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Anatomy of use-inspired researchers: From Pasteur's Quadrant to Pasteur's Cube model

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ABSTRACT

Pasteur's Quadrant model, published by Stokes in 1997, presents a two-dimensional abstract conceptual framework that proved immensely helpful to study and discuss institutional and policy arrangements in science. However, during the last 10 years the PQ model was also applied in a series of large-scale, survey-based studies worldwide to classify individual modern-day researchers according to their research orientation and performance.

This paper argues that such applications are inadequate to capture key characteristics of individual researchers, especially those within the heterogeneous 'Pasteur type' group who engage in 'use-inspired' basic scientific research. Addressing this shortcoming, Pasteur's Cube (PC) model introduces a new heuristic tool. Departing from a three-dimensional conceptual framework of research-related activities, the model enables a range of typologies to describe and study the large variety of academics at today's research-intensive universities. The PC model's analytical robustness was tested empirically in two interrelated 'proof of concept' studies: an exploratory survey among 150 European universities and a follow-up case study of Leiden University in the Netherlands. Both studies, collecting data for the years 2010–2015, applied a metrics-based taxonomy to classify individual academic researchers according to four performance categories: scientific publication output, research collaboration with the business sector, patents filings, and being engaging in entrepreneurial activities.

The collective results of both studies provide more clarity on relevant subgroups of use-inspired researchers. The PC model can be used to guide empirical, metrics-based investigations of research activities and productivities, applies this approach to two case studies, and demonstrates the utility of the method while also reinforcing and enriching the growing body of literature showing that cross-sectoral and cross-functional research activities are more scientifically productive than research carried out in isolation of the context of use. Introducing the 'Crossover Collaborator' subtype helps to explain why Pasteur type researchers tend to outperform other types of researchers in terms of publication output and citation impact.

1. Introduction

During the previous century, general views and expectations with regards science have shifted from traditional 'public good' objectives (such as 'discovering nature' and 'defending the truth') to one where science is seen as commodity for public use and private sector utilization (Godin and Schauz, 2016). In the wake of this revised 'social contract' with its funders and stakeholders, science agenda's and research activities have become more aligned to pressing socioeconomic needs and practical problems – be it local communities, business interests, or other user domains (Sarewitz, 2016). The stronger focus on applications and utilization has ushered in new models of science funding as well as criteria to gauge the performance of research-active organisations and individual researchers. Although discovery-oriented 'basic' researchers may still aim for pure knowledge creation, their driving forces and underlying research questions are increasingly inspired by, or designed to address, specific societal issues or concrete problems. Such 'use-inspired'[1] research tends to have higher rates of 'non-academic' outputs (e.g. policy recommendations, practice guidelines or prototype technologies) and associated impacts outside the scientific community. And since these results can more readily be used externally, they lend themselves more readily to commercialisation,

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[1] The term 'use-inspired' is one of many variants, such as 'strategic research' and 'applications oriented research', to denote research activities that blends discovery-oriented 'basic' research and user-oriented 'applied' research. Opting for 'use-inspired' we follow the terminology by Stokes (1997).

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with or without the need for formal IP protection. Using research commercialization output indicators, several studies have provided evidence that such use-inspired activities show a positive correlation with marketable outcomes and economic impact (O'Shea et al., 2005; Powers and McDougall, 2005; Colombo et al., 2010; Wong and Singh, 2013; Cheah, 2016).[2]

Viewing 21st century science through a use-inspired lens, how should one perceive the value added of such researchers, especially their ability to generate socioeconomic impacts and returns? Given the conceptual and analytical complexities of micro-level impact assessment, this issue has proven to be quite a methodological challenge (e.g. Hughes and Martin, 2012). The main objective of this paper is to tackle this challenge by developing a more appropriate conceptual framework and related classification system of individual researchers. After introducing the underlying theoretical and conceptual framework in the next section, and the analytical models in Section 3, two case studies are presented in Section 4 with empirical results on researchers at European universities.[3] Section 5 presents a concluding discussion of the findings and implications for further work.

2. Theoretical and conceptual framework

2.1. From 'use-inspired' to 'entrepreneurial'

More than twenty years ago, Zucker and Darby (1996) aptly demonstrated the significance of the individual use-inspired researcher as a unit of analysis by introducing their US-based 'star scientists' as those who had published many genetics discoveries as well as being the best corporate partners in biotechnology. These highly productive, researchers tend to have high levels of 'intellectual capital' and the 'transformative powers' to connect and integrate science to technology and innovation (Rosen, 1981; Zucker et al., 1998). Follow-up studies carried in the United Kingdom emphasized the crucial role of these 'linked scientists' (Zucker et al., 2002) in connecting academic scientific knowledge and know-how to a firm's internal R&D. Focusing on the intellectual and cognitive profile of use-inspired academic researchers presents meaningful way for better understanding why some of these individuals are more prone than others to be(come) application-oriented, market-oriented and entrepreneurial (Baron, 2004). Jain et al. (2009) argue that establishing the foundations of academic entrepreneurship requires closer scrutiny of the university scientist as a key actor and micro-level unit of analysis, although clearly such researchers constitute a very heterogeneous group of individuals (Shinn and Lamy, 2006; Markman et al., 2008).

Abreu and Grinevich (2013) define 'academic entrepreneurship' as "any activity that occurs beyond the traditional academic roles of teaching and/or research, is innovative, carries an element of risk, and leads to financial rewards for the individual academic or his/her institution". Adopting this broader view, entrepreneurship not only includes application-oriented 'formal' activities (such as patenting and patent-based licensing, ownership of university spin-out companies), but also other 'informal' academic engagement activities such as conducting contract research, joint research with industry partners, membership of corporate advisory boards, or consultancy firms. Apart from being more widely practiced, Perkmann et al. (2013) see academic engagement as being more closely aligned with research activities, and geared towards accessing additional resources to supporting the research agendas of academics. In their survey, providing micro-data on some 22,000 participants in the United Kingdom, Abreu and Grinevich (2013) found that academics working in user-oriented or applied areas are more likely to be involved in all types of entrepreneurial/engagement activities than more traditional researchers.

Apart from being an accomplished scientific researcher, with a sufficient level of 'intellectual capital', what are those 'transformative powers' or other individual characteristics of researchers help them frame and shape their research activities in order to pursue opportunities for commercial applications and entrepreneurship? Why are some more likely than others to be(come) engaged with user communities outside science, business sector partner or other external 'third parties'? The general concept 'human capital' captures important features of this capacity to generate value from outcomes of research activities. Becker (1993) refers to human capital as "the stock of competencies, knowledge, abilities, and skills gained through education and training".[4] Adopting this perspective, and focussing on human capital in scientific and technical staff, Bozeman et al. (2001) evaluate career trajectories of scientists, and their sustained ability to contribute and enhance their capabilities, as an alternative model for evaluating science and technology projects and programs. Further studies show that the human capital attributes of researchers tend to be a critical resource to entrepreneurial success (Unger et al., 2009; Aldridge and Audretsch, 2010). Scientists and researchers with higher levels of human capital have a greater ability to recognize opportunities and a larger chance of gaining access to those opportunities for exploitation and commercialization of their research outputs (Busenitz et al., 2014). Azoulay et al. (2009) find that academics who file for patents tend to shift their research foci to questions of commercial interest.

A second explanatory factor, social capital, relates to social ties and networks (e.g. Hayter, 2016). Those with an abundance of social capital find easier access to new tangible and intangible resources that may enhance opportunity recognition and collaborative behaviour. Such benefits may for instance increase the likelihood of starting a new company or sitting on scientific boards of business enterprises. Several studies have shown that social capital may boost academic entrepreneurial activity (Karlsson and Wigren, 2012; Aldridge and Audretsch, 2011).

Studies have shown that their personal values and beliefs about the benefits of research commercialization also influence entrepreneurial behaviour (Renault, 2006). Scholars point towards their 'role identities' (a primary 'academic self' and a secondary 'commercial persona') and to 'hybridization processes' identity shifts where academic researchers increasingly share the same values as their business sector counterparts (Colyvas and Powell, 2007; Owen-Smith, 2003). Jain et al. (2009), applying a social-psychological framework to explain their finding that the academic productivity and commercial activity of university scientists reinforce one another. According to a study by Grimaldi et al. (2011), the development of entrepreneurship competencies at the university level is significantly influenced by the extent to which individual researchers and research teams are incentivized and willing to become involved in such activities. Overall, use-inspired researchers are likely to be engaged in activities with (potential) users of their findings, while remaining integrated in academic scientific communities.

Although the academic literature finds individual factors more important than institutional factors in explaining academic entrepreneurship (e.g. D'Este and Patel, 2007; D'Este and Perkmann, 2011), the propensity and ability for commercialisation and entrepreneurship is clearly also affected and driven by organizational or contextual determinants (Autio et al., 2014). Some fields of science are more prone to commercialisation inspired by considerations of use.

[2] The UK survey by Lam (2011) finds a non-significant but negative correlation with being actively involved in basic research, reflecting the ambiguous relationship between discovery-oriented research and commercial engagement. In some areas of science (notably the medical, health and life sciences) academics spent time on basic research as well as applied ('clinical') research.

[3] Throughout this paper the term 'university' refers to any PhD granting higher education organization (public or private) that engages in in-house scientific or technical research activities.

[4] According *to Organization for Economic Co-operation and Development*, 'human capital' is "knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being" (OECD, 2001).

Several studies that have found evidence of greater commercialisation activity in the life sciences (e.g. Link et al., 2007). In a study of the field of materials science, Calderini et al. (2007) find that "scientists that are moving along applied research trajectories find it easier to produce industrial applications than their colleagues engaged in the quest for very fundamental understanding". Being active in knowledge transfer, and creating network career structures at public/private R&D interfaces (Lam, 2007), they also are more likely to be familiar with business interests and (end) user requirements. Collaboration with industry encourages university scientists to commercialize (Agarwal and Henderson, 2002) and engage in academic patenting (Lawson, 2012). University-industry interactions are likely to be more common among academics who self-define their research profile as 'applied' (Gulbrandsen and Smeby, 2005). While these early empirical studies focused their attention on research collaboration and commercialization activities of talented individuals (e.g. Rothaermel et al. 2007), subsequent studies tend to emphasize a wider range of interactions and activities (D'Este & Fontana, 2007; Gulbrandsen et al., 2011; D'Este & Perkmann, 2011; Perkmann et al., 2013).

The collective findings of all above-mentioned case studies illustrates the complex and diverse nature of entrepreneurship and user engagement among 'use-inspired' researchers working in academia and at public/private interfaces. Several large-scale survey-based cases studies – stretching back almost 30 years, and often conducted amongst life sciences academics – provides many inputs as to the kind of empirical information one needs to categorize researchers according to the nature and degree of their 'entrepreneurship orientation' or 'user engagement' (e.g. Louis et al.,1989; Link et al., 2007; Azoulay et al. 2009; Lam, 2011; Aldridge et al., 2014; Wu et al., 2015; Perkmann et al., 2015). In order to better grasp and understand the heterogeneity of researcher profiles, and to contextualize individual performance profiles in their local environments and organisational settings, comprehensive behavioural models and analytical methods are much needed (Etzkowitz, 1998; Owen-Smith and Powell, 2001, 2004; Guerrero et al., 2016).

2.2. Toward classification systems and researcher typologies

Academic human capital formation and human resources management at universities is still an underdeveloped area of systematic inquiry with only a few comparative studies (Pellert, 2000; Van den Brink et al., 2012; Bradley, 2016). Little work has been done to implement empirical findings and insights from the above-mentioned studies of academic entrepreneurship into workable typologies of researchers with regards to their entrepreneurial and commercial activities (e.g. Ankrah et al., 2013; Callaert et al., 2015). The scarcity of large-scale studies is partly due to the fact that human resources policies and practices tend to be institute-specific or country-dependent, but also because authoritative classification systems of individual researchers are still sorely lacking.

Three main types of classification systems have been suggested in recent years. Firstly, by what is described in Mallon et al. (2005) as 'orientational' categories based on *beliefs, wants and plans* in terms of value preferences or individual predispositions. Lam (2011) introduces four categories to describe such orientational differences with regard to commercial engagement: (1) researchers who as seen as 'pure traditionalists' avoid entrepreneurship activities and defy the pressures for commercialization, but they may collaborate with industry without the intention to pursue commercial or entrepreneurial activities; (2) 'pragmatic traditionalists' tend to display a more accommodating attitude with regards to commercial engagement; (3) 'entrepreneurial scientists' believe in the fundamental importance of university-industry collaboration for knowledge application and commercial exploitation, have fully accepted entrepreneurialism in academia; (4) 'hybrids' who maintain commitment to the traditionalists' scientific values, but share the belief in the importance and benefits of university-industry cooperation and perceive such cross-sectoral endeavours as largely legitimate and desirable.

The entrepreneurial scientists, those most likely to be engaged in commercial and entrepreneurial activities, comprised of 70 respondents in Lam's survey of UK scientists (11% of the total survey sample) - some 40 of which were 'engaged in both collaborative and commercial links including patenting/licensing, affiliation with start-ups and company formation' (Lam, 2011; p. 1361). The likelihood to be entrepreneurial is significantly associated with research disciplines, age, career stage and gender. Those in the medical and life sciences, computer science, engineering or chemistry also have a higher probability to participate in commercialization. However, female scientists and researchers younger than 40 are less likely to be active, whereas being a professor has a weak positive effect on commercial engagement.

Due to limited information density and response and recall biases, such surveys of academic perceptions, motivations, values and attitudes are deemed less suitable for providing information on past or current entrepreneurship activities (Perkmann et al., 2013). An alternative classification approach was therefore introduced by Perkmann et al. (2015), in a comprehensive study of researchers at Imperial College London, in which university *administrative and archival records* were complemented with external information from surveys. This study focused on individual entrepreneurship activities and was designed to capture 'independent' activity outside the formal university channels: "by combining information on academics' resource acquisition (e.g., consulting) with records on publications and commercialization outcomes (e.g., patents, firms), it is possible to relate inputs to outputs over time without having to rely exclusively on individuals' self-reported information, as is the case with survey-based systems". The survey data captured three types of academic entrepreneurship activity per scientist: consulting, patenting, and founding directorships. The results unearthed significant underreporting in university records.

A third approach draws on individual self-classifications of academic research activity on the 'basic/applied' spectrum. Surveys among university researchers reveal major conceptual difficulties to apply this classification systems to real-life academic research settings (Gulbrandsen & Kyvik, 2010; Bentley et al., 2015). The latter study, based on a survey of across 15 countries worldwide with some 12 000 university researchers, introduces a crude typology comprising five main categories of individuals: 'pure basic' (14% of the respondents); 'leaning towards basic' (18%); 'equally, basic and applied' (27%); 'leaning towards applied' (24%); 'pure applied' (17%). Some 8% were 'neither basic nor applied'. Except for those who see themselves as 'pure basic' researchers, all other categories may comprise of use-inspired researchers as well as those individuals who are (possibly) engaged in research commercialisation or academic entrepreneurship.

2.3. Crossover researchers

Building on the general observation that a significant share of academic researchers seem to be 'hybrids' in terms of their orientation towards both basic and applied research, the category 'crossover researcher' was first introduced in Tijssen & Yegros (2017) for those university researchers who are explicitly connected to the business sector—either through research cooperation and/or inter-sector job mobility. Crossover researchers have a history of being involved in joint research with corporate R&D staff and therefore some degree of engagement with the business enterprises. Some may have a history of cross-sectoral mobility with prior employment in the business sector; others might be involved in technological development and/or engaged in research-based entrepreneurial activities.

Abramo et al. (2012) find that such 'researcher-entrepreneurs', those who founded university spin-off companies, also showed a better research performance than their non-entrepreneurial peers. The survey-based findings from the study by Bentley et al. (2015) suggest a weak positive relationship between being engaged in application-oriented research and the availability of commercial funding. Similarly, Yegros et al. (2016) find a weak correlation between the quantity of university-industry co-authored research publications and the amount of funding from the business sector - but only for those academic authors who actively participated in business-funded research projects. Moreover, prior employment or work experience in the business sector positively affects the propensity of academics to engage in university–business collaboration, as well as their research commercialization activities (Dietz and Bozeman, 2005; Clarysse et al., 2011; Bozeman et al., 2013). Lin and Bozeman (2006) for instance found that 40% of their sample of researchers drawn from industry-oriented research centres in the USA had work experience in the business sector, but the authors note that this is most likely much lower in universities. In their large survey of UK academics, Abreu and Grinevich (2013) looked at their previous work experience and prior employment in small firms or large firms. Their results showed that industrial work experience, particularly from small/newly established firms, is positively related to engagement in commercialization activities. Gulbrandsen & Thune (2017) collected survey responses in Norway, from employees in universities and colleges, and found that 16% had prior employment in the business sector (i.e. after finishing their master's degree and lasting one year or more); their findings also indicated that academics with a background in the business sector are more active in research commercialization activities than their colleagues.

Collectively, these studies strongly suggest that crossover researchers are likely to act as linking pins and exchange agents between the world of science and the business sector (Mangematin et al., 2014). Given that background, they are most likely the ones to combine or integrate curiosity-based, discovery-driven, use-inspired 'basic research' with an orientation towards business sector applications. The findings of the various surveys support the idea to consider this subgroup of individuals a special breed of use-inspired academic researchers. Being familiar with university-business R&D interfaces they are more prone to be engaged in collaboration, commercialisation and user interaction, these crossovers are the ones with high levels of intellectual capital, and 'transformative' levels of human capital and social capital. The next section will introduce two analytical models and research hypotheses, where these use-inspired 'crossovers' will feature prominently.

3. Analytical models and hypothesis development

3.1. Pasteur's Quadrant model

Each of the three classification approaches mentioned in Subsection 2.2 deal with a different, complementary perspective as regards to the nature of research activities and the propensity to be engaged in commercialisation, entrepreneurship and user engagement. While each classification system captures some information on the heterogeneity of academic researchers engaged in these varied activities, none of these is able to provide a satisfactory general profile of researchers. The methodological challenge is to design and implement a more comprehensive classification system of practical relevance; a consistent system that provides reliable information on key characteristics of individual researchers, and comprises of standardized categories and convincing metrics to enable both in-depth and large-scale comparative studies.

Pasteur's Quadrant model (Stokes, 1997) presents a useful point of departure.[5] The PQ model is a helpful heuristic tool to develop design parameters for a characterization and taxonomy of university scientists. The underlying conceptual framework embodies some elements from

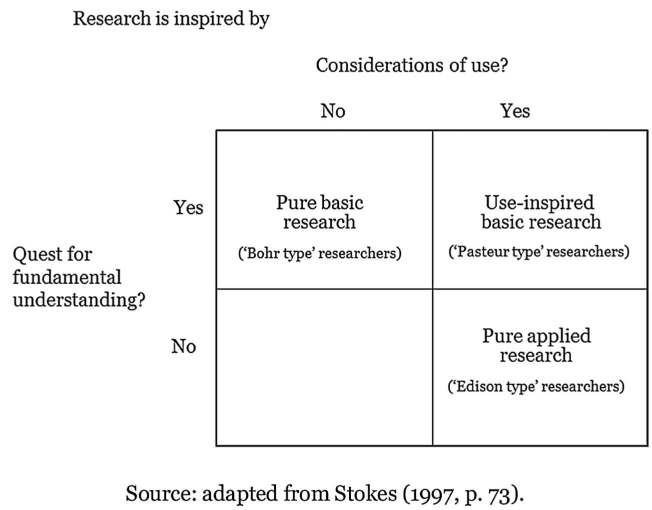

Fig. 1. Stoke's Pasteur Quadrant Model.
Source: adapted from Stokes (1997, p. 73).

the three classification approaches. Departing from the classical one-dimensional model and unidirectional 'linear' knowledge creation and utilization processes (i.e. from 'basic science' to 'applied science' and technology), this model introduces a dual approach where scientists can be classified according to both their 'orientation towards fundamental understanding' and the 'utility of their research'. Introducing these two motivational factors for engaging in scientific research, replaces the outdated dichotomy between 'basic' and 'applied', which is increasingly irrelevant in strategic analyses of general trends and patterns modern-day science (Calvert, 2006; Cantisani, 2006; Tijssen, 2010; Gulbrandsen and Kyvik, 2010; Martínez et al., 2013; Ooms et al., 2015). The quadrants of the graphical representation of the PQ model based on yes/no dichotomies for 'quest for fundamental understanding' and 'consideration of use' (see the diagram in Fig. 1).

The top-left quadrant of the 'Pasteur Quadrant' model consists of 'conventional' academic scientists and scholars who conduct 'pure basic research' and they carry out discovery-oriented research in the pursuit of knowledge and understanding for its own sake; they have little interest in the potential real-world uses of the research findings (represented by Niels Bohr, an archetype 20th century physicist). The bottom-right quadrant, exemplified by Thomas Edison – the 19th century inventor and entrepreneur – refers to researchers and engineers who, motivated by commercial outcomes, conduct applied research, are engaged in related technological development and tend to serve business innovation interests. The upper-right quadrant contains researchers who have the desire to advance scientific understanding, but may also actively pursue commercial applications and engage with the business sector (such as Louis Pasteur, the acclaimed chemist and microbiologist). These 'Pasteur type' scientists, who are likely to be involved in use-inspired basic research, are often at interfaces between the academic world and the business sector, and hence shape co-evolution of scientific and technological development.

It is important to note that Stokes' introduction and his application of the PQ model was not about subjective motivations or aspirations of individual scientists and scholars, nor their research orientation. Stokes applied his model to help explain that scientific research is a complex process, within a larger, complex ecosystem of innovation-related activities, where 'basic versus applied' distinction misrepresents important features of research dynamics and science systems. Within this context it has been a valuable heuristic, especially in explaining a wide range of findings about institutional and policy arrangements in science and its funding mechanisms.

Diverging from Stokes' originally intended purpose, the next

[5] Pasteur's Quadrant model was developed and published by the late Donald Stokes, a former professor of Political Science and Public Affairs, Princeton University, United States. The model's name originates from the title of his 1997 book, wherein it is referred to as the "Quadrant Model of Scientific Research".

subsection provides an overview of how his PQ model was used during the last few years to study the performance profiles individual researchers and scientists.

3.2. Applications of Pasteur's Quadrant model to study researchers

PQ based studies of individual researcher profiles have been either opinion based (self-reported views and perceptions) or 'bibliometrics' based (quantitative measures derived from statistical analysis of research publications or patents). This first stream includes work of Hughes et al. (2010), Hughes (2011) and Nagaoka et al. (2011). These empirical studies show that a substantial portion of the researchers in the US and the UK classify themselves in Pasteur's Quadrant. Nagaoka's study finds a 26% share in the USA and 8% in Japan. In a nationwide survey among thousands of UK academics, 29% considered themselves a 'Pasteur type' researcher (Hughes, 2011; p. 26).[6] The share rises to 70% in the medical and health sciences, and almost 60% in the engineering sciences, but drops to 25% in the arts and humanities.[7] Clearly a significant share of the academic researchers in advanced science systems could be classified as 'Pasteur type'. However, the self-reported information from these opinion-based studies may suffer from questionable degrees of validity and reliability, partly because of ill-defined classification criteria.[8]

Most bibliometric studies were done in (South) Eastern Asia, where the PQ model was used either in an exploratory or explanatory mode. This body of case studies focussed on research performance characteristics of 'Pasteur type' (and 'Edison type'), usually in comparison to conventional 'Bohr type' researchers. Box 1 presents a summary overview of these studies, highlighting some key findings with regards to Pasteur type researchers.

Pasteur type researchers tend to be more productive in terms of scientific publication output, and their research publications are more highly cited by their scholarly peers. Zucker and Darby's 'star scientists' (see Section 2.1) seem to be well-represented in this group. However, a deeper understanding of this apparent concentration of 'research excellence' is lacking, partially because appropriate frameworks to identify these top-achievers are missing. The crudeness of PQ-based classification systems, as exemplified by Bentley et al. (2015) in Section 2.2, illustrates the analytical problem.

To help pinpoint and describe high-performance subtypes, and thus unravel the diversity of researchers within the Pasteur type group, requires a more differentiated model and associated classification system of individuals – with a nuanced characterization of a researcher's professional practices, experiences and achievements. Such advanced classification systems should be able to capture how scientific research connects to a variety of application domains, and how individuals could be classified according to value creation processes, career trajectories or impact pathways. Such systems should also be better equipped for conducting a wide range of comparative, metrics-based studies – within and across countries, organizations and fields of science (Andras, 2011) – and to assess external socioeconomic impacts of academic researchers (Scoble et al., 2010). This call for a shift in the analytical scope – more towards micro-level applications – aligns with some signs that the PQ model is becoming less popular as a policy-relevant studies and discourse.[9]

3.3. Pasteur's Cube model[10]

Obtaining a more empirical and differentiated grasp of Pasteur type researchers requires a functional 'data processing' model that is grounded in a framework with generally recognizable features. Rather than relying on motivational factors and self-classification, the model should focus on capturing the use-inspired identity of individual researchers in terms of their concrete outputs and impacts. Following this logic, and based on pre-specified design criteria[11], the PQ model is expanded into a '*Pasteur's Cube model*' that comprises of three, broadly-defined constructs:

a) *knowledge production and skills creation* (science and scientific research);
b) *technological development and artefacts production* (engineering and technology);
c) *end user engagement* (commercialisation, entrepreneurship and innovation).

The three classes of researcher-embodied general attributes, as described in Subsection 2.1 (intellectual, human and social capital) and the two dimensions of the PQ model, are transformed and operationalized into three observable dimensions.

In contrast to Perkmann et al. (2013), who introduce a distinction between 'commercialisation' and 'academic engagement'[12], the PC model collapses both categories into a single 'end user engagement', which is defined as "responses and interactions with users, often outside the academic research community, with regards to the dissemination, utilization or commercialisation of research-based knowledge, artefacts or skills" where an 'end user' is defined as an individual, community or organisation external to academia that will directly use or directly benefit from the output, outcome or result of the research (examples of such end users include business enterprises, governments, non-governmental and civic organisations). Table 1 provides a more extensive overview of the differences between both models, emphasizing the fact that the PC model is specifically designed to collect empirical evidence at the micro-level of researchers for comparative analysis.

The operationalization of each dimension in the PC model and the values on each low/high scales, depend on the frame of reference (type

[6] 41.7% considered themselves an Edison type researcher; 26.5% regarded themselves a Bohr type.

[7] The significant differences between fields reflect the orientation towards practical outputs and underpinning cognitive knowledge structures of disciplines, which support the analytical guideline that PQ-related findings should be framed within field-dependent interpretations of science systems or research-active organisations (e.g. Weingart, 1997; Woolf, 2008).

[8] For example, Bentley et al. (2015) acknowledge that the key concepts ('basic research' and 'applied research') may have been interpreted differently, and suggest that differences in response to Likert type (rating scale) questions may introduce further biases where respondents may exaggerate their the degree of their orientation, or define their research in accordance with organizational or disciplinary norms rather substantive engagement.

[9] Although the PQ model and its typology of research activities has gained quite an impact in the academic literature and in science policy discussion, its popularity seems to be have reached its zenith a few years ago. Trend analysis of its occurrences in *Google Scholar* web-based searches, shows that the number of scientific and scholarly publications mentioning "Pasteur's Quadrant" has increased from 27 in 1997-1998 to a peak of 249 in 2011/2012, which has slipped back to 185 in 2015-2016. These frequency counts refer to scientific and scholarly publications containing a verbatim mentioning of the phrases "Pasteur's Quadrant" or "Pasteurs Quadrant" (searched in Google Scholar on January 24th 2017 -all languages, excluding search in patents and quotes).

[10] The concept 'Pasteur's Cube' has also been proposed by Roy (2017) in a manuscript dated 7 September 2017 for a research article in *International Journal of Technology Transfer and Commercialisation* (the manuscript of this article was submitted to *Research Policy* on July 27th 2017).

[11] The following design criteria were applied to create a required 'general purpose' comparative model for a range of analytical applications: generally recognizable key concepts (that appeal to diverse audiences and users active in contemporary STI policy debate and decision-making) and a transparent data collection system - with standardized information items, categorization and quantification - that enables up-scaling to meso- and macro levels of data aggregation. The model should allow for integration of information from various sources; not only 'local' information (such as views of researchers, or their background characteristics), but also internationally comparative statistical data (such research performance data).

[12] The study by Perkmann et al. defines 'commercialisation' as "intellectual property creation and academic entrepreneurship", while "academic engagement is distinct from commercialisation in that it is closely aligned with traditional academic research activities, and pursued by academics to access resources supporting their research agendas" Perkmann et al. (2013, p. 423).

Box 1
Pasteur's Quadrant bibliometric studies of researchers.

Baba et al. (2009)

Topic and information source: photo-catalyst research in Japan; 455 firms with at least 5 patents each; 1873 research publications between 1970 and 2004; 23 'Pasteur scientists'.

Definition of Pasteur type researcher: individuals with highly cited research publications and many patents.

Key findings on Pasteur type researchers: university-industry collaboration with 'Pasteur scientists' increased the R&D productivity of firms.

Nagaoka et al. (2011; 2016)

Topic and information source: survey among 2100 researchers in Japan and 2300 in the United States; selected through research publications between 2001 and 2006.

Definition of Pasteur type researcher: individuals who acknowledge both the 'pursuit of fundamental principles/understandings' and 'solving specific issues in real life' as very important motivations for their research.

Key findings: within the subset of highly cited papers, the share in Pasteur's quadrant is more than twice as high in the USA than in Japan (33% vs. 15%); Pasteur type researchers at least as productive as those in the Bohr quadrant in science output, and at least as productive as those in Edison quadrant in technology output.

Shichijo et al. (2015)

Topic and information source: photo-catalyst research in Japan; 3832 research articles published from 1960 to 2010; 21 'Pasteur scientists'.

Definition of Pasteur type researcher: individuals with highly cited research publications and many patents.

Key findings: entrepreneurial scientists (Pasteur type and Edison type) publish more papers than conventional (Bohr type) scientists do; entrepreneurial scientists show higher propensity for publishing high-impact papers than conventional scientists.

Ng et al. (2015)

Topic and information source: 121 researchers at the Engineering Faculty of the National University of Singapore (NUS).

Definition of Pasteur type researcher: individuals with highly cited research publications and many patents.

Key findings: Pasteur type and Edison type researchers have a higher number of university-industry linkages as compared to Bohr type; Pasteur type researchers are essential for research-intensive universities as only they are found to be positive and significantly related to industry research cooperation agreements.

Wong et al. (2017)

Topic and information source: 1769 researchers in 2013–2014 at the Science and Engineering Faculties of the National University of Singapore (NUS).

Definition of Pasteur type researcher: individuals with highly cited research publications, university-industry co-authored publications and many patents.

Key findings: are the most likely to have been employed by industry before joining NUS and have the highest publication output; their technology commercialization performance is higher than Edison type researchers.

Table 1
Pasteur's Quadrant versus Pasteur's Cube: main functional attributes.

	Pasteur's Quadrant	Pasteur's Cube
Analytical scope	Two-dimensional (science; technology)	Three-dimensional (science; technology; end user engagement)
Functional objectives	Conceptual framework and descriptive tool	Analytical framework and data collection tool
Conceptual notions	Driving forces and motivations for research	Research-based practices and performance
Information sources	Internal views and narratives ('reflective')	External empirical evidence ('concrete') collected by external analysts
Information type	Self-reporting on perceptions by individuals; reporting on general perceptions by external analysts	Outputs and impacts observed by external analysts
Information quality	Low to medium	Medium to high

of organisation, field of science, country or region, etc.) and institutional level, which may vary from small research department to main organizations or even entire national science systems. The PC profile of an individual researcher depends on the relative level of activity/output/impact on each of these three dimensions. According to his/her performance profile, a researcher can be classified anywhere within this continuous 3D space. A graphical representation of PC model, depicted in Fig. 2, includes three general archetypes of researchers ('science-oriented'; 'application-oriented'; 'user-oriented') to illustrate the diversity of researchers that can be accommodated. The above-mentioned 'crossover researchers' tend to combine these three orientations and are likely to be scattered across this cube, albeit with a larger probability for positions in the upper-back section.

3.4. Research questions and hypotheses

Determining the general applicability of PC model requires 'proof of concept' studies of the model and empirical tests of its added value compared to the PQ model. This paper addresses the issue of heterogeneity within PQ's Pasteur quadrant. Is the 'intellectual capital' of these Pasteur type researchers equally spread across the various subtypes in the PC model? And how do distributional patterns relate to proxies of human capital and social capital (i.e. academic rank, research collaboration propensities, and business experience)? In view of their distinctive performance profile (see Box 1 in Section 3.2), unravelling the heterogeneity among Pasteur type researchers is examined by studying general characteristics of crossover researchers (see Section 2.3) and comparing their PC performance profile to other types of researchers. They are the ones most likely to qualify as 'star researchers'

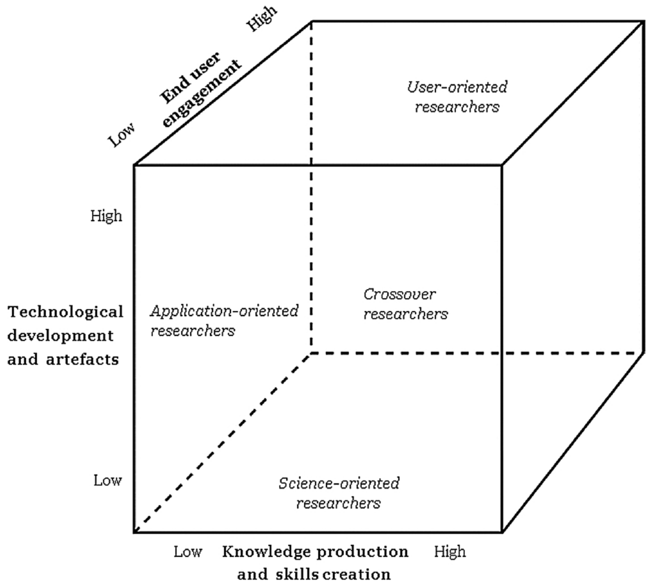

Fig. 2. Pasteur's Cube of researcher activities.

(see Section 2.1), especially if they are actively engaged in commercialisation and/or entrepreneurship. These general assumptions lead to three testable research hypotheses:

H1. Crossover researchers are distinctly different from the other types of researchers in terms of their PC activity profile;

H2. Crossover researchers produce more research publications, and are more highly cited in the research literature, than conventional ('science-oriented') researchers;

H3. Crossover researchers who are actively engaged in commercialisation and/or entrepreneurial activities are more prolific researchers than their counterparts without such activities.

3.5. Case study design: methodology and researcher typology

Operationalization and practical implementation of the PC model requires a multi-criteria approach. The model allows for several ways of anchoring the notion of 'use-inspired research' into tangible categorizations of researchers. Ideally, any PC-based typology should classify researchers according to a rule-based taxonomy with clear criteria and boundaries[13]. The strongest 'robust' version of the PC taxonomy requires a multi-source, multi-metrics framework with extensive comparative measurement on all relevant characteristics – preferably based on objective and consolidated information gathered from a wide range of verified external sources. In practice, core attributes of individuals (in terms of intellectual capital, human capital and social capital) cannot be defined empirically. Given lack of such information, let alone high-quality quantitative data, to capture and compare key characteristics of individuals, less robust 'proxy' versions of the model are forced to rely on the few sources of information that are currently available in which each type of researcher is defined by a 'profile' of common characteristics. Such a profile-based taxonomy can draw on information from both background variables (age, gender, professional background, research competencies, etc.) as well as variables related to the three

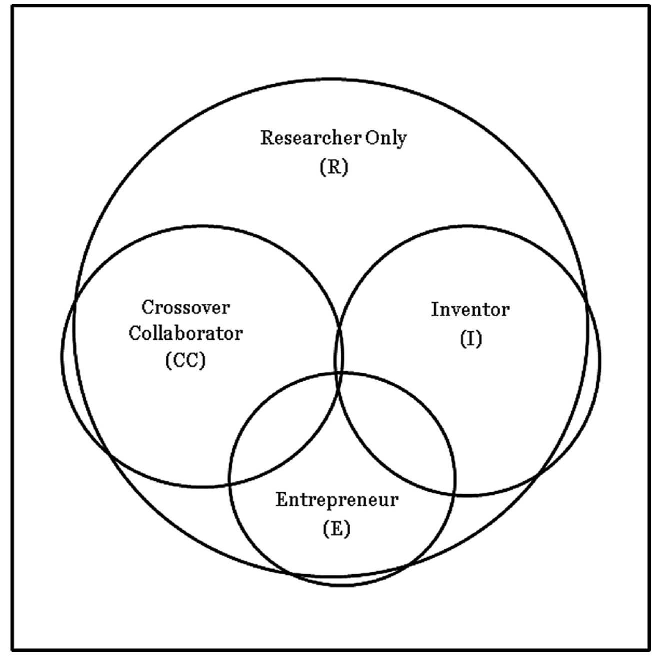

Fig. 3. Pasteur Cube taxonomy of researchers.

performance dimensions in the PC model.

With regards to the dimension 'knowledge production and skills creation' and 'technological development and artefacts', typically the PC taxonomy would operationalize the types within these two dimensions in terms of either peer-reviewed research publications and international patents respectively – both of which are abundantly available in large, consolidated international databases. There is an extensive academic literature on the analytical pros and cons of such bibliographical information sources to capture relevant outputs and impacts of scientific research and technological development (e.g., Tijssen, 2004; Hicks et al., 2015).[14] However, information on 'end user engagement' is scattered across a range of sources where data needs to be verified and consolidated. The same data collection challenges may apply to background information on individuals, where the major sources of information are: in-house administrative databases of organizations, websites of organizations, surveys and interviews, and social media websites.[15]

In this paper the PC-based taxonomy system consists of four categories of researchers: *Researcher Only* (R type); *Crossover Collaborator* (CC type); *Inventor* (I type); *Entrepreneur* (E type). The first two types (R and CC) relate to the 'knowledge and skills creation' dimension, where the CC type researcher operationalizes the notion of 'linked scientists' as mentioned in Section 2.1 and the 'crossover researcher' described in Section 2.3. E type researchers also move across sector boundaries, but specifically for entrepreneurial activities and engagement with users in the business sector.[16]

Fig. 3 presents a stylized 2D graphical impression of this taxonomy that emphasizes interrelationships and overlaps between the three dimensions of the PC types. In addition to the 'baseline' category of

[13] A typology represents concepts rather than empirical cases, which create useful heuristics and provide a systematic basis for comparison. The various types are often based *ad hoc* criteria, are not necessarily exhaustive nor mutually exclusive. A taxonomy classifies items or entities into distinct categories according to empirically observable and measurable characteristics. This paper applies a typology to describe classes of general researchers and a taxonomy to operationalize those types with empirical data.

[14] The general consensus is that both are meaningful sources of information within a limited number of production domains: paradigm-based scientific fields in 'mainstream science', and technology areas that relate to manufacturing industries. In all other domains, such as research the social and behavioural sciences, or technologies in services industries, a wider range of information sources are required.

[15] Data gathering of information of a personal nature might be prohibitively difficult because of restricted access (for reasons of privacy protection and confidentiality) and/or tackling technical obstacles that may entail expensive data-processing facilities.

[16] E type researchers may hold part-time jobs or (honorary) appointments at business companies (for example as a board member or advisor) or may hold a shareholder/owner position at a university spin-off company.

Table 2
Most frequently occurring countries and universities in the survey sample.[a]

Country	Occurrence count	University	Occurrence count
Netherlands	87	Leiden University	12
Italy	48	University of Milan	11
Sweden	41	University of Amsterdam	10
United Kingdom	38	Chalmers University of Technology	9
Greece	30	Eindhoven University of Technology	9
Austria	20	National Technical University of Athens	9
Denmark	20	Utrecht University	9
Serbia	20	Vrije Universiteit Amsterdam	9
Spain	20	Wageningen University & Research Centre	9
Czech Republic	19	Delft University of Technology	8
Germany	19	University of Bologna	8
Croatia	16	University of Crete	8
Finland	16	University of Groningen	8
Portugal	15	University of Split	8
Hungary	14	Aalborg University	7
Poland	14	Aristotle University of Thessaloniki	7
Ireland	13	Masaryk University	7
Switzerland	12	Politecnico di Torino	7
Estonia	11	University of Belgrade	7
Norway	11	University of Debrecen	7
Romania	11	University of Florence	7
Belgium	10	University of Iceland	7
Slovakia	10	University of Novi Sad	7
		University of Warsaw	7
		University of Zagreb	7

[a] Cut-off points for tabular presentation: 10 occurrences at the country level; 7 occurrences at the university level. Total sample: 553 researchers.

‘science-oriented’ researchers (R type), the taxonomy includes various composite categories and subtypes such as the ‘application-oriented’ researcher/inventor (R + I type) or the even more ‘user-oriented’ R + I + E subtype. Longitudinal applications of this classification system, introduces a framework to monitor the nature and direction of careers changes and shifts in professional focus of individual researchers (Bozeman et al., 2001; Gulbrandsen and Kyvik, 2010).[17]

In the two case studies of European academic researchers, described in the next sections, a sufficiently wide range of empirical information was collected to examine the applicability of this PC based taxonomy and to address these hypotheses empirically. Both studies collected their information at the micro-level of individual academics. The first, large-scale exploratory study covers a wide range of European universities (Subsection 4.1); the follow-up is an explanatory small-scale, in-depth study of crossover researchers at Leiden University in the Netherlands (Subsection 4.2). Pairwise the studies should be able to produce the same general patterns that are consistent and understandable, taking into account differences among the studies in terms of scale and scope.

Table 3
Distribution of researchers across PC types: European survey.[a]

Both researcher and ...	Researcher count and share of total[b]
... Entrepreneur (R + E)	215 (39%)
... Crossover Collaborator (R + CC)	108 (20%)
... Inventor (R + I)	107 (19%)
... Entrepreneur and Inventor (R + E+I)	79 (14%)
... Entrepreneur and Crossover Collaborator (R + E + CC)	24 (4%)
... Inventor and Crossover Collaborator (R + I+CC)	21 (4%)
... Inventor, Entrepreneur and Crossover Collaborator (R + I+E + CC)	21 (4%)
Researcher Only (R)	172 (30%)

[a] Includes multiple counts of researchers assigned to more than one (sub) type. The subtypes R + I+CC and R + I+E + CC contain an identical set of researchers.
[b] Total sample of 553 researchers.

Table 4
Research performance profile of PC types: European survey.[a]

Both researcher and ...	Publication output frequency count	Scientific impact citations (MNCS)	Technological impact citations per publication
... Crossover Collaborator (R + CC)	15	1.44	0.006
... Inventor (R + I)	12	1.05	0.002
... Entrepreneur (R + E)	11	1.14	0.004
... Inventor + Crossover Collaborator (R + I+CC)	12	1.16	0.005
... Crossover Collaborator + Entrepreneur (R + E + CC)	12	1.87	0.006
... Inventor + Entrepreneur (R + I +E)	12	0.95	0.012
Researcher Only (R)	9	1.29	0.004

[a] Average scores calculated across all researchers per (sub)category. Subtype R + I+E + CC is omitted because the set of researchers is identical to R + I +CC.

4. Empirical results

4.1. International comparative study of European universities

The data in this a medium-sized sample of European academics was gathered from an online survey on research commercialization, which was conducted in 2015/2016 among thousands of researchers.[18] The sample of respondents comprised 2665 individuals at 148 research-active universities across 30 European countries. A subset of 1547 cases contained sufficient information to establish the identity of each respondent.

A full set of research performance data was gathered for a subsample of 867 researchers, 553 of which produced at least three peer-reviewed research publications during the years 2010–2015. Only ‘research-intensive’ academics were selected for the PC analysis.[19] Table 2

[17] Because of ambiguous definitions and insufficient empirical data to conclusive classifications, any PC-based typology of researchers should be interpreted in terms of data-dependent and context-specific probabilistic attributions rather than a single deterministic classification. For example, in the case of CC type researcher moving towards Inventor type status, the range of technology-related outputs could not only include patents but also invention disclosures, internal technical reports, architectural designs, software development, or prototypes of devices.

[18] The prime objective of the ‘Athena/CWTS Research Commercialization Survey’ was to query individual researchers on their experience with research commercialisation, with an emphasis on their views of university technology transfer offices. The online questionnaire was distributed among research-active staff at universities in the 28 EU member states plus Norway and Switzerland. To select researchers for this survey, individuals were identified by their research papers in international peer-reviewed journals, where they are mentioned in the author list with a university address. Some 60,000 email addresses of European scientists were randomly selected. The response rate was 8.9%. See Van Dongen et al. (2017) for more detailed information on the survey and sample characteristics.

[19] Applying this threshold value discards the researchers with low levels of research activity and creates a more homogeneous sample of comparable individuals for robust

Table 5
Background profile of PC types: European survey.[a]

	Academic rank % full professors	Field % in medical, health & life sciences	Field % in natural, engineering & computer sci.	Cooperation % with co-authored publications: all	Cooperation % with co-authored publications: international
R + CC	37	30	61	77	50
R + I	43	29	70	70	44
R + E	40	32	60	66	41
R + I+CC	62	24	76	72	49
R + E + CC	42	32	53	60	35
R + I+E	38	31	66	69	42
R	23	38	55	67	47

[a] Average scores calculated across all researchers per category.

presents the most frequently occurring countries and universities in this subsample of academics, where we find a large variety of European countries and therefore a reasonable good overview of European academics.

Having access to the author affiliate addresses of researchers, as far as their publications are indexed in the *Web of Science Core Collection* database[20], opens up the possibility to take a closer look at researchers who publish both with their university address and another address referring to a business enterprise, i.e. *university-business co-authored publications* (UBCPs). The definitions of the three 'Pasteur researcher' subtypes are:

- *Crossover Collaborator* (CC type): those with at least 10% UBCPs in their scientific publication output.[21]
- *Inventors* (I type): at least 1 patent (granted or applied) to their name;
- *Entrepreneurs* (E type): researchers who answered affirmative to the survey question "*Have you been personally involved in commercialization of research results between 2010-2015?*".

The four main categories of the classification system, and four composite categories, are presented in Table 3. Ultimately, 172 researchers were classified as 'R type', being neither a CC, I or E type academic. For the sake of comparison with the PQ model, 'R type' researchers are comparable to the 'Bohr type' in Fig. 1, and those who are either CC, I or E type are considered to be varieties of 'Pasteur type' researchers.

The R + E type group is the largest within this sample, which is indicative for the response bias in our sample tilted towards those engaged in research commercialization and academic entrepreneurship. More than 30% of these 'entrepreneurial researchers' are also Inventor (R + E + I), but less than 10% are also Crossover Collaborator (R + E + CC). Some 30% are conventional 'R type' researchers. The CC type researchers represent some 20% of the sample, with relatively small subgroups that are also either I type or E type.

To address the hypotheses, and main research question which of these PC types are likely to be responsible for the above-average scientific performance of Pasteur researchers (see Box 1), a performance profile was created consisting of the following metrics each related to the time-period 2010–2015:

- *Scientific research publication output*: number of research publications in peer-reviewed scholarly and technical journals (full counts);
- *Scientific impact*: Mean normalized citation score (MNCS) of research publications, i.e. citations from other research publications[22];
- *Technological impact*: number of research publications cited in PATSTAT-indexed patent families, relative to the total publication output.

The bibliometric data underlying these three metrics was derived from CWTS in-house version of *Web of Science Core Collection* and the CWTS customized version of the *PATSTAT* database.

Table 4 displays the research performance profile of all types that consisted of more than 20 researchers. As for publication output performance, the 'Researcher Only' R type group is outperformed by all the other types of researchers – especially by the CC types, which confirms earlier studies (see Box 1) where Pasteur type researchers that show relatively high research performance levels. These CC type researchers are also more highly cited than R types, especially the CC type researcher who also happens to be engaged in research commercialization and entrepreneurship (R + CC + E), hinting at the existence of the 'star scientist' researchers in Europe. Judging by the much lower scientific impact of R + E types collaboration and connectivity are a major contributing force. R + E + I type researchers are by far the most highly cited in patents, but are much less cited in the scientific literature.

Overall, the patterns in Table 4 paint a more complex picture of Pasteur type researchers in terms of output and impact. Searching for explanations of the observed differences in performance, Table 5 presents background characteristics of each (composite) category.[23] 'Academic rank', expressed in terms of their self-reported academic status, relates to full professorships (i.e. seniority and professional experience). The information regarding their broad field of science were also extracted from the respondent's self-classification into one of six main fields of science[24]. The data on two indicators regarding research cooperation were collected from jointly authored research publications; both indicators reflect competencies and experiences reflecting team-based research and cross-institutional collaboration. The two variables in the performance profile distinguish between the total number of co-authored research publications ('all' category) and the subset of co-publications with at least one co-author from another country ('international' category).

All other categories contain a much larger share of full professors

(*footnote continued*)
comparisons across the various European countries and universities.

[20] The research publications were extracted from a customized version of the *Web of Science Core Collection* database (available at CWTS, Leiden University), more specifically the *Science Citation Index Expanded*, *Social Sciences Citation Index* and *Arts & Humanities Citation Index*.

[21] The lower threshold value of university-business co-authored publications (UBCPs) is introduced to reduce the risk of incorporating researchers with just a single UBCP, or very low numbers, thereby excluding those who are less likely to be engaged in substantive or longer-term interactions with industry. Setting the threshold at 10% was a somewhat arbitrary.

[22] The Mean Normalised Citation Score (MNCS) corrects for field-specific differences in citation quantities, this enabling comparisons across fields of science. A value equal to one indicates a citation impact level equal to world average in that field; a score of two is twice world average.

[23] These particular characteristics were mainly selected because of data availability.

[24] The pre-specified options in the questionnaire were the following: Earth sciences, Engineering sciences, Mathematics and computer sciences, Medical, health and life sciences, Natural sciences, Social sciences and humanities.

compared to the ‘conventional’ R type category. The R + CC + I type exhibit the most distinct profile: the majority are full professor and these senior researchers tend to concentrate in natural sciences, engineering sciences and computer sciences. The larger share of senior researchers in all ‘Pasteur type’ categories, as compared to the ‘R type’ category, is not surprising. Benefitting from their academic seniority and professional experience, they tend to be less risk adverse, have developed more commercialisation opportunities and networks in business and industry which allows them to engage in entrepreneurial activities with or without using the services of the local TTO (Link et al., 2007; Fini et al., 2010), and are therefore often in a better position to engage in activities such as spinouts and business consultancy (Klofsten and Jones-Evans, 2000; Shane, 2004).

In addition to the abovementioned response bias, in favour of E type researchers, this survey sample also comprises a wide range of European countries and research universities. Such pan-European aggregate-level data conceals heterogeneity among individual countries or universities – for example with regards to national IPR regimes (Van Dongen et al., 2017) that may significantly affect the PC profiles of I type and E type researchers. In view of the diversity among individual European research-intensive universities, it is unclear if and how the general patterns that emerge from this European survey constitute a meaningful empirical basis for further analyses at the institutional levels. However, one may assume that the PC profile of research staff a single university, with its common institutional environment and embedded in nation-specific framework factors, will be more homogeneous that a profile composed of numerous universities in several countries. One would one expect to find more similarly between the PC categories – both in terms of research performance and background variables. In other words, the European survey data constitute a crude comparative framework to assess a university’s degree of ‘PC homogeneity’, and to examine possible organisational determinants. The next subsection describes such an application, for the case of Leiden University – the no. 1 most frequently occurring university in Table 2.

4.2. Case study of Leiden University

Leiden University (LU) is one of large comprehensive universities in the Netherlands. The university system includes a large medical faculty and teaching hospital (Leiden University Medical Center - LUMC). Although the university’s disciplinary profile lacks traditional fields of engineering and technology, it’s research portfolio does include molecular engineering and computer sciences. LU employed almost 2000 research-active staff in late 2015, including some 230 professors. The majority of these academics spend only a limited time on research. LUMC employs about 160 professors. The number of (part time) research-active LUMC staff is estimated at 500 individuals. One may assume that in 2015/2016 LU and LUMC employed a total of 2500 engaged in scientific research, at various levels of activity and intensity. The university is closely connected to Leiden Bio Science Park, one of the largest of its kind in Europe. LURIS, the university’s TTO and knowledge exchange office, is the designated centralized unit for all legal and technical matters regarding research commercialization and technology transfer, and academic entrepreneurship. The LURIS website presents a range of resources and facilities to foster and support university-business cooperation, intellectual property arrangements and academic business development[25].

The coverage of research active staff is restricted to LU or LUMC staff members who were employed on either August 1st 2016 or September 1st of 2016. Background information on the research staff were collected between August 2016 and March 2017. The names of researchers, and associated background information originates from three sources:

[25] http://luris.nl/academics

Table 6
Distribution of researchers across PC types: Leiden University.[a]

Both researcher and …	Researcher count and share of total[b]
… Crossover Collaborator (R + CC)	103 (26%)
… Inventor + Crossover Collaborator (R + I+CC)	29 (7%)
… Inventor + Entrepreneur + Crossover Collaborator (R + I +E + CC)	29 (7%)
… Entrepreneur + Crossover Collaborator (R + E + CC)	10 (3%)
Researcher Only (R)	235 (60%)

[a] Includes multiple counts of researchers assigned to more than one (sub) type. The subtypes R + I+CC and R + I+E + CC contain an identical set of researchers.
[b] Total sample of 393 researchers.

Table 7
Research performance profile of PC types: Leiden University.[a]

Both researcher and …	Publication output frequency count	Scientific impact citations (MNCS)	Technological impact citations per publication
… Inventor + Crossover Collaborator (R + I+CC)	51	1.47	0.19
… Entrepreneur + Crossover Collaborator (R + E + CC)	45	1.27	0.17
… Crossover Collaborator (R + CC)	35	1.49	0.10
Researcher Only (R)	16	1.42	0.02

[a] Average scores calculated across all researchers per category. The type R + I+E + CC is omitted, this set identical to R + I+CC type researchers.

- University’s internal employment database, which captures their employment status per August 1st 2016;
- CVs of researchers on the websites of LU and LUMC, which were accessed during those three months (the LUMC website provides this information only for full professors);
- LURIS database with the names of staff members who applied for university-owned patents or other IP-related arrangements in 2013–2015.

While cross-referencing names of publishing researcher and those mentioned in the LURIS database, we encountered a few names that were missing in the university’s in-house employment records. Essential formation that was lacking on the LU or LUMC sources was collected, as far as possible, from *LinkedIn* or by *Google* searches on the internet. The research publication data were derived from CWTS version of *Web of Science Core Collection* database and the publication years 2009–2015.[26] The study was confined to those who produced four research publications during that time-period.[27] Each individual’s scientific publication output was identified by applying an in-house developed search algorithm (Caron and Van Eck, 2014), based on disambiguated author names, to identify individual researchers and their publication output. The total sample comprises 393 research-intensive academics (some 15% of the total estimated 2500 research-active staff). The definitions of the three ‘Pasteur researcher’ subtypes differs from those applied in the Europe-wide study:

- *Crossover Collaborator* (CC type): at least two university-business co-authored publications during the years 2009-2015.
- *Inventor* (I type): at least 1 patent in 2013–2015 (either as inventor

[26] Data source: CWTS *Web of Science Core Collection* database (all document types).
[27] The lower publication output threshold value was set at 4, rather than 3 as in the European survey, to shift the sample composition and analytical focus towards the more prolific researchers.

Table 8
Background profile of PC types: Leiden University.[a]

	Academic rank % full professors	Field % in medical & health sciences	Field % in natural, engineering & computer sci.	Cooperation % with co-authored publications: all	Cooperation % with co-authored publications: international
R + I+CC	28	66	24	51	30
R + E + CC	20	80	10	68	41
R + CC	21	67	16	54	30
R	51	27	38	44	23

[a] Average scores calculated across all researchers per category.

and/or applicant) registered in the LURIS database.

- *Entrepreneur* (E type): subset of Crossover Collaborators or Inventors who also mention business sector activities and/or affiliations in their CVs.[28]

The study of the Leiden sample focuses on two key outcomes of the European survey findings: (a) the high performance levels of CC type researchers; (b) prominent role of professors. Addressing the research hypotheses in Section 3.4, the data analysis concerns comparisons between the R type category and the three CC subcategories. Table 6 lists the number of researchers per PC category; their research performance profiles are presented in Table 7. The numbers of researchers per category are relatively small in some cases and results need to interpreted with due caution. The R + CC group comprises 26% of the sample, slightly more than the 20% in the European survey. The majority of these researchers were employed at LUMC and thus assigned to the field of medical and health sciences. The CC group as whole is much more productive than those in the R type category, which aligns with the European survey results (Table 4). Interestingly, two CC subgroups (R + I + CC and R + E + CC) show a significantly higher publication output than R + CC, which suggests positive relationships between I and E-type activities and research performance.

Not surprisingly, the technological impact of the CC researchers is also significantly larger than their science-oriented R type colleagues. As for scientific impact, the R + CC and R + I + CC researchers show the same high impact scores as R types.[29] However, in contrast to the European survey findings, the R + E + CC type researchers produce less impact (which may also relate to the fact that E type researchers are defined differently in the Leiden case study).

Table 8 clearly illustrates this study's emphasis on research-intensive, high-output researchers, the R type category consisting of a relatively large fraction of full professors. The strong representation of LUMC senior researchers in this study is manifest in the CC type categories, where the medical and health sciences represent a majority share. As expected, and in sync with the findings of the European survey, the R + CC researchers are more involved in research collaboration than R types – both with international research partners and overall.

5. Discussion

Given the current high priority among many national and regional policy makers to create sustainable, effective links between university science and technological innovation, policy analysts requires a better understanding of key processes within universities. Identifying and categorizing the researchers involved in such processes is crucial for evidence-informed research management and science funding initiatives. This paper introduced a Pasteur's Cube (PC) model, and its typology and taxonomy of individual researchers employed at research-intensive universities, to address this information gap. The PC model was specifically designed to resolve analytical shortcomings of Pasteur's Quadrant (PQ) model, notably its ambiguous definition and the heterogeneous composition of use-inspired 'Pasteur type' researchers who are able to bridge or reconcile longer-term research agenda's and application-oriented work with expected economic impacts. Any analytical framework of empirical classification system that can help identify and monitor this particular category of researchers may prove beneficial for STI policy discussion and analysis – both at the national or regional 'macro' level, where there is the need for policy frameworks and measures that balance and connect investments for short-term 'application-oriented research' with those geared towards longer-term 'discovery-oriented research', but also at organisational levels, where one for example needs a critical mass of Pasteur type researchers within 'entrepreneurial universities' to create sustainable and effective university-business interfaces.

The two case studies described in this paper, both targeted at highly active researchers at European universities, tested the technical feasibility and analytical power of a PC based taxonomy of researchers. Bringing together different types of researchers under the PC model, enables a more systematic analysis of their engagement profiles and their relationship with R&D performance. These studies focussed on the performance of the 'Crossover Collaborator' researchers, a subclass of those Pasteur type researchers. Their research performance profiles are found to be fairly consistent in the two case studies: CC type researchers produce more research publications and tend to have a much larger impact on scientific and technological progress that more conventional academics mainly engaged in 'basic research'. The research cooperation activities and associated collaborative networks of CC researchers is an important contributing factor why Pasteur type researchers are more likely to be high-performance 'star scientists'.

It is not clear whether CC types who are also inventor or academic entrepreneur, are more prolific researchers than their counterparts without the benefit of such Pasteur type activities. Although the Leiden University study shows relative high impact scores for CC researchers who are also inventors - both with regards to their scientific impact and technology impact, this pattern does not occur in the survey data across European universities. The results of the Leiden study also suggests that, as expected, single-university PC profiles are likely to be more homogeneous than aggregate-level profiles across a diversity of universities; the performance data and background data of CC researchers in Leiden shows a much larger degree of similarity than the aggregate profile of surveyed European universities. Further case studies, at other universities, should examine how national framework conditions and/or organisational determinants affect the specificity of a university's PC profile.

Although the two studies describe in this article refrained for examining causal relationships between explanatory variables (notably,

[28] We assume these individuals have business sector experience, either currently or previously (mostly as consultant or advisor, or as an executive, board member or owner of a firm).

[29] This finding is consistent with Calderini et al. (2007) who studied the propensity academic researchers to produce patents among Italian researchers in materials science. They observed a curvilinear relationship between research performance levels and the likelihood to patent, noting that "patents are more likely to come from medium-to-high impact research. Yet, scientists engaged in very high impact research seem to be less likely to patent, especially if they are also very productive".

the role of research collaboration with industry) and the propensity to engage in commercialization activities, the results strongly suggest that CC type researchers are indeed the ones most likely to possess or develop the right profile of transformative skills and competences (in terms of sizeable volumes of intellectual, human and social capital) to operate as academic inventors and/or entrepreneurs. Cumulative advantage processes work in their favour: intellectually successful use-inspired researchers are likely to profit from attracting more resources as well as seizing commercialisation opportunities, which enables them to boost their human capital, social capital and entrepreneurial acumen.

The PC model, and derivative classification systems of individual researchers, can inform a larger-scale systems for measuring academic entrepreneurship, commercialization and user engagement. Building such an empirical reference base one faces the inevitable challenge of dealing with data scarcity and trying to fill information gaps. One has to rely on a variety of information sources (survey data or university administration databases) and grapple with idiosyncrasies in terms of descriptions and definitions of underlying key concepts such as 'research commercialization', 'entrepreneurship' and 'user engagement'. The case study by Perkmann et al. (2013), of a single research-intensive university in the UK, has aptly demonstrated that data-gathering from university-held archival records is insufficient to produce reliable PC profiles of individual researchers. This is a time consuming and resource intensive exercise, exacerbated by the fact that for each type of 'end user engagement' activity, separate external data sources need to be developed or accessed – either through surveys among researchers or data collection via online sources and public registers of companies.

There is clearly a need to move away from stereotyping 'university inventors' and 'entrepreneurial academics', crude labels which should be replaced by a more divers and fine-grained classification system that captures the wide variety of use-inspired researchers that populate today's universities. Although the research performance profiles in both case studies, especially with regards to CC researchers, indicate a measure of convergent validity, it is not clear whether the PC taxonomy in these study is sufficiently applicable and robust to provide guidance for large-scale 'global' classification systems. The applied taxonomy resolves some ambiguities of the PQ typology, especially the heterogeneity of researchers (self-)assigned to the Pasteur Quadrant, but it does not necessarily produce a high-quality classification system marked by a broader set of more homogeneous groupings of comparable researchers.

At this stage of development, the PC model may already find some use as a heuristic tool in micro-level empirical studies of knowledge creation and utilization processes within scientific research environments. However, several methodological issues and challenges remain to evolve this toolkit for wider use. For example, how to include information on impact of a researcher's discovery-oriented research on subsequent application-oriented research. Such data on such 'next-stage' impact between basic and applied research would enable a more accurate view of knowledge spill-overs and R&D trajectories. Another major issue concerns the PC model's 'user engagement' dimension, where the current taxonomy lacks a subcategory for those heavily engaged with public sector users. Similarly, the current research performance profile lacks information and indicators on knowledge transfer and impacts in civic society. Here one would expect to find more contributions from researchers in the social sciences and humanities fields who contribute to public sector innovation and generate societal benefits.

Moving towards human resources analytics and policy-relevant applications, the validity and generalizability of the PC model as a framework to develop or refine micro-level classification systems should be further assessed, in a series of standardized case studies, especially the sensitivity to country-dependent or university-specific parameters. Although the PC model and its taxonomy of individuals is geared towards university-based 'academic' researchers, the methodology may have wider use among research-active organisations outside the higher education sector - especially among government research institutes that support industrial R&D.

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