rid of the unobserved heterogeneity between firms that is the most obvious source of simultaneity bias in the estimates. Equation (4) still suffers from the other concerns we discussed above, however, in particular those arising from input endogeneity and regime choice.

We run a Chow test of parameter stability on (4) to check whether there are significant asymmetries between innovative and non-innovative firms. We expect the

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[11] We have 21 sector dummies, with a sector breakdown based on the Ateco2007 classification of Italy's industries, equivalent to the NACE rev.2 European code. We allow for four geographical dummies (North-West, North-East, Centre and South). Firm size dummies are three for small, medium and large firms. Size is measured following the European Commission definition, see Appendix B.

[12] We also estimated equation (5) and model (6) without weights. The main results did not change at all, but the standard errors were slightly higher in the un-weighted case, so in the paper we only report the weighed estimates.

parameters (β_K,$\beta_{IC,}$ $\beta_{L,}\gamma$,μ) to differ between the two types of firms. This test is first carried out without allowing for endogenous regime switching, simply by comparing the estimates of equation (4) for the two subgroups (innovative and non-innovative, unconstrained model) and for the entire sample (constrained model). The null hypothesis is that the constrained model is the true model. The test always rejects this null. 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 these results, we let the parameters of inputs and experience variables vary across groups as in equation (5):

(5)

$$\Delta_2 y_{i2003} = \sum_j D_j (d_j + \beta_{Kj}\Delta_2 k_{i2003} + \beta_{ICj}\Delta_2 ic_{i2003} + \alpha_{Li}\Delta_2 l_{i2003} + \gamma_j Age_i + \mu_j tshare_{i2001}) + \Delta_2 \varepsilon_{i2003}$$

where j=1 refers to innovative firms, j=2 refers to non-innovative firms, D_j is a dummy variable. Moreover, to gain further evidence on the role played by family firms, we also run regressions with a drift for family firms and a family firm dummy interacted with board age. As previous studies have shown, in a non-family firm an "old" manager would remain in place only if he/she delivers good results. Hence one should find that the negative impact of age is stronger in family firms than in firms with other control types. The results of these regressions are reported in Table 3.

Nonetheless, as we have discussed, the choice of being innovative may be endogenous. Firms introduce innovations because they intensively invest in R&D activities or innovative capital, or maybe because they have more cash flows. The age profile of the board members and/or the share of temporary workers might also influence this mechanism.

In order to embody this choice into the labor productivity growth equation we employ the endogenous switching model of Maddala (1983) – the innovation literature version of a Heckman selection model. Using Maddala's terminology, we 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 specification can be written as:

(6)

$$\begin{cases} \Delta_2 y_{it} = d_1 + \beta_{K1}\Delta_2 k_{it} + \beta_{IC1}\Delta_2 ic_{it} + \alpha_{L1}\Delta_2 l_{it} + \gamma_1 Age_i + \mu_1 tshare_{it-2} + \Delta_2 \varepsilon_{1it} \text{ if innovative} \\ \Delta_2 y_{it} = d_2 + \beta_{K2}\Delta_2 k_{it} + \beta_{IC2}\Delta_2 ic_{it} + \alpha_{L2}\Delta_2 l_{it} + \gamma_2 Age_i + \mu_2 tshare_{it-2} + \Delta_2 \varepsilon_{2it} \text{ if noninnovativ} \end{cases}$$

where t=2003 and j=1,2 according to the regime. Equation (5) and model (6) differ for the treatment of the error terms.[13] The two equations in model (6) are estimated consistently with OLS after adding the first-stage estimate of the selection mechanism. Clearly, if none of the parameters varied across groups, system (6) would reduce to its original formulation expressed in (4). We need to add an inverse of Mills' ratio to adjust standard errors and thus take care of the selectivity bias in the second stage.

Notice however that, as previously pointed out, the right-hand side input variables are potentially endogenous and need to be instrumented. For this reason we shall apply 2-step efficient GMM and LIML estimators to the

[13] The marginal distribution of the error terms $\Delta\varepsilon_{jit}$ j=1,2, can be assumed normal with zero mean and constant variance σ_j^2. The conditional means of the error terms are instead different from zero. We need to correct for the error conditional mean in order to calculate the correct standard errors. The idiosyncratic errors are in fact assumed correlated with a common shock ω_{it}, such that $E(\Delta_2\varepsilon_{1it}\,\omega_{it})=\sigma_{1\omega}$, $E(\Delta_2\varepsilon_{2it}\,\omega_{it})=\sigma_{2\omega}$. Their estimates are reported in Table 4. If at least one covariance is significantly different from zero, the endogenous switching model appears to be appropriate.

switching regression model in the second stage, so we need to choose valid instruments. As to the growth rates of the capital/labor ratio, the intermediate inputs per worker and the labor input of the innovative firms, we test (and cannot reject) the validity of the following instruments: the log-levels of gross fixed capital formation per worker in 1999 (from the AIDA balance sheet), intermediate consumption per worker in 1999, employment in 2000, the levels of investment in 2001 (as reported in the Unicredit-Capitalia questionnaire), total assets in 1999, and the age of the firm in 2001. The instruments used for the non-innovative firms are the log-levels of gross fixed capital formation per worker in 1999, intermediate consumption per worker in 1999, employment in 2000 and the age of the firm in 2001. These are the so-called “excluded instruments”, while size, area, sector, group dummies, average age of boards and past share of temporary workers are the “included instruments”.

6. Results

6.1. *Estimates when the choice to become innovative is exogenous*

If the decision to innovate is exogenous, equation (5) can be estimated with the robust OLS estimator, weighing observations as previously discussed. Table 3 shows the coefficient estimates and robust standard errors of the variables of interest on labor productivity growth, interacted with the innovation dummy. Column (1) reports estimates related to eq.(5) for the full sample. Column (2) reports estimates related to eq.(5) as well, but with family firms drift and interactions. All the regressions include control variables such as size, geographical areas, industry dummies, as well as a group dummy which in previous work (see for instance Parisi, Schiantarelli and Sembenelli, 2006) was shown to be a significant correlate of firms' productivity performance.

The innovation dummy drift is statistically significant at the one per cent level, with a point-wise estimate of 32.8. There is also a significant marginal effect (adding up the drift and the slope coefficients) of innovation of about 2 percentage points for the innovative firms, even in the slowdown years considered. Other estimates, not reported here, indicate that the drift is even higher for firms introducing process innovations, while it is smaller and only borderline significant for firms introducing product innovations.

For all types of firms, the coefficient of the log-employment is strongly significant and negative. This implies that the OLS estimates of long difference regressions deliver decreasing returns to scale in our sample. In particular, the estimated coefficients of capital and intermediates are small (even significantly negative for capital among non-innovative firms), comparatively much smaller than the numbers obtained from standard production function regressions. Yet the standard estimates of about one third for capital and about one half for intermediates arise from level specifications, while here we chose to adopt a (long) difference specification. This is known to lead to an attenuation bias, as found in Olley and Pakes (1996) and, with Italian data, Pozzi and Schivardi (2012). We checked however how results would change when estimating the production function in levels as well as in first differences. Level 2SLS-estimates delivered more conventional results for the size of the coefficients of capital and intermediates and did not reject the assumption of constant returns to scale. First difference regressions gave instead results in line with our findings. Both sets of results are not reported here but are available on request.[14]

Our main variables of interest are the proxies of experience on the manager and the worker side. Here the asymmetry between innovative and non-innovative firms matters. For the group of the innovative firms, the OLS estimate of the managerial age coefficient is negative and statistically significant. The point-wise estimates indicate that a one-year increase in the average age of the board translates into lower productivity growth of some 0.43 percentage points. The effect is instead zero (positive but statistically insignificant) for the firms that belong to the non-innovative group. Seemingly, then, being endowed with older board members and managers does not hamper productivity growth for 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 asymmetry is not there. The estimated coefficient for the share of temporary workers is statistically negative for both categories of firms, with point-wise estimates of -0.13 for innovative firms and -0.17 for non-innovative firms. Again, though, the estimated parameter for the innovative group is more precisely estimated. The

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[14] More precisely, upon substituting equation (2) and (3) in equation (1), we estimated the latter in levels, to verify the "attenuation bias" effect – assuming different distributions of the error term and by also adding dynamic terms in the equation. We found higher coefficient estimates for the capital stock and intermediate consumption than our estimated coefficients in equation (5) and system (6). This indicates consistency with other studies.

Wald test for parameter equality, in this case, cannot reject the null hypothesis. In a nutshell, a firm endowed with a high share of temporary workers always exhibits lower productivity growth, no matter what its innovation activity. The equality tests for age, the capital-labor ratio and labor coefficient all reject the null of equal parameters (the p-value of the tests is less than 0.01). In general, the Wald tests show that the constrained model should be rejected. This is why we apply an endogenous-regime-switching regression whose results are reported further below.

As to family firms, the family dummy enters the specification both as a constant and as an interaction term with age. We can thus test whether being a family firm changes the drift in productivity growth and changes the slope of the age impact. It appears that the drift is not significant,[15] but the marginal effect (drift + slope of board age) on productivity growth is +1.85 per cent for family firms, and +1.05 per cent for non-family firms, at the same mean age. On the other hand, if age varies, age has a significantly negative impact (-0.22 per cent) on productivity growth for non-family firms, and even greater negative impact (-0.33 per cent) for family firms, as expected. If they innovate, the impact of one more year in age is even greater (-0.48 per cent) – as shown in column (2) – for family firms.

6.2 Estimates when the choice to become innovative is endogenous

Firms may be innovative or non-innovative depending on the amount of money they spend in R&D, the amount of

[15] In our sample, the average productivity long-run growth in 2001-03 is lower for family firms than for other firms as shown in Table 2.

cash flow they are endowed with and – possibly – the stock of experience of their workers and managers. If we can measure their effort in "innovation investment", we can estimate the probability for them to become innovative. Table 4 shows the results from the two-stage model (6), which takes into account the endogenous formation of the two sub-samples of firms. First, it reports the results from the first-stage probit. The probability of introducing an innovation depends positively and significantly on engaging into R&D activity, having R&D workers, cash-flow, and slightly on being a family firm. It depends negatively on the share of temporary workers, and board age in family firms.

The second stage is estimated through OLS, efficient GMM and LIML methods. The OLS (with jackknifed residuals) estimates of column (1) and (2) – expectedly – rather closely replicate the results in Table 3, with improved precision. As to the overall goodness of fit, the regressions for the innovative firms tend to exhibit a larger R^2 (0.44 vis-à-vis 0.33). Capital and intermediates are positively related to productivity growth, though with "too low" coefficients (but statistically significant and rightly signed). Returns to scale are still decreasing. Managerial age is negatively related to productivity for innovative companies and unrelated to productivity for non-innovative companies. Workers' experience (i.e. the share of temporary workers) is negatively correlated with productivity, with coefficients now precisely estimated but stronger for non-innovative firms than for innovative firms. The switching regression correction (the coefficient of Mills' ratio) is negative and non statistically significant for OLS estimation. The OLS estimates of the endogenous switching regressions are unfortunately biased, however, when inputs are endogenous, as is the case of a production function framework. Hence the model must be re-estimated using an instrumental variable method.

We apply a 2-step efficient GMM estimator [16] on the “excluded” and “included” instruments listed in the Empirical strategy section. The p-values of the Sargan-Hansen test are reported for each column in the last row of Table 4. The test never rejects the validity of these instruments.

The GMM results in column (3) and (4) tend to replicate most of the OLS results reported above, with two main important differences. First of all, the decreasing returns to scale disappear. The returns to scale coefficient is no longer significantly different from zero. This is the likely side effect of having input levels in the instrument list. The intermediate inputs’ coefficient goes up to 0.55 for innovative firms and 0.65 for non-innovative firms. These numbers are consistent with commonsense and resemble the results of previous studies. The capital coefficient remains instead rather low and not too far from 0.05. This is not very surprising, however, bearing in mind that (as in Burnside, Eichenbaum and Rebelo, 1996) the relatively high coefficient of the intermediates may also be capturing the effect of capacity utilization, hence effectively “stealing” a part of the effect of capital on productivity.

We also notice that the switching regression correction is positive and significant for innovative firms and negative and significant for non-innovative ones. In other words, the selection correction does play a role: the unmeasured factors affecting innovation and productivity are positively or negatively correlated, conditional on measured factors.

Another noticeable feature concerns size and significance of the experience variables. The impact of board members’ age on productivity is again negative and statistically significant for innovative firms, slightly

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[16] This is consistent and efficient in the presence of arbitrary heteroskedasticity of the residual variance.

lower than in the OLS case ($\gamma_{1,GMM}$ = -0.31). For non-innovative firms, the positive but statistically insignificant OLS parameter becomes a positive and well determined significant coefficient ($\gamma_{2,GMM}$ = 0.52). The asymmetry between innovative and non-innovative firms in terms of managerial age is quite evident here. Finally, the GMM estimates of the correlation between workers' experience and productivity appear reinforced with respect to the OLS case.

To gauge the numerical implications of our GMM findings, one may run a simple thought experiment and ask what would occur to productivity if, contrasting current demographic trends, firms were endowed with less experienced managers and workers. Suppose first that board members were younger by five years in both groups of firms (about one half of a standard deviation in the board members' age distribution). Our estimates suggest that yearly productivity growth would be 1.6 per cent higher for innovative firms, and 2.2 per cent lower for non-innovative firms. A similar experiment can be run for the share of temporary workers. If this share were higher by 5 percentage points with respect to its observed average, our estimates would predict lower productivity growth by 1.7 per cent for innovative firms, and by 3 per cent for non-innovative firms. These are large numbers. Yet even lowering managerial age by five years and the share of temporary workers by five percentage points would almost entail a revolution in Italy's management and labor practices. So these effects are not implausibly large.

To further check the robustness of our results, we also apply the Limited Information Maximum Likelihood (LIML) estimator (for endogenous regressors and excluded instruments) and the results are shown in column (5) and (6). This estimator is consistent and efficient under homoskedasticity and independence of the residuals.[17] They do not greatly differ, though, from the GMM results commented above.

Despite our efforts to make up for the potential endogeneity of our regressors and, notably, of our main variables of interest we cannot rule out that at least a fraction of the correlation of managerial age and temporary workers with productivity growth is driven by reverse causation. Evaluating the extent of the potential bias is not obvious though. Take managerial age first. We estimated that average age is negatively related to productivity growth for innovative firms ($\hat{\gamma}$<0) and positively for non-innovative firms ($\hat{\gamma}$>0). We may capture the fact that fast growing firms attract the best managers. If the best managers for innovative firms are young, then the true coefficient for innovative firms would be less negative (hence closer to zero) than the value provided in our estimates. For non-innovative firms, the argument is less clear-cut instead. The innovativeness advantage of youth might be offset by experience, hence the presence of a bias is less likely in this case. As to the share of temporary workers, $\hat{\mu}$<0 for both types of firms. This may also be the result of reverse causation, if firms whose productivity is growing less are more inclined to disproportionately hire temporary workers or transform permanent into temporary positions. If this were the case, our coefficients would

[17] Nonetheless, Davidson and MacKinnon (2004) show that the jack-knifed IV estimator is almost always inferior to LIML in terms of consistency and efficiency, particularly when instruments are weak. LIML is equivalent to a "continuously updated" GMM estimator that maximizes the criterion function using an optimal weighting matrix at each iteration (more than 2-steps). For these reasons we prefer the 2-step efficient robust GMM to all other results.

overestimate the effect of workers' lack of experience on productivity. In any case, the extent of the possible bias would depend on the covariance structure of the variance-covariance matrix of the regressors.

7. Robustness checks

In Table 5 we implement three robustness checks concerning column (1) and (3) of Table 4. First of all, we check the validity of our identifying assumption that R&D affects productivity growth only through the decision to innovate. The results for this experiment are shown in column (1) and (2) of Table 5. 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. On the other hand some firms, not introducing innovations in the period, appear to have sunk resources into R&D activities, and plausibly this has directly increased productivity. A caveat stems from the measure of R&D investments: this is missing for several firms in the questionnaire, including those reporting that they were active in R&D.[18] This is why in our preferred two-stage regressions we use the information given by the dummy "R&D active": all firms answered that question.[19] The results are more clear-cut for cash flow, see column (3) and (4). The second-stage coefficient of the cash flow is not

[18] So we must make a strong assumption on the investment levels of those firms, to be able to use R&D per worker as a regressor. Coefficients estimates could thus be biased.

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

significant for both types of firms.[20] The coefficients of the other variables do not change with respect to Table 4. Altogether, in our opinion, these results do not give enough room to modify our preferred model.

Third, we want to check whether our results are partly driven by having almost half of the sample being family-owned. Both the drift and the interaction with board age (slightly significant in the probit estimation) are not significant in the second stage.

As a further check, we used the "Movestay" algorithm by Lokshin and Sajaia (2004) to estimate the model with ML-Endogenous Switching. This method allows us to estimate the parameters in an efficient way, but requires the right-hand-side variables to be exogenous. We do not report that evidence here, because we consider LIML in Table 4 more suitable for our case.

8. Conclusions

In this paper we have exploited micro data from a sample of innovative and non-innovative firm-observations to describe the pattern of correlation between experience, innovation and productivity growth during a period of serious productivity slowdown in the Italian economy. Although using specific proxies for experience, i.e. average board members age for "managerial experience" and the share of temporary work for "workers' experience", our results seem to indicate that both workers' and managerial experience matter for productivity growth.

As far as we know, no previous study jointly evaluated

[20] 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.

the role of board members' and workers' experience as determinants of the company decision to innovate and raise productivity. Our contribution is thus threefold. We consider at the same time board members' demography and workers' tenure as relevant factors for a firm to become innovative and raise its productivity. We do so using a two-stage decision process that has not been used in previous studies. And we apply our method to a case in point, Italy's manufacturing firms caught at a time of a technological revolution.

To capture the twofold role of experience, the whole sample is split into innovative and non-innovative clusters and the decision to innovate is endogenously modeled. Managerial age appears to be positively correlated or uncorrelated with productivity growth if firms are non-innovative, while it is robustly negatively correlated with productivity growth for the innovative ones. This pattern is consistent with common sense and the evidence reported in previous studies that indicate a more positive role of experience in firms with relatively standardized and stable business practices. Seniority and old age are instead damaging innovative firms that are supposed to swiftly adopt new technologies as they become available. Lack of experience on behalf of workers is instead unambiguously bad for both categories of firms: the share of temporary workers in the firm workforce is always negatively correlated with productivity growth. Altogether, the robustness checks that we implemented indicate that the partial correlation between workers' and managerial experience, innovation and productivity is a robust one.

We are aware of the fact that the study of averaged firm data is not problem free. Yet the potential biases from cross-sectional estimates arise if and only if the unobserved (unmeasured) firm characteristics are correlated with the included explanatory variables. We take care of this potential bias by employing GMM and LIML estimators on a long-differenced specification.

Finally, a flurry of studies has lent considerable attention on the reverse chain of causation, namely the labor market implications of product and process innovation. Our expectation is that, by choosing predetermined instruments such as the age of the firm, we are lessening such simultaneity problems. Surely, a lot of unobserved heterogeneity in plant productivity is still in the data even if we have augmented the list of determinants with dummies and other control variables. Future work in this area will shed more light on issues whose understanding is crucial to make sense of the determinants and the consequences of innovation.

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Appendix A: Checking for sample selection bias

We controlled for sample selection that could actually come up when Capitalia-Unicredit IX survey data were matched with AIDA balance sheet/account statements of firms present in 2001-2007. Not all Capitalia firms exist in AIDA. Nonetheless, we managed to retain almost 86% of the Capitalia sample. Therefore, we checked how firms differ in-sample and out-of-sample.

Figure A1 shows the distribution, by class of workers, of the firms falling in and out of our 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 $\chi(4) = 25.75$, p-value = 0.0) meaning that being in or out of sample depends in a certain way on firm size.

We lose 15.6% of firms located in the North-West of Italy, 13.9% of the firms located in the North-East, 13.5% of the firms located in the Centre and 15.8% of the firms located in the South. The Pearson $\chi(4) = 3.42$ with p-value = 0.49 says that being in or out of sample does not depend on the regional distribution.

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 independence between in and out of sample (Pearson $\chi(1)$ test = 0.39 with p-value=0.53).

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 the firms outside the sample are on average three years older than those in sample (32 versus 29 years, approximately), and the difference in means is statistically significant, as indicated by the results reported below.

Table A1. Difference in firm age in and out of sample

	Mean	Std. Err.	[95% Conf. Interval]	
Diff in age out vs in	3.00	0.887	1.259	4.742
Ha: diff < 0	Ha: diff ≠ 0		Ha: diff > 0	
t = 3.379	t = 3.379		t = 3.379	
P < t = 0.9996	P > |t| = 0.0007		P > t = 0.0004	

Note: Degrees of freedom for the test: 4037. Ho: mean(out) - mean(in) = diff = 0

Finally, we run 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 panel. The Pearson chi-square tests are listed below for the various types of innovation activity.

Table A2. Test for independence between innovation activity and in or out-of-sample firms.

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

We reject the hypothesis of independence for R&D expenditure (at 10% level) and product innovation only (at 1% level). This implies that firms investing in 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 provides a firm equal probability to remain in our sample.

Figure A1. In and Out Sample distribution of Capitalia-AIDA firms by size

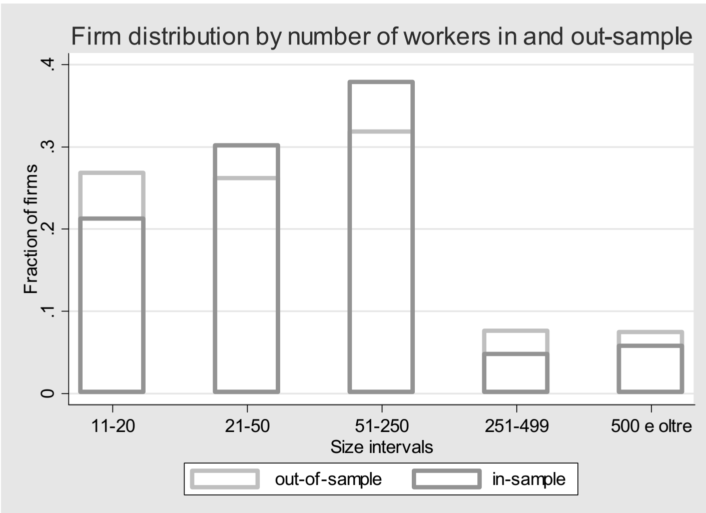
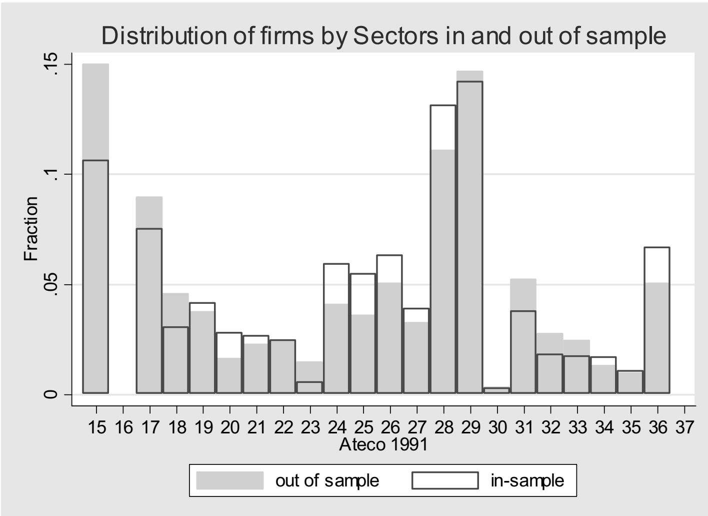


Figure A2. Distribution of firms by Ateco 1991 classification, in and out-sample



Appendix B: Sample distribution by strata

The distribution of our final sample is reported in the following table. As explained in the text, our analysis is concentrated on manufacturing sectors. The questionnaires to collect survey data were submitted to a representative sample of 4177 firms. The sample construction is based on a stratification method for firms up to 500 employees, while all firms with more than 500 employees are surveyed. Strata are formed by sectors, areas and size.

Macro areas are defined by the Italian National Institute of Statistics (ISTAT) which groups Italian regions into: 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). Small firms have at most 50 employees, Medium firms have 50-250 employees and Large firms more than 250 workers.

Table B1. Geographical distribution of the sample

Firms	Small	Medium	Large	Total
North West	59 (5.66%)	235 (22.55%)	82 (7.87%)	376 (36.1%)
North East	63 (6.05%)	230 (22.07%)	61 (5.85%)	354 (33.9%)
Centre	37 (3.55%)	99 (9.50%)	24 (2.30%)	160 (15.4%)
South	47 (4.51%)	94 (9.02%)	11 (1.06%)	152 (14.6%)
Total	206 (19.8%)	658 (63.1%)	178 (17.1%)	1042 (100%)

We also report the distribution of board size in the sample, for all and innovative firms, and the mean board age within each cell. This distribution is used to weigh our OLS and GMM or LIML estimates.

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Table B2. Firms distribution by board age

Board members	Firms	Innovative	Mean board age	Members age Class	Firms
1-2	122 (11.7%)	90	48.8	<29	6
3-5	188 (18%)	127	50.7	30-39	33
6-7	200 (19.2%)	144	50.2	40-49	439
8-10	334 (32.1%)	258	49.4	50-55	295
11+	198 (19%)	149	48.6	56-60	83
Total	1042 (100%)	768	49.6	61-65	33
Max n. = 65	1 (0.1%)	1	47.0	>65	15

Table 1. 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 2001-03 period, [b] in percentage points, [€] in thousands of euro.

Table 2. Average characteristics by type of firms.

	INNOVATIVE	NON INNOVATIVE	FAMILY	NON FAMILY
$\Delta_2$log(Production/L)$_{2003}$	2.62 (29.5)	0.68 (32.9)	1.56 (27.6)	2.60 (32.7)
$\Delta_2$log(Capital Stock/L)$_{2003}$	19.1 (43.1)	13.5 (38.5)	17.4 (42.3)	15.7 (36.0)
Temporary Workers Share$_{2001}$	3.98 (11.8)	4.87 (14.1)	4.88 (14.5)	3.6 (9.9)
Average Board Age (years)	49.4 (12.4)	50.4 (12.6)	49.5 (6.6)	49.7 (6.3)
Part of a group	51.1	45.9	25.1	72.9
Undertake R&D activity	73.7	34.3	61.3	65.3
Share of R&D workers$_{2001}$	9.5 (39.4)	1.8 (6.2)	3.9 (6.4)	3.9 (8.6)
Cash flow/L$_{2001}$ (euro)	22916 (39106)	23579 (33804)	21339 (23373)	24794 (47751)
Number of firms	768 (73.7%)	274 (26.3%)	514 (49.3%)	528 (50.7%)

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 in 2001-03.

Table 3. OLS estimates of productivity growth determinants as in equation (5)

Dependent variable	(1)		(2)	
$\Delta_2 \ln y_{it}$	Coefficients	Robust Std. Error	Coefficients	Robust Std. Error
Innovative firms (indexed as "1" firms in the tests below)			**with family drift and interact.**	
δ_1 (intercept for innovative)	32.13***	6.308	32.80***	6.479
δ_2 (family)			7.20	5.117
δ_3 (family x age)			-0.48***	0.068
γ (Age)	-0.43***	0.046		
μ (share of temporary work)	-0.13***	0.023	-0.13***	0.023
β_K (capital per worker)	0.05***	0.014	0.05**	0.014
β_{ic} (intermediates per worker)	0.13***	0.013	0.13***	0.013
α_L (returns to scale)	-0.50***	0.035	-0.50***	0.035
Constant	-10.91§	6.574	-16.13*	8.004
Non innovative firms (indexed as "2" firms in the tests)				
δ_3 (family x age)			0.11	0.115
γ (Age)	0.18	0.117		
μ (share of temporary work)	-0.17	0.112	-0.17	0.113
β_K (capital per worker)	-0.03	0.024	-0.03	0.024
β_{ic} (intermediates per worker)	0.12***	0.020	0.12***	0.020
α_L (returns to scale)	-0.31***	0.055	-0.31***	0.056

Tests of parameter homogeneity between innovative and non-innovative firms				
$\beta_{K1} = \beta_{K2}$	[0.008]**		[0.009]**	
$\beta_{IC1} = \beta_{IC2}$	[0.794]		[0.821]	
$\beta_{L1} = \beta_{L2}$	[0.000]***		[0.000]***	
γ_1=γ_2 (F=1 and F=0)	[0.000]***		[0.000]***	
γ_1=γ_2 (D=1)			[0.271]	
γ_1=γ_2 (D=0)			[0.111]	
μ_1=μ_2	[0.693]		[0.736]	
CRS/D_1	[0.000]***		[0.000]***	
CRS/D_2	[0.000]***		[0.000]***	
R^2	0.333		0.334	
N	7977		7977	

note: The table reports coefficient estimates and drifts of equation (5). F = family-owner dummy, D = innovating firm. Family firms are 514 in our sample, 49.3% of total sample. § p<0.10, * p<0.05, ** p<0.01, *** p<0.001. P-values are reported in brackets. Size, area, sector, group dummies are included. Wald tests are Chi-square(1). Rejection means that the estimates are statistically different for the two groups (for γ the test is performed on inno (D=1) or non-inno (D=0) and family (F=1) or non-family (F=0) firms). CRS tests whether $\alpha_L = -[1-(\beta_K + \beta_{IC} + \beta_L)]$=0. Its rejection is a symptom of non-constant returns to scale.

Table 4. Two-stage endogenous switching estimation of system (6).

First stage $P(D=1)$	(F1) Probit	Second stage $\Delta_2 \ln \frac{Y}{L}$	(1) OLS Innov	(2) OLS Non Innov	(3) GMM Innov	(4) GMM Non Innov	(5) LIML Innov	(6) LIML Non Innov
R&D yes	0.699***	β_K (Capital)	0.0424**	0.0494*	0.0611**	0.0216	0.0590*	0.0233
			(0.0148)	(0.0247)	(0.0231)	(0.0837)	(0.0239)	(0.0844)
ln-R&D labor_{t-1}	0.290***							
		β_{IC} (Interm.)	0.132***	0.171***	0.550***	0.657***	0.578***	0.664***
Cash flow_{t-2}	0.0013*		(0.0132)	(0.0259)	(0.138)	(0.140)	(0.147)	(0.142)
CDA Age	-0.004	α_L	-0.509***	-0.206***	-0.0560	-0.0448	-0.0354	-0.0465
			(0.0359)	(0.0588)	(0.122)	(0.367)	(0.128)	(0.371)
Tshare_{t-2}	-0.01***							
		γ (CDA Age)	-0.418***	0.158	-0.314***	0.523**	-0.311***	0.528**
Firm age	-0.0006		(0.0472)	(0.137)	(0.0778)	(0.196)	(0.0802)	(0.197)
F	0.64*	μ (tshare)	-0.121***	-0.265*	-0.172***	-0.469***	-0.177***	-0.471***
			(0.0230)	(0.125)	(0.0447)	(0.111)	(0.0464)	(0.112)
F#CDA Age	-0.013*							
		$-\sigma_{\varepsilon_1\omega}$	-1.338		-13.33**		-14.12**	
			(1.286)		(4.302)		(4.549)	
		$\sigma_{\varepsilon_2\omega}$		-3.251		-5.899*		-5.971*
				(2.889)		(2.967)		(2.991)
Constant		Constant	35.32***	-12.37	34.92***	-38.44**	35.22***	-38.82**
			(3.204)	(8.296)	(4.489)	(11.88)	(4.643)	(11.98)
Observations		Observations	5827	1914	5564	1882	5564	1882
R^2		R^2	0.441	0.161	0.0125	-0.201	-0.0483	-0.213
		β_L (Labor)	0.316	0.573	0.333	0.277	0.327	0.266
		Sargan p-val.			[0.710]	[0.447]	[0.719]	[0.448]

Note: Probit at stage 1, OLS, 2-step GMM, LIML on weighted observations at stage 2. Sector, size, area, group dummies included. Jackknifed standard errors in parentheses and p-values in brackets. § *p<0.10*, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *F* = family firm. Instruments used in column 3 and 5, for innovative firms: ln-Gross Fixed Capital Formation per worker in 1999, ln-Intermediate Consumption per worker in 1999, ln-Employment in 2000, ln-investments, Total assets in 1999, age of the firm at the beginning of the period 2001. Instruments used in column 4 and 6, for non innovative firms: ln-Gross Fixed Capital Formation per worker in 1999, ln-Intermediate Consumption per worker in 1999, ln-Employment in 2000, age of the firm at the beginning of the period 2001.

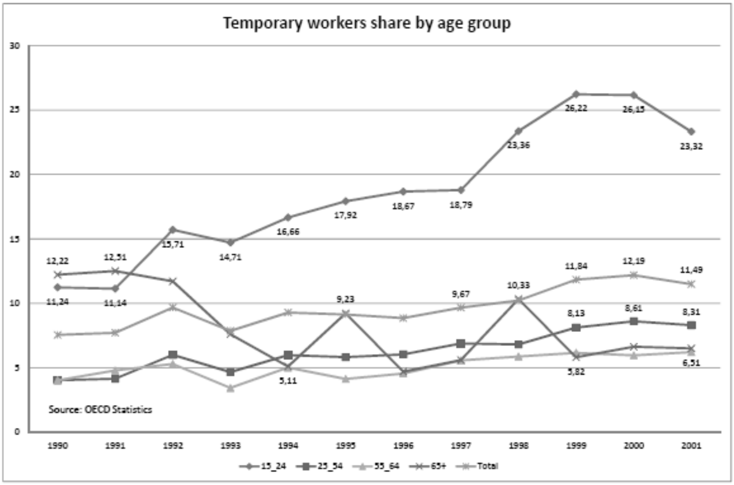
Table 5. Robustness checks for identifying restrictions, in the two stage endogenous switching regressions (innovative)

	(1) OLS	(2) GMM	(3) OLS	(4) GMM	(5) OLS	(6) GMM
β_K (Capital)	0.0193	0.0395*	0.0353*	0.0610**	0.0419**	0.0655**
	(0.0173)	(0.0199)	(0.0152)	(0.0223)	(0.0148)	(0.0219)
β_{IC} (Intermediates)	0.213***	0.305***	0.155***	0.514***	0.132***	0.516***
	(0.0229)	(0.0734)	(0.0166)	(0.142)	(0.0133)	(0.120)
α_L (returns to scale)	-0.491***	-0.540***	-0.503***	-0.0356	-0.511***	-0.0833
	(0.0409)	(0.0737)	(0.0366)	(0.129)	(0.0362)	(0.107)
γ (Age)	-0.557***	-0.494***	-0.414***	-0.340***	-0.457***	-0.446***
	(0.0666)	(0.0731)	(0.0494)	(0.0746)	(0.0692)	(0.109)
μ (tshare)	-0.0436	-0.0244	-0.125***	-0.178***	-0.121***	-0.163***
	(0.0246)	(0.0391)	(0.0228)	(0.0453)	(0.0228)	(0.0417)
$-\sigma_{\varepsilon_1\omega}$	2.624	-6.158	-4.237**	-12.27**	-1.388	-12.59**
	(4.256)	(5.541)	(1.316)	(4.316)	(1.291)	(3.897)
R&D per w.	-0.437	-0.382				
	(0.592)	(0.590)				
Cash flow int.$_{t-1}$			-1.874	-0.00123		
			(5.478)	(0.00102)		
F					-2.925	-12.15
					(5.064)	(7.572)
Age#*F*						0.233
						(0.151)
Constant	41.27***	38.17***	35.19***	35.51***	36.66***	41.41***
	(4.997)	(3.953)	(3.340)	(4.564)	(4.229)	(6.368)
Observations	3848	3701	5433	5502	5827	5564
R^2	0.563	0.571	0.457	0.0822	0.442	0.0809
β_L (Labor)	0.277	0.116	0.307	0.389	0.315	0.335
Sargan test p-val.		[0.0000126]		[0.782]		[0.648]

Notes: OLS and GMM on weighted observations. Sector, size, area, group dummies included. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

R&D per w. = ln-R&D expenditure per worker, lagged Cash flow int. = Cash flow over Production, F = family firm. Due to many missing values in R&D investments, the sample in column (1) and (2) reduces significantly.

Figure 1: The share of temporary employment goes up after 1996 and is much higher for youngsters



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