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**Abstract**

This paper presents evidence that firms face a trade-off between the quantity and quality of their research output. The econometric analysis uses survey data on patent applicants at the European Patent Office and addresses the identification problem caused by differences in firms' propensity to patent. The existence of a trade-off emphasizes the need to take the quality of research output into account when assessing research productivity. It also raises questions about the optimal quantity–quality mix that firms should target.

**JEL classification:** D83, L25, O31, O33

**Keywords:** Innovation performance, invention quality, invention quantity, patent explosion, propensity to patent, research productivity

## 1. Introduction

An important topic in the economic and management of innovation literature is the study of firms' research productivity (e.g. Henderson and Cockburn, 1996; Penner-Hahn and Shaver, 2005; Girotra et al., 2010). Research productivity is the quality-constant measure of the efficiency at which inputs to the innovation process are converted into output. The quantity of output is the number of inventions created and it is often proxied with the number of patents, as imperfect a proxy as it is (Griliches, 1990). The quality of output is more difficult to define and, a fortiori, to measure. Following Lanjouw and Schankerman (2004), the quality of output encompasses both the technological and economic value of inventions.

The existing research has mostly focused on the determinants of the quantity of inventions created, with quality considerations usually relegated to the background. Yet, the quality dimension is just as critical to the understanding of research productivity as the quantity dimension. Little is known about the relationship between the quantity of inventions created and their quality, in particular with respect to a potential trade-off between these two dimensions. For any given level of research inputs, it seems obvious that an increase in the number of inventions created would be associated with inventions of lower average value. This is not necessarily the case, however. For one thing, some otherwise comparable firms may be more productive than others due to a better use of IT resources, more appropriate contracting and management practices, or more skilled researchers. For another, it is difficult to target a quality level due to the uncertain nature of the innovation process. A firm investing all its resources in a risky but promising project may end up with a limited output of low value. And further, dynamics of the invention process itself may affect the quantity/quality trade-off. For instance, Fleming (2001) shows that inventors' experimentation with new components and combinations leads to less success on average, but it also increases the variability of success that can lead to breakthrough inventions. To the best of our knowledge, the existence of a trade-off has yet to be shown.

Only a handful of studies have looked at the hypothesis of a trade-off and none has come up with conclusive evidence. A first group of studies has tested the hypothesis using firm-level patent data. Lanjouw and Schankerman (2004) regress the number of patents per dollar invested in R&D on an index that captures the mean quality of patent applications for a panel of U.S. firms. Within-firm regressions provide no support for the hypothesis, while between-firm regressions provide only weak support. Sørensen and Stuart (2000) provide an indirect test of the hypothesis. Applying organizational theory, they argue that firm age should be positively associated with the rate of innovation, but negatively associated with how influential the innovations are. They find strong evidence that firm age increases the rate of (patented) inventions, but only weak evidence on the impact of firm age on patent quality. A second group of studies uses patent data at the inventor level. Mariani and Romanelli (2007) use data from the PatVal-EU survey of inventors to test whether the quantity of patents produced affects their average value as measured by patent indicators. They find a positive effect of the quantity of patents on the average quality using forward citations but no effect using a composite value indicator. Gambardella et al. (2011) propose a related test of the hypothesis. The authors also use data from the PatVal-EU survey of inventors but rely on a self-assessed measure of value. They find a negative relationship between the number of inventions and the average value of the patents in the portfolio, but the effect is not statistically significant.[1]

A limitation of existing studies is that they rely on patent data but do not address the confounding effect of the propensity to patent. Were the decision to patent an invention independent of its value, the trade-off would easily be estimated with patent data. One would simply regress the number of patents against average patent value. A negative coefficient would signal a trade-off. However, since the marginal value of inventions patented is likely to decrease with the propensity to patent (defined as the proportion of inventions patented), a negative correlation between patent quantity and patent quality would not be evidence of a trade-off.

The objective of this paper is to test whether innovative firms face a trade-off between the quantity and the quality of their inventions (holding research inputs constant). An attempt to address the identification problem caused by heterogeneous patent propensities is a distinguishing feature of this study. We put forward an empirical model that links the average quality of inventions with the average quality of patents (or more precisely, inventions patented) and adopt an instrumental variable approach to account for differences in the propensity to patent. The econometric analysis uses cross-sectional survey data on patent applicants at the European Patent Office (EPO) and finds evidence of a trade-off between invention quantity and quality, as measured by the patent family size. The existence of a trade-off has profound implications for the economics of science and the management of innovation. It stresses the need to take the quality of inventions into account to properly assess – and to study the determinants of – the productivity of research spending. It also raises questions regarding the optimal quantity–quality mix that firms should target.

The paper is organized as follows. Section 2 introduces the empirical framework and the data is presented in section 3. Section 4 presents the econometric results and the final section discusses the implications of the findings.

## 2. Empirical framework

A careful econometric analysis is needed to control for the potentially confounding effect of patent propensity. The next section introduces the building blocks that are necessary to test the existence of a trade-off, while the following section presents the econometric implementation.

### *2.1 The model*

#### *2.1.1 The invention production function*

The number of inventions created is modeled by a traditional Cobb-Douglas knowledge production function of the form (Griliches, 1979; Jaffe, 1986):

$$n_i = q_i \, r_i^{\alpha} \qquad (1)$$

[1] Studies in the new product development literature have investigated the hypothesis of a trade-off at the project level, with similarly mixed findings (Swink et al., 2006:544).

Where $n_i$ is the number of inventions created (the index $i$ indicates a firm-specific variable), $r_i$ represents the input to the knowledge production function (such as the number of researchers or the research expenditures), α captures the returns to scale and $q_i$ is the rate at which the research input generates inventions (that is, $q_i$ is a generic firm-specific quantity-enhancing parameter). Although there is a stochastic component to $q_i$ due to the uncertain nature of R&D, it is to some extent influenced by the firm's research practices.

*2.1.2 Propensity to patent and average value of inventions patented*

We assume that invention value is a random variable ($x$) that follows an exponential distribution with a firm-specific shape parameter $v_i$:

$$f(x; v_i) = \frac{1}{v_i} e^{-\frac{x}{v_i}}$$

The negative exponential distribution has its support on [0, ∞) and mimics the shape of invention value distribution: a majority of low value inventions and a minority of high value inventions (Sanders, 1965; Schankerman and Pakes, 1986). The mean of the distribution is given by $v_i$, which can be interpreted as the mean invention value. The existence of a trade-off would imply that the quantity parameter ($q_i$) is inversely related to the average value of inventions ($v_i$).

Unfortunately, since the value of inventions not patented is not observed, the mean invention value (the true $v_i$) is not directly observed by the econometrician. All that is observed is the value of inventions patented.[2] It is, however, possible to establish a link between average invention value ($v_i$) and the mean patent value ($a_i$) by modeling the firm's decision rule concerning patenting. We assume that a firm protects an invention with a patent if the invention passes a certain value threshold $v_i^*$ (which is unknown and firm-specific). Under this assumption, the propensity to patent can be given a general functional form:

$$\pi_i = \int_{v_i^*}^{\infty} \frac{1}{v_i} e^{-\frac{x}{v_i}} dx = e^{-\frac{v_i^*}{v_i}} \tag{2}$$

And the average value of inventions patented ($a_i$) is given by:

$$a_i = \frac{\int_{v_i^*}^{\infty} \frac{x}{v_i} e^{-\frac{x}{v_i}} dx}{\int_{v_i^*}^{\infty} \frac{1}{v_i} e^{-\frac{x}{v_i}} dx} = v_i \left(1 + \frac{v_i^*}{v_i}\right) \tag{3}$$

Note that the only reason we need to model the propensity to patent is to account for the possibility that the propensity to patent, through its effect on observed quality, may lead to incorrect inference on the source of the trade-off. This explains why the cut-off value $v_i^*$ is the only parameter that influences the patenting decision in our model. Of course, we acknowledge that the patenting decision is subject to a range of additional considerations.

[2] Our model refers to patent applications instead of patents granted. By abuse of language we use the term "invention patented" when we should use "invention for which patent protection is sought".

### *2.2 Econometric implementation*

The objective of the econometric analysis is to estimate the correlation coefficient between $q_i$ and $v_i$. The econometric estimation proceeds in two steps. First, an estimate for $q_i$ is obtained. Second, the correlation between $q_i$ and $v_i$ is investigated. There are $N$ firms in the sample. Matrices are denoted with a bold capital letter (**B**) and vectors with a bold lower case letter (**b**).

#### *2.2.1 Estimation of the quantity parameter $q_i$*

A key element in the econometric identification is that the survey data contains an estimation of firms' propensity to patent ($\pi_i$). Hence, the quantity parameter ($q_i$) can be directly estimated as the residual of equation (1), where the number of inventions ($n_i$) is estimated as the ratio between the number of priority patent applications and the propensity to patent. Because the number of inventions is a count variable and exhibits overdispersion, the invention production function is estimated with a negative binomial regression.[3] The expected number of inventions is assumed to be an exponential function of the firm's log number of researchers and other characteristics:

$$E[n_i|\boldsymbol{C_i}] = \exp(\boldsymbol{C_i\gamma}) \tag{4}$$

where $\boldsymbol{C}$ is the N×L matrix of covariates ($\boldsymbol{C_i}$ is the -ith line of the matrix) and $\boldsymbol{\gamma}$ the L×1 vector of parameters. The quantity parameter ($q_i$) is estimated as the ratio of the observed number of inventions to the predicted number of inventions.

#### *2.2.2 Estimation of the correlation between $q_i$ and $v_i$*

Equation (3) provides a general formulation of the link between the mean invention value ($v_i$, unobserved), and the average value of inventions patented ($a_i$, observed). Taking the logarithm of equation (3):

$$\ln(a_i) = \ln(v_i) + \ln\left(1 + \frac{v_i^*}{v_i}\right)$$

Notice from equation (2) that $-v_i^*/v_i$ is the log of the propensity to patent. Hence:

$$\ln(a_i) = \ln(v_i) + \ln(1 - \ln(\pi_i)) \tag{5}$$

The econometric counterpart of equation (5) is obtained by taking the first order series expansion of the expression $\ln(1 - \ln(\pi_i))$ at $\pi_i = 0.5$:

$$\ln(a_i) \cong c + \ln(v_i) - \beta\pi_i \tag{6}$$

where $c = \ln(1 - \ln 0.5)$ and $\beta = 2/(1 - \ln 0.5)$.[4] Equation (6) is consistent with the intuition that the average value of inventions patented increases with the mean invention value and decreases with the propensity to patent.

[3] A formal test of overdispersion is provided in section 4.

[4] The value 0.5 roughly corresponds to the sample mean (see Table 1).

One can now insert the estimated $q_i$ (denoted $\hat{q}_i$) into equation (6) and test whether the associated coefficient is significant. Since $q_i$ does not belong to the equation, a significant coefficient would be evidence of a correlation between $q_i$ and $v_i$ and would provide evidence of a trade-off (see section 2.1.2). However, in order for this approach to be valid, one needs to control for the fact that $q_i$ may have both a direct effect on $\ln(a_i)$ through $v_i$ or an indirect effect through the propensity to patent. For this reason, the propensity to patent is instrumented in a standard IV framework:

$$\begin{cases} \boldsymbol{\pi} = \tilde{\boldsymbol{q}}\beta_1 + \boldsymbol{C}\boldsymbol{\gamma_1} + \boldsymbol{Z}\boldsymbol{\gamma_2} + \boldsymbol{\varepsilon} & \text{(7a)} \\ \tilde{\boldsymbol{a}} = \tilde{\boldsymbol{q}}\beta_2 + \hat{\boldsymbol{\pi}}\beta_3 + \boldsymbol{C}\boldsymbol{\gamma_3} + \boldsymbol{\nu} & \text{(7b)} \end{cases}$$

where $\tilde{q}_i = \ln(\hat{q}_i)$, $\tilde{a}_i = \ln(a_i)$, $\hat{\pi}_i$ is the fitted value of $\pi_i$, and $\boldsymbol{Z}$ is the set of instruments. The data is presented in the next section.

In a nutshell, the two steps of the econometric analysis are the following. First, the quantity parameter $q_i$ is estimated as the residual of equation (4). Second, the quality regression in equations (7a) and (7b) is estimated. The hypothesis test consists of determining whether the direct effect of $\tilde{q}_i$ on $\tilde{a}_i$ (coefficient $\beta_2$ in equation (7b)) is negative and significant. If $\tilde{q}_i$ adversely affects the average value of inventions patented $\tilde{a}_i$, and knowing that the effect of $\tilde{q}_i$ on the propensity to patent has been controlled for, then it must be the case that firms with a higher quantity of inventions also have inventions of lower quality on average. Loosely speaking, $\beta_2$ can be interpreted as a measure of the correlation between $q_i$ and $v_i$.

## 3. The Data

The data come from the Applicant Panel Survey carried out from June to September 2006 by the EPO. The main purpose of the survey is to provide information on filing intentions for the EPO's forecasting exercise for budgetary planning purposes. The population is composed of all applicants that have filed at least one patent application at the EPO in the year 2005. A sample of 2,098 applicants was selected, partly from among the largest applicants and partly at random, covering overall about 31 per cent of the total applications at the EPO in 2005.[5] Contact details were successfully established for 1,524 applicants and 772 responses were returned (leading to a response rate of 51 per cent of the contacted applicants, or 37 per cent of the initial sample). The survey was carried out via telephone and mail interviews, in German, French, Japanese, and English, with the pre-established contact persons. Participants were asked to answer at the level of the branch or the subsidiary where possible; the unit of observation is thus the smallest available unit. The final data was provided to us directly by the EPO. The next paragraphs present the variables that are used in the empirical analysis.

[5] The sampling methodology used implies that larger applicants are over-represented. The reader must bear in mind that our results are not representative of the population of applicants at the EPO.

### *3.1 Dependent variables*

**Number of inventions** (*inv*). This variable corresponds to $n_i$. It is defined as the ratio between the number of priority patent applications filed worldwide in 2005 and the propensity to patent (see Arora et al., 2008 for a similar approach).[6] Because the number of inventions is a count variable, the ratio has been rounded to the nearest integer. A priority patent application is the first application describing an invention (as opposed to a second filing, which is used to extend the patent right to another jurisdiction). It is essential to capture the worldwide patented output to avoid a truncation of the data that would result in misestimating $q_i$. This is all the more important given the international nature of our sample. Should the count be limited to patents filed at the EPO, then the number of patents would be poorly captured for, say, U.S. companies that file mainly at the U.S. Patent and Trademark Office. Needless to say, counting only priority filings and not second filings is equally important in order to avoid potential double counting. The propensity to patent (*pi*) is a self-assessed measure of the proportion of inventions that were patented throughout the world in 2005.[7]

**Average value of inventions patented** (*val*). This variable corresponds to $a_i$. Citations, renewals and family size are the three most commonly used variables that are correlated with patent value. However, the international nature of our sample makes it difficult to build a homogeneous value measure; there is both between- and within-firm heterogeneity in the location of priority filings.[8] The use of citations would induce a severe selection bias since citation practices – and citations availability in patent databases – differ across jurisdictions. The most internationally comparable value indicator that can be built is the average family size, defined as the average number of countries in which patent protection is sought. This measure has been introduced as a value indicator by Putnam (1996) and Lanjouw et al. (1998). It has been shown to be strongly correlated with economic value, both in terms of self-assessed patent value and in terms of firm market value. For instance, using estimates of the value of patent rights from a survey of patent-holders, Harhoff et al. (2003) find that the family size is a particularly powerful predictor of (private) value. Neuhäusler et al. (2011) come to a similar conclusion using firm's market value and return on investment as performance indicators. Family size has also been shown to capture the 'technological' value of an invention. For instance, Lanjouw and Schankerman (2004:448) show that family size is significantly correlated with forward citations, which is often seen as an indicator of technological quality. Chan (2010) provides direct evidence that invention quality plays an important role in firms' decisions to patent abroad. Finally, family size has the advantage of being available early, in comparison with citations and renewals, since second filings are based on priority claims, which generally lapse 12 months after the priority application has been filed. The variable is computed as the ratio of the total number of patents filed worldwide in 2005 and 2006 (both priority and second filings) to total priority filings filed worldwide in 2005 and 2006. The two-year time frame acknowledges the fact that priority filings may be extended abroad during the 12 month period following the first filing date.

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[6] It follows that the number of inventions is a measure that directly depends on the reported propensity to patent. In theory, patent law requires 'unity of invention', meaning that a patent shall relate to one invention or one inventive concept only. In practice, the propensity to patent is affected by respondent perceptions regarding a 'quantum of invention'. We investigate this issue in greater detail in section 4.

[7] Note that we observe patent applications but that the propensity to patent is expressed in terms of patents granted. Hence, the number of inventions for firms that have a larger-than-average share of patents refused is overestimated. However, this does not compromise the validity of the empirical analysis.

[8] For instance, only 16 firms in the sample filed all their priority patent applications at the EPO.

### *3.2 Covariates*

**Number of researchers** (*res*). This variable corresponds to $r_i$. It is the number of full-time equivalent researchers in 2005.

We control for specific characteristics that might affect the quality of the family size as a proxy for value, such as firm size and whether the firm belongs to a group of companies.

**Number of employees** (*emp*). Categorical variable capturing the size of the firm to account for potential differences in financial resources that might affect a firm's capacity to extend its patent protection abroad. The categories are: 1:1; 2:2–9; 3:10–49; 4:50–249; 5:250–999; 6:1,000–4,999; 7:5,000–9,999; 8:10,000–49,999; and 9:50,000+ employees.

**Part of a group** (*group*). Dummy variable taking the value of 1 if the firm belongs to a group of companies and 0 otherwise. This variable is used to control for the fact that companies belonging to a group of companies may have additional incentives to seek patent protection abroad.

**Country and technology dummies**. All the regressions are net of country and technology effects. The technology taxonomy used by the EPO is organized around 14 'joint clusters', each representing a technological area (e.g. biotechnology, industrial chemistry, measuring and optics, etc.).

### *3.3 Instrumental variable*

As explained in section 2, the endogeneity of the propensity to patent in equation (6) needs to be addressed. The economic literature often models the decision to patent as a trade-off between the positive protective effect and the negative disclosure effect (e.g. Anton and Yao, 2004; Erkal, 2005; Zaby, 2010). Simply said, a firm applies for a patent when the benefit arising from increased protection against imitation outweighs the cost of disclosing the invention. Our choice of an instrumental variable is motivated by this theory. We use firm agreement, on a 1–7 Likert scale, to the following statement: 'I patent mainly to protect from imitation by competitors' (variable 'imitation') as an instrument, as well as the square of this variable to capture non-linearities in $\pi$. Firms that rank the protective motive highly are concerned about the threat of imitation, such that it is more likely that the benefit of patent protection offsets the cost of disclosure, leading to a greater propensity to patent, everything else being equal. Regarding the exclusion restriction for the instrument in equation (7b), it is hard to think of a reason why the instrument would have an effect on patent quality other than through the effect on the propensity to patent. To the best of our knowledge, theory provides no indication that the protection-against-imitation motive has a direct effect on research productivity.

### *3.4 Descriptive statistics*

Table 1 presents descriptive statistics for both the full sample and the sample that is used in the empirical analysis (the 'working sample', defined as the largest subsample of private companies with more than one employee for which all the information is available – universities, public research organizations and individual inventors are thus excluded).

**Table 1:** Descriptive statistics.

| | Full Sample | | Working Sample (N = 260) | | | | Difference |
|---|---|---|---|---|---|---|---|
| | N | Mean | Min. | Mean | Max. | Std. Dev. | P-value |
| Patent applications | 772 | 242.16 | 1 | 160.05 | 4,553 | 461.24 | 0.14 |
| Average value (*val*) | 736 | 2.49 | 1 | 2.43 | 37.00 | 2.56 | 0.71 |
| Researchers (*res*) | 453 | 761.26 | 0.50 | 515.91 | 15,000 | 1,212 | 0.03 |
| Propensity (*pi*) | 404 | 0.54 | 0.01 | 0.54 | 1.00 | 0.28 | 0.83 |
| Employees (*emp*) [c] | 688 | 5.52 | 2 | 5.55 | 9 | 1.83 | 0.81 |
| Group (*group*) [d] | 670 | 0.56 | 0 | 0.62 | 1 | - | 0.01 |
| Imitation (*imitation*) [l] | 604 | 4.60 | 1 | 4.69 | 6 | 1.41 | 0.32 |

**Notes:** [c], [d] and [l] indicate a categorical, dummy and Likert-scale variable respectively. The last column reports the p-value for a t-test of difference in means between observations included in the sample and those excluded from the sample. P-values for the Mann-Whitney rank sum test reported for the last three variables.

Overall, firms in the working sample filed 160 priority filings in 2005 and extended their patent applications in 1.43 foreign countries (average value of 2.43). They have more than 500 researchers, have between 250 and 1,000 employees, and 62 per cent of firms belong to a group of companies. More than half the inventions created by these firms were patented. The average company is thus a relatively large corporate group. The last column reports the p-value for the statistical test of a difference in means between observations in the working sample and observations that were excluded from the working sample. The means are very similar, except that firms excluded were more likely to have a higher number of researchers and not to belong to a group of companies. This is consistent with the facts that universities, public research organizations and individual inventors were deliberately excluded. The variables are largely uncorrelated with each other, with the exception of size variables, as indicated in Table 2.

**Table 2:** Correlation table

| | $p$ | $\bar{a}$ | $r$ | $\pi$ | *emp* | *group* | *imitation* |
|---|---|---|---|---|---|---|---|
| Patent applications | 1.00 | | | | | | |
| Average value (*val*) | -0.08 | 1.00 | | | | | |
| Researchers (*res*) | 0.24 | -0.01 | 1.00 | | | | |
| Propensity (*pi*) | 0.03 | -0.06 | -0.01 | 1.00 | | | |
| Employees (*emp*) [c] | 0.35 | -0.01 | 0.46 | 0.02 | 1.00 | | |
| Group (*group*) [d] | 0.13 | 0.08 | 0.08 | 0.02 | 0.30 | 1.00 | |
| Imitation (*imitation*) [l] | 0.00 | 0.03 | -0.13 | 0.12 | -0.02 | 0.15 | 1.00 |

**Notes:** [c], [d] and [l] indicate a categorical, dummy and Likert-scale variable respectively. Correlation coefficients estimated on the working sample.

## 4. Results

The first step, the estimation of the quantity parameter from equation (4), is only an intermediary step and is not reported. The dependent variable is the number of inventions (*inv*) and the covariates are the number of researchers (*res*), the number of employees (*emp*), a dummy representing whether the firm is part of a group (*group*), as well as country and technology dummies. Since the number of inventions is a count variable and exhibits overdispersion (the observed variance is larger than the predicted mean), a negative binomial regression model is used. The overdispersion parameter has a mean of 1.34 and is significantly different from 0.

The second step involves plugging the residual from the first step ($\hat{q}_i$) into the quality regression (equations (7a) and (7b)) and estimating it with two-stage least squares. The results are reported in Table 3, with various specifications.

**Table 3:** Regression coefficients (equation 7b)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $\hat{\pi}_i$ | -0.15 | -1.06* | -1.02* | -0.24 | -1.36*** | -0.63 | -1.52** |
| | *(0.58)* | *(0.57)* | *(0.59)* | *(0.51)* | *(0.52)* | *(0.69)* | *(0.63)* |
| $\tilde{q}_i$ | -0.12* | -0.22*** | -0.21*** | -0.22* | -0.26*** | -0.23* | -0.31*** |
| | *(0.07)* | *(0.08)* | *(0.08)* | *(0.11)* | *(0.07)* | *(0.12)* | *(0.08)* |
| emp | -0.00 | 0.00 | -0.02 | -0.00 | -0.00 | -0.07* | -0.00 |
| | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* | *(0.02)* | *(0.06)* | *(0.03)* |
| group | 0.16*** | 0.14** | 0.19*** | 0.16** | 0.14* | 0.50** | 0.09 |
| | *(0.06)* | *(0.07)* | *(0.07)* | *(0.06)* | *(0.07)* | *(0.19)* | *(0.09)* |
| freedom | | | | | 0.04 | | |
| | | | | | *(0.03)* | | |
| licensing | | | | | -0.04* | | |
| | | | | | *(0.02)* | | |
| Constant | 0.60** | 1.03*** | 1.09*** | 1.09** | 1.16*** | 0.77 | 1.36**** |
| Technology dummies | Y* | Y** | Y** | Y** | Y*** | Y** | Y |
| Country dummies | Y** | Y*** | Y** | Y** | Y*** | Y | Y*** |
| *IV validity tests:* | | | | | | | |
| Weak instrument | 5.80 | 5.66 | 5.22 | 4.16 | 7.00 | 3.18 | 3.31 |
| Overidentification | 0.23 | 0.26 | 0.27 | 0.46 | 0.21 | 0.13 | 0.29 |
| DWH endogeneity | 0.73 | 0.12 | 0.26 | 0.94 | 0.01 | 0.96 | 0.06 |
| Observations | 260 | 260 | 260 | 260 | 260 | 52 | 168 |
| $R^2$ | 0.23 | 0.19 | 0.19 | 0.20 | 0.18 | 0.05 | 0.16 |

**Notes:** The dependent variable is the logarithm of the average value of inventions patented. The row labeled: 'Weak instrument' reports the F Stat associated with the test of joint significance of excluded instrument in the first stage; 'Overidentification' reports the p-value associated with the Sargan-Hansen test of overidentifying restrictions; and 'DWH endogeneity' reports the p-value associated with the Hausman test for endogeneity. '$R^2$' is the square of the correlation coefficient between the predicted value and the actual value. Robust standard errors in parentheses. ***, **, * denote significance at the 1 per cent, 5 per cent and 10 per cent probability threshold respectively (test of joint significance for technology and country dummies).

The results of the baseline specification are presented in column (1). The log of the propensity to patent is instrumented with the variable 'imitation' and its square (the excluded instruments denoted $\boldsymbol{Z}$ in equation (7a)). The coefficient associated with $\tilde{q}_i$ (parameter $\beta_2$ in equation (7b)) is negative and significant, supporting the hypothesis of a trade-off between quality and quantity. Note that, although we expect a negative coefficient, we have reported the two-sided hypothesis test to present conservative estimates. However, there is concern that the chosen instruments may be weak. The value for the first-stage F Stat is 5.80, which is below the threshold of 7.25 corresponding to a maximal size of test of 25 per cent (see Stock and Yogo, 2005:101).

It could be argued that the non-linearities in the propensity to patent variable, which arise from the fact that the variable is bounded between 0 and 1, are not well modeled with the linear specification of equation (7a). In column (2), the propensity to patent is estimated in a non-linear way with the following regression model:

$$E[\boldsymbol{\pi}|\boldsymbol{Z}] = G(\tilde{\boldsymbol{q}}\beta_1 + \boldsymbol{C}\boldsymbol{\omega_1} + \boldsymbol{Z}\boldsymbol{\omega_2}) \quad (8)$$

where *G(.)* denotes a link function such as the logistic function to account for the bounded nature of the dependent variable. The econometric method used is the quasi-maximum likelihood estimator developed by Papke and Wooldridge (1996) for fractional data. However, directly plugging the fitted propensity to patent from equation (8) into equation (7b) is known as the 'forbidden regression' (Wooldridge, 2002:236), because it cannot be guaranteed that the first-stage residuals are not correlated with fitted values and covariates. Hence, an extra step is performed, in which the fitted propensity to patent is used as an additional instrument in a conventional linear regression model. In other words, equation (7a) becomes:

$$\boldsymbol{\pi} = \tilde{\boldsymbol{q}}\beta_1 + \boldsymbol{C\gamma_1} + \hat{\boldsymbol{\pi}}\gamma_2 + \boldsymbol{\varepsilon} \quad (9)$$

where $\hat{\boldsymbol{\pi}}$ is the fitted propensity to patent from equation (8). The results are presented in column (2). The first-stage F Stat is 5.66, which lie between the critical values of 6.46 and 5.39 corresponding to a relative bias that is at most between 20 per cent and 30 per cent (Stock and Yogo, 2005: 100).[9] The p-value associated with the Sargan-Hansen test of overidentifying restrictions is 0.26 meaning that the null hypothesis of valid instruments cannot be rejected. The Hausman test for endogeneity suggests that the null hypothesis that a simple OLS estimation is consistent is rejected at the 12 per cent probability threshold. The coefficient associated with the focal variable $\tilde{q}_i$ is negative and highly significant.

Several alternative specifications were tested to ensure the validity of the results, using the IV approach of column (2). First, the quantity variable in the first step was estimated with a Poisson regression model (Hausman et al., 1984) instead of a Negative Binomial regression model. The advantage of the Poisson quasimaximum likelihood regression is that it is consistent as long as the mean is correctly specified (see Gourieroux et al., 1984). The results are presented in column (3) and are very similar to those of column (2).

Second, it could be conceived that the negative coefficient associated with the variable $\tilde{q}_i$ on the average value of inventions patented could be an artifact of the data (an increase in the number of inventions is likely to increase $\tilde{q}_i$ but also to mechanically decrease $a_i$, which is scaled by the number of priority filings). However, this concern is explicitly addressed by the structural model adopted. On a more practical basis, the threat of spurious results is also mitigated by the facts that: i) the first stage is estimated with the number of priority filings in 2005, while the second stage is estimated with patent filings in 2005 and 2006 – as explained in section 3.1; ii) the number of priority filings is included in both the numerator and the denominator of $a_i$; and iii) the variable $\hat{q}_i$ is taken to the log. An alternative specification is presented in column (4) in which the variable $\hat{q}_i$ is transformed into an ordinal variable with ten values: the value 1 is given to observations below the 10th percentile; the value 2 is given to observations between the 10th and the 20th percentiles; etc. Again, the main result is confirmed (although the instrument is weaker).

Third, one wonders how sensitive the results are to the modeling of the propensity to patent in equation (2). The current approach fails to capture the broader influence of 'strategic patenting' that may push firms to adopt a different patenting behavior. Column (5) reports the results of a regression that controls for two important motives to patent that are available from the survey questionnaire: patenting with a view to licensing out the technology

[9] The F Stat reported in column (1) of Table 3 cannot be compared with the F Stat reported in column (2) since the number of instrument variables differs.

('licensing'); and patenting to protect freedom of operation ('freedom').[10] The variable associated with the licensing motivation is negative and significant but this specification leaves the main result unchanged.

A fourth concern relates to the fact that the propensity to patent is a self-assessed measure that could thus be affected by respondent perceptions regarding a 'quantum of invention'. For example, for a given set of research outcomes, one firm may see 10 inventions while another sees 100 of them. Even though it is impossible to control directly for firm perceptions, it is nevertheless possible to observe, and to control for, the effects. In all likelihood, firms of the former type (those that see 10 inventions) are likely to have a lower number of 'inventions' per researcher than firms of the latter type. Column (6) reports the result of a regression that excludes firms with a very low and a very high number of inventions per researcher. In order to select firms which are as homogeneous as possible, we selected firms with a relative number of inventions that lie within the 40th and 60th percentiles. Again, the main result is confirmed. However, tests for the validity of the IV approach have particularly low score, owing to the limited number of observations (*N*=52).[11]

In the last column, the quantity parameter $\tilde{q}_i$ is estimated holding both the number of researchers and the R&D budget constant. In other words, the specification of the invention production function in the first step (equation 4) includes the number of researchers and the R&D budget as independent variables. Although the sample drops to 168 firms due to data availability, the hypothesis of a trade-off is confirmed.

Finally, some considerations regarding the dependent variable should be briefly discussed. Although our definition of invention quality encompasses both the economic and technological values of an invention, it is important to note that the 'quality' measure used captures mainly the private economic value of inventions rather than their technological value. This approach is consistent with the economic literature, which uses price levels to measure productivity improvements (e.g. Jorgenson and Griliches, 1967). It is known, however, that the two dimensions are strongly correlated with each other. For instance, Jensen et al. (2011) present survey evidence that patents covering radical inventions are also more valuable.

Additional robustness tests related to the measurement of value were performed but are not reported. First, the variable $\tilde{q}_i$ was regressed on the share of PCT applications among total patent applications. The PCT is an international treaty that provides a unified procedure for filing patent applications in each of the 146 contracting states (as of January 2013). It makes it possible to seek patent protection by filing an 'international application' within a single patent office. PCT applications are often found to be more valuable than patent applications filed through other routes (Guellec and van Pottelsberghe, 2000; Jensen et al., 2011) such that this approach provides an alternative measure of value. A significant negative correlation is obtained, confirming the hypothesis of a trade-off. Second, patent applications at the EPO may be validated into more than one country such that our value measure underestimates the value of EPO applications (a second filing at the EPO increases the family size by one, and not by the number of countries in which the application is validated). We

[10] The motive variables have been studied by de Rassenfosse (2012) in a different context. Please refer to this article for additional information.

[11] An additional test was performed in order to evaluate the information content of the propensity variable. The test involved plugging the propensity to patent variable directly into a patent production function. The variable had a positive and significant effect on the patent count, suggesting that it conveys meaningful information on the 'true' propensity to patent.

have estimated the quality regression with a variable that captures the ratio of second filings at the EPO to total second filings. The associated coefficient is negative and significant, confirming that our value measure is downwardly biased for companies that filed their patent applications at the EPO. However, the coefficient associated with the variable $\tilde{q}_i$ remains negative and significant.

## 5. Discussion and conclusion

This paper tests whether firms face a trade-off between the quantity and the quality of their inventions. The empirical test is not trivial because inventions are usually observed at the point of patent application. Since the marginal value of inventions patented is likely to decrease with the propensity to patent, a negative correlation between patent quantity and patent quality would not necessarily be evidence of a trade-off. The empirical analysis addresses the identification problem caused by heterogeneous patent propensities across firms by using an instrumental variable approach. Using survey data on applicants at the EPO, we find that firms with a higher rate of invention also have inventions of lower average value as measured by the patent family size.

Important implications for the economics of science and the management of innovation follow from the present findings. First, the existence of a trade-off suggests that a higher number of inventions, and a fortiori patent applications, per unit of research input is not necessarily associated with a higher research productivity. Researchers should strive to take the quality of inventions into account to properly assess – and to study the determinants of – the productivity of research spending. However, this task is particularly difficult because the propensity to patent truncates the innovative output that can be observed. The propensity to patent is usually not observed by researchers and, even if it is, appropriate instrument to account for it may not be available. Second, the existence of a trade-off implies that firms should be very cautious in setting their quantity target, as this may affect the average quality of their inventions. This decision is not only important in a static context but may also have far-reaching consequences. We know from previous research that the quality of available knowledge determines the potential for future inventions because the invention process is cumulative and because existing knowledge enhances the absorptive capacity of the firm (Cohen and Levinthal, 1990). Hence, firms that trade invention quality for immediate research output may undermine their knowledge base and consequently compromise their long-term innovation capabilities.

If considered in a broader context, the results provide an insight into the patent 'explosion'. It is well documented that patent offices worldwide are facing a rise in patenting rates, together with a drop in patent quality (e.g. van Pottelsberghe and van Zeebroeck, 2008). Two broad explanations can be proposed to account for the increase in patent filings. Because only a fraction of inventions are patented, a rise in patent rates could reflect either an increase in the propensity to patent – patent/invention ratio – or a real increase in invention rates – invention/R&D ratio. Although it is generally believed that the current boom in patent applications is the result of an increase in firms' propensity to use the patent system (Hall, 2005; Encaoua et al., 2006; de Rassenfosse and van Pottelsberghe, 2012), the question of whether co-occurring changes in the organization of science may explain these stylized facts has received little attention (to the notable exception of Kortum and Lerner, 1999). In particular, the culture in corporate research labs is reported to be more driven by business imperatives than before, resulting in an increase in applied R&D projects with immediate returns, at the expense of long-term and riskier endeavors (see e.g. Rosenbloom and Spencer, 1996; Ernst, 1998; Coombs and Georghiou, 2002; Varma, 2002). The results presented in this paper are consistent with the second explanation of the patent explosion. It is shown that an increase in the rate of inventions spurred, for instance, by a shift towards more applied R&D projects, can lead to a decrease in the average quality of inventions. Clearly, some firms operating in today's context, of a market-oriented and results-driven approach to technology generation, may have traded quality for quantity. Although this observation is not sufficient to infer that the boom in patent applications is driven by a genuine increase in the quantity of research output; it does suggest that it may be an additional explanation, together with the observed increase in the propensity to patent. Interestingly, the changes in the nature of R&D may also have increased the incentives to patent, since applied projects are presumably easier to imitate.

To conclude, we note that the empirical analysis is silent on the determinants of the quantity–quality decision and the factors that mitigate the trade-off. Although this has the advantage of not constraining the econometric analysis, it also raises more questions than it answers. Such questions require an analysis of their own and it is hoped that future research will contribute to improving our understanding in this area. For instance, it would be interesting to study the extent to which the optimal quantity–quality mix depends on firms' and industry (e.g. complex vs. discrete) characteristics. Similarly, the impact of the quantity–quality choice on the returns to innovation and the innovation potential is unclear, and represent opportunities for further research.

## References


Anton, J., Yao, D., 2004. Little patents and big secrets: Managing intellectual property. *RAND Journal of Economics* 35(1), 1–22.

Arora, A., Ceccagnoli, M., Cohen, W., 2008. R&D and the patent premium. *International Journal of Industrial Organization* 26(5), 1153–1179.

Chan, H., 2010. Determinants of international patenting for nine agricultural biotechnology firms. *Journal of Industrial Economics*, 58(2), 247–278.

Cohen, W., Levinthal, D., 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* 35(1), 128–152.

Coombs, R., Georghiou, L., 2002. A new "industrial ecology". *Science* 296(5567), 471.

Duguet, E., Kabla, I., 1998. Appropriation strategy and the motivations to use the patent system: An econometric at the firm level in French manufacturing. *Annales d'Economie et de Statistique* 49/50, 289–327.

de Rassenfosse, G., 2012. How SMEs exploit their intellectual property assets: Evidence from survey data. *Small Business Economics* 39(2), 437–452.

de Rassenfosse, G., van Pottelsberghe, B., 2012. On the price elasticity of demand for patents. *Oxford Bulletin of Economics and Statistics* 74(1), 58–77.

Encaoua, D., Guellec, D., Martinez, C., 2006. Patent systems for encouraging innovation: Lessons from economic analysis. *Research Policy* 35(9), 1423–1440.

Erkal, N., 2005. The decision to patent, cumulative innovation, and optimal policy. *International Journal of Industrial Organization* 23(7-8), 535–562.

Ernst, H., 1998. Industrial research as a source of important patents. *Research Policy* 27(1), 1–15.

Fleming, L., 2001. Recombinant uncertainty in technological search. *Management Science* 47(1), 117–132.

Gambardella, A., Harhoff, D., Verspagen, B., 2011. The determinants of the private value of patented inventions. Mimeo, Bocconi University.

Girotra, K., Terwiesch, C., Ulrich, K., 2010. Idea generation and the quality of the best idea. *Management Science* 56(4), 591–605.

Gourieroux, C., Monfort, A., Trognon, A., 1984. Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica* 52(3), 701–720.

Griliches, Z., 1979. Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics* 10(1), 9 –116.

Griliches, Z., 1990. Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, 28(4), 1661–1707.

Guellec, D., van Pottelsberghe, B., 2000. Applications, grants and the value of patent. *Economic Letters* 69(1), 109–114.

Hall, B., 2005. Exploring the patent explosion. *Journal of Technology Transfer* 30(1/2), 35–48.

Harhoff, D., Scherer, F., Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. *Research Policy* 32(8), 1343–1363.

Hausman, J., Hall, B., Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. *Econometrica* 52(4), 909–938.

Henderson, R., Cockburn, I., 1996. Scale, scope, and spillovers: The determinants of research productivity in drug discovery. *RAND Journal of Economics* 27(1), 32–59.

Jaffe, A., 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review* 76(5), 984–1001.

Jensen, P., Thomson, R., Yong, J., 2011. Estimating the patent premium: Evidence from the Australian Inventor Survey. *Strategic Management Journal* 32(10), 1128–1138.

Jorgenson, D., Griliches, Z., 1967. The explanation of productivity change. *Review of Economic Studies* 34(3), 249–283.

Kortum, S., Lerner, J., 1999. What is behind the recent surge in patenting? *Research Policy* 28(1), 1–22.

Lanjouw, J., Pakes, A., Putnam, J., 1998. How to count patents and value intellectual property: The uses of patent renewal and application data. *Journal of Industrial Economics* 46(4), 405–432.

Lanjouw, J., Schankerman, M., 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. *Economic Journal* 114(495), 441–465.
Mariani, M., Romanelli, M., 2007. "Stacking" and "picking" inventions: The patenting behavior of European inventors. *Research Policy* 36(8), 1128–1142.
Neuhäusler, P., Frietsch, R., Schubert, T., Blind, K., 2011. Patents and the financial performance of firms – An analysis based on stock market data. Fraunhofer ISI Discussion Papers Innovation Systems and Policy Analysis No. 28, Karlsruhe.
Papke, L., Wooldridge, J., 1996. Methods for fractional response variables with an application to 401 (K) plan participation rates. *Journal of Applied Econometrics* 11(6), 619–632.
Penner-Hahn, J., Shaver, J., 2005. Does international research and development increase patent output? An analysis of Japanese pharmaceutical firms. *Strategic Management Journal* 26(2), 121–140.
Putnam, J., 1996. The value of international patent protection. Ph.D. Thesis, Yale University.
Rosenbloom, R., Spencer, W., 1996. The transformation of industrial research. *Issues in Science and Technology* 12(3), 68–74.
Sanders, B., 1964. Patterns of commercial exploitation of patented inventions by large and small corporations. *Patent, Trademark, and Copyright Journal of Research and Education* 8(1), 51–93.
Schankerman, M., Pakes, A., 1986. Estimates of the value of patent rights in European countries during the post-1950 period. *Economic Journal* 96(384), 1052–1076
Sørensen, J., Stuart, T., 2000. Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly* 45(1), 81–112.
Stock, J., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: J. Stock and D. Andrews (Eds), *Essays in Honor of Thomas Rothenberg*, Chapter 5, 80–108.
Swink, M., Talluri, S., Pandejpong, T., 2006. Faster, better, cheaper: A study of NPD project efficiency and performance tradeoffs. *Journal of Operations Management* 24(5), 542–562.
van Pottelsberghe, B., van Zeebroeck, N., 2008. A brief history of space and time: The scope-year index as a patent value indicator based on families and renewals. *Scientometrics* 75(2), 319–338.
Varma, R., 2000. Changing research culture in U.S. industry. *Science, Technology & Human Values* 25, 395–416.
Wooldridge, J., 2002. Econometric analysis of cross section and panel data. Massachusetts: MIT Press.
Zaby, A., 2010. Losing the lead: The patenting decision in the light of the disclosure requirement. *Economics of Innovation and New Technology* 19(2), 147–164.