The Effect of R&D Workforce Composition on Technology Transfer: Hybrid Professional Models and the Role of Non-Doctoral Researchers in Public-Private Research Centres

Sandro Giachi

sgiachi@iesa.csic.es

National Research Council (CSIC), Institute for Advanced Social Studies (IESA) / University of Malaga (UMA), Spain

Abstract

The objective of this study is understanding the effect of Human Resource Management (HRM) strategies on the outcomes of the Knowledge and Technology Transfer (KTT) process at the organisational level. We focus on those organisations that are oriented toward the transfer of knowledge and technology from science to industry for innovation ends, like public-private Cooperative Research Centres (CRC). Our research question is the following: do the researchers working in CRCs have adequate skills and aptitudes for performing cooperative research, producing industrially relevant knowledge and transferring technology? We tackle this problem by suggesting that the educational mix of the R&D workforce would reflect different knowledge bases and therefore different "modes" for innovation policy and management. We test the effect of the R&D workforce composition on measures reflecting the outcomes of the KTT process, using data from a survey to public-private research centres in Spain (n=128, 59,3% of the universe). Performing a cluster analysis, we found three HRM strategies: "Academic", "Technical", and "Mixed". Then, through several regression analyses, we found that "Academic" CRCs show a good performance in terms of transfer of codified scientific knowledge, while "Mixed" CRCs seem to be good for transferring both scientific and technical knowledge. In short, our findings suggest that CRCs in Spain are promoting the emergence of a hybrid professional model between science and industry; in particular, we suggest that non-doctoral researchers play a role in facilitating the exchange or the absorption of both scientific and technical knowledge.

Keywords

Absorptive Capacity; Cooperative Research; Human Capital; Innovation; Knowledge Exchange

1. Introduction[1]

The aim of this study is understanding the effect of Human Resource Management (HRM) strategies on Knowledge and Technology Transfer (KTT) outcomes at the organisational level. To do so, we focus on those organisations that are oriented toward the transfer of knowledge and technology from science to industry for innovation ends. Examples of such types of organisations are university-industry structures for open innovation (Perkmann and Walsh 2007), public-private RTD institutes (Arnold et al. 2010) or Cooperative Research Centres (CRC). In particular, CRCs encompass a general concept for including almost all such experiences: formal organisational structures performing R&D with the mission of "promoting cross-sector collaboration, knowledge and technology transfer and, ultimately, innovation" (Boardman and Gray 2010; Gray et al. 2013). For our research, we maintain that CRCs also represent a useful "organisational laboratory" (Bozeman 2013) for the study and development of new scientific and technical skills for innovation ends, due to their collaborative and complex inter-organisational nature.

Our research question is the following: do the researchers working in CRCs have adequate skills and aptitudes for performing cooperative research, producing industrially relevant knowledge and transferring technology? Therefore, our research objective is twofold:

1. Identifying HRM strategies employed by CRCs, for example in terms of scientific and technical professional workers composing the R&D workforce.
2. Estimating the effect of such HRM strategies on the outcomes of the KTT process, such as production of scientific and technical tangible outputs (i.e. publications, patents, spin-off, etc.), or perceived impact of activities and overall organisational performance.

In sum, we hope that our research will shed some light on the HRM strategies employed by cooperative research organisations and their effect on the innovation process.

The paper is structured as follows: in Section 2 we briefly review the state of the art about the HRM strategies employed by CRCs and the dynamics of the industry-collaboration KTT process; we adopt an "educational mix" viewpoint reflecting different "modes" for innovation policy and management. In Section 3 we describe our data and variables, based on a survey to Spanish CRCs. Section 4 contains the findings of our multivariate statistical analyses, and in Section 5 we discuss their implications for the study of KTT and the innovation process.

2. Theoretical Framework

HRM strategies and the KTT process in science-industry organisations

[1] I acknowledge the financial support of the Spanish R&D Scheme through the FPI *Formación del Personal Investigador* Programme (ref. BES-2011-047258).

There are some examples of "grey literature" providing data for describing the R&D workforce composition of CRCs, at least for the Australian (Garrett-Jones and Turpin 2002) or the U.S. (Cohen et al. 1997; Gray et al. 2015) case. Although we have no space here for a full review, we can highlight some spots. For example, empirical row data tell us that centres usually employ a high number of postdoctoral fellows, as well as doctoral, graduate and undergraduate students. In addition, we observe that almost all centres have some kind of management staff, because of the need of managing external relations and funding. Many PIs are also tenured-track university professors, but they usually represent only a small fraction of the total workforce. We also observe a strong diversity in workforce composition.

In spite of such data availability, there are few studies (i.e. journal articles) that specifically tackle on this topic, and almost none of them focus its effect on KTT outcomes and the innovation process. Existing studies about HRM strategies of CRCs focussed on adjacent but different topics, like the effect on researcher professional careers (i.e. Klenk et al. 2010; Ponomariov and Boardman 2010; Su and Keneson 2013), or the management of the diverging objectives of the collaboration process producing role strain and other organisational conflicts (Boardman and Ponomariov 2013; Garrett-Jones et al. 2013).

An interesting finding from such available studies about HRM in CRCs is the following: participation in cooperative research is usually related with high levels of scientific productivity of individual researchers and it usually increase social capital, but centres still lack adequate levels of human capital for managing collaborative relationships. Does such lack could affect KTT outcomes? Recently, a review of CRC studies has suggested (Boardman and Gray 2010) to analyse more accurately HRM strategies for understanding its effect on the innovation process, because this approach showed to be useful in industry settings (Laursen and Foss 2003; Cano and Cano 2006). For example, it's possible that centres with greater amounts of management and relational human capital show a stronger capacity of transferring knowledge and technology.

Studies about KTT outcomes from cooperative research usually focussed on the industry perspective, analysing characteristics of collaborating firms that facilitate the absorption of knowledge and technology produced by external scientific researchers (Russo and Herrenkol 1990; Gopalakrishnan and Santoro 2004). Most of these studies use the concept of "absorptive capacity" (Cohen and Levinthal 1990) for understanding this process, focussing on firm's characteristics like industry sector, size, organisational structures, communication, etc. They showed that the success of KTT are related with the determinants of firm's absorptive capacity, defined as the quantity and quality of prior knowledge available within the firm's boundaries. If "quantity" is a quite clear concept, what does it mean "quality" of prior knowledge?

Educational Mix, Knowledge Base and Innovation Mode of CRCs

Literature about organisational learning (Cohen and Levinthal 1990; Nonaka and Takeuchi 1995) suggested the existence of two types of knowledge embodied in workers:

- codified knowledge, achieved mainly by formal education;
- tacit knowledge, achieved mainly by experience and learning-by-doing.

Both types of knowledge are relevant for internal organisational learning as well as external knowledge acquisition. Then, absorptive capacity strongly relies on the educational mix of the firm; in this sense, some studies showed that the share of workers holding a PhD is a good predictor for the acquisition of external scientific knowledge (Beltramo et al. 2001; Spithoven and Teirlinck 2010; Teirlinck and Spithoven 2013). But, by the science viewpoint, which type of knowledge is needed for producing and transferring industrially relevant knowledge?

Recent studies about innovation policies and learning systems suggested the existence of different "modes" of innovation, relying respectively on different types of knowledge (Jensen et al. 2007, Asheim et al. 2011). Namely, they highlight two big modes: The Science, Technology and Innovation (STI) mode is based on the production and application of codified scientific and technical knowledge with universal characteristics, namely "analytic" knowledge; by contrast, the Doing-Using-Interacting (DUI) mode is based on mutual informal dynamics, learning-by-doing and transfer of know-how and cultural practices. There is a lot of literature about this topic, especially about regional development and innovation policies (Jensen et al. 2007, Asheim et al. 2011). What we highlight here is that the educational mix of an organisation reflects different knowledge bases and therefore different modes for innovation policy and management.

Adopting this approach for analysing scientific organisations, we use the educational mix of research centres' workforce as a dimension for determining their capacity of transferring knowledge and technology to industry. In fact, some previous studies showed that the shares of non-permanent doctoral researchers and non-research positions within public research organisations increase its patenting productivity (Carayol and Matt 2004), while involving faculties in university-industry licensing facilitate direct interactions in the knowledge exchange process (Thursby and Thursby 2004). Thus, we hope that the educational mix of the R&D workforce could determine the outcomes of the KTT process.

In resume, we defend the opportunity of analysing the outcomes of CRC's KTT process adopting the viewpoint of the organisation producing such knowledge, and using measures of the educational mix of its R&D workforce as proxies of the knowledge base and the innovation mode characterising collaboration. In such sense, we can suppose three ideal situations for CRCs:

- CRCs following a STI mode, employing many faculties and doctoral researchers, and specialised in producing and transferring highly codified and formal scientific and technical knowledge (i.e. publications, patents).
- CRCs following a DUI mode, employing many technicians, managers and students, and specialised in recombining and transferring existing knowledge and know how through informal channels and shared practices.
- CRCs combining elements from both modes (STI and DUI), probably employing different types of personnel, and specialised in producing and transferring different types of knowledge at the same time.[2]

3. Methodology

Data

We analyse cooperative research organisations existing in Spain. We use data coming from the research Project "Emerging Forms of Cross Sector Collaboration between Science and Industry: Cooperative Research Centres in the Spanish R&D System" (ES/CRCs) launched by IESA-CSIC in 2012. This was a three-years project that included three surveys to: (1) cooperative research centres, (2) firms and (3) researchers involved in the centres. Here we report results on the first survey to CRC's head directors.

In order to obtain our final sample, we tried to identify the whole population of CRCs. Due to the diversity of Spanish public-private collaboration initiatives carried out at different administrative levels ─ national and regional ─, there is not a complete directory of Spanish CRCs. Therefore, we mapped the existing R&D collaborative arrangements in Spain through a systematic review of secondary sources of data and web search (Giachi et al. 2012). We operationalised the description of CRCs, following the definition of Boardman and Gray (2010), as organisations that explicitly recognise:

- To have a formal structure and a separate legal entity,
- to conduct R&D activities and
- to have least one public and one private actor among their partners.

We reached a final population of CRCs in Spain of 216 centres. We sent the questionnaire using a postal/web mixed-mode technique (Diment and Garrett-Jones 2007) and telephone reminders using CATI system targeting mainly to the directors of the centres. On-line access to the questionnaire has been opened from August to October 2012. We sent 6 e-mail and 3 postal

[2] Asheim et al. (2011) pointed out that this is the case for the Scandinavian Centres of Expertise, which are organisations that share many characteristics with CRCs.

remainders to the centres. We had a response rate of 59.3%, reaching a "strategic" sample of 128 CRCs.

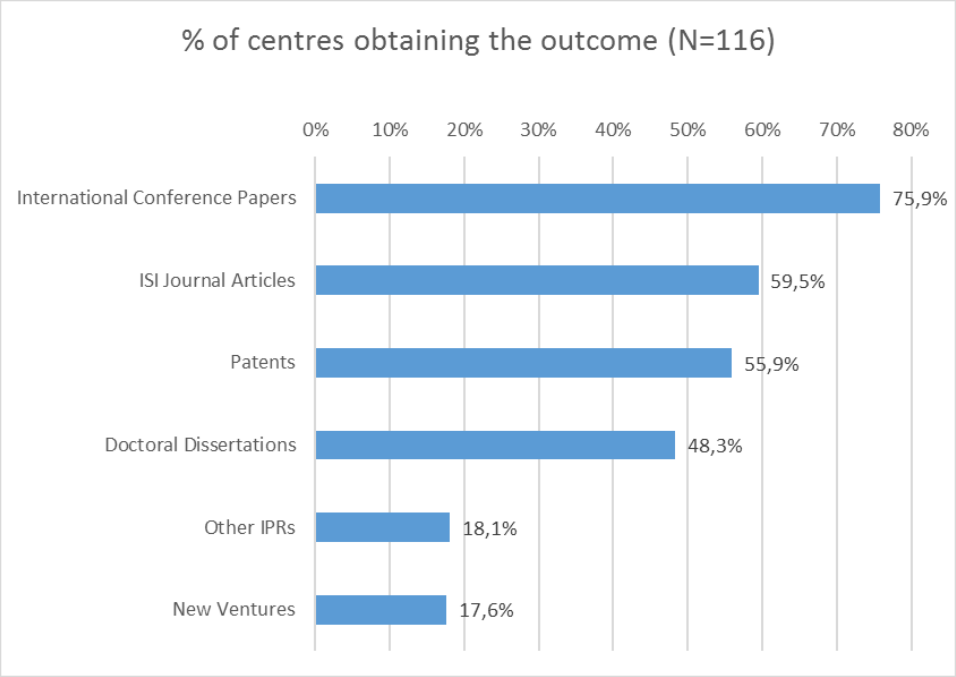
According to our method of sampling and due to such technical limitations, we cannot extract a probabilistic sample of centres. Therefore, we checked the representativeness of our sample only through an ex-post control, using three variables available for both the population and the sample: centre's official denomination, region and age. The differences in the distribution of these variables between the population and the sample are small (see Table A1, A2 and A3 in the Annex); in particular, both the population and the sample share the following basic facts: more than half of the centres are Innovation and Technology Centres (ITC);[3] regions with more centres are Andalusia and the Basque Country; centre's age distribution is heterogeneous, although more than half of the cases are less than 10 years. Therefore, we defend that our sample is a valid for exploring the characteristics and dynamics of cooperative research organisations in Spain.

Dependent Variables

As dependent variables, we use both tangible and intangible measures of scientific and technical performance of the centres (Cohen et al. 1997). Tangible outcomes include the number of outputs such as publications, patents, spin-off, etc. We select only a small set of indicators (6) among all available measures in the questionnaire (12, including also technical reports, books, book chapters, etc.), because of their relevance. Each indicator is transformed in a dummy variable for estimating the probability to obtain different types of outputs (Graph 1). The most frequent outputs are papers presented to international conferences (75.9%), ISI journal articles (59.5%) and patents (55.9%), while doctoral dissertations (48.3%), other Intellectual Property Rights (18.1%) and new ventures (17.6%) are less frequent. Generally, Spanish CRCs seem to concentrate their effort on scientific publications and the production of codified knowledge.

[3] Origins of ITCs in Spain date to 60s and the pioneering experience of Industrial Research Associations. Many of them evolved during the 80s and the 90s as Technology Centres: private-based R&D organisations with the aim to support local technology development and innovation. Although their private base, many of them have been promoted by Regional Governments and receive public funds. Recently, many ITCs have changed their orientation toward excellence and applied research ends, closer to the "scientific excellence" than the "industrially relevant" knowledge production mission. Nowadays, many Spanish ITCs fully accomplish the defining criteria to be designed as CRCs (Fernández-Zubieta et al. 2016).

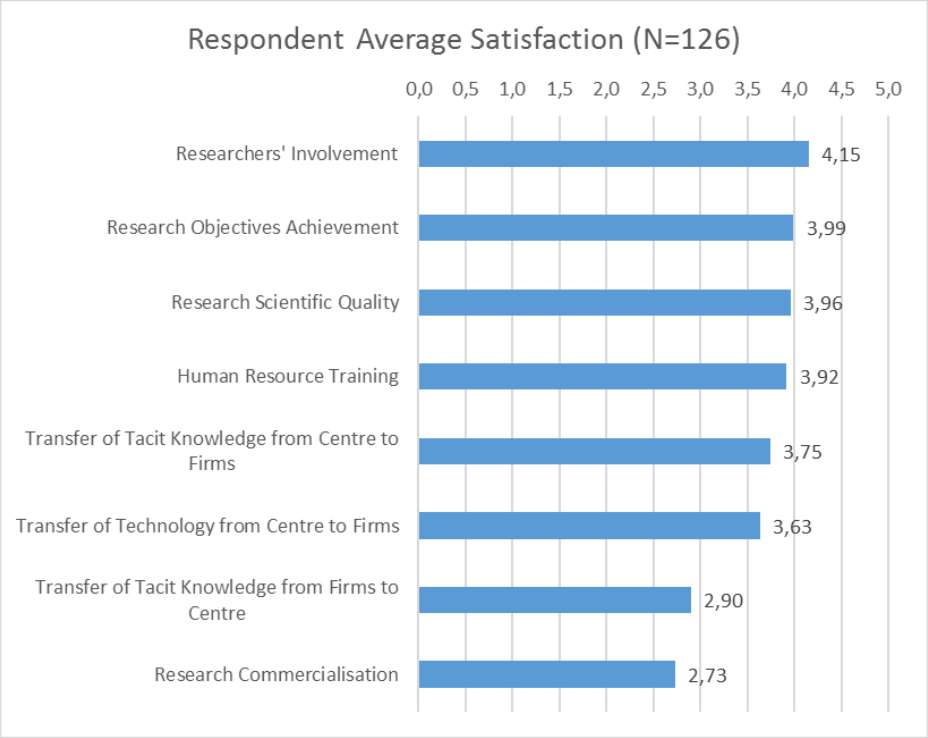
Graph 1 – CRC Tangible Scientific and Technical Outcomes



Source: ES/CRC Research Project (2012); own elaboration

Intangibles outcomes include respondents' satisfaction about centre's performance, measured by a subjective numeric scale ranging from 1 (low) to 5 (high) for evaluating 12 items related to several dimensions of centre's activities (Graph 2), but we selected only 8 of such 12 items because of their relevance for our research. The item obtaining the best score is satisfaction about researchers' involvement in centre's activities (mean: 4.15). Other satisfactory items are achievement of research objectives (3.99), scientific quality of performed research (3.96) and training of human resources (3.92). Less satisfactory items are related with centre's absorptive capacity of tacit knowledge proceeding by firms (2.90) and research commercialisation (2.73). Therefore, Spanish CRCs seem to be good in performing "excellent" research but they have shortages for "connecting" with firms and the market.

Graph 2 – CRC Intangible Outcomes: Organisational Performance

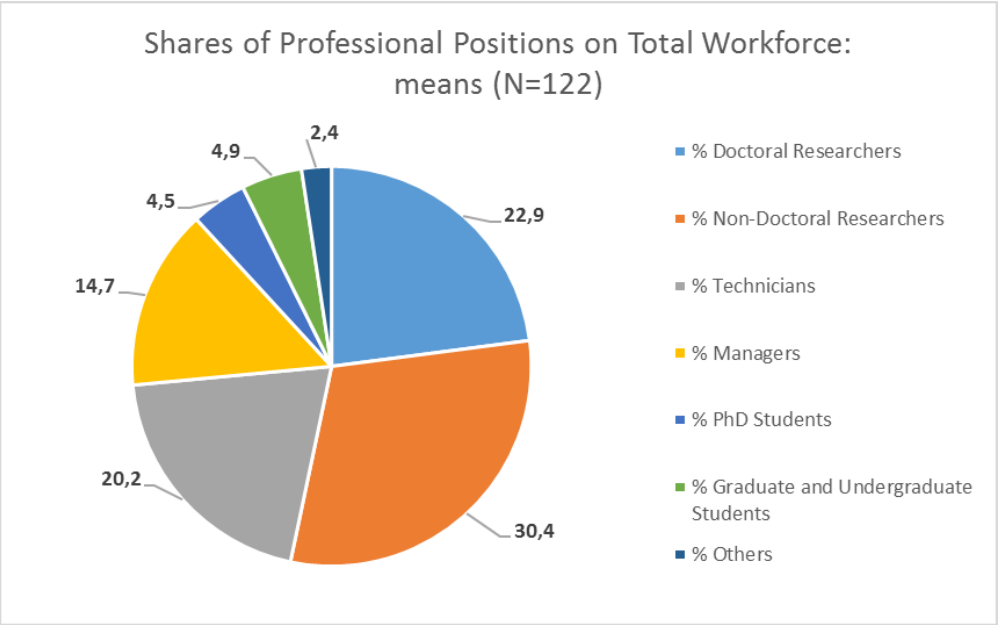


Source: ES/CRC Research Project (2012); own elaboration

Independent Variables

As independent variables, we use the share of each professional position on the total workforce for measuring the heterogeneity and the educational mix of CRCs (Carayol and Matt 2004; Spithoven and Teirlinck 2010; Teirlinck and Spithoven 2013). We differentiate between doctoral researchers, non-doctoral researchers, technicians, managers, PhD students, graduate and undergraduate students, plus an "Other", residual category (i.e. international visiting fellows). We observe that non-doctoral researchers are the most common working position in Spanish CRCs (30.4%), although doctoral researchers (22.9%) and technicians (20.2%) are frequently employed too; other positions, such as managers (14.7%), PhD students (4.5%) and other types of students (4.9%) are less frequent (Graph 3).

Graph 3 – Workforce Composition of CRCs by Professional Positions



Source: ES/CRC Research Project (2012); own elaboration

In addition, we calculate a synthetic measure for CRC workforce heterogeneity based on the Shannon Entropy Index, using the shares of the different professional positions on the total workforce: the resulting measure ranges approximately between 0,41 (higher homogeneity) and 1.89 (higher heterogeneity), while its average score is equal to 1.17. [4]

Control Variables

We consider usual control variables for analysing cooperative research arrangements (Cohen et al. 1997; Bozeman and Dietz 2001), such as the following:

- Size: Total number of personnel employed by the centre (average = 94.07).
- Age: Measured by the difference between 2012 (year of survey) and the year of centre foundation (average = 11.2).
- Scientific field: We differentiate between the following fields: "Life and Health", including Biology, Biotechnology, Medicine, Biomedicine, etc. (26.6%); "Other Engineering and Natural Sciences" (66.4%); and "Humanities and Social Sciences" (7.0%).

[4] The Shannon Index was originally an indicator of biodiversity in ecological systems, but now is frequently used to measure diversity in categorical data. The index is calculated by summing the products of each funding sources' (or species) I share p with the natural logarithm of the same share and multiplying by -1. (S= -Σ[pi*ln(pi)]). In a recently published study about CRCs in Spain, we applied this technique for analysing the composition of the budget of the centres according to several funding sources (Fernández-Zubieta et al. 2016).

- Funding public program: We use the official denomination of the centre, differentiating between Innovation and Technology Centres (64.1%), by other types such as government-based or university-based centres (35.9%).

Method of Analysis

We follow a three-step analysis scheme:

1. We classify CRCs according to their workforce composition (shares of professional positions) through a cluster analysis.
2. We estimate several logistic regression models for analysing how the probability of obtaining scientific and technical outcomes varies between different workforce composition models, controlling for other organisational variables.
3. We estimate several linear regression models for analysing how the satisfaction about centre's performance varies between different workforce composition models, controlling for other organisational variables.

As our approach is mainly exploratory, we did not consider necessary to perform more sophisticated analyses, at least at this stage of research.

4. Findings

Classifying CRCs according to Workforce Composition

We applied a cluster analysis to resume the heterogeneity of the educational mix of the centres, using the share of each one of the six professional positions on the total number of the workforce.[5] Through a previous exploratory Hierarchical Cluster Analysis (HCA) we found an optimal segmentation around four groups (although one of them was formed only by one "outlier" case). Therefore, we applied a K-Means Cluster Analysis (KMCA) procedure, setting by default a 4-group classification. Outputs of our KMCA are consistent with previous HCA and they discriminate very well for all the variables included in the analysis, according to the Analysis of Variance (ANOVA) test.[6]

Observing outputs of the KMCA, we observed that Group 1 was composed only by two cases (see Table A4 in the Annex); in addition, this group exhibited a surprisingly high (and anomalous) share of graduate and undergraduate students too. Therefore, we decided to make a discretionary re-classification, distributing these two cases into an other group, according to the values they

[5] We excluded the "Other" category from the analysis because of its residual nature and for synthesis.
[6] We did not include the results of the ANOVA tests (as well as other validity measures of cluster analysis) in this paper for synthesis. Anyway, the Author can provide all data and outputs at request.

exhibit in the variables included in the analysis and looking for similarities. Our aim was providing a more consistent, useful and theoretically relevant classification. According to this aim, we finally decided to integrate the cases of Group 1 into Group 3. The reason is the following: Group 3 exhibited the highest average share of graduate and undergraduate students; at the same type, this group exhibited an average share of researchers (doctoral and non-doctoral) similar to Group 1 (see Table A4 in the Annex). Results of an additional ANOVA test showed that there are no significant changes after re-classification, with the only exception of the variable related with the share of graduate and undergraduate students becoming non-significant.

Table 1 shows the average scores of each share of professional positions across the clusters after our post-analysis reclassification. We observe that Group 2 exhibits the highest share of doctoral researchers (53.42%): they represent on average most than half of the workforce of these centres; in addition, they also have the highest average share of PhD students (10.34%). Group 3 is characterised by the high share of technicians (41.60%) and managers (20.47%), but they also have the highest average share of graduate and undergraduate students (7.85%). Group 4 exhibits a very high average share of non-doctoral researchers (51.74%), but we did not find any other relevant feature for this group, neither in a high nor in a low amount of positions.

Table 1 – Share of Professional Positions by Final Clusters: Means

Group	**2**	**3**	**4**	**Total**
% Doctoral Researchers	**53,42**	7,34	12,92	22,94
% Non-Doctoral Researchers	11,66	17,36	**51,74**	30,38
% Technicians	8,79	**41,60**	13,45	20,19
% Managers	9,55	**20,47**	14,18	14,66
% PhD Students	10,34	0,61	3,21	4,51
% Graduate and Undergraduate Students	3,98	7,85	3,56	4,91
% Others	2,26	4,77	0,95	2,42
N	**35**	**35**	**52**	**122**

Source: ES/CRC Research Project (2012); own elaboration

We interpret these findings in the following way:

- We label Group 2 the "Academic" model, because doctoral researchers are the most frequent professional position but they also exhibit the highest average score of PhD students; so, they probably represent such centres following a STI innovation mode.
- We label Group 3 the "Technical" model, because technicians and managers are the most frequent professional position but they also exhibit the highest score of graduate and undergraduate students; so, they probably represent such centres following a DUI innovation mode.

- We label Group 4 the “Mixed” model, because of the heterogeneity of the workforce composition of the centre; they could represent a kind of combination of the STI and DUI mode.

We resume the findings of our classification analysis in Table 2. We observe that centres from our sample are (more or less) equally distributed between such three models, although the “mixed” one is the most frequent (42.6%).

Table 2 – Classification of CRCs in Spain by Workforce Composition

Types of CRCs by Workforce Composition	N	%
"Academic" (mainly Doctoral and Pre-Doctoral Researchers)	35	28,7
"Mixed" (mainly Non-Doctoral Researchers)	52	42,6
"Technical" (mainly Technicians and Managers)	35	28,7
Total	**122**	**100,0**

Source: ES/CRC Research Project (2012); own elaboration

Effect of Workforce Composition on Scientific and Technical Outcomes

We estimated a logistic regression model for each dependent variable measuring centres’ scientific and technical outcomes. We included in each model all independent and control variables detailed in methodology (Section 3). We want to check if there is a significant effect of the workforce composition model of the centres on their probability to obtain different types of outcomes.

Table 3 shows the logistic regression models estimated for dependent variables related with scientific publications: ISI journal articles, international conference papers and doctoral dissertation. We observe that scientific outcomes vary significantly between the three types of centres. In particular, being an “Academic” CRC increases the probability to obtain ISI journal articles and doctoral dissertation; effect on articles is particularly strong (the probability is more than 82 times higher). Being a “Mixed” CRC increase the probability to obtain international conference papers, as well as the other outcomes, but its effect is lower than “Academic” CRCs. “Technical” CRCs, taken as reference category, have lower probabilities to produce any type of output. The workforce heterogeneity index has a strong positive effect on all outcomes; centre’s age has a positive effect on the probability to obtain doctoral dissertations, while centre’s size has a positive effect on ISI journal articles too.

Table 3 – Scientific Publications: Logistic Regression Models [7]

	ISI Journal Articles	International Conference Papers	Doctoral Dissertations
"Technical" (mainly Technicians and Managers)	***	**	**
"Academic" (mainly Doctoral and Pre-Doctoral Researchers)	82,554 ***	3,723	7,462 **
"Mixed" (mainly Non-Doctoral Researchers)	5,904 **	4,818 **	3,811 **
Workforce Heterogeneity (Shannon Index)	25,538 ***	12,020 ***	5,577 **
Innovation and Technology Centre	1,677	,690	0,969
Age	0,976	1,024	1,085 ***
Size	1,011 **	,999	1,004 *
Humanities and Social Sciences			
Other Engineering and Natural Sciences	0,592	,575	0,375
Life and Health Sciences	0,360	,582	0,212
Constant	0,004 ***	,126	0,028 ***
N	112	112	112
Chi Test	61,611 ***	22,232 ***	34,984 ***
-2 Log Likelihood	90,064	101,486	119,96
Cox and Snell R2	0,423	,180	,268
Nagelkerke R2	0,570	,269	,358
Hosmer and Lemeshow Test	14,976 *	5,076	6,091
% Right Predictions	83,0%	77,7%	75,0%

Source: ES/CRC Research Project (2012); own elaboration

Table 4 shows the logistic regression models estimated for dependent variables related with technical innovations: patents, other IPRs, and the creation of new ventures. We observe that technical outcomes vary significantly between the three types of centres. In particular, being an "Academic" CRC increases the probability to obtain a patent; by contrast, being a "Mixed" CRC increases the probability to obtain other IPRs and new ventures, as well as patents, although in this last case the effect is lower. Also in this case "Technical" CRCs, taken as reference category, show lower probabilities to obtain any type of output. In addition, the workforce heterogeneity index is not significant in any model, while both centre's age and size increase the probability to obtain patents and create new ventures.

[7] Table 3 (as well as Table 4) contains the exponential transformation of regression coefficients; they indicate the probability to obtain such result. The table also contain other tests and measures for checking the validity and the fitness of the model.

Table 4 – Technical Innovations: Logistic Regression Models

	Patents	Other IPRs	New Ventures
"Technical" (mainly Technicians and Managers)	**	*	*
"Academic" (mainly Doctoral and Pre-Doctoral Researchers)	5,251 **	6,005	2,808
"Mixed" (mainly Non-Doctoral Researchers)	3,991 ***	12,150 **	5,909 **
Workforce Heterogeneity (Shannon Index)	2,441	0,837	1,123
Innovation and Technology Centre	1,884	2,431	2,559
Age	1,056 *	1,031	1,063 **
Size	1,005 *	1,001	1,002 *
Life and Health Sciences	0,515	2,192	1,094
Constant	0,045 ***	0,010 ***	0,008 ***
N	122	122	120
Chi Test	30,496 ***	20,942 ***	23,197 ***
-2 Log Likelihood	137,45	94,199	88,097
Cox and Snell R2	,221	,158	,176
Nagelkerke R2	,296	,258	,291
Hosmer and Lemeshow Test	15,113 *	7,679	6,600
%Right Predictions	68,0%	79,5%	82,5%

[8]

Source: ES/CRC Research Project (2012); own elaboration

Effect of Workforce Composition on Organisational Performance

We estimated a linear regression model for each dependent variable measuring the organisational performance of the centres. We included in each model all the independent and control variables that we detailed in our methodology (Section 3). We want to check if there is a significant effect of the workforce composition model of the centres on the respondent's satisfaction about items related with centre's organisational performance.

Table 5 shows the linear regression models estimated for dependent variables related with research and training issues: researchers' involvement in centre's activities; scientific quality of research; achievement of research objectives; and training of human resources. We observe that there are some significant relations: being an "Academic" CRC strongly increase the satisfaction related with research quality, researchers' involvement and objectives achievement, while being a "Mixed" CRC only increase weakly the satisfaction about researchers' involvement in centre's activities. By contrast, workforce heterogeneity increases the satisfaction about the training of

[8] In these models we reclassified the variable related to centre's science and technology field due to the fact that all cases in the "Humanities and Social Sciences" field exhibit a constant value ("0") for all the dependent variables. Therefore, we grouped this category within the "Other Engineering and Natural Sciences" category, for contrasting the effect of the "Life and Health Sciences" category. In fact, many previous studies indicate that this field usually show a higher number of IPRs and innovations than others.

human resource. Being an Innovation and Technology Centre increases the satisfaction about researchers' involvement but decreases the training performance, whereas this last one is increased by centre's size and age. Centres in the "Others Engineering and Natural Sciences" fields exhibit higher levels of satisfaction about research quality and objectives achievement.

Table 5 – Satisfaction about Research and Training: Linear Regression Models[9]

	Researchers' Involvement	Research Scientific Quality	Research Objectives Achievement	Human Resource Training
"Academic" (mainly Doctoral and Pre-Doctoral Researchers)	0,666 **	0,992 ***	0,422 *	-0,061
"Mixed" (mainly Non-Doctoral Researchers)	0,382 **	0,256	0,178	0,119
Workforce Heterogeneity (Shannon Index)	-0,061	-0,223	-0,147	0,576 **
Innovation and Technology Centre	0,614 ***	0,148	-0,167	-0,385 *
Age	-0,006	0,000	0,022 **	0,016 *
Size	0,000	0,000	0,000	0,001 *
Life and Health Sciences	0,304	0,696 **	0,473	-0,107
Other Engineering and Natural Sciences	0,271	0,763 **	0,747 **	0,021
Constant	3,280 ***	2,989 ***	3,176 ***	3,222 ***
N	120	120	120	120
R	0,351	0,480	0,386	0,359
R2	0,123	0,230	0,149	0,129
Adjusted R2	0,060	0,175	0,088	0,066
F-Change	1,948 *	4,148 ***	2,434 **	2,050 **
Durbin-Watson Test	2,296	2,320	2,207	2,212

Source: ES/CRC Research Project (2012); own elaboration

Table 6 shows the linear regression models estimated for dependent variables directly related with KTT outcomes: transfer of tacit knowledge from centre to firms, and from firms to centre; technology transfer from centre to firms; and commercialisation of research outputs. We observe that there are some significant relations: being a "Mixed" CRCs weakly increases the satisfaction related with the transfer of tacit knowledge from firms to centre, and with the transfer of technology from centre to firms; by contrast, being an "Academic" CRC decreases the satisfaction about all these items and, in particular, about research commercialisation. In addition, workforce heterogeneity strongly decreases the satisfaction about absorption of firms' tacit knowledge, while centre's size weakly increases the satisfaction about technology transfer performance.

[9] Table 5 (as well as Table 6) contains the estimation of non-standardised regression coefficients for each independent and control variable. The table also contain other tests and measures for checking the validity and the fitness of the model.

Table 5 – KTT Outcomes: Linear Regression Models

	Transfer of Tacit Knowledge from Centre to Firms	Transfer of Tacit Knowledge from Firms to Centre	Transfer of Technology from Centre to Firms	Research Commercialisation
"Academic" (mainly Doctoral and Pre-Doctoral Researchers)	- 0,566 *	-0,218	-0,594 *	-0,634 *
"Mixed" (mainly Non-Doctoral Researchers)	0,268	0,390 *	0,369 *	0,091
Workforce Heterogeneity (Shannon Index)	-0,027	-0,580 **	-0,017	0,359
Innovation and Technology Centre	0,092	0,232	0,226	-0,103
Age	0,012	0,000	0,011	0,012
Size	0,000	0,001	0,001 *	0,000
Life and Health Sciences	0,481	0,598	0,604	-0,472
Other Engineering and Natural Sciences	0,223	0,387	0,577	-0,547
Constant	3,317 ***	2,834 ***	2,786 ***	2,842 ***
N	120	120	120	120
R	0,434	0,426	0,524	0,315
R2	0,189	0,181	0,274	0,100
Adjusted R2	0,130	0,122	0,222	0,035
F-Change	3,228 ***	3,074 ***	5,241 ***	1,534
Durbin-Watson Test	1,765	2,086	2,001	2,057

Source: ES/CRC Research Project (2012); own elaboration

5. Conclusions

Synthesis of the Findings

We identified three HRM strategies used by centres for composing their R&D workforce: an "Academic" model, based on a high share of doctoral researchers and students; a "Technical" model, based on a high share of technicians and managers (as well as non-doctoral students); and a "Mixed" model, where composition is heterogeneous but there is a strong presence of non-doctoral researchers.

We observed that scientific and technical knowledge production and KTT outcomes vary significantly across CRCs adopting different HRM strategies. "Academic" CRCs show a good performance in terms of codified knowledge production, measured by scientific publications and patents, as well as satisfaction about research quality and commitment, but they show low levels of satisfaction about KTT outcomes. By contrast, "Technical" CRCs (taken as reference category in all regression models) showed overall low levels of performance in all the dimensions of analysis. "Mixed" CRCs show higher probability to obtain technical innovations and higher levels of satisfaction about KTT outcomes, especially about the absorption of firms' tacit knowledge and transfer of technology to firms; they also show a higher probability to participate in international conferences and good levels of satisfaction about researchers' commitment too.

The heterogeneity of the workforce composition, measured by the Shannon Index, contributed to explain the effect of the R&D educational mix on CRC performance: in particular, it increases the probability to obtain scientific publications as well as the satisfaction about the training of human resource. Control variables occasionally help to explain part of the variance of dependent variables; in particular, centre's size and age tend to increase positively some items, while the type of funding program (being a technology centre) and the science and technology field seem to be not relevant.

Discussion of the Findings

An "Academic" strategy for composing the R&D workforce seems to be related with a stronger orientation toward the so called "Research" mission (Laredo 2007) and the production of codified knowledge through scientific publications or patents. Instead, adopting a "Mixed" strategy seems to be related with a stronger orientation toward the so called "Knowledge Transfer" mission (Laredo 2007), represented by the exchange of both codified and tacit knowledge with the firms and the generation of technical innovations. The heterogeneity of the workforce could be related with the so called "Education" mission (Laredo 2007), including activities such as training and doctoral dissertations. By last, a "Technical" strategy seems to be the worst approach in terms of both KTT outcomes and overall organisational performance.[10]

In order to assess our theoretical framework, it seems that the distinction between innovation modes adopting a HRM viewpoint has been useful: the educational mix of the CRCs seems to reflect the knowledge base of the organisation and to determine its KTT outcomes. Centres adopting an "Academic" strategy should be closer to the STI mode of innovation, while "Mixed" centres seem to combine elements from both the STI and the DUI mode. By contrast, we are not completely sure about our understanding of centres adopting a "Technical" strategy: it's possible that they are closer to the DUI approach, but we have no conclusive evidence about it.

In conclusion, our findings suggest that CRCs in Spain are promoting the emergence of a hybrid professional space at the intersection of science and industry career models (Lam 2005; Sauermann and Stephan 2013): on the one hand, we find the academic career path, based on publications and teaching; on the other hand, we find the industry career path, oriented toward technical innovations and entrepreneurship. In particular, we suggest that the "Mixed" model is

[10] This result could be explained by taking into account other variables for measuring centre's outcomes: it's possible that activities performed by "Technical" CRCs can be measured easily nor by conventional indicators such as publications or patents (Ramos-Vielba and Fernández-Esquinas 2012), neither by satisfaction about KTT outcomes. For example, we can suppose that these centres are specialised in providing different types of training, R&D management and technical services to firms and other organisations. Therefore, to measure adequately the outcomes of such activities, we should use other indicators, like the amount of funds or the number of contracts attracted from the industry sector.

representing an emerging organisational and professional space for R&D workers, where doctoral researchers and PhD students collaboratively work with technicians and managers to perform applied research and transferring knowledge to the industry. In addition, we suggest that non-doctoral researchers could play a kind of "lubricant" role in this changing environment, facilitating the circulation of both codified and tacit knowledge between science and industry. It's possible that non-doctoral researchers working in Spanish public-private R&D organisations accumulate greater amounts of namely "scientific and technical human capital" (Bozeman et al. 2001), due to their strategic position between scientific and industry research.

Limitations and Further Research

Our study presents strong limitations that also suggest new lines for further research. First, due to the technical limitations mentioned in Section 3, we cannot guarantee the full representativeness of our sample and we could object that our findings are not fully generalizable to the whole population of CRCs in Spain; then, further research using a more complete dataset could avoid this problem. Second, we did not exploit all the possibilities offered by statistical techniques of analyses for checking the effect of workforce composition on the outcomes; then, applying stronger statistical models could avoid this problem and maybe provide more fine-grained insights. Third, our analysis focussed only on the organisational level; then, analysing data at the individual level (i.e. researchers, R&D workers) could shed light on other interesting issues, as the professional orientation of workers or the amount of time they spent between different activities. Fourth, we recognise that we focussed only the professional qualification of the workforce as independent variable; further analysis could include additional variables (i.e. funding, types of firms) for explaining larger proportion of variance.

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Annex

Table A1 – Centres by Official Denomination: difference between population and sample

Cramer's V=0,132 (P=0,289)	Estimated Universe		Sample		Response Rate (%)	%Differences with Total Response Rate
	N	%	N	%		
Innovation Technology Centres	139	64,4%	82	64,1%	59,0%	-0,3%
Public Networks of Centres	27	12,5%	19	14,8%	70,4%	11,1%
Stand-alone Research Institutes	50	23,1%	27	21,1%	54,0%	-5,3%
Total	**216**	**100,0**	**128**	**100,0**	**59,3%**	

Source: ES/CRC Research Project (2012); own elaboration

Table A2 – Centres by Region of Residence: difference between population and sample

Cramer's V=0,212 (P=0,139)	Estimated Universe		Sample		Response Rate (%)	%Differences with Total Response Rate
	N	%	N	%		
Andalusia	36	16,7%	24	18,8%	66,7%	7,4%
Basque Country	30	13,9%	19	14,8%	63,3%	4,1%
Catalonia	26	12,0%	12	9,4%	46,2%	-13,1%
Galicia	17	7,9%	12	9,4%	70,6%	11,3%
Madrid	20	9,3%	9	7,0%	45,0%	-14,3%
Valencia	20	9,3%	8	6,3%	40,0%	-19,3%
Other Regions	67	31,0%	44	34,4%	65,7%	6,4%
Total	**216**	**100,0**	**128**	**100,0**	**59,3%**	

Source: ES/CRC Research Project (2012); own elaboration

Table A3 – Centres by Organisational Age: difference between population and sample

Cramer's V=0,187 (P=0,111)	Estimated Universe		Sample		Response Rate (%)	%Differences with Total Response Rate
	N	%	N	%		
1-5 Years	48	22,2%	27	21,1%	56,3%	-3,0%
6-10 Years	64	29,6%	43	33,6%	67,2%	7,9%
11-15 Years	41	19,0%	24	18,8%	58,5%	-0,7%
16-20 Years	22	10,2%	16	12,5%	72,7%	13,5%
20+ years	41	19,0%	18	14,1%	43,9%	-15,4%
Total	**216**	**100,0%**	**128**	**100,0%**	**59,3%**	

Source: ES/CRC Research Project (2012); own elaboration

Table A4 – Output of KMCA (4 groups)

Centres of Final Clusters				
%Professional Position on Total Workforce	**Cluster**			
	1	**2**	**3**	**4**
% Doctoral Researchers	10,18	53,42	7,17	12,92
% Non-Doctoral Researchers	14,34	11,66	17,54	51,74
% Technicians	4,54	8,79	43,85	13,45
% Managers	3,70	9,55	21,49	14,18
% PhD Students	3,52	10,34	,44	3,21
% Graduate and Undergraduate Students	63,73	3,98	4,46	3,56
N (Total N=122)	**2**	**35**	**33**	**52**

Source: ES/CRC Research Project (2012); own elaboration