Department of Economics and Statistics "Cognetti de Martiis"
Campus Luigi Einaudi, Lungo Dora Siena 100/A, 10153 Torino (Italy)
www.est.unito.it

Dipartimento Economia e Statistica Cognetti de Martiis

Working Paper Series

04/15

CORPORATE GOVERNANCE, INNOVATION AND FIRM AGE: INSIGHTS AND NEW EVIDENCE

STEFANO BIANCHINI, JACKIE KRAFFT, FRANCESCO QUATRARO and JACQUES RAVIX

Bureau of Research on Innovation, Complexity and Knowledge

UNIVERSITÀ DEGLI STUDI DI TORINO

The Department of Economics and Statistics "Cognetti de Martiis" publishes research papers authored by members and guests of the Department and of its research centers. ISSN: 2039-4004

Corporate Governance, Innovation and Firm Age: Insights and New Evidence

Stefano Bianchini[a,b], Jackie Krafft[c], Francesco Quatraro[c,d,e*], Jacques Ravix[c]

a) Sant'Anna School of Advanced Studies

b) BETA, Université de Strasbourg

c) Université de Nice Sophia Antipolis and GREDEG-CNRS

d) Collegio Carlo Alberto

e) Department of Economics and Statistics Cognetti de Martiis, University of Torino

ABSTRACT. This paper investigates the relationship between corporate governance (CG) and innovation according to firms' age by combining insights from the recent strand of contributions analysing CG and innovation with the lifecycle literature. We find a negative relationship between CG and innovation which is stronger for young firms than for mature ones. The empirical analysis is carried out on a sample of firms drawn from the ISS Risk Metrics database and observed over the period 2003-2008. The parametric methodology provides results that are consistent with the literature and supports the idea that mature firms are better off than young ones. We check for possible non-linearities by implementing a non-parametric analysis and suggest that the negative relationship between CG and innovation is mostly driven by higher values of CG.

JEL Classification Codes : G30, L20, L10, O33

Keywords : Corporate governance, Age, Lifecycle, Innovation, Non-parametric regression, ISS Risk Metrics

*Corresponding address: Francesco Quatraro, Department of Economics and Statistics, University of Torino, Lungo Dora Siena 100 A, 10153 Torino (Italy). Email: Francesco.quatraro@unito.it.

The relationship between corporate governance (CG) and innovation has received increasing attention in recent years. This strand of literature is grounded on the core theoretical underpinnings of CG dating back to Jensen and Meckling (1976) who showed that better governed firms have more efficient operations resulting in higher expected future cash-flow streams, also favoured by the market for corporate control (Jensen, 1986). Principal-agent theory is the starting point of most discussions of CG (Shleifer and Vishny, 1997). Agency problems can affect firm value and performance via expected cash flows for investors and the cost of capital. Good CG means that 'more of the firm's profit would come back to (the investors) as interest or dividends as opposed to being expropriated by the entrepreneur who controls the firm' (La Porta, Lopez-de-Silvanes and Shleifer,2002, p. 1147). Risk and expected returns are negatively related and thus investors perceive well-governed firms as less risky and better monitored and tend to apply lower expected rates of return which leads to higher firm valuation.

In this framework, R&D investments are considered as similar to any other type of investment and much of the empirical focus has been on international comparisons inspired by the influential work of LaPorta, Lopez-de-Silvanes, Shleifer and Vishny (1997, 1998, 2000a, 2000b). Theoretical and empirical contributions identify differences between countries' legal systems and show that these differences relate to the way in which economies and capital perform (Levine, 2005; LaPorta, Lopez-de-Silvanes and Shleifer, 2008). In the meantime, a substantial body of research shows that not only cross-country but also cross-firm differences related to governance have significant effects on firm value and performance (Bebchuk, Cohen and Ferrell, 2008; Bebchuk and Weisbach, 2010; Core, Guay and Rusticus, 2006; Gompers, Ishii and Metrick, 2003). This literature on international comparisons investigates firm-level differences in more detail. Aggarwal, Erel, Stulz and Williamson (2010) contribute by comparing non-US and comparable US firms in terms of corporate governance scores, showing that, on average, non-US firms fare worse than comparable US firms.

Firm-level analyses suggest that R&D investments of firms can hardly be considered equal to other investments and this could lead to potential underestimation of important issues. Factors such as appropriability, asymmetric information and high risk in decision-making induce more careful monitoring, resulting eventually in higher costs of capital. This may involve firms opting for short-term rather than long-term strategies (Holmstrom, 1989).

The mechanism through which CG probably affects innovation performance is indeed at least twofold. On the one hand, good governance involves better monitoring, greater transparency and public disclosure, an increase in investor trust, a decrease in manager discretion and rent expropriation, less risk, efficient operations, etc. This should be beneficial to all investments, including innovative ones. On the other hand, good governance puts a large emphasis on the interests of the shareholders as a primary goal and this may be detrimental to innovative investments since shareholders and investors are mostly interested in dividends and returns on investments rather than R&D or patent strategy per se, and a short-term perspective may prevail while innovation is long term.

Many empirical studies focus on the impact of anti-takeover provisions on firm innovation so as to ascertain whether the managerial myopia hypothesis (Stein, 1988) or the quiet life hypothesis (Bertrand and Mullainathan, 2003) hold. According to the first hypothesis, the threat of hostile acquisition can lead managers to avoid undertaking long-term, risky investments because these projects can lead to a wide divergence between market and intrinsic values. Takeover provisions may shield managers from concerns related to short-term performance and permit a more long-term, value-maximizing investment strategy that encourages greater innovation. Alternatively, based on the second assumption, if the presence of takeover protection reduces the effectiveness of the external disciplinary market then managers may be able to avoid difficult and risky investments, especially if these show that managers are of lower quality. In a recent paper, Atanassov (2013) combines financial data available in S&P's Compustat database with the NBER patent file. The data includes 13 339 US firms, over the period 1976 to 2000. The results show a significant decline in the number of patents and citations per patent for firms located in the US states that pass anti-takeover laws compared with the ones that did not. In the meantime, Becker-Blease (2011) uses the IRRC and merges the data with Financial accounting standards and NBER patent database. The study covers the period 1984-1997 and the sample is composed of 600 US firms. The results show that higher levels of 23 takeover provisions are associated with innovation efforts (R&D expenditures, awarded patents, quality of patents, number of patents awarded per $ of R&D), suggesting that innovation is positively correlated with anti-takeover provisions. Indeed, some provisions appear more important than others in this positive correlation and firm-level provisions are significant, while state-level provisions are not.

Another related strand of empirical analysis focuses on the quality of the investor. In this context Fang, Tian and Tice (2014) show that increased liquidity is associated with a reduction in future innovation. The authors identify as possible determinants increased exposure to hostile takeovers as well as the type of investors involved, especially the ones that do not gather information or do not monitor. In Brown, Martinsson and Petersen (2013), long-run R&D investments are correlated to a high level of shareholder protections, while Manso (2011) finds that a combination of stock options with long vesting periods, option repricing, golden parachutes and managerial entrenchment are necessary conditions for innovation. A similar conclusion is put forward by Baranchuk, Kieschnick and Moussawi (2014) according to whom managers are better motivated to pursue innovation when their incentive compensation scheme is over long vesting periods and when anti-takeover protection exists. Finally, Brossard, Lavigne and Sakinc (2013) report a positive relationship on R&D and provide evidence of the negative influence from impatient institutional investors on R&D spending.

The wide body of the literature on the topic seems rather mixed and is not yet conclusive on the effects of good governance practices on innovation.

With a view to disentangling how CG affects innovation, some neglected aspects must be included in the analysis. In particular, we must take into account the fact that CG may change over time: firms, depending on their stage of development throughout the life cycle, may perform differently in terms of CG and innovation. Some learning dynamics may occur over time, affecting the way in which firms manage long-term investments throughout the life cycle. This paper aims to contribute to dealing with these issues by grafting the literature on corporate lifecycle onto an analysis of the relationship between CG and innovation.

The weight of the different attributes of corporate governance is indeed likely to change across the stages of firm evolution. O'Connor and Byrne (2006) suggest that individual governance provisions such as independence, accountability and transparency can have differential importance at different moments. On average, they show that governance quality increases when firms are mature and more resources are devoted to value preservation than to value creation. This would imply that mature firms are less prone to invest in innovative projects. A completely different conclusion is reached by Saravia (2013) according to whom mature firms are likely to be characterized by increasing cash flows and decreasing investment opportunities that would stimulate overinvestments in risky projects with uncertain paybacks (such as innovation projects).

These somewhat contradictory results call for new studies linking together firms' strategic decisions and corporate governance lifecycle. Filatochev, Toms and Wright (2006) provide a framework for understanding the link which gathers together agency issues with a resource-based view of the firm. In such a context, mature firms are characterized by an extensive resource base, i.e. tacit knowledge that has been accumulated over time as well as production facilities, trade secrets, engineering experience and human capital assets. Mature firms seem to possess all the resources that are needed to manage successful innovative projects. On the contrary, young firms are characterized by a narrow resource base and are mostly dependent on external knowledge sources. In this process, the heterogeneity of investors matters with impatient capital having a focus on short-term dividends, while more committed long-run capital takes into consideration the basic characteristics of innovation of uncertainty and risk and recognizes innovation as a major driving force of economic growth.

Our paper investigates the impact of CG on innovation and stresses the importance of a firm's age in moderating such a relationship. In so doing, we gather together theoretical considerations grounded on agency theory which provide expectations on the effects of good governance practices on innovation efforts, and the literature about corporate governance and a firm's lifecycle. The contribution to the extant literature is manifold. First, there are neither empirical nor theoretical analyses focused on the interplay between CG, age and innovation. This is all the more surprising, given, on the one hand, the long documented importance of firms' lifecycles in the strategic decisions concerning the commitment of resources to innovative projects (Abernathy and Utterback, 1978) and, on the other hand, the recent interest in the impact of firms' age on their performances (Haltiwanger, Jarmin and Miranda, 2013). Our paper develops a framework and an empirical setting where CG has an impact on innovation and where firm age is explicitly considered. Second, we implement both parametric and non-parametric methodologies to estimate such relationships. Non-parametric estimations allow for the detection of non-linearities which are often not detected in parametric settings even when explicitly included in the model to be estimated. Using a Generalized Additive Model (GAM), we provide a broader understanding of the relation so we can explore and solve issues on the impact of CG on innovation that were unexplained with other techniques, such as FE and GMM. In particular, we can identify what drives and amplifies the econometric results in terms of CG scores. Third, we compare results obtained by using both input and output measures of innovation, i.e. R&D expenditures and patent applications, to get a complete picture of the impact on innovation including input and output measures. Finally, while previous studies mostly focused on single attribute measures and national data, we use an original dataset of listed firms drawn from the ISS Risk Metrics database, one of the largest international database providing a multi-attributes metrics of CG, and merged with the Bureau van Dijk ORBIS database.

The results of the paper are consistent with Holmstrom's views (1989) of the good governance model, according to which firms tend to privilege shorter-term rather than long-term strategies. We show that CG is negatively related to innovation performances and that such negative relationship is even stronger for younger listed firms. The latter may be hindered by narrower resource bases, insufficient knowledge and underdeveloped capacity to successfully manage innovation projects. Because of the younger firm age and taking into account the higher level of risk in their successful development, investors may be even more motivated to gain rewards from the innovative strategy quickly. Non-parametric analyses also suggest that non-linearities are at stake. In particular, the average negative relationship observed through parametric estimations seems to be driven mostly by innovation performances of firms with extremely high CG scores.

The rest of the paper is organized as follows. Section II presents the data and variables, while Section III describes in detail the employed methodologies and in Section IV, we show and discuss the empirical results. Finally, we relate our results to the extant literature and draw some conclusions on future research.

II. Data, measurement and sample characteristics

A. The Dataset

In this paper we use the CGQ index (Corporate Governance Quotient) from *RiskMetrics / Institutional Shareholder Services*. We focus on overall (aggregate) corporate governance ratings for a large range of international firms. Our sample is constructed using information on 2203 firms in 24 countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong (China), Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, South Korea, Spain, Sweden, Switzerland, UK) and 21 industries. The CGQ is calculated on the basis of a rating system that incorporates 8 categories of corporate governance, leading to an improved qualitative measure of 55 governance factors. The study period covered is 2003-2008 which includes the largest number of reporting firms with complete and consistent data.

The ISS Risk Metrics has been matched to the Bureau van Dijk Orbis database by using the ISIN identification code. This passage enabled us to assign patent applications to sampled firms in order to calculate their patent stock for each year.

B. Variables and descriptive statistics

B.1 Corporate Governance Quotient

Prior to being acquired by *RiskMetrics* in 2007, *Institutional Shareholder Services* operated independently as the world's largest corporate governance data provider. *Institutional Shareholder Services* developed its corporate governance rating system to help institutional investors evaluate the impact that a firm's corporate governance structure and practices might have on performance. The rating is aimed at providing objective and complete information on firm's governance practices. Importantly, these ratings are not tied to any other service provided by *RiskMetrics / Institutional Shareholder Services* and firms do not pay to be rated, although they are invited to check the accuracy of the ratings. The only way a firm can improve its rating is to publicly disclose changes to its governance structure and/or practices.

The CGQ is the output of a corporate governance scoring system that evaluates the strengths, deficiencies and overall quality of a company's corporate governance practices. It is updated daily for over 7,500 companies worldwide. Each company's CGQ rating is generated from detailed analysis of its public disclosure documents (i.e. Proxy Statement, 10K, 8K, Guidelines, etc.), press releases and company web site. CGQ is calculated by adding 1 point if the firm under scrutiny meets the minimum accepted governance standard. The score for each topic reflects a set of key governance variables. Most variables are evaluated on a standalone basis. Some variables are analysed in combination based on the premise that corporate governance is improved by the presence of selected combinations of favourable governance provisions. For example, a company whose board includes a majority of independent directors and independent board committees (audit, etc.) receives higher ratings for these attributes in combination than it would have received for each separately. Next, each company's CGQ is compared with other companies in the same index (here the index is MSCI EAFE index).[1] For example, Company A scores 24% (or 0.24) for its CGQ index which means that Company A is performing better (outperforming) in relation to corporate governance practices and policies than 24% of the companies in the MSCI EAFE index.

Table I presents the corporate governance variables. A detailed description of governance standards using the eight categories (board of directors, audit committee, charter/bylaws, anti-takeover provisions, compensation, progressive practices, ownership and director education) is provided in Krafft, Qu, Quatraro and Ravix (2014).

>>>INSERT TABLE I ABOUT HERE<<<

Our sample is composed of 2,203 non-US firms operating in 24 countries and 21 industries. Table II reports information on the composition of our sample according to NACE classification. Almost half of the sample is composed of firms operating in manufacturing, followed by financial and insurance activities. Despite a few exceptions, we have data on firms that are active in almost all sectors. As in the original database, CGQ refers to 55

[1] This is a stock market index of foreign stocks from the perspective of North American investors. The index is market capitalization weighted (meaning that the weight of securities is determined based on their respective market capitalizations). The index aims to cover 85% of the market capitalization of the equity markets of all countries that are a part of the index. It is maintained by Morgan Stanley Capital International. EAFE is Europe, Australia, Asia and the Far East.

governance factors spanning the 8 categories of corporate governance. The data are thus firm-level; all our scores are relative (percentiles) allowing for within-country as well as cross-country differences (the data explicitly consider anti-takeover provisions under national (local) law).

>>>INSERT TABLE II ABOUT HERE<<<

B.2 Innovation and other firm-level variables

Micro-level accounting data comes from the Bureau van Dijk ORBIS dataset which also provides information on firms' patent applications. Innovation performance is measured by using two conventional (and widely adopted) input and output indicators, namely R&D-to-sales intensity (i.e. total R&D expenditure over total turnover) and a number of patent applications. This choice allows us to partially control for innovation process multidimensionality.

Beside demographic characteristics such as age and size (proxied by total turnover), we introduce in our analysis a measure of cash flow to capture firm operating performance which is likely to affect a firm's innovative initiatives.

The full list of variables is reported in Table III.

>>> INSERT TABLE III ABOUT HERE <<<

Table IV shows some basic descriptive statistics. To obtain a clearer picture, in Figure I we also plot the kernel densities of the main variables under investigation, i.e. corporate governance, R&D-to-sales intensity, patent applications and age[2].

>>>INSERT TABLE IV ABOUT HERE<<<

>>>INSERT FIGURE I ABOUT HERE<<<

CGQ ranges from 0 to 1, with mean and median equal to 0.47 and 0.45 respectively. Its kernel density (Figure I) displays wide support, hence confirming the huge heterogeneity

[2]Kernel densities are computed by pooling all the observations. We estimate the density with an Epanechnikov kernel.

underlying corporate governance practices. This evidence motivates us to explicitly account for idiosyncratic firm fixed-effects in our econometric setting. Besides the CGQ in level, we also account for changes in governance practice by calculating the growth rates of CGQ. Its high standard deviation suggests that corporate governance index is indeed a quite volatile variable.

Firms in our sample are also quite heterogeneous in terms of age. The latter ranges in fact from 0 (newborn companies) to 536 years old (old established enterprises), with a mean and median of 54.38 and 44. To compress the scale we will apply a log-transformation. Basic statistics suggest that, although we have information on new nascent firms, our sample is primarily composed of incumbent established units. This evidence will drive us, when selecting a cut-off point to distinguish young/middle vs. mature firms, to look for an age threshold which is a reasonably good compromise between sample size and coherence.

Turning to innovation variables, we notice that a considerable proportion of firms in our sample (almost 10%) do not perform R&D activities (or at least they do not report any information), whilst only a few companies invest more than their turnover (see Figure I). These firms are primarily young and operating in high-tech industries.

We also account for variation in R&D intensity by computing the log-difference for each subsequent year.

On the output side, the average patent application per year has a value of 2.29. The statistical distribution displays a positive skewness so that the mass of the density is concentrated on the left tail. It should be noted that almost two-thirds of the total number of observations has value equal to zero (no patent applications). We will explicitly take into account this evidence by adopting econometric tools designed for the presence of many zeros.

With regard to the control variables, we proxy the size of the firm by using total turnover (or alternatively the total number of employees). Since cash flow (here measured in millions) is essential to solvency, its range of values depicts a robust stylized fact, meaning that there are many financially constrained companies.

To appreciate a first screenshot of the contemporaneous relationship between the entire set of variables, Table V reports the pair-wise correlation matrix (significance at 5% level are indicated by asterisks). Interestingly, there is a negative association between corporate governance index GGQ and age, as with the size of the firm. Beyond some expected relationships (for instance, the positive correlation between age and size), it should be noted that CGQ and patent applications are negatively and significantly correlated. R&D-to-sales intensity and CGQ appear, on the contrary, characterised by a positive association. However, when we look at the correlation between age and innovation variables (R&D intensity and patent applications), we detect negative relations. All in all, we can conclude that the relationships at work appear to be very complex.

>>>INSERT TABLE V ABOUT HERE<<<

III. Methodology

In this empirical study we carry out two types of statistical analyses. First, R&D-to-sales intensity and patent applications are used as response variables in a standard parametric setting to ascertain the average relationship between corporate governance, age and innovation and establish some comparisons with the extant literature. Secondly, we exploit non-parametric regression techniques to explore potential non-linearities in the relationships between corporate governance and innovation.

A. Parametric setting

We set different specifications. We first model (Fixed Effects - within transformation) the variation in R&D-to-sales intensity (RDI) as a function of corporate governance, age and a set of key controls. The baseline specified model is the following:

$$\Delta\, ln(RDI)_{i,t} = \alpha + \beta_1 ln(RDI)_{i,t-1} + \beta_2 CGQ_{i,t-1} + \beta_3 \Delta CGQ_{i,t} + \beta_4\, ln(Age)_{i,t} + \tag{1}$$

$$+\boldsymbol{\beta} \times \boldsymbol{X}_{i,t-1} + u_i + \varepsilon_{i,t}$$

while the fully specified model is as follows:

$$\Delta\, ln(RDI)_{i,t} = \alpha + \beta_1 ln(RDI)_{i,t-1} + \beta_3 \Delta CGQ_{i,t} + \beta_4\, ln(Age)_{i,t} + \tag{2}$$

$$+\sum\nolimits_k \gamma_k CGQ_{i,t-1} \times dAge_k + \boldsymbol{\beta} \times \boldsymbol{X}_{i,t-1} + u_i + \varepsilon_{i,t}$$

for each firm *i* at time *t*. $\boldsymbol{X}$ is a vector of control variables such as size, cash flow, etc. All the non-time varying determinants (e.g. technological opportunities) which are likely to influence R&D activities are subsumed in the fixed-effect term u_i. The lagged variables partially reduce the potential endogeneity between the set of covariates and the innovation proxy, but we refrain from giving any causal interpretation. In Equation (2) the variable $CGQ_{i,t-1}$ is interacted with dummy variables identifying age groups according to the distribution of age. In particular, we chose as cutoffs age_1: age <= 25° percentile; age_2: 25° percentile< age <= 50° percentile; age_3: 50° percentile< age <= 75° percentile; age_4: age>75° percentile. Thus, we cover the full age distribution of sampled firms which leads us to drop $CGQ_{i,t-1}$ from the equation. For the sake of clarity, we label the four classes as follows: i) young firms, ii) medium-aged firms, iii) old firms, iv) very old firms.

The advantage of selecting the cut-off points by splitting the distribution of age rather than choosing specific arbitrary values is that our criterion is fully data-driven; however, a series of robustness checks (see Section IV.A.1) are undertaken in order to deliver more reliable evidence.

We start by regressing CGQ index on the variation in R&D-to-sales intensity. Step-by-step we augment the model with several explanatory variables to verify whether our estimations are robust across different configurations. Although the time window we span is quite short, we include time dummies to account for potential macro-economic changes.

Subsequently, we model the innovative effort in level by implementing the Arellano and Bond (1991) two-step robust GMM estimators. The implementation of the dynamic model is derived from equation (1), by considering that $\Delta\, log(RDI)_{i,t} = log(RDI)_{i,t} - log(RDI)_{i,t-1}$.

This leads us to the following specification:

$$ln(RDI)_{i,t} = \alpha + \gamma_1 ln(RDI)_{i,t-1} + \beta_2 CGQ_{i,t-1} + \beta_3 \Delta CGQ_{i,t} + \beta_4\, ln(Age)_{i,t} + \qquad (3)$$

$$+\sum_k \gamma_k CGQ_{i,t-1} \times dAge_k + \boldsymbol{\beta} \times \boldsymbol{X}_{i,t-1} + u_i + \varepsilon_{i,t}$$

where $\gamma_1 = \beta_1 + 1$.

Turning to the innovation outcome, as highlighted in Section II.B the patent application variable presents a very skewed distribution with the presence of many zeros.

Moreover the conditional variance exceeds the conditional mean to a large extent. Thus, to analyse the effect of corporate governance on patent applications, it seems appropriate to abandon the OLS setting and adopt a zero-inflated negative binomial model (henceforth, ZINB), explicitly designed for the nature of our response variable. Indeed zero-inflated models estimate two equations simultaneously, one to describe the relationship between the response variable and the set of covariates and one to model the excess of zeros. The equation to be estimated through the ZINB is the following:

$$Patents_{i,t} = \alpha + \beta_1 ln(RDI)_{i,t-1} + \beta_3 \Delta CGQ_{i,t} + \beta_4 \, ln(Age)_{i,t} + \qquad (4)$$

$$+ \sum\nolimits_k \gamma_k CGQ_{i,t-1} \times dAge_k + \boldsymbol{\beta} \times \boldsymbol{X}_{i,t-1} + \varepsilon_{i,t}$$

We substantially re-estimate the model in eq.(1) and eq.(2), substituting patent application as a response variable. The computation burden (i.e. the convergence of the likelihood maximization problem is not achieved) of the ZINB model does not allow us to introduce firm-level fixed effects. To this end, we re-estimate a conditional Poisson (with no zero-inflation) to account for the unobserved heterogeneity[3] As for the zero-inflation, we use R&D intensity as an inflator since we expect firms will lower R&D investment to exhibit a lower propensity to patent.

B. Non-parametric modelling

We employ a Generalized Additive Model (henceforth, GAM) to incorporate non-linear forms of the covariates and examine the relation between corporate governance, innovation and age more deeply.

A brief introduction to GAM is in order. An intuitive generalization of the multiple regression model adopted so far is to maintain its additive nature but replace at least some (possibly all) terms of the linear equation $\beta_i x_i$ with $f_i(x_i)$ where f_i is a non-parametric function of the covariate x_i. The family distribution of the response variable y (R&D-to-sales

[3]Results are consistent with the ones we present throughout the article and are available on request.

intensity or, alternatively, patent applications) is specified along with a link function *g(.)* that relates the predicted values of *y* to the set of covariates $\boldsymbol{X}$. Formally:

$$g(E(y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_k(x_k) \tag{5}$$

Instead of single coefficients (i.e. the conventional beta), GAM provides a non-parametric function for each predictor. The shape of the function describes how the relationship between the covariate x_i and the response variable *y* varies along the whole spectrum of x_i. In other words, this function represents how the marginal effect varies across the full distribution of the explanatory variable under consideration, thus detecting potential non-linearities.

We follow the approach proposed by Wood (2006) by implementing a cubic spline as a smoothing function *f(x)*, essentially a connection of multiple cubic polynomial regression, that is:

$$f(x) = \sum_{j=1}^{4} b_j(x)\beta_j \tag{6}$$

where for basis we have: $b_1(x) = 1,\ b_2(x) = x,\ b_3(x) = x^2,\ b_4(x) = x^3$

As for the link function, when modelling patent applications, we set a negative binomial family distribution.

The baseline models are the equivalent to eq.(3) and eq.(4), and the main focus is on the interactions between CG index and age classes. We proceed as follows: (i) points of an explanatory variable, also known as knots, are used to generate sections (knots are placed evenly throughout the covariate values to which the term refers); (ii) separate cubic polynomials are fitted at each section according to equation (6); (iii) polynomials are joined at the knots to build a continuous curve. The estimation is conducted via penalized likelihood approach and is then separated into parametric and smooth or non-parametric parts. In our setting the only parametric component is the intercept.

IV. Econometric results and discussion

A. Parametric estimations

The first step of our empirical strategy concerns the parametric estimation of the interplay between CG, age and innovation. This latter is the dependent variable in the econometric setting and is proxied first by R&D-to-sales intensity and then by patent applications.

The results of the estimations using R&D-to-sales intensity as response variable are shown in Table VI and Table VII. In particular, Table VI reports the results obtained by estimating a static model through fixed effect panel techniques. Column (1) shows the baseline model. The growth rate of R&D intensity is regressed just against the CG index (level and growth rate). Only the CG growth rate seems to yield a statistically significant coefficient, the sign of which is negative. This supports the conjecture that the improvement of governance mechanisms leads to a decrease in R&D intensity, due to the shareholders value maximization target, which leads managers to prefer value preservation and a short-term horizon instead of value creation and long-term development.

>>>INSERT TABLE VI ABOUT HERE<<<

The second column shows the estimation including some control variables, such as age, past levels of R&D and size. The results on CG are persistent as far as both the level and the growth rate are concerned. Moreover, the statistical significance of the coefficient of ΔCGQ is largely improved. The negative sign on the lagged level of R&D is largely expected since the R&D growth rate is the dependent variable. As for size, we find a negative and significant effect on the growth of R&D intensity. This evidence contradicts the primordial conjecture advanced by Schumpeter (1943) according to which large firms should have greater economies of scale and scope at their disposal, together with an easier access to capital. Our result is more in line with the literature which hypothesizes a negative relation between size and innovation propensity, based on the potential loss of managerial control in research allocation, typical of large companies (Cohen, 1995). As argued in Acs and Audretsch (1987), size may also be interpreted as a proxy for market concentration and product market competition, thus leading to different effects depending on the sector in which firms operate. We cannot exclude a priori such a hypothesis in our data but its testing goes largely beyond the purpose of the paper.

In columns (3) and (4) the differential effects of the CGQ variable across different age classes is appreciated by taking the quartiles of the distribution of the variable age and then calculating the interactions with CGQ. It is worth stressing that the use of age quartiles is mainly motivated by the need to avoid any arbitrary choice of thresholds. The results show that the coefficient is negative and significant only as far as firms belong to the first quartile of age distribution. This means that the negative effect of CG on innovation is augmented by the young age of the firm. This result is consistent with the resource-based view approach to corporate lifecycle, according to which younger firms have on average a narrower knowledge base and weaker absorptive capacity. It is fair to note that so far our econometric specification includes the simultaneous value of size. However, regressing R&D-to-sales intensity against the simultaneous level of sales engenders severe reverse causality problems so that estimation results are likely to be biased. For this reason, in columns (5) and (6) we report the estimations obtained by including the lagged value of sales as a proxy for size. The results do not seem to be much affected by this change since the coefficient is still negative and significant and the magnitude is largely stable. We notice, however, that the standard error has increased so that the coefficient is now significant only at 10% level, while it was at 5% in the previous specifications.

Reworking equation (1), the static panel model can be turned into a dynamic one, as shown in equation (2). The results of the two-step difference GMM estimation are reported in Table VII. We follow the same structure as Table VI. Column (1) actually shows the results for the baseline model. Here the situation is reversed, with respect to Table V, as only the lagged level of CGQ has a significant (and negative) coefficient, while the growth rate of GCQ is not significant. The sign of the coefficient still suggests that improved corporate governance is associated with lower levels of R&D intensity, supporting the idea that good governance can have a perverse effect on uncertain, long-term investments.

>>>INSERT TABLE VII ABOUT HERE<<<

The situation is not altered by the introduction of control variables in column (2). These latter but size have non-significant coefficients. Size is instead characterized by a negative and significant coefficient, which is consistent with our previous results. In columns (3) and (4) we have introduced the four dummies identifying the quartiles of the distribution of sampled firms. Also in these estimations the only group showing a negative and significant coefficient is the one including the youngest firms. This result is also robust to the introduction of the cash flow variable which should minimize the confounding effect of liquidity constraints, above all, as far as young firms are concerned, or that of overinvestments also in risky projects as far as older firms are concerned. Columns (5) and (6) includes the lagged value of size, instead of contemporaneous one, so as to minimize issues due to reverse causality. The coefficient of CG for younger firms keeps being negative and significant only in the first case, as in column (6), when we add cash flow as a control variable, it is no longer significant.

In sum, when R&D-to-sales intensity is used as a measure of firms' innovation efforts, the analysis of the effects of innovation does not provide a stable picture. On the one hand, when adopting a fixed effect panel data estimator, only the growth rate of CGQ is significant (and not the level), while CGQ for younger firms yields a negative and significant effect on R&D intensity across the different specifications. On the other hand, in the estimation through dynamic panel techniques, only the lagged value of CGQ shows a negative and significant coefficient. Moreover, CGQ for younger firms yields statistically significant effects across all different specifications but that including the lagged value of size and cashflow.

While R&D intensity is a measure of input for the innovation process, patents can be considered as an output indicator. Both measures have their pros and cons. For the purposes of our analysis, patents seem to be better suited to grasping the effects of corporate lifecycle related to the accumulation of technological competences and absorptive capacity. R&D efforts are not necessarily conducive to patented innovations, as some innovative projects are successful and some others are not. The share of unsuccessful innovative projects is likely to decrease as firms get more mature as an effect of learning dynamics. Besides this, the use of R&D expenditures as a variable is not fully reliable due to different regulatory settings concerning the reporting of these expenditures in different countries.

We estimate the effects of CGQ on firms' patenting activity and the results are reported in Table VIII. Since the number of patents is a count variable and a large share of zeros is observed in the dataset, we implement a zero-inflated negative binomial (ZINB) estimation, as explained in Section VIII.A.

>>>INSERT TABLE VIII ABOUT HERE<<<

Consistently with previous estimations, we begin by reporting the baseline model in column (1). In line with GMM estimations in Table VII, only the lagged level of CGQ is negative and significant, while the growth rate is not. On average, this suggests that the better the corporate governance score, the lower the innovative output for firms. The persistence of this result provides further robustness to the hypothesis concerning the adverse effects of good governance on risky investments involving innovation. The inclusion of control variables in column (2) does not alter the picture. It should be noted that age yields a positive and significant coefficient which is largely in line with a resource-based view of the firm. Also (contemporaneous) size is characterized by a positive and significant coefficient. In columns (3) and (4), the effect of CGQ is interacted with the four dummies identifying the quartiles of the firms' age distribution. Once again the results are in line with previous estimation and show that only for firms in the first quartile, i.e. younger firms, the effects of CGQ are negative and significant, and this holds also when the cashflow variable is included in the estimation. Finally, in columns (5) and (6) we replicate the previous two estimations by including the lagged level of size instead of the contemporaneous one. The results are consistent with the evidence discussed so far, as CG is negative and significant only as far as younger firms are concerned. For firms belonging to the second, third and fourth age group, we do not obtain any significant coefficient on CGQ.

A.1. Robustness checks

The results we have shown in the previous Section may be to some extent driven by the choice of the cutoffs for the age classes, even though these are based on the distribution of the variable. For the sake of a robustness check, we report in Table VIII the estimations of the effects of CG on innovation across differently aged firms by choosing different threshold values.

>>> INSERT TABLE IX ABOUT HERE <<<

Columns (1) and (2) report the results of the ZINB estimation by using 15 years and 20 years respectively as critical values to discriminate between young and old firms. In the first case (the least inclusive one), CG is characterized by a negative and significant coefficient on both old and young firms, although for the former category the statistical significance is rather weak. If we extend the group of young firms so as to include companies aged up to 20 years, then only CG for young firms is negative and significant and the statistical significance is dramatically improved compared with the previous estimation.

Columns (3) to (6) report the estimation results of the model in which R&D intensity is the dependent variable. In these estimations, we notice that the coefficient is never significant, neither for young nor for old firms. The result is robust to different techniques (FE and GMM) and to different thresholds for the age classes.

The conclusion we can derive is that results on R&D-to-sales intensity are quite sensitive to different specifications, whereas the evidence on patent applications is very robust.

B. Non-parametric analysis: exploring non-linearities in the CGQ-innovation relationship

Previous empirical investigations have focused on the relationship between corporate governance and innovation and have extensively relied upon the implementation of parametric estimations. As stressed in Section III.B, these econometric techniques have not allowed scholars to capture potential non-linearities in such a relationship. We try to fill this gap by providing the results of non-parametric GAM estimations[4].

Figure II shows the diagrams obtained with the GAM estimation of the determinants of R&D-to-sales intensity (the grey band represents the 95% confidence interval). We show only the plots concerning the interaction of CGQ with the four age classes. Each plot shows how the coefficient of the relevant variable (y-axis) changes in response to different values of the variable (x-axis). Put differently, it shows how the marginal effect varies across the full distribution of the covariate. In the top-left diagram, we can see a straight horizontal line in correspondence to the value 0 of the coefficient. This implies that the effect of CG young seems to be null and that this holds no matter the value of CGQ. The top-right diagram concerns medium-aged firms. Here some recursive non-linearities can be detected, though the coefficient always revolves around zero. In the bottom diagrams, we can see the effects of CG for old (left) and very old (right) firms. In both cases, a quasi-straight line can be observed in correspondence to the zero value, suggesting that CG in these cases yields no significant

[4]Some notes of caution: in performing this exercise we do not account for firm-level fixed effects since the computation burden would be too high. Moreover, it should be noted that the statistical literature on non-parametric regression in panel framework is still underdeveloped. However, we account for country and industry dummies.

effects on innovation and that this holds for the whole distribution of CG. All in all, this evidence supports the results of the parametric estimation.

>>>INSERT FIGURE II ABOUT HERE<<<

In Figure III we show similar diagrams which are obtained by implementing GAM estimations in which the dependent variable is a firm's patenting activity. The top-left diagram shows the effects of CG on innovation as far as young firms are concerned. Here the result is interesting in that first of all the relationship seems to be non-linear[5] and moreover, we find evidence of negative effects (as in the parametric case), but for high values of corporate governance. This result provides further support for the idea that for younger firms the negative values for the coefficient are enacted only by very good governance practices (i.e. very high values of CGQ) that discourage risky investments, focus on short-term projects and maximize shareholders' value in a perspective of value preservation rather than value creation.

INSERT FIGURE III ABOUT HERE

The top-right plot shows the evidence concerning medium-aged firms. In this case, non-linearity is less pronounced and statistically not significant. For old firms (bottom-left) and very old firms (bottom-right), the evidence is even smoother and the coefficient always stays very close to zero.

C. Relationship with the literature

In a nutshell the results of our empirical investigations show that CG yields negative effects on innovation and that this negative relationship mostly applies to younger firms with very high standards of governance practice.

These results thus broadly contribute to the increasing strand of empirical literature that investigates the impact of CG on innovation. As for the impact of anti-takeover on innovation (Stein, 1988; Bertrand and Mullainathan, 2003; Atanassov, 2013, Becker-Blease, 2011), we generalize the prediction by Holmstrom (1989) saying that CG negatively impacts

[5]It should be noted that a quadratic from in a standard parametric setting does not capture this non-linearity.

innovation. Our data considers anti-takeover as one attribute among many others, such as a board of directors, an audit committee, charter/bylaws, compensation, progressive practices, ownership and director education. On the basis of a multi-attribute measure of CGQ the negative relationship is largely confirmed in our results, beyond pure moral hazard issues. The effect is even stronger for firms that perform well in scores, suggesting that short termism and value preservation prevail even more in their decision making. As for the quality of investors, the inconclusive and mixed results stressed in the literature can be clarified by considering different firm ages. Contradictory findings opposing long-run R&D investments correlated to a high level of shareholder protection (Brown, Martinsson and Petersen, 2013) *versus* stock options with long vesting periods, golden parachutes and managerial entrenchment as necessary conditions for innovation (Manso, 2011), may be related to the non-linearities linked to firm age. In the same vein, arguments concerning liquidity and impatient capital can be rationalized by age. Ownership structure, as well as investor characteristics, may differ radically between young firms just gone public and more mature listed firms. Innovation will be stronger as managers are encouraged to opt for value creation rather than value preservation and investors are more committed to long-run perspectives than shorter term ones. However, this should even be more so as firms are young and face a lot of uncertainty. In the literature, some contributions go towards suggesting that CG may lead to underinvestment in resource creation. Motivating the managers to give back free cash flow to shareholders is not necessarily beneficial to innovation if dividends yields are systematically preferred to re-investment in product and process innovation (Lazonick, 2007; Lazonick and O'Sullivan, 2002). Other examples exist. In a study of large French listed business groups Lhuillery (2011) notes that there is no significant influence of good governance on R&D decisions (GMM and FE), resulting in possible doubts regarding the Anglo-Americanization of European firms. Driver and Guedes (2012) test the possibility of a perverse effect of good governance on uncertain, long-term investments. Using UK data, they end up with a long-run negative effect of governance on R&D (FE and GMM). With IRRC data, O'Connor and Rafferty (2012) obtain a negative but non-robust relationship (OLS), or slightly positive one (GMM).

Our analysis opens up a new perspective by taking into account the interacting effects of a firm's age while drawing light on contrasting results in the literature based on a closer identification of what drives the observed shift in regressions. Some further theoretical efforts are expected to provide systemic account on the changes of corporate practices across the corporate lifecycle, in the same vein as O'Connor and Byrne (2006) and Saravia (2013) on the quality of CG in mature firms, and Filatotchev, Toms and Wright (2006) on the quality of resource base across different firms age. As a matter of fact, CG and its impact on innovation changes across the different percentiles and we get to know more about what drives these changes from stage to stage throughout the life cycle. In these efforts, we need to compare the results obtained by using both R&D and patents as a measure of innovation, due to the basic limitations of R&D statistics. The quality of corporate financial reporting on R&D activity and intangibles in general is often inadequate for economic analysis purposes. Therefore, R&D investments can be a source of greater information asymmetries between ownership and management and may not be properly valued by the market. In addition, national accounting laws often do not require corporation to disclose the amount of their annual R&D expenditures. Patent statistics mitigate the bias caused by these problems although they are concerned by other issues (Griliches, 1990; Pavitt, 1986) which however do not dramatically affect their explanatory power.

D. Conclusions

Empirical analyses of the relationships between CG and firm performances have mostly focused on the impact on financial performances and market value. Only recently some contributions have begun to investigate the impact of CG on innovation performances, by showing in most cases that good governance practices are associated with low levels of innovation. No attention has been devoted in this framework to the differential impact of CG on innovation across the different stages of a firm's lifecycle. This paper aims to fill this gap by investigating whether a firm's age moderates the relationship between CG and innovation and, if so, in which direction.

We carried out empirical analyses on a sample of listed firms extracted by the ISS Risk Metrics database, observed in the time period 2003-2008. The results of the parametric estimations provide support to the idea that high CG scores are associated with low levels of innovation, suggesting that good managers are likely to maximize shareholders' utility by privileging value preservation rather than value creation. In this framework, the effect of age is such that young new listed firms are characterised by an even stronger negative relationship between CG and innovation. The impact of good governance practices is augmented by a lack of necessary competences in younger firms which ensure effective management of successful innovation projects. The non-parametric analysis allows us to appreciate the non-linearities in these relationships by showing that the negative impact of CG on innovation is driven by firms characterized by extremely high CG scores.

V. REFERENCES

Abernathy, W. J., & Utterback, J. M. (1978). Patterns of industrial innovation. *Technology Review.64*, 254-228.

Acs, Z. J., & Audretsch, D. B. (1987). Innovation, market structure, and firm size. *The Review of Economics and Statistics*, 567-574.

Aggarwal, R., Erel, I., Stulz, R., &Williamson, R. (2010), Differences in governance practices between US and foreign firms: measurement, causes and consequences. *Review of Financial Studies*, 23(3), 3131-3154.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297.

Atanassov, J. (2013), Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting. *The Journal of Finance*, 1097–1131.

Baranchuk N., Kieschnick, R. &Moussawi, R., 2014, Motivating innovation in newly public firms. *Journal of Financial Economics*, 111(3), 578–588.

Bebchuk, L., Cohen, A. & Ferrell, A. (2008), What Matters in Corporate Governance? *Review of Financial Studies*, 22, 783-827.

Bebchuk, L., & Weisbach, M. (2010), The state of corporate governance research. *Review of Financial Studies*. 23(3), 939-961.

Becker-Blease, J. R. (2011). Governance and innovation. *Journal of Corporate Finance.17*(4), 947-958.

Bertrand, M., & Mullainathan, S. (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy*, *111*(5), 1043-1075.

Brossard, O., Lavigne, S. & Sakinc, M., (2013), Ownership structures and R&D in Europe: the good institutional investors, the bad and ugly impatient shareholders. *Industrial and Corporate Change*, 22(4), 1031-1068.

Brown, J.R., Martinsson, G. &Petersen, B.C. (2013), Law, Stock Markets, and Innovation. *The Journal of Finance*, 68(4), 1517–1549.

Cohen, (1995)

Core, J., Guay, W. & Rusticus, T. (2006), Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations. *The Journal of Finance*, 61, 655-687.

Driver, C., & Guedes, M. J. C. (2012). Research and development, cash flow, agency and governance: UK large companies. *Research Policy*, *41*(9), 1565-1577.

Fang, V.W., Tian, X., &Tice, S. (2014), Does Stock Liquidity Enhance or Impede Firm Innovation? *The Journal of Finance*, 69(5), 2085–2125.

Filatotchev, I., Toms, S., & Wright, M. (2006). The firm's strategic dynamics and corporate governance life-cycle. *International Journal of Managerial Finance*,*2*(4), 256-279.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate Governance and Equity Prices. *The Quarterly Journal of Economics*, 118, 107-155.

Griliches, Z. (1994). Productivity, R&D, and the data constraint. *The American Economic Review*, 1-23.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics*, *95*(2), 347-361.

Holmstrom, B., (1989), Agency costs and innovation. *Journal of Economic Behavior and Organization*, 12, 305-327.

Jensen, M., & Meckling, W. (1976). Theory of the firm: managerial behaviour, agency costs and ownership structure. *Journal of Financial Economics*, 3, 305-360.

Jensen, M. (1986), Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2), 323-329.

Krafft, J., Qu, Y., Quatraro, F., & Ravix, J. L. (2014). Corporate governance, value and performance of firms: New empirical results on convergence from a large international database. *Industrial and Corporate Change*,23(2), 361-397.

LaPorta, R., Lopez-de-Silanes, F., & Shleifer, A. (2008), The economic consequences of legal origin. *Journal of Economic Literature*, 46, 285-332,

LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. & Vishny, R. (1997), Legal determinants of external finance. *The Journal of Finance*, 52, 1131-1150.

LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. & Vishny, R. (1998), Law and finance. *Journal of Political Economy*, 107, 1113-1155.

LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. & Vishny, R. (2000a), Agency problem and dividend policies around the world. *The Journal of Finance*, 55, 1-33.

LaPorta, R., Lopez-de-Silanes, F., Shleifer, A. & Vishny, R. (2000b), Investor protection and corporate governance. *Journal of Financial Economics*, 58, 3-27.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2002). Investor Protection and Corporate Valuation. *The Journal of Finance*, 57, 1147-70.

Lazonick, W. (2007), The US stock market and the governance of innovative enterprise. *Industrial and Corporate Change*, 16(6), pp. 983-1035.

Lazonick, W. and O'Sullivan, M. (eds) (2002), *Corporate Governance and Sustainable Prosperity*, New York: Palgrave.

Levine, R. (2005), Law, endowments, and property rights. *Journal of Economic Perspective*, 19, 61-88.

Lhuillery, S. (2011). The impact of corporate governance practices on R&D efforts: a look at shareholders' rights, cross-listing, and control pyramid. *Industrial and Corporate Change*, *20*(5), 1475-1513.

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

Martynova, M., & Renneboog, L. (2011), Evidence on the international evolution and convergence of corporate governance regulations. *Journal of Corporate Finance*, 17: 1531-1557.

O'Connor, M, & Byrne (2006). Governance and the corporate lifecycle.

O'Connor, M., & Rafferty, M. (2012). Corporate governance and innovation. *Journal of Financial and Quantitative Analysis*, *47*(02), 397-413.

Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research policy*, *13*(6), 343-373.

Saravia (2013). The lifecycle of the firm, corporate governance and investment performance.

Shleifer, A., & Vishny, R. (1997). A Survey of Corporate Governance. *Journal of Finance*, 52, 737-783.

Schumpeter, J. (1943). *Capitalism, socialism and democracy*. London, Unwin.

Stein, J. C. (1988). Takeover threats and managerial myopia. *The Journal of Political Economy*, 61-80.

Wood, S. (2006). *Generalized additive models: an introduction with R*. CRC press.

Table I. Corporate Governance Quotient criteria

BOARD	**AUDIT**
Board Composition	Audit Committee
Nominating Committee	Audit Fees
Compensation Committee	Auditor Rotation
Governance Committee	Auditor Ratification
Board Structure	**EXECUTIVE AND DIRECTOR COMPENSATION**
Board Size	Cost of Option Plans
Changes in Board Size	Option Re-Pricing
Cumulative Voting	Shareholder Approval of Option Plans
Boards Served On - CEO	Compensation Committee Interlocks
Boards Served On - Other than CEO	Director Compensation
Former CEO's	Pension Plans for Non-Employee Directors
Chairman / CEOs Separation	Option Expensing
Board Guidelines	Option Burn Rate
Response To Shareholder Proposals	Corporate Loans
Boards Attendance	**PROGRESSIVE PRACTICES**
Board Vacancies	Retirement Age for Directors
Related Party Transactions	Board Performance Reviews
CHARTER/BYLAWS	Meetings of Outside Directors
Features of Poison Pills	CEO Succession Plan
Vote Requirements	Outside Advisors Available to Board
Written Consent	Directors Resign upon Job Change
Special Meetings	**OWNERSHIP**
Board Amendments	Director Ownership
Capital Structure	Executive Stock Ownership Guidelines
	Director Stock Ownership Guidelines
ANTI-TAKEOVER PROVISIONS	
Anti-Takeover Provisions Applicable	Officer and Director Stock Ownership
Under Country(local)Laws	
	DIRECTOR EDUCATION
	Director Education

Table II. Sectoral Distribution of Sampled Firms

Industry	# firms	Frequency
A – Agriculture, forestry and fishing	7	0.318
B – Mining and quarrying	62	2.814
C – Manufacturing	811	36.813
D – Electricity, gas, stream and air conditioning supply	56	2.541
E – Water supply; sewerage, waste management and remediation activities	9	0.409
F – Construction	71	3.223
G – Wholesale and retail trade; repair of motor vehicles and motorcycles	165	7.489
H – Transportation and storage	105	4.766
I – Accommodation and food service activities	39	1.777
J – Information and communication	214	9.714
K – Financial and insurance activities	346	15.706
L – Real estate activities	88	3.995
M – Professional, scientific and technical activities	118	5.356
N – Administrative support service activities	48	2.179
O – Public administration and defence; compulsory social security	0	0.000
P – Education	2	0.091
Q – Human health and social work activities	11	0.499
R – Arts, entertainment and recreation	20	0.907
S – Other service activities	16	0.726
T – Activities of households as employers	0	0.000
U – Activities of extraterritorial organisations and bodies	0	0.000
Missing information	15	0.681
Total	2203	100%

Table III. Definition of variables

Variables	Definition
CGQ	Corporate Governance Quotient) from *Risk Metrics / Institutional Shareholder Services*
ΔCGQ	Variation in CGQ index
ln(Age)	Logarithm of firm's age
ln(SZ)	Logarithm of firm's total turnover
ln(RDI)	Logarithm of R&D expenditure over total turnover (R&D-to-sales intensity)
Δln(RDI)	Growth rate of R&D-to-sales intensity
Patents	Number of patent applications
CF	Firm's cashflow (in Millions of $)

Table IV. Descriptive Statistics

Variables	Mean (std)	Min	1st quartile	Median	3rd quartile	Max
CGQ	0.47 (0.26)	0	0.26	0.45	0.69	1
ΔCGQ	0.17 (2.57)	-1	-0.16	-0.02	0.12	3.41
Age	54.38 (47.90)	0	17	44	81	536
ln(SZ)	14.76 (1.86)	1.39	13.27	14.49	15.56	19.94
ln(RDI)	0.98 (1.12)	0	0.05	0.65	1.53	12.39
Δln(RDI)	-0.01 (0.68)	-5.98	-0.06	0	0.05	6.77
Patents	2.29 (4.98)	0	0	0	2	47
CF	0.80 (2.39)	-7.30	0.04	0.16	0.55	44.51

Table V. Correlation Matrix

Variables	CGQ	ΔCGQ	ln(Age)	ln(SZ)	ln(RDI)	Δln(RDI)	Patents	CF
CGQ	1							
ΔCGQ	-0.0042	1						
ln(Age)	-0.1910*	0.0068	1					
ln(SZ)	-0.0509*	0.0065	0.2334*	1				
ln(RDI)	0.0635*	-0.0159	-0.0845*	-0.3843*	1			
Δln(RDI)	-0.0122	-0.0214	0.0229	-0.0743*	0.2703*	1		
Patents	-0.1519*	-0.0206	0.1640*	0.1550*	0.1471*	0.0214	1	
CF	0.0964*	0.0118	0.0085	0.4387*	-0.0309*	0.0018	0.0798*	1

Note : *, p-value < 0.05

Table VI. CGQ effect on Δln(RDI) – Fixed-effects

	(1)	(2)	(3)	(4)	(5)	(6)
CGQ $_{t-1}$	-0.1121	-0.0671				
	(0.0749)	(0.0634)				
ΔCGQ $_{t}$	-0.0071*	-0.0077***	-0.0080***	-0.0080***	-0.0082***	-0.0080***
	(0.0040)	(0.0025)	(0.0026)	(0.0026)	(0.0028)	(0.0028)
ln(Age) $_{t}$		0.0172	-0.0179	0.0279	-0.1074	-0.0829
		(0.1937)	(0.1940)	(0.2029)	(0.2413)	(0.2573)
ln(RDI) $_{t-1}$		-1.0686***	-1.0691***	-1.0700***	-1.0876***	-1.0907***
		(0.0311)	(0.0307)	(0.0309)	(0.0438)	(0.0446)
ln(SZ) $_{t}$		-0.5491***	-0.5493***	-0.5704***		
		(0.0717)	(0.0712)	(0.0731)		
ln(SZ) $_{t-1}$					0.0379	0.0405
					(0.0418)	(0.0440)
CF $_{t-1}$				-0.0009		-0.0100
				(0.0106)		(0.0101)
CGQ*Young			-0.3491**	-0.3591**	-0.3625*	-0.3566*
			(0.1504)	(0.1512)	(0.2118)	(0.2156)
CGQ*Medium-aged			-0.1576	-0.1565	-0.2434*	-0.2377
			(0.1144)	(0.1158)	(0.1423)	(0.1451)
CGQ*Old			-0.0267	-0.0244	-0.0999	-0.0993
			(0.0765)	(0.0771)	(0.0862)	(0.0875)
CGQ*Very old			0.0255	0.0230	-0.0024	-0.0024
			(0.0821)	(0.0827)	(0.0826)	(0.0833)
Time dummies	yes	yes	yes	yes	yes	yes
N	3754	3712	3712	3668	3712	3668
R^2	0.0023	0.6997	0.7006	0.7054	0.5882	0.5891

Notes: this table reports coefficients of Fixed-Effects (FE) estimations of Equation (2) with firm-level fixed effects. The response variables is Δln(RDI) and all other explanatory variables are defined in Table III. To identify how the relationship between CG and innovation is moderated by age, we interact the CGQ index with four age classes. Robust standard errors in parentheses: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table VII. CGQ effect on ln(RDI) – GMM

	(1)	(2)	(3)	(4)	(5)	(6)
CGQ $_{t-1}$	-0.3122**	-0.3852**				
	(0.1590)	(0.1640)				
ΔCGQ $_{t}$	-0.0224	-0.0186	-0.0115	-0.0078	-0.0124	-0.0106
	(0.0167)	(0.0182)	(0.0197)	(0.0179)	(0.0193)	(0.0242)
ln(Age) $_{t}$		0.0641	-0.0774	0.0218	0.0071	-0.0166
		(0.1724)	(0.2053)	(0.1996)	(0.1875)	(0.1792)
ln(RDI) $_{t-1}$		-0.0536	-0.1434	-0.1569	-0.1028	-0.0666
		(0.1264)	(0.1502)	(0.1236)	(0.2130)	(0.1768)
ln(SZ) $_{t}$		-0.5488***	-0.4667***	-0.3593**		
		(0.1920)	(0.1777)	(0.1591)		
ln(SZ) $_{t-1}$					0.0661	0.0599
					(0.1534)	(0.1408)
CF $_{t-1}$				0.0028		0.0022
				(0.0084)		(0.0080)
CGQ*Young			-1.1318*	-1.0511*	-1.1338*	-0.9500
			(0.6051)	(0.5738)	(0.6408)	(0.5874)
CGQ*Medium-aged			-0.2014	-0.2459	-0.3377	-0.2693
			(0.2225)	(0.2101)	(0.2191)	(0.2229)
CGQ*Old			-0.2359	-0.1669	-0.2479	-0.1737
			(0.1838)	(0.1712)	(0.1899)	(0.1847)
CGQ*Very old			-0.1042	-0.0660	-0.0843	0.0100
			(0.2051)	(0.1906)	(0.2083)	(0.2015)
Time dummies	yes	yes	yes	yes	yes	yes
N	3007	2743	2743	2705	2743	2705
AR(1)	0.000	0.007	0.060	0.035	0.109	0.031
AR(2)	0.452	0.515	0.293	0.172	0.740	0.828
Sargen	0.347	0.030	0.352	0.560	0.248	0.425
Hensen	0.408	0.532	0.805	0.563	0.640	0.672

Notes: this table reports coefficients of the two-step robust GMM estimations of Equation (3). The response variables is ln(RDI) and all other explanatory variables are defined in Table III. AR(1) and AR(2) are the *p*-values for the Arellano-Bond tests for the first and second order autocorrelation. Sargen and Hensen are the p-values for the tests of overidentifying restrictions. To identify how the relationship between CG and innovation is moderated by age, we interact the CGQ index with four age classes Robust standard errors in parentheses: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Table VIII. CGQ effect on patent applications – ZINB

	(1)	(2)	(3)	(4)	(5)	(6)
CGQ $_{t-1}$	-0.2557**	-0.2607**				
	(0.1261)	(0.1319)				
ΔCGQ $_t$	-0.0080	-0.0063	-0.0069	-0.0065	-0.0068	-0.0064
	(0.0105)	(0.0107)	(0.0105)	(0.0106)	(0.0105)	(0.0106)
ln(Age) $_t$		0.0632**	-0.0023	0.0212	-0.0025	0.0204
		(0.0315)	(0.0587)	(0.0591)	(0.0585)	(0.0588)
ln(RDI) $_{t-1}$		0.0345	0.0396	0.0236	0.0502*	0.0308
		(0.0252)	(0.0254)	(0.0254)	(0.0265)	(0.0274)
ln(SZ) $_t$		0.0476***	0.0475***	0.0207		
		(0.0159)	(0.0158)	(0.0183)		
ln(SZ) $_{t-1}$					0.0535***	0.0274
					(0.0160)	(0.0191)
CF $_{t-1}$				0.0207**		0.0192**
				(0.0091)		(0.0094)
CGQ*Young			-0.6276**	-0.5777**	-0.6492**	-0.5876**
			(0.2615)	(0.2634)	(0.2588)	(0.2617)
CGQ*Medium-aged			-0.2052	-0.1473	-0.2125	-0.1524
			(0.1909)	(0.1925)	(0.1911)	(0.1927)
CGQ*Old			-0.2153	-0.2153	-0.2170	-0.2158
			(0.1509)	(0.1526)	(0.1512)	(0.1527)
CGQ*Very old			-0.1972	-0.2142	-0.2053	-0.2194
			(0.1560)	(0.1550)	(0.1575)	(0.1561)
Time dummies	yes	yes	yes	yes	yes	yes
Industry dummies	yes	yes	yes	yes	yes	yes
Country dummies	yes	yes	yes	yes	yes	yes
Inflation :						
ln(RDI) $_t$	-7.9037***	-8.7567***	-8.6102***	-8.3749***	-8.7365***	8.4436***
	(1.6645)	(1.7682)	(1.7627)	(1.7972)	(1.8144)	(1.8291)
N	4023	3712	3712	3668	3712	3668
Vuong	11.39***	10.29***	10.24***	9.94***	10.14***	9.86***
Log likelihood	-9572.68	-9043.59	-9040.27	-8980.36	-9039.40	-8979.96

Notes: this table reports coefficients of the Zero Inflated Negative Binomial estimations of Equation (4). The response variables is patent applications and all other explanatory variables are defined in Table III. Vuong is the statistic for the test of ZINB versus negative binomial model. To identify how the relationship between CG and innovation is moderated by age, we interact the CGQ index with four age classes Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IX. Robustness Checks

	(Age<15) Patent	(Age<20) Patent	(Age<15) Δln(RDI)	(Age<15) ln(RDI)	(Age<20) Δln(RDI)	(Age<20) ln(RDI)
CGQ*Young	-0.5006**	-0.5623***	-0.4970	-0.7400	-0.2130	-0.4388
	(0.2195)	(0.2062)	(0.3731)	(0.6870)	(0.1826)	(0.4377)
CGQ*Old	-0.2379*	-0.2175	-0.0821	-0.1593	-0.1075	-0.1664
	(0.1345)	(0.1345)	(0.0735)	(0.1578)	(0.0716)	(0.1645)
ΔCGQ_t	-0.0066	-0.0068	-0.0079***	-0.0097	-0.0080***	-0.0071
	(0.0106)	(0.0105)	(0.0027)	(0.0254)	(0.0027)	(0.0290)
$\ln(Age)_t$	0.0281	0.0057	-0.1392	-0.0030	-0.0909	0.0776
	(0.0392)	(0.0422)	(0.2425)	(0.1912)	(0.2423)	(0.1911)
$\ln(RDI)_{t-1}$	0.0477*	0.0481*	-1.0854***	-0.1686	-1.0865***	-0.1911
	(0.0263)	(0.0262)	(0.0430)	(0.2371)	(0.0441)	(0.2296)
$\ln(SZ)_{t-1}$	0.0535***	0.0550***	0.0426	-0.0793	0.0397	-0.0641
	(0.0161)	(0.0162)	(0.0416)	(0.1270)	(0.0415)	(0.1286)
Time dummies	yes	yes	yes	yes	yes	yes
Industry dummies	yes	yes	-	-	-	-
Country dummies	yes	yes	-	-	-	-
Inflate :						
$\ln(RDI)_t$	-8.8104***	-8.7107***				
	(1.8087)	(1.8009)				
N	3712	3712	3712	2743	3712	2743
R^2			0.0871		0.0881	
Vuong	10.18***	10.17***				
AR(1)				0.069		0.082
AR(2)				0.836		0.687
Sargen				0.016		0.012
Hensen				0.444		0.550

Notes: this table reports coefficients of the robustness checks: FE, GMM, and ZINB estimations. Two age classes have been defined according to two arbitrary threshold of firm's age, namely 15 and 20 years. All variables are defined in Table III. AR(1) and AR(2) are the *p*-values for the Arellano-Bond tests for the first and second order autocorrelation. Sargen and Hensen are the p-values for the tests of overidentifying restrictions. Vuong is the statistic for the test of ZINB versus negative binomial model. To identify how the relationship between CG and innovation is moderated by age, we interact the CGQ index with four age classes Robust standard errors in parentheses: $^{*}p< 0.10$, $^{**}p< 0.05$, $^{***}p< 0.01$

Figure I - Kernel density for main variables

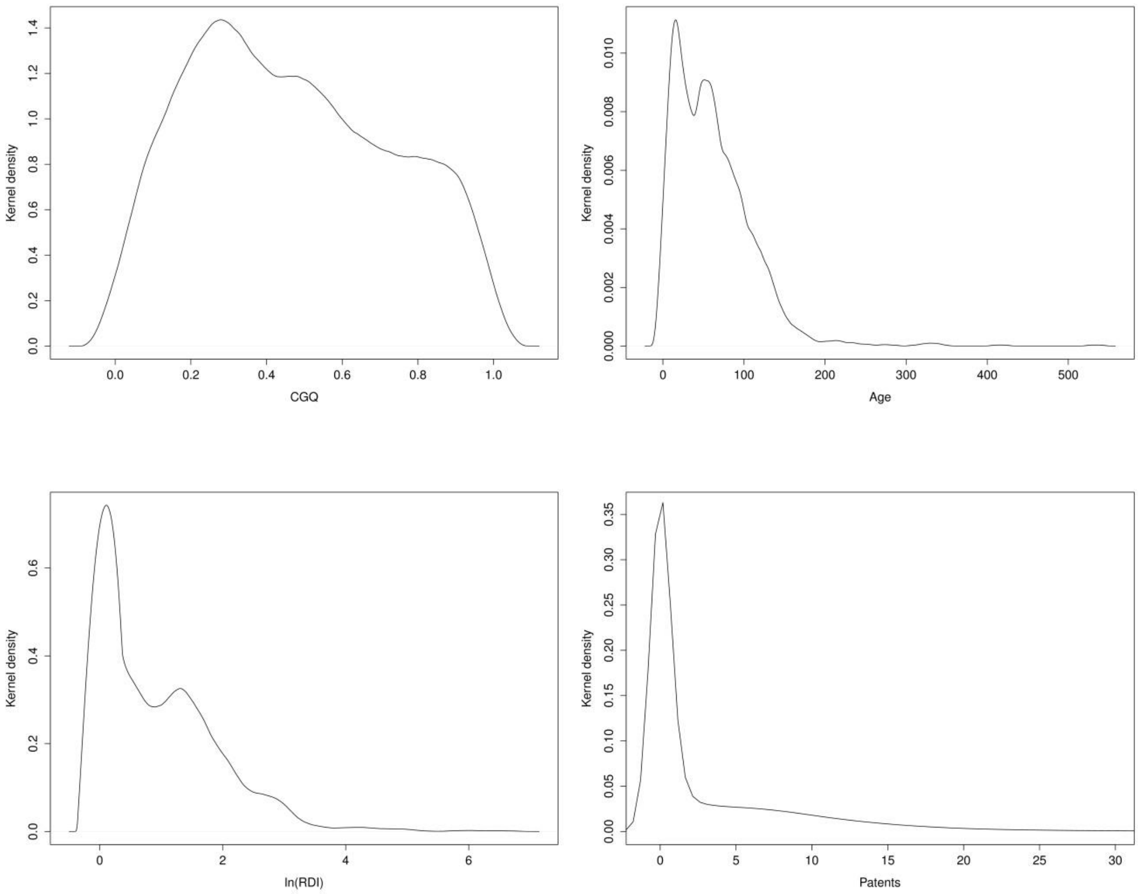

Figure II - R&D, age and CG, non-parametric GAM estimation

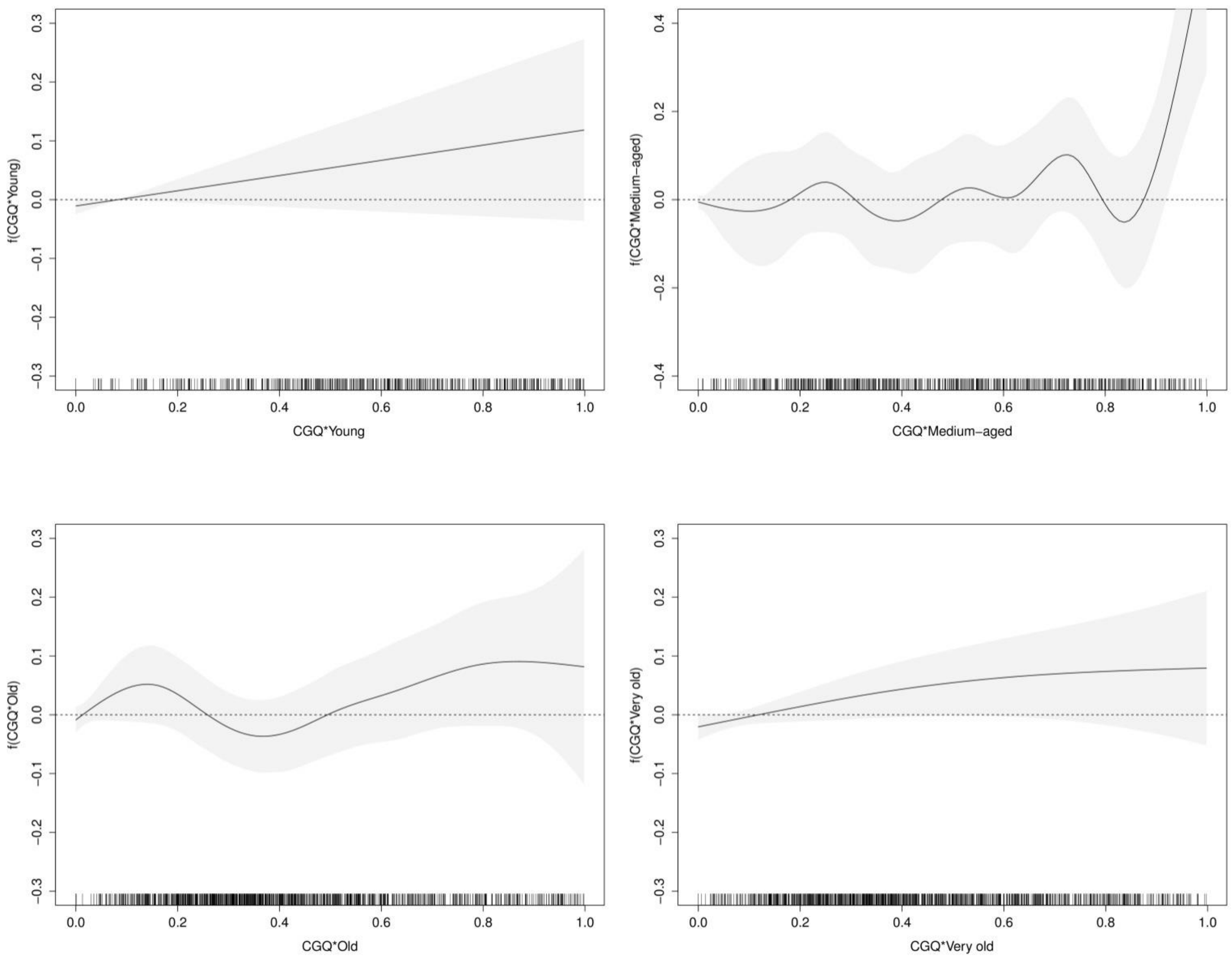

Figure 1– Patents, age and CG, non-parametric GAM estimation