Gender, occupational diversity of R&D teams and patents generation: an application to Spanish firms

Mercedes Teruel and Agustí Segarra-Blasco

Research Group of Industry and Territory, Department of Economics & ECO-SOS, Universitat Rovira i Virgili, Av. Universitat, 1, Reus, 43204, Spain. mercedes.teruel@urv.cat agusti.segarra@urv.cat

This paper studies the relationship between gender and occupational diversity in R&D teams and their capacity to generate patents. It is based on an extensive sample of 4,085 firms from the Spanish Community Innovation Survey over the 2004-2014 period. Applying an exponential Poisson regression that controls for endogeneity through the generalised method of moments, the empirical results show that gender diversity has an ambiguous effect. Although it affects patents negatively, this impact is non-significant for patents with international protection. Patent generation is however positively affected by the diversity of categories in the R&D teams. Hence, the key question is not gender *per se* but rather the occupational status of the R&D teams.

1. Introduction

In an increasingly complex world, the appropriability of knowledge is still of key importance in maintaining a competitive advantage (Arrow, 1962; Pisano and Teece, 2007). The generation of patents is a creative activity and requires a significant investment of resources such as time, skills and labour. Employee diversity has become relevant for enhancing the innovative potential of firms. We suggest that the ability of R&D teams to generate new knowledge depends on their composition since that critically affects a firm's R&D capabilities (Dewett, 2007). R&D team members need to have the skills to generate new knowledge, and their joint skills will affect team output quality.

Most of the previous studies have analysed the gender either of the board members (Torchia et al., 2011; Galia and Zenou, 2012) or of the workers (Marinova et al., 2016). However, few studies have focussed on the R&D team (see Gallie, 2002, Turner, 2009, Díaz-García et al., 2013, Fernandez-Sastre, 2015; Garcia Martinez et al., 2017). These studies have mainly considered the impact of gender diversity on innovation. This paper investigates the relationship between gender and occupational diversity in R&D teams and their capacity to generate patents. This is relevant as we must not only assess women's access to R&D teams but also, in order to fully explore the human capital available in the labour market for the generation of new knowledge, assess their tasks in the R&D department.

Additionally, we know little about how firms choose international, as opposed to national, protection for their knowledge. When firms decide to patent, they must choose geographical protection and this choice is nontrivial, since changing the geographical protection location changes both the costs and benefits. Until recently, however, internationalisation and the geographical protection aspects of patents have received little attention – few papers explore the reasons for choosing international versus national patenting.

To investigate this, we test if the composition of R&D teams in terms of gender and occupations affects their productivity (as measured by the firm's propensity to register patents in different territories). As in Garcia Martinez et al. (2017), we consider the effect of heterogeneity using two complementary approaches. Firstly, we calibrate the effect of diversity on a firm's capacity to register patents. Secondly, we undertake a joint occupational category analysis of gender composition and the task specialisations that men and women develop within R&D teams. We use firm-level data drawn from the Spanish Technological Innovation Panel (hereafter PITEC) between 2004 and 2014. Based on panel data of 4,085 Spanish manufacturing and service innovative firms, we apply a two-step procedure that controls for endogeneity. Our results show that diversity has heterogeneous effects. Firstly, gender diversity negatively affects a firms' capacity to register a patent. Secondly, occupational diversity exerts a significant positive impact which is more marked in relation to international patent offices and is indicative of the different characteristics of the firms registering patents. Finally, our results highlight the importance of diverse occupations inside R&D teams. Overall, we conclude that the roles are undertaken inside an R&D team, rather than its gender composition, have a greater impact on its generation of patents.

This paper contributes to three aspects of the literature. Firstly, we show evidence for the impact of diverse R&D teams on the generation of patents. This paper adopts a dual perspective that includes both the gender dimension and the tasks performed by each R&D employee. As in Gallie (2002), we include the occupational diversity of an R&D team as a key variable. Our results highlight the importance of women having access to different roles in R&D teams. We also apply econometric techniques to control for endogeneity which is rarely found in the literature. Finally, we consider the impact of diversity on a patent category in terms of territorial protection. This is important since, in a more globalised technological market, the patent strategy adopted by a firm will affect its capacity to protect and exploit knowledge and worldwide technological diffusion.

The structure of the paper is as follows. Section 2 outlines the literature. Section 3 presents the database used and several descriptive statistics. Section 4 describes the econometric methodology. Section 5 details the main results. Conclusions are drawn in Section 6.

2. Literature review

In this section, we analyse the theoretical and empirical relationship between the composition of R&D teams and patent generation. Firstly, we present the relationship between R&D teams and their capacity to generate patents. Secondly, we analyse the roles of gender and occupational diversity in R&D teams.

2.1. R&D teams and their capacity to generate new patents

The generation of new knowledge is a complex and long-lasting process in which several actors participate. According to Gupta et al. (2007), innovations are a two-level phenomenon that involves, firstly, agents and, secondly, their environment where the protagonists interact. The composition of an R&D team affects its performance and the return on R&D investment. In this line, Amoroso and Audretsch (2020) found that only female-led firms are able to benefit from some external sources. Patents are one of the outputs of R&D investment, they are codified knowledge arising from the tacit knowledge embodied in each R&D team member, together with other codified knowledge (existing stock of knowledge, R&D investment, etc.) and other tacit knowledge (know-how, etc.).

Indeed, one of the most important aspects of the creation of patents, and knowledge in general, is the value of different research approaches – termed 'parallel development' (Klein and Meckling, 1958). Decisions are made under uncertainty and the capacity to handle this uncertainty, and apply it to convert existing into new knowledge, depends on the R&D team and defines a firm's capacity to patent.[1]

Different approaches point to the positive impact of diversity on patent activity. From the inventor's perspective, Frietsch et al. (2009) analysed patent and publication databases for 14 European countries and found substantial differences across countries in terms of women's relative contribution to science and technology. Adopting a macroeconomic approach, Bosetti et al. (2015) departed from the R&D-based models where the generation of ideas depends on the number of skilled employees in the research sector and on their average productivity. They modelled the productivity per researcher as a function of the diversity of the R&D team involved in the process of generation of patents. There still are few studies, however, which analyse the relationship between the heterogeneity of R&D teams and their patent generation.

A wider range of studies investigates the impact of the R&D team's gender composition on innovation output. For instance, Milliken and Martins

(1996) suggest that a diverse team has access to a larger network and to a larger pool of information, skills and support coming from within the network. *A priori*, more diverse skills and competencies might be expected to increase team creativity and innovation. Studies, such as Lazear (1999), Baer et al. (2013), Laursen (2012), Østergaard et al. (2011), take a broad view of the firm's environment and confirm that diversity facilitates better decision-making. However, negative impacts may be also expected, especially in sectors that require a quick response to market shocks, when the time required to make decisions is increased (Carter et al., 2003).

Existing previous empirical studies lead us to expect that more diverse teams would positively influence a firm's capacity to patent. Patents are the result of complex tasks which require problem-solving. In the quest for novelty, the literature has found that diversity facilitates the recombination of distant knowledge and expertise (Fleming, 2001; Chen et al., 2009; Rzhetsky et al., 2015; Shi et al., 2015). Additionally, Díaz-García et al. (2013) find a positive relationship between gender diversity in R&D teams and the probability of carrying out radical innovation. Generally, we expect diverse teams to adopt more diversified approaches and their final output to be more innovative.

Patenting is expensive and patent office decisions are critical, so only high-potential inventions apply for patents (Narin et al., 1987; Long, 2002). More radical and innovative patents are expected to have a larger patent value which needs wider territorial protection. Firms will adopt merely national protection if they anticipate a lower patent value. In this regard, Deng (2007) found that European patents granted through EPO are more valuable than those granted via national routes. For instance, in the telecom industry, several companies have strategically located their corporate HQ for Strategic Technology with a view to making patents effective other than where they were generated.[2]

2.2. *Gender and occupational diversity and the generation of patents*

A large empirical literature has studied diversity based on demographical and task-related characteristics. These two dimensions assume that cognitive patterns tend to vary systematically with these two characteristics, both observable (Thomas and Ely, 1996; Campbell and Mínguez-Vera, 2008). In the current subsection, we briefly analyse those works that have focussed on the relationship between gender and tasks diversity at the firm level and the firm's innovation.

Despite the strong empirical interest in analysing the effects of gender on firm performance, few works have evaluated its impact on innovation at the firm level (Alsos et al., 2013). Some works have considered the gender diversity of executive teams and the board of directors (Østergaard et al., 2011; Torchia et al., 2011; Galia and Zenou, 2012; Ritter-Hayashi et al., 2016), others the total workforce (Marinova et al., 2016; Teruel and Segarra, 2017), barely a handful have focussed on the R&D departments. Amongst the final group, Turner (2009) showed how the composition of R&D teams improves innovation in firms. For Spanish firms, Díaz-García et al. (2013) and Fernandez-Sastre (2015) find that the gender composition of R&D teams affects the innovation activity. However, the only analysis of the patent activity of R&D teams is that of Gallie (2002). His results show that gender heterogeneity does not increase the propensity to apply for an EPO patent. As there are gender differences between employees' skills and knowledge, we expect that the gender composition of an R&D department will have an impact on a firm's capacity to develop patents once we consider the tasks developed.

Concerning occupational diversity, Faems and Subramanian (2013) assess the impact of R&D manpower diversity on technological performance for a sample of 938 Singaporean firms. They hypothesise that both demographical and task-related sources of heterogeneity within a firm's R&D workforce influence technological performance and find substitutive relationships between (a) educational and gender diversity and (b) nationality and knowledge area diversity.

Most studies analyse demographical and task-related heterogeneity independently, but scholars point out potential interaction effects (Van Knippenberg and Schippers, 2007; Faems and Subramanian, 2013). Jehn et al. (1999), for instance, observed that the positive relationship between task-related diversity and group performance was negatively moderated by demographical heterogeneity. The main argument here is that task-related diversity will most benefit those groups with greater difficulties in occupying some categories. Given the difficulties that women encounter in accessing higher occupational categories, we would expect female, rather than male, occupational diversity to exert a greater positive influence on a firm's capacity to patent. Hence, the occupational category provides information on which are the tasks and skills that an employee must develop in their job place.

3. Database

The econometric work is based on PITEC, a database jointly developed by the Spanish National Institute of Statistics, the Spanish Foundation for Science and Technology (FECYT) and the Foundation for Technical Innovation.[3] PITEC has two primary advantages. Firstly, it contains detailed information on innovation behaviour at the firm level following the Oslo Manual guidelines (OECD, 2005). Secondly, it is compiled from successive Spanish Community Innovation Survey waves and has a temporal dimension.[4]

We apply two filters to obtain our final sample. Firstly, we only select firms with complete information. Secondly, we exclude firms with any employment-related problems (such as companies in sectors of high seasonality or involved in merger/acquisition processes). The data cleansing process guarantees that we have a comparable set of firms in similar economic conditions. Our final sample contains 40,032 observations belonging to 4,085 firms observed between 2004 and 2014.

Table 1 describes the mean tests with respect to the capacity of these firms to generate patents. We observe that, regardless of the type of patent, firms with an R&D department have a higher capacity to register patents. Most commonly patents are registered in the Spanish registry (OEPM), less so with the US Patent and Trademark Office (USPTO).

We note that 60.7% of firms in our sample possess R&D departments. Of the total number of firms that register patents, 12.9% have an R&D department. Hence, we corrected for selectivity bias and the lag between patent registration and R&D using a two-step procedure (see Section 4).

Although there are other options for measuring diversity (see Harrison and Klein, 2007), the Blau index (B) is preferred for measuring demographical heterogeneity (Blau, 1977).[5] It is defined as follows:

$$B = \left[1 - \sum_{i=1}^{N} p_i^2\right],$$

where p_i is the proportion of members in the ith of N categories.

4. Econometric specification

As stated in Section 2.1, innovation output is the result of the interaction of several actors. Previous results show that gender and occupational composition of R&D teams will affect the capacity for generating patents. Following Berliant and Fujita (2011), we adopt an endogenous growth model methodology. Our model assumes that the production function of new knowledge depends on the knowledge diversity of researchers. Similarly, researchers are horizontally differentiated by their knowledge, where individual knowledge composition is endogenous and evolves over time. We consider the gender and occupational category compositions of the research team. Our starting point is that there is a certain complementarity of individuals' knowledge which accelerates the generation of new ideas. Following previous literature (Hall et al., 1986), we take a two-step approach where the firm decides to have an R&D department and later we estimate the influence of the team composition on the patents generation. Hence, the diversity of R&D teams interacts directly with the production function of patents.

We estimate the determinants of an R&D team's capacity for registering patents. Firms with an R&D department may have a greater propensity to register patents than those without one, so there may be a sample selection bias. The omission of non-observable characteristics, such as firms with R&D departments that perhaps have better-defined innovation processes, will bias our results. To deal with this, we apply a two-step procedure. Firstly, Equation 1 considers the probability that a firm decides to have an R&D department:

$$y_{1i,t} = \begin{cases} 1 \text{ if } y^*_{1i,t} = f(X_{1i,t-1}\beta_1 + \gamma_{1,t} + \varepsilon_{1i,t}) > 0 \\ 0 \quad \text{otherwise} \end{cases}, \quad (1)$$

where $y_{1i,t}$ is a dummy variable that indicates whether a firm has an R&D department. We define

Table 1. Number of patents (2004-2014) per firm broken down by presence/absence of an R&D department

	Number of patents		Prob ($T < t$) = Mean test (H0:)
	Firms with R&D department	Firms without R&D department	
All patents	1.0183	0.0724	0.0000
OEPM	0.5360	0.0517	0.0000
EPO	0.2858	0.0135	0.0000
USPTO	0.1405	0.0032	0.0000
PCT	0.2108	0.0072	0.0000
Observations	23,932	16,100	

The values indicate the number of patents registered by the firm. OEPM: Spanish Office of Patents and Brands; EPO: European Patent Office; USPTO: United States Patent and Trademark Office; PCT: Patent Cooperation Treaty.
Source: Own elaboration from PITEC.

latent-dependent variables $y^*_{1i,t}$ and a set of explanatory variables $X_{i,t-1}$. Firm 'i' has an R&D department if $y^*_{1i,t}$ is positive. From Equation 1, we obtain the Mills ratio to control for sample selection bias in our main Equation 2, which estimates the capacity of a firm to generate patents:

$$y_{2i,t} = \beta_{20} + Z_{i,t-1}\beta_{21} + \beta_{22}gender_{i,t-1} + \beta_{23}occ_{i,t-1} + \gamma_{2t} + \varphi_{i,t} + \varepsilon_{2i,t}, \tag{2}$$

where $y_{2i,t}$ is the number of patents generated by firm 'i' in period 't'. The variables $gender_{i,t-1}$ and $occ_{i,t-1}$ are proxies for gender and occupational diversity defined as the Blau index, $Z_{i,t-1}$ is a vector of controls. $\gamma_{.t}$ is a time-fixed effect, $\varepsilon_{i,t}$ is a random error, β are the coefficients to be estimated and $\varphi_{i,t}$ corresponds to the inverse Mills ratio. The inverse Mills Ratio picks up the expected value of the error in the patent equation, conditional on a firm having an R&D department. The coefficient of the inverse Mills ratio (see Tables 2 and 3) being significant means that there is a sample selection bias to be controlled. A negative $\varphi_{i,t}$ coefficient implies that firms with an R&D team are more likely to register patents. Hence, our analysis assumes that well-functioning R&D teams achieve higher patents.

Equation 1 includes the so-called exclusion restrictions, control variables ($X_{i,t-1}$) for firm age, firm size and other explanatory variables, to reduce collinearity between the inverse Mills ratio and the control variables of Equation 2. For this reason, we included the capital-labour intensity of the firm in addition to sectoral dummies.

Equation 2 includes other explanatory variables ($Z_{i,t-1}$) that affect the capacity of the R&D team to generate patents. Firstly, we introduce variables related to firm characteristics such as size (as measured by employees) and age. Secondly, we include three dummy explanatory variables for the firm's environment (whether the firm exports, belongs to a group, or is a parent establishment). Thirdly, we introduce a set of characteristics regarding the R&D team such as gender, occupation, education and number of researchers. Fourthly, we include variables related to the innovation effort of the firm (internal and external R&D investment intensity) and its R&D cooperation. Finally, we include dummies identifying the technological and knowledge intensity of the sector where they operate (high-tech manufacturing, knowledge-intensive services [KIS] and non-KIS firms).[6]

The link between patent registration and R&D work has a considerable lag that cannot be ignored (Hall et al., 1986). Hence, all the explanatory variables are lagged one period to mitigate double causality. However, past levels of diversity are still possibly correlated with the current capacity to generate patents, as a firm may decide to modify the composition of their R&D team in order to reinforce their capacity to generate knowledge.

Following previous contributions (Blundell et al., 1995, 2002), we apply an exponential (Poisson) regression with an endogenous regressor using a two-step generalised method of moments (GMM) which presents several advantages. Firstly, it introduces dynamics. Secondly, controlling for the unobserved heterogeneity generates consistent parameter estimates. Thirdly, it shows low sample bias when the time series show a high degree of persistence (as is the case with the diversity of R&D teams). The econometric problem that arises is that diversity may be an endogenous variable relative to the dependent variable and thus correlated with $\varepsilon_{i,t}$. Endogeneity arises from there being some unobservable variables that may simultaneously affect both diversity and the capacity to generate patents. Diversity might, by way of example, be correlated with ability levels in the R&D team or even with the team's work ethic (both unobserved variables). This suggests that estimating Equation 2 may produce inconsistent results and lead to misleading inferences.[7] We employ a system estimator using lagged differences of the endogenous variables as instruments.[8] As additional instruments, we include the sectoral value of gender and occupational diversity and three dummies identifying organisational innovative performance.[9] Finally, standard errors are estimated by allowing correlation at the firm level.

5. Results

Table 2 presents the impacts of the diversity in the R&D department on the number of patents registered by a firm. The estimated effect associated with the variable gender diversity is negative, although statistically non-significant for our main estimation with all patent types. When differentiating according to territorial protection, the coefficient becomes non-significant. Our results are similar to those of Gallie (2002), who finds for a sample of Danish firms that gender diversity is not significant for generating EPO patents.[10] Our results confirm that the generation of patents has a different nature from that of innovations (Table 2).

The lack of impact of gender diversity in the R&D teams may be explained by the relationship between the Blau index and the number of patents. Here, we used kernel-weighted local polynomial smoothing techniques to obtain non-parametric estimates of

Table 2. Estimation of the determinants of a firm's capacity to register patents

	All	OEPM	EPO	USPTO	PCT
Patents $_{i,t-1}$	0.0132***				
	(0.0013)				
OEPM patents $_{i,t-1}$		0.0389***			
		(0.0045)			
EPO patents $_{i,t-1}$			0.0264***		
			(0.0023)		
USPTO patents $_{i,t-1}$				0.0537***	
				(0.0093)	
PCT patents $_{i,t-1}$					0.0466***
					(0.0027)
blauGender $_{i,t-1}$	−0.602*	−0.500	−0.554	−0.0976	0.668
	(0.3210)	(0.3080)	(0.3810)	(0.5980)	(0.4830)
blauCateg $_{i,t-1}$	0.514**	0.442*	0.779*	1.317	0.562
	(0.2480)	(0.2590)	(0.4030)	(0.8230)	(0.4740)
blauEduc $_{i,t-1}$	−0.18	−0.111	−0.188	−1.103**	−0.0755
	(0.2000)	(0.1880)	(0.2690)	(0.4420)	(0.2500)
sizeRDdept $_{i,t-1}$	0.209**	0.00145***	0.307***	0.373***	0.13
	(0.0834)	(0.0006)	(0.1120)	(0.1430)	(0.1300)
size $_{i,t-1}$	0.363***	0.297***	0.293***	0.231	0.243**
	(0.0831)	(0.0688)	(0.1090)	(0.1650)	(0.1220)
age $_{i,t-1}$	0.0119	0.0546	0.0418	0.124	−0.149
	(0.0847)	(0.0880)	(0.1160)	(0.1830)	(0.1130)
exp $_{i,t-1}$	0.545***	0.243**	0.612***	0.657**	0.331***
	(0.1030)	(0.1060)	(0.1640)	(0.3040)	(0.1130)
group $_{i,t-1}$	−0.042	−0.219	0.348*	0.607**	0.143
	(0.1500)	(0.1540)	(0.2020)	(0.2600)	(0.2320)
matrix $_{i,t-1}$	0.208	0.278	0.00659	0.417	0.518**
	(0.1960)	(0.1760)	(0.2630)	(0.2600)	(0.2130)
RDext $_{i,t-1}$	0.0088*	−0.0006	0.0130**	0.0123	0.011
	(0.0049)	(0.0046)	(0.0062)	(0.0089)	(0.0091)
RDint $_{i,t-1}$	0.261***	0.241***	0.320***	0.487***	0.419***
	(0.0638)	(0.0555)	(0.0841)	(0.1030)	(0.0765)
coopera $_{i,t-1}$	0.0118	0.342***	−0.0803	−0.456***	0.0575
	(0.0966)	(0.1230)	(0.1250)	(0.1500)	(0.1330)
High-tech	0.127	−0.097	−0.0937	−0.264	−0.286
	(0.2110)	(0.2650)	(0.2300)	(0.2890)	(0.2550)
KIS	0.0671	−0.172	−0.126	−0.362	−0.46
	(0.2590)	(0.3020)	(0.3000)	(0.4020)	(0.3150)
constant	−4.847***	−4.442***	−6.843***	−9.204***	−6.689***
	(0.7970)	(0.7780)	(1.0170)	(1.3360)	(0.9040)
Mills ratio	−0.592*	−0.69	−1.304***	−0.909**	−1.642***
	(0.3420)	(0.4540)	(0.3820)	(0.4520)	(0.5060)
Observations	16,524				
			Test of over-identifying restriction		
Hansen's J χ^2	4.1258	16.483	2.7625	5.0833	4.1164
$P > \chi^2$	0.5314	0.0056	0.7365	0.4058	0.5328

***Significant at 1%, **Significant at 5%, *Significant at 10%. Numbers in parenthesis are the standard errors of the coefficients.

the dependence of patent numbers on the Blau index (Figure 1).

Concerning the diversity of education and occupations inside R&D departments, we observe that education level does not exert a significant impact and, in fact, shows a negative impact on the number of US patents. Conversely, the diversity of occupations has a positive and significant effect on the number of patents registered by a firm. Our results highlight the higher relevance of the diversity of occupations inside a firm rather than the education level. This difference shows the potential complementarity between the different roles inside an R&D department, where the activities of technicians and researchers may be complementary. This coefficient remains significant for patents both in OEPM and EPO.

Figure 1 uses a logarithmic scale to plot the link between gender and occupational diversity and the number of patents. Figure 1a displays an inverted U-shape with a global maximum at an x-value of approximately 0.15. Once the firm surpasses this value, the relationship is still positive, but the impact has a slight negative slope. This pattern is similar to the patents in OEPM, while the relationship is smoother for patents in the EPO, USPTO and other Patent Cooperation Treaties.[11] However, this pattern differs from that of occupational diversity which typically has two local maxima (at x-values of about 0.15 and 0.75). Therefore, we argue that we must consider not only gender but also the tasks developed by each researcher inside the R&D team and indeed their education level.

To further investigate how gender diversity interacts with other characteristics from the R&D team, we investigate alternative indicators of the heterogeneity of occupations and education. Hence, departing from the previous Equation 2, we now estimate two different equations:

$$\begin{aligned} y_{3i,t} &= \beta_{30} + Z_{i,t-1}\beta_{31} + \beta_{32}OccFEM_{i,t-1} \\ &+ \beta_{33}OccMALE_{i,t-1} + \ldots + \gamma_{3t} + \varphi_{i,t} + \varepsilon_{3i,t}, \end{aligned} \quad (3)$$

$$\begin{aligned} y_{4i,t} &= \beta_{40} + Z_{i,t-1}\beta_{41} + \beta_{42}EducFEM_{i,t-1} \\ &+ \beta_{43}EducMALE_{i,t-1} + \ldots + \gamma_{4t} + \varphi_{i,t} + \varepsilon_{4i,t}. \end{aligned} \quad (4)$$

All the variables remain equal to Equation 2, however, now our explanatory variables of interest are the diversity of occupations amongst females (*OccFEM*) and males (*OccMALE*) and also the diversity of education categories between the genders (*EducFEM*, *EducMALE*). These variables are also defined as the Blau index.

The diversity of categories (Table 3, panel A) shows a positive and significant impact for both genders. However, the coefficient is significant only for the whole sample of females. Conversely, male occupational diversity is positive and significant for patents registered with USPTO or PCT. Our education level diversity index remains negative but is only significant for USPTO patents. Further analysis of educational diversity by gender (Table 3, panel B) does not provide a qualitative change. The education diversity of males in the R&D team exerts a significantly negative impact on OEPM and USPTO patent registrations. Conversely, occupational diversity becomes positive and significant.

Our results point out two important findings. Firstly, the complementarity between different occupations is crucial in order to register more patents – this result is higher for females. These results are in line with the importance and need for women to follow STEM paths and to facilitate their populating

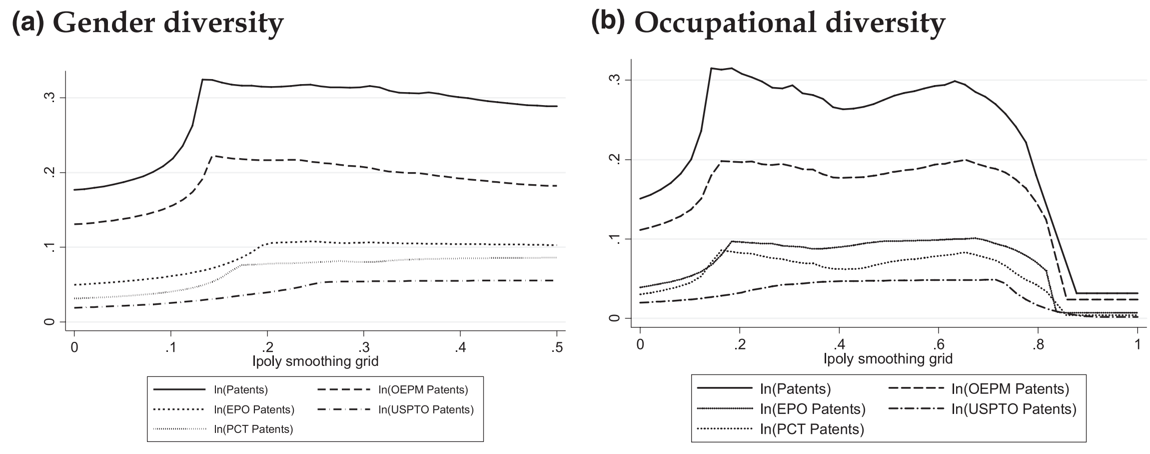

Figure 1. Graphs of gender and occupational diversity in R&D departments for the period 2004-2014. The y-axis is a kernel-weighted local polynomial smooth estimation of the Blau index. The x-axis is the natural logarithm of a chosen source of patent data. OEPM: Spanish Office of Patents and Marks; EPO: European Office of Patents; USPTO: US Patents and Trademark Office; PCT: Treats of cooperation of patents. *Source:* Own elaboration.

Table 3. Estimation of the determinants of a firm's capacity to register patents

	All	OEPM	EPO	USPTO	PCT
Panel A. Disaggregation according to the category					
$OccFEM_{i,t-1}$	1.043**	1.122**	0.474	1.342	0.428
	(0.5000)	(0.5180)	(0.6950)	(1.1330)	(0.5640)
$OccMALE_{i,t-1}$	0.312	0.26	0.503	1.308*	1.064**
	(0.2670)	(0.2740)	(0.4090)	(0.7580)	(0.4890)
$blauEduc_{i,t-1}$	−0.163	−0.0894	−0.0589	−1.042***	−0.0769
	(0.2010)	(0.2040)	(0.2570)	(0.3660)	(0.2490)
Mills ratio	−0.587*	−0.673	−1.294***	−0.953**	−1.653***
	(0.340)	(0.445)	(0.375)	(0.451)	(0.508)
Hansen's J χ^2	4.714609	18.976	1.9724	4.9299	3.7041
$P > \chi^2$	0.451	0.0019	0.8529	0.4245	0.5927
Panel B. Disaggregation based on the education level					
$blauOcc_{i,t-1}$	0.489**	0.708***	0.805**	1.431*	0.538
	(0.2430)	(0.2730)	(0.3970)	(0.8220)	(0.4570)
$EducFEM_{i,t-1}$	0.429	0.353	−0.169	−1.454	−0.326
	(0.6130)	(0.4150)	(0.6890)	(1.0140)	(0.6880)
$EducMALE_{i,t-1}$	−0.386	−0.420*	−0.459	−1.455***	0.304
	(0.2440)	(0.2320)	(0.3510)	(0.5250)	(0.3910)
Mills ratio	−0.601*	−1.032*	−1.306***	−0.984**	−1.696***
	(0.347)	(0.537)	(0.374)	(0.464)	(0.513)
Hansen's J χ^2	4.4628	21.2692	2.5646	5.6430	4.4477
$P > \chi^2$	0.4849	0.0007	0.7667	0.3425	0.4869

***Significant at 1%, **Significant at 5%, *Significant at 10%. Numbers in parenthesis are the standard errors of the coefficients.

all categories. Secondly, the negative impact of male education diversity on the registration of patents is at first glance puzzling – it may perhaps be explained by the advantage of having more well-educated members in the R&D team to foster knowledge generation.

Our result suggests that the mechanism that makes firms develop and produce more complex patents is quite different from that which encourages firms to protect their knowledge and do this through the Spanish system. Patents in EPO, USPTO and PCT are measures of the internationalisation of inventive activities.

6. Conclusions

Despite the growing number of studies of diversity and firm performance, the empirical evidence remains inconclusive. This work addresses that gap by emphasising the different dimensions that determine the diversity of R&D teams and their propensity to generate new patents. We conduct a joint analysis of gender and tasks effect on the patenting activities of Spanish manufacturing firms during the period 2004–2014 using the PITEC panel.

Our results show that the gender diversity of R&D teams has a dual effect. The impact is statistically negative with regards to the capacity to generate OEPM patents, while this sign becomes positive for more occupationally diversified R&D teams that register patents with OEPM and EPO (the effect not being significant for USPTO and PCT). Our results seem to indicate that the mechanism that makes firms to develop and produce more complex patents is quite different from that which drives firms to protect knowledge and protect through the Spanish system. Furthermore, our results highlight that the complementarity of tasks developed amongst the members of the R&D team may be more important than gender composition in fostering the development of new, patent-protectable, knowledge.

These results suggest several different lines of argument. Firstly, since the EU and US markets are much larger than that of Spain, firms may be interested in protecting their most significant innovations abroad. Secondly, these patents are more likely to include the most economically important inventions, those whose anticipated returns are high enough to outweigh the cost of filing a patent abroad. Therefore, the difference encountered in terms of diversity may capture the relationship between the environment of the R&D team and the different nature of the inventions being produced. We might conclude that, for firms with R&D departments, having more diverse teams is not a crucial determinant in registering EPO, USPTO and/or PCT patents. The opposite is, however, true in respect of the capacity to generate OEPM patents.

Our findings are relevant for managers since the paper disambiguates the interaction between gender and task diversity. In a competitive world, where knowledge is a key asset, firms must reinforce their internal capacity to better position themselves. Our results highlight that coordination between members in the R&D teams improves knowledge production. Consequently, we recommend facilitating a degree of task diversity for each gender. Furthermore, our evidence shows the particularity of firms that adopt a more internationalised knowledge protection strategy. Finally, the paper enhances our understanding of the performance implications of R&D team diversity by considering the interactions between gender and occupations in R&D teams (Lau and Murnighan, 1998). From a policymaker's perspective, it is crucial to understand how organisational composition may affect the generation of internationally competitive new knowledge. Our results suggest that policymakers should facilitate, or even ensure, equal scientific careers for both genders.

Future lines of research are to analyse in more depth several points which emerge from this paper in regards to the management and functioning of R&D personnel. The first of these is how the different scientific careers of men and women affect their tasks in R&D teams and their later efficiency. The second is to explore possible relationships between R&D team diversity and external R&D intensity in regards to absorbing external knowledge.

Acknowledgements

We are very much indebted to Sara Amoroso, José García-Quevedo, Ester Martínez-Ros, Pierre Mohnen, Harald Oberhofer, Fabio Pieri and other participants at the Sixth European Conference on Corporate R&D and Innovation CONCORDi2017 (Seville, 17–29 September 2017), the Workshop on Challenges of Innovation Policy (Reus, 24 November 2017), the 12th Workshop on 'The Organization, Economics and Policy of Scientific Research' (Bath, 27–28 April 2018), XXI Applied Economics Meeting (Sevilla, 7–8 June 2018), DRUID conference (Copenhaguen, 11–13 June 2018) and Workshop on the modern drivers of firm performance (Trento, 13–14 December 2018). We are grateful to three anonymous referees for useful comments and suggestions and to Verònica Gombau for her research support. The usual disclaimers apply.

Funding

This paper is part of the investigations carried out with the financial support of the competitive project ECO2015-68061-R 'Gender Diversity as a Determinant of Innovation: An Analysis of the Impact of Gender Diversity on Firm Innovation' funded by the Ministry of Economics and Competitiveness Spanish Government and by European funds from FEDER. This work was also supported by Universitat Rovira i Virgili (2019PFR-URV-B2-80), the Consolidated Group of Research (2017-SGR-00493) and the Xarxa de Referència en Economia Aplicada (XREAP).

References

Al-Laham, A., Tzabbar, D., and Amburgey, T.L. (2011) The dynamics of knowledge stocks and knowledge flows: innovation consequences of recruitment and collaboration in biotech. *Industrial and Corporate Change*, **20**, 555–583. https://doi.org/10.1093/icc/dtr001

Alsos, G.A., Ljunggren, E., and Hytti, U. (2013) Gender and innovation: state of the art and a research agenda. *International Journal of Gender and Entrepreneurship*, **5**, 236–256. https://doi.org/10.1080/09585192.2011.561961

Amoroso, S. and Audretsch, D.B. (2020) The role of gender in linking external sources of knowledge and R&D intensity. *Economics of Innovation and New Technology*. https://doi.org/10.1080/10438599.2020.1844038

Arrow, K.J. (1962) Economic welfare and the allocation of resources for invention (Reprint). In: Stephan, P.E. and Audretsch, D. B. (eds), *The Economics of Science and Innovation*, Vol. 1, Cheltenham, UK: Edward Elgar Publishing. pp. 61–77.

Baer, M., Vadera, A.K., Leenders, R.T.A.J., and Oldham, G.R. (2013) Intergroup competition as double-edged sword: how sex composition regulates the effects of competition on group creativity. *Organization Science*, **25**, 892–908. https://doi.org/10.1287/orsc.2013.0878

Berliant, M. and Fujita, M. (2011) The dynamics of knowledge diversity and economic growth. *Southern Economic Journal*, **77**, 856–884. https://doi.org/10.4284/0038-4038-77.4.856

Blau, P.M. (1977) *Inequality and Heterogeneity: A Primitive Theory of Social Structure* (Vol. 7). New York: Free Press.

Blundell, R., Griffith, R., and Van Reenen, J. (1995) Dynamic count data models of technological innovation. *Economic Journal*, **105**, 333–344. https://doi.org/10.2307/2235494

Blundell, R., Griffith, R., and Windmeijer, F. (2002) Individual effects and dynamics in count data models.

Journal of Econometrics, **108**, 113–131. https://doi.org/10.1016/S0304-4076(01)00108-7

Bosetti, V., Cattaneo, C., and Verdolini, E. (2015) Migration of skilled workers and innovation: a European perspective. *Journal of International Economics*, **96**, 311–322. https://doi.org/10.1016/j.jinteco.2015.04.002

Campbell, K. and Mínguez-Vera, A. (2008) Gender diversity in the boardroom and firm financial performance. *Journal of Business Ethics*, **83**, 435–451. https://doi.org/10.1007/s10551-007-9630

Carter, D.A., Simkins, B.J., Simpson, W.G., Borokhovich, K., Crutchley, C., Elson, C., and Longhofer, S. (2003) Corporate governance, board diversity, and firm value. *The Financial Review*, **38**, 33–53. https://doi.org/10.1111/1540-6288.00034

Chen, C., Chen, Y., Horowitz, M., Hou, H., Liu, Z., and Pellegrino, D. (2009) Towards an explanatory and computational theory of scientific discovery. *Journal of Informetrics*, **3**, 191–209. https://doi.org/10.1016/j.joi.2009.03.004

Deng, Y. (2007) Private value of European patents. *European Economic Review*, **51**, 1785–1812. https://doi.org/10.1016/j.euroecorev.2006.09.005

Dewett, T. (2007) Linking intrinsic motivation, risk taking, and employee creativity in an R&D environment. *R&D Management*, **37**, 197–208. https://doi.org/10.1111/j.1467-9310.2007.00469.x

Díaz-García, C., González-Moreno, A., and Sáez-Martínez, F.J. (2013) Gender diversity within R&D Teams: Its impact on radicalness of innovation. *Innovation: Management, Policy and Practice*, **15**, 149–160. https://doi.org/10.5172/impp.2013.15.2.149

Dwyer, S., Richard, O.C., and Chadwick, K. (2003) Gender diversity in management and firm performance: the influence of growth orientation and organizational culture. *Journal of Business Research*, **56**, 1009–1019. https://doi.org/10.1016/S0148-2963(01)00329-0

Faems, D. and Subramanian, A.M. (2013) R&D manpower and technological performance: the impact of demographic and task-related diversity. *Research Policy*, **42**, 1624–1633. https://doi.org/10.1016/j.respol.2013.06.001

Fernandez-Sastre, J. (2015) The impact of R&D teams' gender diversity on innovation outputs. *International Journal of Entrepreneurship and Small Business*, **24**, 142. https://doi.org/10.1504/IJESB.2015.066154

Fleming, L. (2001) Recombinant uncertainty in technological search. *Management Science*, **47**, 117–132. https://doi.org/10.1287/mnsc.47.1.117.10671

Frietsch, R., Haller, I., Funken-Vrohlings, M., and Grupp, H. (2009) Gender-specific patterns in patenting and publishing. *Research Policy*, **38**, 590–599. https://doi.org/10.1016/j.respol.2009.01.019

Galia, F. and Zenou, E. (2012) Board composition and forms of innovation: does diversity make a difference? *European Journal of International Management*, **6**, 630–650. https://doi.org/10.1504/ejim.2012.050425

Gallie, D. (2002) Skill, gender and the quality of employment. In: Crompton, R., Gallie, D., and Purcell, K. (Eds.), *Changing Forms of Employment*. London: Routledge. pp. 145–171.

Garcia Martinez, M., Zouaghi, F., and Garcia Marco, T. (2017) Diversity is strategy: the effect of R&D team diversity on innovative performance. *R&D Management*, **47**, 311–329. https://doi.org/10.1111/radm.12244

González, A., Díaz, C., and Sáez, F. (2018) R&D team composition and innovation: gender diversity makes a difference. *European Journal of International Management*, **12**, 423–446. https://doi.org/10.1504/EJIM.2018.092843

Gupta, A.K., Tesluk, P.E., and Taylor, M.S. (2007) Innovation at and across multiple levels of analysis. *Organization Science*, **18**, 885–897. https://doi.org/10.1287/orsc.1070.0337

Hall, B.H., Griliches, Z., and Hausman, J.A. (1986) Patents and R&D: is there a lag? *International Economic Review*, **27**, 265–283. https://doi.org/10.2307/2526504

Harrison, D.A. and Klein, K.J. (2007) What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, **32**, 1199–1228. https://doi.org/10.5465/amr.2007.26586096

Jehn, K.A., Northcraft, G.B., and Neale, M.A. (1999) Why differences make a difference: a field study of diversity, conflict and performance in workgroups. *Administrative Science Quarterly*, **44**, 741–763. https://doi.org/10.2307/2667054

Klein, B.H. and Meckling, W.H. (1958) Applications of operations research to development decisions. *Operations Research*, **5**, 352–363. https://doi.org/10.1287/opre.6.3.352

Lau, D. and Murnighan, J.K. (1998) Demographic diversity and faultlines: the compositional dynamics of organizational groups. *Academy of Management Review*, **23**, 325–340. https://doi.org/10.5465/amr.1998.533229

Laursen, K. (2012) Keep searching and you'll find: what do we know about variety creation through firms' search activities for innovation? *Industrial and Corporate Change*, **21**, 1181–1220. https://doi.org/10.1093/icc/dts025

Lazear, E.P. (1999) Globalisation and the market for teammates. *Economic Journal*, **109**, C15–C40. https://doi.org/10.2307/2565904

Long, C. (2002) Patent signals. *University of Chicago Law Review*, **69**, 625–679. https://doi.org/10.2307/1600501

Marinova, J., Plantenga, J., and Remery, C. (2016) Gender diversity and firm performance: evidence from Dutch and Danish boardrooms. *The International Journal of Human Resource Management*, **27**, 1777–1790. https://doi.org/10.1080/09585192.2015.1079229

Milliken, F.J. and Martins, L.L. (1996) Searching for common threads: understanding the multiple effects of diversity in organizational groups. *Academy of Management Review*, **21**, 402–433. https://doi.org/10.5465/amr.1996.9605060217

Narin, F., Noma, E., and Perry, R. (1987) Patents as indicators of corporate technological strength. *Research Policy*, **16**, 143–215. https://doi.org/10.1016/0048-7333(87)90028-X

OECD. (2005) *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*. Paris and Luxembourg: OECD Publishing.

Østergaard, C.R., Timmermans, B., and Kristinsson, K. (2011) Does a different view create something new? The effect of employee diversity on innovation. *Research Policy*, **40**, 500–509. https://doi.org/10.1016/j.respol.2010.11.004

Pisano, G.P. and Teece, D.J. (2007) How to capture value from innovation: shaping intellectual property and industry architecture. *California Management Review*, **50**, 278–296. https://doi.org/10.2307/41166428

de la Potterie, B.V.P. and François, D. (2009) The cost factor in patent systems. *Journal of Industry, Competition and Trade*, **9**, 329. https://doi.org/10.1007/s10842-008-0033-2

Ritter-Hayashi, D., Vermeulen, P., and Knobenwe, J. (2016) *Gender Diversity and Innovation: The Role of Women's Economic Opportunity in Developing Countries*. Institute for Management Research, Radboud University. Working Paper.

Rzhetsky, A., Foster, J.G., Foster, I.T., and Evans, J.A. (2015) Choosing experiments to accelerate collective discovery. *Proceedings of the National Academy of Sciences*, **112**, 14569–14574. https://doi.org/10.1073/pnas.1509757112

Shi, F., Foster, J.G., and Evans, J.A. (2015) Weaving the fabric of science: dynamic network models of science's unfolding structure. *Social Networks*, **43**, 73–85. https://doi.org/10.1016/j.socnet.2015.02.006

Singh, J. and Agrawal, A. (2011) Recruiting for ideas: how firms exploit the prior inventions of new hires. *Management Science*, **57**, 129–150. https://doi.org/10.1287/mnsc.1100.1253

Teruel, M. and Segarra, A. (2017) The link between gender diversity and innovation: what is the role of firm size? *International Review of Entrepreneurship*, **15**, 319–340.

Thomas, D. and Ely, R. (1996) Making differences matter. *Harvard Business Review*, **74**, 79–90.

Torchia, M., Calabrò, A., and Huse, M. (2011) Women directors on corporate boards: from tokenism to critical mass. *Journal of Business Ethics*, **102**, 299–317. https://doi.org/10.1007/s10551-011-0815-z

Turner, L. (2009) Gender diversity and innovative performance. *International Journal of Innovation and Sustainable Development*, **4**, 123–134. https://doi.org/10.1504/IJISD.2009.028067

Van Knippenberg, D., and Schippers, M.C. (2007) Work group diversity. *Annual Review of Psychology*, **58**, 515–541.

Wooldridge, J.M. (2010) *Econometric Analysis of Cross Section and Panel Data*, 2nd edn. Cambridge, MA: MIT Press.

Notes

[1] Previous evidence shows that firms that recruit scientists increase their patenting propensity and the quality of their patents (Al-Laham et al., 2011; Singh and Agrawal, 2011).

[2] Interestingly, patenting costs are lower in the United States than in Europe or Japan (de la Potterie and François, 2009) and this also plays a role in the decision.

[3] A more detailed description can be found on the FECYT website.

[4] The temporal dimension facilitates researchers in dealing longitudinally with the innovative behaviour of Spanish firms and also in treating standard econometric issues, such as unobserved heterogeneity and simultaneity problems, which are hard to detect in simple cross-sectional data or time series.

[5] The Shannon-Weaver Entropy Index is expressed as a logarithm and cannot be calculated when a category is not represented.

[6] See Tables A1 and A2 for definition and a statistical description of the explanatory variables.

[7] We apply a test of endogeneity following Wooldridge (2010). The results confirm the endogeneity. We thank a referee's for this suggestion.

[8] The data are strongly skewed to the right, so a potential model is more appropriate. However, the standard Poisson model can be misspecified under the assumption of equidispersion. In our case, by summarising our key variable (number of patents) for firms with R&D teams, we obtain that a mean equal to 1.02 and an SD equal to 8.70. The high presence of zeros in the dependent variable accepts the application of a zero-inflated binomial negative model. However, the presence of individual heterogeneity and the need to control for the endogeneity can severely bias the estimation. GMM provides a framework for dealing with moment conditions avoiding strong distributional assumptions and controlling for the potential endogeneity and heterogeneity (Wooldridge, 2010).

[9] Organisational innovations provide an environment in the firm which may promote the labour productivity of employees in R&D departments and any other department, while not directly contributing to the capacity to generate patents (Dwyer et al., 2003). Three dummies identify if firms have introduced: (i) new practices affecting the organizational procedures, (ii) new organisational methods to improve the decision-making process, (iii) new external relations managerial methods.

[10] Gallie (2002) finds that ethnic diverse R&D teams may facilitate R&D teams' EPO patents by increasing the propensity to patent, increasing the number of patent applications and enlarging the breadth of patenting technological fields.

[11] Table A3 presents the mean values of the Blau index distributions. For firms with R&D departments, the gender and occupation compositions are similar between those that generate patents and those that do not. Firms with lower know-how protection (at a national level only) have a lower mean percentage of women in their R&D departments. Our results are in line with González et al. (2018) who find that the maximum propensity for product innovation takes place when gender diversity is around 0.25.

Mercedes Teruel is an Associate Professor at the Department of Economics of the Universitat Rovira i Virgili (URV). After studying Business Management (1999) and Economics (2001), she obtained an MSc in Economics from the University of Essex in 2005 and a PhD from the URV in 2006. Her research interests include firm growth, empirical industrial organisation and innovation. Her work has been published in *Small Business Economics*, the *Journal of Economic Behaviour and Organization*, *Industrial and Corporate Change and also Research Policy*, *Growth and Change*, *Economics of Innovation and New Technology*, amongst others. She is also a winner of the Richard R. Nelson Prize (2016).

Agustí Segarra-Blasco is a Professor of Applied Economics at the Universitat Rovira i Virgili. His fields of research are firm dynamics, economic growth and innovation. In the field of innovation and productivity, he studied the determinants of co-operation in R&D and the innovation process at the firm level, as well as the relationship between competitive intensity and firms' productivity. He coordinated several research projects and collective publications. His works have been published in *Small Business Economics*, *Research Policy*, *Review of Industrial Organization*, *International Economics of Innovation and New Technology*, *International Entrepreneurship and Management Journal*, *Structural Change and Economic Dynamics, Journal of Economic Behaviour and Organization, Industry and Innovation, Energy Policy*, amongst others.

APPENDIX

Table A1. Description of variables

Dependent variables	*Patents*	Number of patents (in logs)
	OEPMpatents	Number of patents registered in OEPM
	EPOpatents	Number of patents registered in EPO
	USPTOpatents	Number of patents registered in USPTO
	PCTpatents	Number of patents registered under PCT treaties
Independent variables	*blauGender*	Blau index for the gender diversity of the R&D team
	blauCateg	Blau index for the diversity of categories of the R&D team (researchers, technicians and auxiliary research staff)
	sizeRDdept	Total number of researchers (in logs)
	size	Total number of employees (in logs)
	age	Firm age and its quadratic value (in logs)
	exp	Dummy equal to 1 if a firm exports
	group	Dummy equal to 1 if a firm is part of a group
	matrix	Dummy equal to 1 if a firm is the parent establishment
	RDext	Expenditure on external R&D per employee (in logs)
	RDint	Expenditure on internal R&D per employee (in logs)
	coop	Dummy equal to 1 if a firm cooperates with other companies
	High-tech, kis	Dummy variables equal to 1 if a firm operates in high-tech manufacture or KIS respectively.

Table A2. Statistical summary (mean, standard deviation and Pearson correlations). Period 2004–2014

	Mean	Std. Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Patents	0.638	6.756	1.000																				
(2) OEPMpatents	0.341	4.912	0.813*	1.000																			
(3) EPOpatents	0.176	2.315	0.619*	0.173*	1.000																		
(4) USPTOpatents	0.085	1.334	0.366*	0.116*	0.466*	1.000																	
(5) PCTpatents	0.129	1.892	0.568*	0.135*	0.631*	0.408*	1.000																
(6) Patents	0.656	6.956	0.462*	0.165*	0.567*	0.253*	0.486*	1.000															
(7) OEPMpatents$_{t-1}$	0.351	5.106	0.169*	0.121*	0.151*	0.093*	0.111*	0.819*	1.000														
(8) EPOpatents$_{t-1}$	0.196	2.441	0.560*	0.160*	0.838*	0.350*	0.550*	0.634*	0.176*	1.000													
(9) USPTOpatents$_{t-1}$	0.089	1.391	0.300*	0.075*	0.403*	0.700*	0.350*	0.366*	0.115*	0.471*	1.000												
(10) PCTpatents$_{t-1}$	0.143	1.996	0.512*	0.113*	0.608*	0.349*	0.777*	0.582*	0.137*	0.631*	0.413*	1.000											
(11) blauGender$_{t-1}$	0.238	0.202	0.042*	0.015*	0.047*	0.046*	0.051*	0.040*	0.014*	0.050*	0.050*	0.053*	1.000										
(12) size$_{t-1}$	4.057	1.415	0.087*	0.052*	0.089*	0.075*	0.065*	0.085*	0.047*	0.093*	0.077*	0.069*	0.194*	1.000									
(13) age$_{t-1}$	3.059	0.731	0.027*	0.011*	0.028*	0.005	0.010*	0.027*	0.011*	0.033*	0.006	0.014*	0.013*	0.342*	1.000								
(14) exp$_{t-1}$	0.615	0.487	0.046*	0.031*	0.040*	0.033*	0.035*	0.048*	0.032*	0.046*	0.033*	0.039*	0.003	0.166*	0.166*	1.000							
(15) group$_{t-1}$	0.377	0.485	0.055*	0.028*	0.059*	0.060*	0.051*	0.055*	0.029*	0.062*	0.062*	0.054*	0.150*	0.484*	0.089*	0.089*	1.000						
(16) matrix$_{t-1}$	0.071	0.257	0.022*	0.010*	0.020*	0.038*	0.027*	0.019*	0.011*	0.019*	0.038*	0.029*	0.080*	0.195*	0.100*	0.062*	0.319*	1.000					
(17) lRDext$_{t-1}$	−9.308	10.528	0.081*	0.050*	0.078*	0.072*	0.070*	0.086*	0.051*	0.084*	0.076*	0.078*	0.154*	0.138*	0.001	0.150*	0.146*	0.065*	1.000				
(18) lRDint$_{t-1}$	−1.104	11.853	0.071*	0.047*	0.063*	0.057*	0.057*	0.072*	0.048*	0.068*	0.058*	0.061*	0.187*	0.049*	−0.059*	0.207*	0.077*	0.065*	0.356*	1.000			
(19) blauCATEG$_{t-1}$	0.626	0.344	−0.036*	−0.026*	−0.029*	−0.027*	−0.028*	−0.039*	−0.028*	−0.031*	−0.028*	−0.032*	0.219*	−0.008	0.095*	−0.130*	−0.043*	−0.036*	−0.260*	−0.847*	1.000		
(20) blauEDU$_{t-1}$	0.795	0.280	−0.036*	−0.022*	−0.033*	−0.036*	−0.029*	−0.036*	−0.023*	−0.036*	−0.032*	−0.031*	0.087*	−0.041*	0.080*	−0.110*	−0.070*	−0.034*	−0.184*	−0.594*	0.642*	1.000	
(21) coop$_{t-1}$	0.314	0.464	0.067*	0.043*	0.063*	0.052*	0.056*	0.067*	0.044*	0.064*	0.050*	0.065*	0.169*	0.172*	−0.014*	0.096*	0.172*	0.083*	0.376*	0.332*	−0.250*	−0.172*	1.000
(22) sizeRDdept$_{t-1}$	10.364	38.208	0.197*	0.103*	0.228*	0.220*	0.157*	0.189*	0.095*	0.232*	0.223*	0.161*	0.142*	0.291*	0.026*	0.066*	0.138*	0.071*	0.176*	0.219*	−0.149*	−0.105*	0.208*

*$P < 0.01$.

Table A3. Mean Blau index and percentage of women in the R&D department based on types of patents. Period 2004–2014

	Women in the R&D department (%)	Gender diversity	Researchers (%)	Technicians (%)	Aux Research Staff (%)	Occupational diversity	Observations
No patents	26.46	0.2352	48.75	34.67	16.58	0.3870	19,235
All patents	27.82	0.2701	48.42	35.11	16.47	0.4207	4,697
OEPM	26.56	0.26282	47.89	35.00	17.09	0.4202	3,527
EPO	30.10	0.2853	47.31	36.67	16.00	0.4401	1,657
USPTO	32.71	0.3067	47.96	36.46	15.57	0.4427	779
PCT	32.45	0.3026	49.76	34.04	16.19	0.4363	1,296

Source: Own elaboration from PITEC.