Engineering Impact

Analyzing the Scientific and Technological Outcomes of Collaborative Research between Universities and Firms

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Checkmate!

ABSTRACT

This Ph.D. dissertation analyzes collaborative research between universities and firms in the field of electrical engineering in Sweden. It conceptualizes such collaborations as one form of academic engagement that fosters knowledge networks among individuals and organizations. It is essential to expand our understanding of this phenomenon as it holds significant implications for technological advances and economic progress.

The purpose is to analyze the impacts of collaborative research between universities and firms, as compared with the impacts of similar research conducted without firms. In doing so, this dissertation examines and selects among measures of impact, including both scientific and technological impacts, as well as variables that capture relevant dimensions of collaborative research.

By developing and utilizing a dataset based on employment records of faculty members from five leading Swedish (engineering) universities, this dissertation analyzes scholarly publications in the domains of biomedical, communication, control, and signal processing engineering. The analysis encompasses 8455 scholarly publications authored by 184 professors affiliated with Chalmers University of Technology, the Faculty of Engineering at Lund University, KTH Royal Institute of Technology, Linköping University, and Uppsala University.

The research reveals that 17.3% of the examined publications are defined as outcomes of prior academic engagement, showcasing an upward trend over the period from 2000 to 2018. These collaborative publications are associated with

greater article and technological impacts than those of purely academic research, evidenced by higher citation counts in both scholarly literature and patents. However, they are also associated with a lower journal reputation, suggesting that these articles are less frequently published in high-impact journals.

Notably, dual-affiliated professors, constituting one type of boundary spanner between academia and industry, as well as a greater number of authors are associated with higher article impact. Moreover, publications with firms led by academics — i.e., those with a university-affiliated first author—are associated with high article and technological impacts, whereas those led by industry partners show a pronounced technological impact compared with purely academic projects. The influence these variables have on the journal reputation was found to be less pronounced.

This dissertation contributes to the literature on academic engagement, particularly in the engineering sciences, underscoring the benefits of integrating diverse knowledge from academia and industry for more impactful scientific and technological outputs. Additionally, the findings add to the discussion on academic success metrics, emphasizing the need for a balanced approach in which the real-world application of research is recognized alongside academic prestige, while being cautious of the pitfalls associated with overreliance on journal reputation alone.

These findings offer valuable insights for academic institutions, firms, and policymakers, specifically emphasizing the importance of fostering effective collaborations between individuals to combine academic and industrial expertise in engineering research. Future research directions include a deeper examination of the roles of industrial co-authors, dual-affiliated researchers, and lead authors in these collaborations, as well as broadening the scope beyond electrical engineering in Sweden to enhance the generalizability of the results.

Keywords: university-industry collaboration, academic engagement, collaborative research, knowledge networks, team size, boundary spanner, lead author, scientific impact, technological impact, bibliometrics, engineering.

SAMMANFATTNING PÅ SVENSKA

Den här doktorsavhandlingen har analyserat resultat av forskningssamverkan mellan universitet och företag, jämfört med liknande forskning på universitet som genomförs utan företags deltagande. Konceptuellt främjar dessa samarbeten kunskapsnätverk mellan individer och organisationer. Det är viktigt att utöka vår förståelse för detta fenomen då det har betydande påverkan för tekniska framsteg och därmed ekonomisk tillväxt.

I detta avseende undersöker och väljer avhandlingen bland mätningar av vetenskapliga och teknologiska resultat, samt variabler som fångar relevanta dimensioner av forskningssamverkan. Genom att utveckla ett dataset som analyserar den här avhandling 8455 vetenskapliga publikationer författade av 184 professorer vid Chalmers Tekniska Högskola, Kungliga Tekniska Högskolan, Lunds Tekniska Högskola, Linköpings Universitet och Uppsala Universitet inom elektroteknik, specifikt inom områdena biomedicin, kommunikation, reglerteknik och signalbehandling.

Forskningsresultatet visar att 17,3 % av de undersökta publikationerna definieras som resultat av tidigare forskningssamverkan mellan universitet och företag. Förekomsten av dessa samarbetspublikationer visade en uppåtgående trend under perioden 2000 till 2018. De är också förknippade med högre citeringssiffror från både vetenskaplig litteratur och patent. Dock antyder resultaten att dessa artiklar publiceras mindre frekvent i högt rankade tidskrifter.

Det är anmärkningsvärt att adjungerade professorer, som utgör en typ av gränsöverskridare mellan akademin och industrin, samt ett större antal författare, är förknippade med högre citeringssiffror från vetenskaplig litteratur. Dessutom är samarbetspublikationer där första författaren är akademiker förknippade med höga citeringssiffror från både vetenskaplig litteratur och teknologiska patent, medan de som har första författare från industrin är förknippade med ännu högre citeringssiffror från patent. Dessa variabler har liten påverkan på att publicera i högt rankade tidskrifter.

Den här avhandlingen bidrar till litteraturen om forskningssamverkan mellan universitet och företag, särskilt inom ingenjörsvetenskaperna, och understryker fördelarna med att integrera olika kunskaper från akademin och industrin för mer betydelsefulla utfall inom vetenskap och teknologi. Dessutom tillför resultaten till diskussionen om akademiska framgångsmått, och betonar behovet av ett balanserat tillvägagångsätt där forskningens verkliga tillämpning erkänns vid sidan av den akademiska, samtidigt som man är försiktig med fallgroparna som är förknippade med enbart fokus på publiceringar i högt rankade tidskrifter.

Dessa resultat erbjuder värdefulla insikter för akademiska institutioner, företag och politiker. Specifikt betonas vikten av att främja effektiva samarbeten mellan individer som kan kombinera akademisk och industriell expertis inom ingenjörsforskning. Framtida forskningsinriktningar inkluderar en djupare granskning av industriella medförfattares bakgrund och roller, adjungerade forskare, och ledande författare i dessa samarbeten, samt att bredda analysen utöver elektroteknik i Sverige för att öka resultatens generaliserbarhet.

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1 INTRODUCTION

Engineering Impact is the title of my Ph.D. dissertation, which analyzes how collaborative research between universities and firms may impact society. This opening chapter provides an overview of this dissertation's purpose, research questions, and key themes. It establishes the groundwork for the subsequent chapters, which explore these aspects in greater detail.

The chapter begins with a concise introduction outlining the overall purpose of the dissertation. Thereafter, it introduces the overarching purpose of the dissertation and state its main contributions. Subsequently, an introduction to the empirical context in which the studies are situated is given. This is followed by a presentation of the empirical studies incorporated in this dissertation. Next, notable activities and papers related to research, but extending beyond the scope of the Ph.D. dissertation, are outlined. Finally, the remaining chapters of the dissertation are described.

1.1 Introduction

In the realm of technological advances and economic progress, the role of university research is pivotal, yet questions linger about the mechanisms by which new technologies emerge from university–industry interactions. Extensive literature acknowledges that technological inventions often draw on university research (Ahmadpoor & Jones, 2017; Jaffe et al., 1993; Mansfield, 1991; Narin et al., 1997) and underscores the broader societal and economic impacts of both universities and new technologies (Mansfield, 1991; Lundvall, 1992; Nelson & Rosenberg, 1993; Rosenberg, 1974). This dissertation delves into these dynamics within the electrical engineering field, placing a particular emphasis on comparing two distinct types of research collaborations: collaborative projects between universities and firms, and collaborative academic–academic projects (i.e., academic projects).

Universities contribute to society in many ways, but specifically in relation to technological development in firms. The importance of universities appears to lie in their roles as repositories of existing scientific knowledge, through teaching, as well as generators of new knowledge, through research. Universities, by being organizations that host diverse scientific knowledge, in turn, can attract certain firms to collaborate, with the aim of using such knowledge for technological inventions. Firms may use these new technologies and inventions to develop innovations that are introduced on the market.

However, many questions remain about how and why new technologies result from the interactions between firms and universities. One aspect is that these interaction processes may have changed over time, one view being that, traditionally, universities did not engage directly in commercial design and development, but rather stimulated and enhanced research and development (R&D) activities in industry (Rosenberg & Nelson, 1994). Today, however, debates about universities and their impact on technology and economic growth suggest that there are many ways in which universities and firms interact.

The significance of university–industry collaborations and their associated challenges have attracted considerable attention in recent years, as evidenced by numerous systematic literature reviews conducted by scholars such as Figueiredo and Ferreira (2022), Perkmann et al. (2013, 2021), and Rybnicek and Königsgruber (2019). Despite the growing interest, this research domain remains nascent, with many avenues yet uncharted. Consequently, many interesting questions remains. This Ph.D. dissertation endeavors to enrich the discourse by delving into a selection of these unexplored topics.

The perceived positive effects of universities on industry have been stressed as a way to develop society, especially by policymakers. The underlying argument in recent decades is that universities could enhance their contribution to the economy by increasing their level of collaboration with industry and by engaging more in entrepreneurship and business-related activities, such as academic patenting, licensing, and the creation of academic start-ups. This has led several OECD member nations to extend the mission of universities beyond education and research to include a third mission that directly emphasizes such activities (Gulbrandsen & Slipersæter, 2007); for example, Sweden implemented this third mission in 1998 (SOU, 1998:128).

Partly as a result of these changes to policy, per se, in addition to other trends such as the changing funding landscape (Vincent-Lancrin, 2006), the role of universities has undergone a transformation to one of more directly impacting firms and the economy. Some researchers argue that universities have shifted from being social institutions primarily focused on developing new areas of knowledge through long-term research and widening the societal knowledge base through teaching and student diffusion. Instead, they have become competing knowledge businesses with a primary objective of producing immediately useful knowledge for students, businesses, and society (Deicaco et al., 2009a, 2009b; McKelvey & Holmén, 2009).

Other scholars have emphasized that the evolution of universities' role initially involved activities directly intended to compete with firms, such as providing solutions to specific problems and capitalizing on those solutions through patenting and licensing. Over time, this role expanded to encompass activities aimed at ensuring that individuals thrive in the (knowledge) economy by providing thinking, leadership, and activity intended to enhance entrepreneurship capital (Audretsch et al., 2014; Audretsch, 2014).

Each of these different views of the transformation of the university as a societal institution captures only part of the picture, so these theories of the evolution of universities' roles are not necessarily mutually exclusive. Yet what matters here is that all these views suggest that an important contemporary phenomenon is the more direct involvement of universities with firms and in influencing society.

Many concepts have been used to differentiate between types of this fairly diverse phenomenon. To delve deeper into collaborative research projects and for the purpose of this Ph.D. dissertation, the taxonomy and conceptualization proposed by Perkmann et al. (2013) is used. These authors differentiate between two main types of university–industry collaboration: academic engagement and academic commercialization.

Academic commercialization is defined as "intellectual property creation and academic entrepreneurship" (Perkmann et al., 2013, p. 423), and can be further subdivided into components such as patenting, licensing, and establishing spin-offs. Here, the impact of the university is specifically related to the market, and to individual university scientists who do these activities and directly contribute to the transfer of university knowledge and technologies to the commercial sphere, fostering innovation and economic growth.

In contrast, their definition of academic engagement captures many other types of impacts on society, as it is defined as "knowledge-related collaboration by university scientists with non-academic organizations" (Perkmann et al., 2013, p. 424). This type of collaboration can take different forms, such as co-publishing articles, serving on advisory boards, delivering public lectures, providing informal advice, and participating in conferences. Although these forms of collaboration do not directly involve commercialization by university scientists, knowledge-based collaborations can still benefit the collaborating firm by developing capabilities that are valuable for future technological innovations, as argued by McKelvey and Ljungberg (2017).

For instance, empirical research in Sweden suggests that firms can develop specific capabilities through different forms of academic engagement, including by hiring Ph.D. students who simultaneously work at the firm while completing their studies as well as by participating in dedicated university–industry centers (Berg & McKelvey, 2020; Hemberg, 2023). This Ph.D. dissertation contributes to the literature on academic engagement by further analyzing collaborative research projects between universities and firms over a long period.

Yet even though we know that such interactions may be beneficial for society, the literature indicates that collaborations between firms and universities can encounter difficulties, or challenges, due to the disparate nature of these organizations. These challenges are especially pronounced in academic engagement, in which individuals from different organizations collaborate. This is in contrast to collaborations within academia or within industry. The root of these difficulties lies in the divergence between the incentives and goals of universities and firms, a phenomenon often described as "competing institutional logics" (Sauermann & Stephan, 2013). Specifically, these two types of organizations differ primarily in their perspectives on knowledge creation and solving business problems (i.e., technological problems) as means to achieve their respective goals.

Universities prioritize knowledge creation as their primary objective, viewing solving business problems as a means to reach that goal. In contrast, firms prioritize capitalizing on solving business problems (i.e., advancing technology) as their primary objective, considering knowledge as a means to accomplish that goal (cf. Friedman, 1962; Merton, 1973; Nightingale, 1998). These competing institutional logics also influence the activities of collaborators from the two types of organizations. A case in point is that university researchers tend to patent fewer inventions than do researchers employed by firms, while firm-employed researchers publish fewer journal articles than do university scientists (Sauermann & Stephan, 2013).

Therefore, at least initially based on this literature, this Ph.D. dissertation posits two fundamental assumptions. First, universities and firms, when collaborating, prioritize divergent outcomes: universities emphasize scientific impacts, while firms focus on technological advances. Second, collaborations between universities and firms typically exhibit a richer diversity of knowledge bases than do purely academic projects. In such collaborations, firms contribute profound application knowledge crucial for practical problem-solving, whereas academic participants offer more theoretical and extensive exploration within the realm of engineering science. Consequently, this dissertation seeks to investigate how these different collaborative models affect the research conducted and its subsequent impact, whether scientific or technological.

1.2 Purpose and main contributions

The purpose of this Ph.D. dissertation is to analyze the impacts of collaborative research between universities and firms. By comparing such collaborative research to similar research conducted without firms, this dissertation examines and selects among measurements of scientific and technological impacts, as well as variables that capture relevant dimensions of collaborative research.

This dissertation conceptualizes these collaborative projects as one form of academic engagement because such collaborative research likely builds knowledge networks between individuals and organizations. The empirical studies (see Section 1.3) use data on electrical engineering in Sweden and deliberately center on a single outcome of collaborative research projects: co-authored research publications, primarily comprising journal articles and conference proceedings. The underlying conceptual assumption is that co-authored research publications with at least one author from a university and one author from a firm reflect one form of knowledge-based collaboration, namely, active involvement in previous collaborative research projects between the partners.

The principal aim of this undertaking is to contribute to the academic engagement literature. This stream of literature examines the antecedents, processes, and consequences of knowledge-related collaborations between universities and firms, with a particular focus on academics as individuals (Perkmann et al., 2013, 2021). Notwithstanding the extensive body of literature on academic engagement, there are still several research avenues that remain relatively unexplored or characterized by inconclusive findings.

One such area, as previously highlighted, concerns understanding the specific outcomes, or impacts, of academic engagement (Perkmann et al., 2013, 2021). Two additional pivotal areas pertain to the function of boundary spanners, as well as the role of the lead author, in the context of academic engagement. While boundary spanners are individuals who serve as intermediaries and translators of diverse information and knowledge (Leifer & Delbecq, 1978; Tushman, 1977; Tushman & Scanlan, 1981[1]), the lead author is simply the researcher contributing the most to the project within the team.

Concerning boundary spanners, prior studies indicate that they play a distinct role in facilitating the interaction and transfer of knowledge between academic institutions and corporate entities (Fagrell et al., 2016; Gertner et al., 2011). Regarding lead authors, generally analyzed via examining the effect the first author has on the outcome, they play an important role in influencing the outcome, not least when it comes to publishing in journals with higher reputations (Thelwall et al., 2023). However, there is a need for a more comprehensive understanding of the functions and impacts of these positions in the context of academic engagement.

[1] See also Haas (2015) for a review.

By pinpointing the particular factors that facilitate or impede the desired outcomes—while also examining the role and influence of boundary spanners and lead authors—we can gain a more profound understanding of the optimization of processes and practices related to collaborative research projects between universities and firms, ultimately fostering the establishment of impactful collaborations.

This dissertation enriches our understanding and analysis of collaborative research projects between universities and firms by incorporating insights from two interrelated fields: knowledge networks (Phelps et al., 2012) and research collaboration (Bozeman et al., 2013). By integrating these literature streams with the academic engagement literature, the approach to the research topic becomes multifaceted. This integration exploits the strengths of each literature stream, facilitating a comprehensive understanding of the phenomena under investigation, robust analyses, and a thorough explanation of the results.

First, knowledge networks play a pivotal role in facilitating knowledge creation, transfer, and learning through collaborative interactions. As the process of knowledge creation increasingly takes place through collaborations (Ductor, 2015; Gazni & Didegah, 2011; Guimerá et al., 2005; Hudson, 1996; Laband & Tollison, 2000; Wuchty et al., 2007a), it has become crucial to comprehend the dynamics of knowledge networks. A knowledge network can be defined as "a set of nodes—individuals or higher-level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge—interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge" (Phelps et al., 2012, p. 1117).

In a knowledge network, nodes[2] (e.g., individuals) engage in collaborations to acquire, share, and create knowledge. These collaborations, represented by edges[3] in the network, contribute to the accumulation of human capital at individual nodes. In essence, a knowledge network can be seen as a concept that captures the pattern of knowledge-related interactions between different components of a system. These patterns of interactions can significantly affect the behavior of the individual components and of the overall system (Newman, 2018). Understanding the behavior of knowledge networks is thus crucial for comprehending knowledge creation, transfer, learning, and adoption, which are fundamental to economic growth (Lucas, 1988; Menger, 1871; Romer, 1990).

Within the context of this Ph.D. dissertation, incorporating the concept of knowledge networks provides a framework for explaining the phenomenon of interest. Specifically, the knowledge network literature offers a relevant perspective by considering co-authored publications to be manifestations of knowledge networks, which likely arise from previous collaborative research projects between firms and academic researchers within engineering sciences. In this conceptualization, authors from both the academic and industrial sectors act as nodes, and co-publications serve as connections (i.e., edges) between them. This approach aligns with the well-established tradition in social network research in which co-authorship has been extensively utilized to analyze patterns of scientific collaboration (e.g., Barabási et al., 2002; Newman, 2004).

Adopting this perspective enables the utilization of knowledge-network–related concepts and tools, such as egocentric (network) measures, to examine the

[2] Other commonly used terms are, for example, “actor” and “vertex” (Knoke & Yang, 2008; Newman, 2018).

[3] Other commonly used terms are, for example, “link” and “tie” (Knoke & Yang, 2008; Newman, 2018).

phenomenon of academic engagement. By examining the structural properties of these networks, such as the overall network structure and position as well as the role of actors within the network, valuable insights can be gained into the flow of information and knowledge, facilitating a deeper understanding of the outcomes (Phelps et al., 2012).

To clarify, these insights mainly relate to advancing our understanding of the phenomena under investigation, rather than having a key role in the regression models. They nevertheless play an important role in this dissertation by fostering an understanding that linkages among individuals in different organizations appear to be key mechanisms for academic engagement to occur.

Second, the research collaboration literature provides a comprehensive examination of collaborative research processes, particularly valuable in relation to areas where literature on the academic engagement field is scarce, ambiguous, or absent, thus offering empirical insights into these processes (Bozeman et al., 2013). Within this research stream, the focus lies on team dynamics concerning knowledge creation. While emphasizing team size, as well as the aforementioned role of boundary spanners and lead authors, this undertaking extends to other pertinent factors (e.g., geographical proximity). Enhancing comprehension of the impact of team size on outcomes proves crucial due to the growing prevalence of larger teams and their potential for improving outcomes.

One reason why teams are superior to working solo in terms of knowledge creation is that all collaborators, in this case, researchers, bring unique human capital derived from their prior experiences, including their education and work backgrounds. By pooling individuals' human capital and facilitating the exchange of information and ideas, knowledge outcomes are enhanced (Becker & Murphy, 1992; Bozeman et al., 2013; Katz & Martin, 1997; Phelps et al., 2012; Powell & Grodal, 2006). However, these benefits must outweigh the potential drawbacks associated with larger teams, such as increased difficulty in management and coordination (Becker & Murphy, 1992; West & Anderson, 1996) and a higher risk of "groupthink" (Janis, 1982; Whyte, 1998).

While several studies have explored how team size influences impact (e.g., Anderson & Richards-Shubik, 2019; Gazni & Didegah, 2011; Kuld & O'Hagan, 2018; Larivière et al., 2015; Wu et al., 2019; Wuchty et al., 2007a), this Ph.D. dissertation is intended to provide a more in-depth understanding by examining this phenomenon within the context of collaborative research projects between firms and academic researchers in the field of electrical engineering.

To conclude, deepening our understanding of the phenomenon under investigation can provide valuable insights that benefit not only researchers but also practitioners and policymakers. These findings can serve as a foundation for future research, allowing scholars to build upon them. Additionally, practitioners can apply the research findings to create more impactful and reputable collaborative research projects. Policymakers, too, can leverage this knowledge to formulate policies that support and promote such endeavors. It is important to recognize that the implications of this improved understanding extend beyond the academic realm. It has the potential to stimulate economic growth and enhance industrial competitiveness, making it a valuable resource for various stakeholders in academia, industry, and government.

1.3 Empirical studies and research questions

The dissertation comprises three empirical studies, all situated in the context of university research in the field of electrical engineering in Sweden. Collectively, these aim to achieve this Ph.D. dissertation's purpose. Each of the three studies pertains to a distinct aspect of the overall purpose, leading to the following three research questions:

RQ1

How does the scientific impact of publications resulting from academic engagement projects differ from that of publications resulting from academic projects?

In Chapter 5, the first research question is addressed through a comprehensive analysis and comparison analyzing the scientific impact of publications resulting from academic engagement as opposed to those resulting solely from academic projects. This chapter pays particular attention to the influence of the number of co-authors and the presence of dual-affiliated professors, i.e., professors simultaneously employed by both a firm and a university, representing one type of boundary spanner.

In this context, “scientific impact” refers specifically to two quantifiable measures: article impact and journal reputation. Article impact concerns the number of forward citations received by the publication from other scientific papers. It serves as an indicator of the extent to which the scientific community perceives the publication as valuable (Merton, 1973; Moed, 2005). On the other hand, journal reputation emphasizes scientific rigor and quality, and is determined by the impact factor of the journal in which the work was published (Garfield, 2006; McKiernan et al., 2019). While there is some overlap between these constructs, they can be distinguished by considering the emphasis placed on perceived value in the case of article impact and on scientific rigor and quality in the case of journal reputation. These two constructs are commonly utilized for quantitatively approximating the scientific impact of research and have been extensively employed in various papers, including those by Abramo et al. (2009), Bekkers and Freitas (2008), Frenken et al. (2010), McKelvey and Rake (2020), and Salimi et al. (2015).

This chapter adopts a quantitative approach, focusing on the scientific outcomes resulting from collaborative research, specifically the resulting publications. These publications serve as a reliable, albeit partial, measure of successful and substantial scientific knowledge creation (Perkmann et al., 2011; Tijssen, 2009).

RQ2

How does the technological impact of publications resulting from academic engagement projects differ from the impact of those resulting from academic projects?

In Chapter 6, the second research question is addressed, with the focus shifting from analyzing scientific impact to analyzing the technological impact of the aforementioned publications. Similar to the assessment of article impact, technological impact primarily concerns the quantification of citations received. However, in this context, the focus changes from citations within the scientific domain to citations coming from the technological domain, that is, from other patents. The approach of using patent citations as a proxy for technological impact is widely employed (e.g., Fleming & Sorenson, 2001, 2004; Petruzzelli & Murgia, 2020; Verhoeven et al., 2016).

This chapter also aims to analyze the prevalence of the two possible pathways through which science can contribute to technological impacts for the involved parties. These two pathways represent distinct mechanisms for the development, application, and utilization of scientific knowledge in technologies: an individual approach and an organizational approach. The first pathway, individual technological impact, focuses on author–inventor pairs and emphasizes the personal aspect of knowledge (Nonaka, 1994; Polanyi, 1958). It recognizes that knowledge developed in one setting (e.g., collaborative research) or project can be applied to another (e.g., technological development). The second pathway, organizational technological impact, centers on affiliation–assignee pairs. It highlights the transfer of knowledge within organizational boundaries, demonstrating that knowledge transfer within specific organizations differs from knowledge transfer, or more accurately, knowledge spillover, across organizational boundaries (Kogut & Zander, 1992; Nahapiet & Ghoshal, 1998).[4]

In addition to these two pathways, it is worth noting that a third pathway exists, although it is not the primary focus of the study. This pathway is known as knowledge spillover, which emphasizes the knowledge that "spills over" to external actors. It refers to the phenomenon "by which one or a few agents investing in research or technology development will end up facilitating other agents' innovation efforts (either unintentionally, as it happens when innovation is imitated, or intentionally, as it may happen when scientists divulge the result of their research" (Breschi & Lissoni, 2001, p. 975). Knowledge spillover thus considers the technological impact of the publications on individuals and/or organizations beyond the immediate scope of the research.

RQ3

How does the scientific and technological impact of the papers resulting from academic engagement depend on the affiliation of the lead author?

The significance of the lead author's role in shaping the outcomes of these studies is the chief focus in Chapter 7, where the third research question is addressed. While there are variations across fields, countries, and even years regarding the sequence of authors in the byline of multi-authored research papers (Yu & Yin, 2021), the first

[4] To clarify, the first pathway emphasizes the impact when the same individual is involved in both the science and the technology (referred to as an author–inventor pair), while the second pathway emphasizes the impact when the same organization is involved in both activities (referred to as an affiliation–assignee pair).

author is generally regarded as the one contributing the most (Bhandari et al., 2014; Corrêa Jr. et al., 2017; Nylenna et al., 2014; Thelwall, 2023; Wren et al., 2007).

However, it should be noted that perceptions of authors' contributions can be influenced by the identity of the corresponding author (Bhandari et al., 2014; Wren et al., 2007). Nonetheless, an extensive bibliometric analysis encompassing over 10 million research papers published between 2000 and 2008 suggests that the first author is frequently also the corresponding author. Specifically, this holds true for approximately 80–90% of the papers published in engineering, mathematics, and computer and information technology (Yu & Yin, 2021; see also Mattsson et al., 2011).

Accordingly, this chapter quantitatively analyzes the influence exerted by the lead (i.e., first) author on both the scientific and technological impacts of the publications, specifically examining how their type of affiliation, distinguishing between academia, industry, and dual affiliation, shapes the overall outcomes.

1.4 Empirical context and sample

The empirical context of this study is electrical engineering in Sweden, a field involving collaboration among diverse actors, including universities, multinational enterprises (MNEs), and knowledge-intensive entrepreneurial (KIE) firms (Berg, 2019; Ljungberg et al., manuscript to be submitted for publication). This selection is supported by several reasons, which are summarized below.

The field of engineering sciences was chosen due to its unique combination of scientific and applied knowledge—in the words of Stokes (1997, p. 73), it can be characterized as "use-inspired basic research." According to this understanding, the engineering sciences encompass a combination of basic knowledge and applied knowledge. These sciences aim to enhance the understanding of fundamental phenomena within a scientific domain (basic), while simultaneously being motivated by societal needs and practical applications (applied). This suggests relatively close linkages between academic and industrial (i.e., firm-employed) researchers, which aligns well with the purpose of this dissertation. Empirical research supports this notion, as research has consistently found that applied fields participate more in academic engagement (e.g., Abreu & Grinevich, 2017; Aschhoff & Grimpe, 2014; Lawson et al., 2019; Schuelke-Leech, 2013; Tartari & Breshi, 2012).

Moreover, electrical engineering, in particular, is interesting due to its vital yet often overlooked role in technological development. The seemingly invisible nature of technology and its compositions has led to the misconception that engineering, including electrical engineering, is less creative than other fields, which is not entirely accurate. Arthur (2009) argued that the perceived lack of creativity in engineering stems from two primary notions: first, the general public is not trained to grasp a well-executed piece of technology and, second, the largely hidden nature of the components constituting technology. The final noteworthy reason is that electrical engineering, both broadly and in a variety of subfields related to signals, systems, and algorithms, is and has been a key enabling technology for the success of some of Sweden's best-known companies, such as AstraZeneca, Ericsson, Volvo Cars, and Volvo AB.

More concretely, the sample utilized in this dissertation was derived from employment data encompassing professors employed at the five main engineering universities in Sweden, specifically in the fields of biomedical, communication, control, and signal processing engineering. Professors were chosen as the ideal sample due to their role in advancing scientific knowledge and shaping the research direction of their respective departments or units. Moreover, professors in Swedish universities tend to exhibit relatively low job mobility compared with other professions (Askling, 2001), allowing for a longer analysis period per professor, which is beneficial as it increases the sample size.

After identifying the sample using employment data, bibliometric data was collected spanning the period from 1995 to 2018, primarily focusing on scientific documents from Web of Science, the patent-to-article dataset Reliance on Science in Patenting, developed and published by Marx and Fuegi (2020, 2022), and patent data from EPO via the OECD REGPAT database, July 2020 edition (OECD REGPAT, 2020). For clarification purposes, the Web of Science database was used to identify the sampled professors' co-authored publications and the number of citations those papers receive from other scientific papers, the Reliance on Science in Patenting database was used to identify the number of times those papers have been cited by patents, and the OECD REGPAT database was used to control for the number of patents the sampled professors have applied for.

The analysis period extended from 2000 to 2018, primarily due to three logical considerations. First, this allowed for an adequate sample size, as suggested by Glänzel and Moed (2013) and Rogers et al. (2020). Second, data constraints limited the availability of Swedish academic employment data prior to 2000. Finally, this timeframe allowed for a sufficient gap (i.e., three years) between the last publication year and the measurement of article impact (see, e.g., Amin & Mabe, 2000). Regarding the unit of analysis, the final sample consists of 8455 scientific documents, co-authored by the 184 professors.

1.5 Noteworthy activities in relation to the Ph.D. dissertation

At my Unit, the Unit of Innovation and Entrepreneurship, the Ph.D. program requires a minimum of 90 credits for courses and 150 credits for work on the Ph.D. dissertation. As a Ph.D. student, I have taken courses totaling 141 credits. These courses have played a crucial role in arming me with the necessary knowledge and skills, not only for writing my dissertation but also for broader applications extending beyond the scope of the dissertation itself.

As part of the Ph.D. process, the research presented in this Ph.D. dissertation has been thoroughly examined and discussed in planning, midway, and pre-defense seminars at the Unit. The research reported here has been conducted independently. Ergo, both the aforementioned seminars and the dissertation itself can be considered the author's original manuscript, in accordance with the current standards of open access. Furthermore, the process of actively participating in academic conferences and developing research papers throughout my Ph.D. education has facilitated the writing of this dissertation. These activities are presented below in Table 1.1, which also lists all submitted and published journal articles completed during my Ph.D. education.

Overall, I have delivered six external conference and workshop presentations, published three journal articles, and co-authored one book. It is worth mentioning that the published journal articles were completed during my tenure as the Research Manager of Esmaeilzadeh Holding. As of the current date, 18 February 2024, I have one additional journal article under review and one being finalized for submission, both of which were written during my tenure as Ph.D. student at the Unit.

Table 1.1. Noteworthy activities in relation to the Ph.D. dissertation.

Year	Type	Author(s)	Title
2019	Workshop presentation (Workshops on Medical Innovation and Healthcare—WOMI)	K. Berg, D. Ljungberg, M. McKelvey, V. Ström*	Academic engagement seen through university–industry co-authorship: Who are these industry collaborators?
2021	Workshop presentation (Doctoral Education and the Private Sector: European Perspectives)	V. Ström, M. McKelvey, E. Gifford	Investigating the scientific contributions of academic engagement with industry
2021	Conference presentation (Policies, Processes and	V. Ström, M. McKelvey,	Which factors matter for the scientific contributions of professors' publications with industry?

	Practices for Performance of Innovation Ecosystems—P4IE)	E. Gifford	
2021	Book	M. McKelvey, K. Berg, E. Bourelos, L. Brunnström, E. Gifford, D. Hemberg, I. Hermansson, S. Lindmark, D. Ljungberg, R. Saemundsson, V. Ström, O. Zaring	Forskningssamverkan och kommersialisering. Samhällets långsiktiga försörjning av ingenjörsvetenskaplig kunskap [Research collaboration and commercialization. Society's long-term supply of engineering knowledge]
2022	Workshop presentation (Dimensions of Knowledge and Technology Transfer: Actors, Channels and Implications)	V. Ström, M. McKelvey, E. Gifford	Doing academic engagement together: Investigating co-publishing between universities and firms in electrical engineering in Sweden, 2000 to 2018
2023**	Journal article (*Economic Affairs*)	N. Sanandaji, V. Ström, M. Esmaeilzadeh, S. Esmaeilzadeh	The evolution of the Swedish market model
2023	Seminar presentation (International Center for Higher Education Research—INCHER, University of Kassel)	V. Ström	Academic engagement with industry as a research activity: The scientific and technological impact of university–industry co-authored publications, in the engineering sciences
2023**	Journal article (*Journal of Business Strategy—JBS*)	V. Ström, P. Braunerhjelm, S. Esmaeilzadeh	Making an M&A work: Equal strategic partnerships smooth the path
2023**	Journal article (*International Journal of Innovation Science*)	V. Ström, N. Sanandaji, S. Esmaeilzadeh, M. Esmaeilzadeh	Equity capital financing of Swedish SMEs, innovation, and decentralized management
2023	Journal article (under review)	V. Ström, M. McKelvey, E. Gifford	Scientific outcomes of academic engagement in electrical engineering: Investigating the scientific impact of firms on co-publishing in Sweden, 2000 to 2018

2023	Workshop presentation (“Samverkans forum/Collaboration forum,” Department of Electrical Engineering, Chalmers University of Technology)	M. McKelvey, V. Ström	The impact and role of dual-affiliated professors and researchers on scientific and technological impacts
2024	Journal article (finalizing for submission)	D. Ljungberg, M. McKelvey, V. Ström	Characterizing industry collaborators in engineering research: Academic engagement between firms and Chalmers University of Technology, 2009-2018

* The authors are in alphabetical order.

** Activity conducted during employment at Esmaeilzadeh Holding.

1.6 Outline

This section outlines the rest of the chapters in this dissertation.

Chapter 2, entitled “Theoretical framework,” presents a comprehensive overview of the main research streams cited in this dissertation. The chapter begins by examining the concept of academic engagement and highlighting the individual characteristics of researchers as antecedents to academic engagement. Thereafter, the chapter examines the evolving role of universities in Sweden, situating them as playing a particular role in the knowledge economy, encompassing an analysis of the knowledge economy, university–industry collaboration, and the universities’ third mission, highlighting the evolving role of universities in this context. The chapter then redefines academic engagement analysis given knowledge network and knowledge creation insights, offering an in-depth analysis of core concepts and approaches, and of the influence of knowledge networks in science. Following that, the outcomes and impact of academic engagement are thoroughly examined, with a primary focus on the impacts of publications resulting from academic engagement. Finally, by combining these research streams, the chapter establishes the overall theoretical framework that underpins the research, providing a conceptual framework and theoretical perspectives that guide the subsequent analysis and findings.

Chapter 3, entitled "Empirical setting," explores the specific context and setting. The chapter begins by defining and discussing three related concepts: engineering, science, and technology. The chapter then shifts focus to the universities in Sweden that actively engage in the field of electrical engineering, offering descriptive insights into their contributions. The empirical context also includes specifics of university–industry collaboration in Sweden, shedding light on the collaborative initiatives and partnerships between universities and industries within the country. Lastly, it explores the institutional concept of teachers' exemption, addressing its relevance and implications in the research context.

Chapter 4, entitled "Sample, data, and descriptive statistics," offers an in-depth overview of the sample, data sources, and descriptive statistics employed in this research. The chapter begins with a comprehensive description of the sample, elucidating the characteristics and composition of the researchers included in the study. Furthermore, it delves into the data utilized for the research, with a specific focus on the bibliometric data employed in the analysis. Additionally, it addresses the process of data preprocessing, outlining the steps and techniques implemented to clean and prepare the data for analysis. Furthermore, it evaluates the quality of the data used, discussing potential limitations and/or biases associated with the dataset. Lastly, the chapter presents some descriptive statistics, offering summarized findings and key measurements that characterize the data.

Chapters 5, 6, and 7 present the constituent empirical studies of this dissertation; these chapters are entitled "The scientific outcomes and impacts of collaborative research as one form of academic engagement," "The technological impacts of collaborative research as one form of academic engagement," and "The impact of the lead author in collaborative research as one form of academic engagement," respectively. The structure of these chapters follows a consistent pattern. They commence with a short introduction, followed by a discussion of the more specifically relevant theory, leading to hypotheses. The chapters then explore the data and methods employed in the investigation, encompassing a discussion of the datasets, the operationalization of variables, and the empirical strategy utilized. The chapters go on to present the study's results, emphasizing both descriptive findings and regression analyses. Additionally, robustness checks are executed to evaluate the validity and reliability of the findings. The discussion sections provide a comprehensive analysis and interpretation of the results, drawing comparisons and contrasting their significance within the broader scientific community. Furthermore, each chapter explores the implications arising from the research, considering how the findings can be practically applied and the potential theoretical contributions they offer. Finally, each chapter concludes by summarizing the key insights and conclusions derived from the analysis. Additionally, limitations are discussed and recommendations for future research are outlined.

Chapter 8, entitled "Conclusion," is the final chapter of this dissertation and provides a summary of and closure to the research. This chapter begins by addressing the research questions posed at the outset of the dissertation, offering concise and clear answers based on the findings and analysis presented throughout the monograph. By directly answering the research questions, the chapter ensures a comprehensive understanding of the study's contributions and outcomes. Following this, the chapter moves on to highlight the implications of the research findings, including practical applications, policy recommendations, and contributions to existing knowledge and theory. In addition to discussing the research implications, the chapter also addresses the limitations of the research. It acknowledges the most significant shortcomings and/or constraints encountered during the research process, such as limitations in the sample size, data quality, and methodological approach. By acknowledging these limitations, the chapter ensures transparency and provides a balanced assessment of the studies' validity and reliability. Lastly, the chapter offers ideas for future research based on the findings and limitations identified in the current research. It suggests potential directions and avenues for further investigation, highlighting areas that could benefit from additional research or where the present results could be expanded upon. This discussion of future research will help inspire and guide academic scholars in building on this dissertation’s foundations.

Finally, the “References” section lists all scholarly works and other sources cited in this dissertation, while Appendices A–D present supplementary information and data, as follows:

- Appendix A: Additional descriptive statistics
- Appendix B: Correlation tables
- Appendix C: Additional regression analyses (robustness tests)
- Appendix D: Allocating credit in science

2 THEORETICAL FRAMEWORK

In this chapter, elaboration is provided on the theories, concepts, constructs, and variables that constitute the core of this dissertation in order to develop a theoretical framework. This entails a presentation and discussion of combining the existing body of research within three distinct yet interconnected streams of literature, i.e., academic engagement, knowledge networks, and research collaboration, that are relevant to this dissertation.

This chapter should be considered the foundation of the empirical chapters that follow. It should be noted that this chapter does not delve into all the conceptual aspects specific to the empirical chapters; instead, it provides a broad overview of existing research. A detailed discussion of the theoretical literature pertaining to very specific questions in the empirical investigations can be found in their respective chapters. This approach has been adopted to reduce redundancy and enhance clarity.

The chapter is structured into five sections. The first section discusses the literature on academic engagement, with a primary focus on its definitions, motivations, and antecedents. The second section delves into the role of universities in the knowledge economy. This includes outlining key background information, such as what constitutes the knowledge economy, a brief review of the innovation system literature, and the evolving identity of universities. The third section explores the literature on knowledge networks and knowledge creation. It concentrates on defining and elaborating on core concepts and approaches, as well as delving into knowledge networks in science and technology, emphasizing four key aspects: team size and human capital, knowledge-related team diversity, team longevity, and team members' geographical proximity. The fourth section centers on academic engagement but shifts the focus to its outcomes and impacts. This separation is necessary because a comprehensive understanding of these outcomes requires comprehension of the broader literature on knowledge networks and knowledge creation. Building on the insights from these sections, the fifth and final section presents a theoretical framework that integrates the most relevant aspects from these bodies of literature.

Additional insights into what can be expected in relation to the first four sections, as well as the following two chapters, are presented in Figure 2.1 below. This figure is primarily based on Perkmann et al.'s (2021) theoretical framework, depicted in its original form in the subsequent section. In essence, it illustrates the connection between individual characteristics and knowledge network properties, which in turn are linked to various forms of academic engagement and their impacts. In this chapter, the primary focus is on examining the black boxes, while the grey boxes provide valuable insights into the content of the following two chapters.

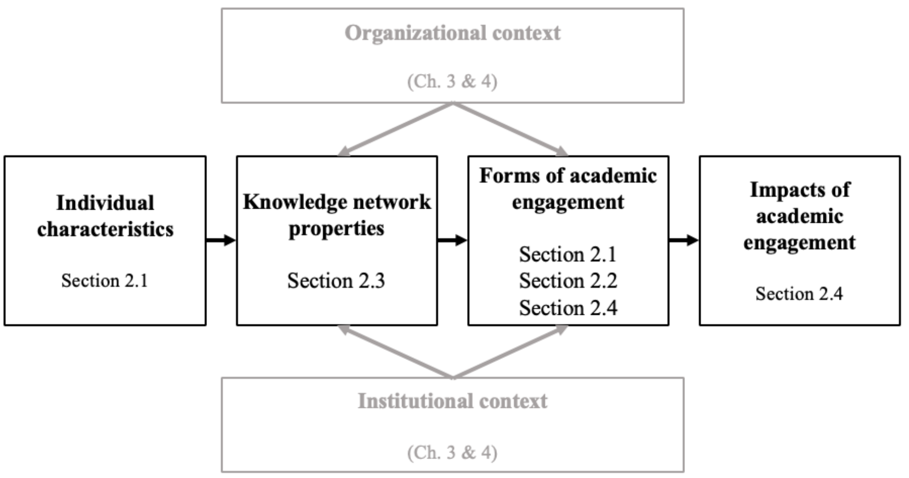

Figure 2.1. Overview, Chapter 2.

2.1 Academic engagement

This section first reviews the literature concerning the motivations driving collaboration between universities and firms. Second, it comprehensively examines the factors leading to academic engagement (i.e., its antecedents). Third, it discusses publications as an outcome of academic engagement and considers their resulting scientific impact.

2.1.1 Defining academic engagement

University–industry collaboration refers to several forms of collaborations between one or more universities and one or more firms. The broad nature of university–industry collaboration allows for various pathways of engagement, and numerous taxonomies have been developed to classify these different types of collaboration (e.g., Abreu & Grinevich, 2017; D'Este et al., 2019; D'Este & Patel, 2007; Lawson et al., 2016; Perkmann et al., 2013).

For the purpose of this dissertation, the definition of university–industry collaboration is based on the taxonomy initially proposed by Perkmann et al. in their 2013 structured literature review. The authors categorized university–industry collaboration into two types: academic engagement and academic commercialization. According to their taxonomy, academic engagement refers to "knowledge-related collaboration by university scientists with non-academic organisations" (Perkmann et al., 2013, p. 424). This type of university–industry collaboration can take various forms, including co-publishing articles, advising boards, delivering public lectures, providing informal advice, and participating in conferences. On the other hand, academic commercialization is defined as "intellectual property creation and academic entrepreneurship" (Perkmann et al., 2013, p. 423). Similar to academic engagement, academic commercialization can be further subdivided into components such as patenting, licensing, establishing spin-offs, and engaging in consultancy work.

The primary reason for selecting this review article and its conceptual framework as the foundation of this research is its explicit emphasis on synthesizing existing literature on academic engagement, which is the empirical context of this entire dissertation. In other words, the main reason for choosing this taxonomy as the definition of university–industry collaboration is its clear distinction between the knowledge-related aspects of collaboration, which center on knowledge creation, transfer, and diffusion, and the activities associated with commercialization, which in the typical case aim for economic gain by making inventions available to the public.

In their original review published in 2013, Perkmann et al. delineated various analytical paths where research is needed. Subsequently, in a follow-up review published in 2021, they presented a revised framework, once again highlighting areas requiring further investigation. This framework is illustrated in Figure 2.2, below. It illustrates that academic engagement is shaped by individual characteristics, the organizational and relational context, and the institutional context. The dashed boxes in the figure indicate areas where research is scarce, ambiguous, or absent, while the solid boxes indicate areas where research provides a relatively more coherent understanding. As shown, the areas where this research intend to make the biggest contributions—investigating the consequences of academic engagement in terms of research impact and quality—are areas where the review calls for further research.

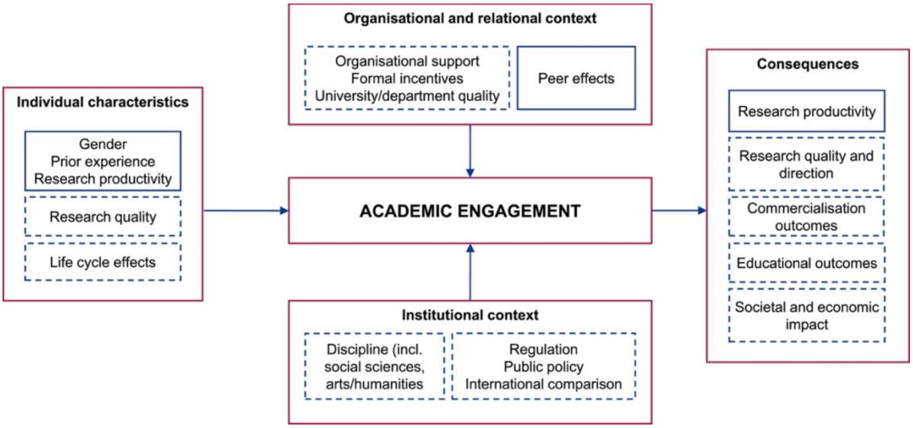

Figure 2.2. Perkmann et al.'s (2021) analytical framework of academic engagement.

Moving forward, the various motivations that drive academic researchers to engage in collaborative research activities with firms, as well as the motivations that drive firms to engage in such collaborations with academic researchers, will be explored. Following this exploration, an examination of researchers' individual characteristics as antecedents to their academic engagement will be conducted (left box in Figure 2.2). These sections are primarily designed to enrich the understanding of academic engagement. In other words, their primary purpose is to contribute to a comprehensive understanding of the phenomenon under investigation, rather than serving as vital components of the empirical research. Subsequently, the key insights gained from these sections will be presented.

2.1.2 Motivations for both academia and industry to conduct collaborative research

At an individual level, university scientists have several motivations for collaborating with their counterparts in industry. Such motivations encompass augmenting their own research careers by accessing complementary expertise (Ankrah et al., 2013; D'Este & Perkmann, 2010; Hughes et al., 2016; Kongsted et al., 2017; Sjöö & Hellström, 2021), contributing to societal progress on a larger scale

(Ankrah et al., 2013; Hughes et al., 2016; Iorio et al., 2017), gaining access to cutting-edge facilities and equipment (Ankrah et al., 2013; Kongsted et al., 2017), evaluating the practical applicability of research (Ankrah et al., 2013; Hughes et al., 2016; Kongsted et al., 2017), and keeping their teaching up to date (Kongsted et al., 2017; Lawson et al., 2016; Sjöö & Hellström, 2021).[5]

Additionally, it is conceivable that university scientists are compelled to collaborate with industrial counterparts due to tougher competition for academic positions. This stems from the globalization of the academic job market (Avveduto, 2005; see also Carson et al., 2012/2013) and the fact that the production of doctoral graduates has surpassed the growth rate of available tenured positions, a situation observed not least in Germany (Buenstorf et al., 2019) and France (Jalowiecki & Gorzelak, 2004, as cited by Goastellec et al., 2013). This reality implies a greater incentive to distinguish oneself within the academic crowd, potentially by conducting a large amount of successful university–industry collaborative research.

From the industry perspective, particularly at the organizational level, the motivation to enhance collaboration with universities arises from the mounting pressures of an increasingly competitive global landscape. This shift is a consequence of various factors, including reduced transportation costs (Anderson & de Palma, 2000; Forman et al., 2018), diminished communication costs (Forman et al., 2018; Florida & Mellander, 2018), streamlined search expenses (Forman et al., 2018), the emergence of new innovations with heightened returns to scale (Anderson & de Palma, 2000; Forman et al., 2018), and shorter product life cycles (Bonaccorsi & Piccaluga, 1994).

The motivations for industrial researchers to engage with their university counterparts encompass developing their human capital through access to

[5] See Ankrah and Al-Tabbaa (2015) and Vick and Robertson (2018) for two thorough reviews.

complementary knowledge (Ankrah et al., 2013; Broström, 2012; Sjöö & Hellström, 2021), accessing cutting-edge facilities and equipment (Ankrah et al., 2013), developing their social capital through access to new research networks (Ankrah et al., 2013; Broström, 2012; Sjöö & Hellström, 2021), and stimulating their capabilities to innovate (Siegel et al., 2003).[6]

The inquiry into why firms seek collaboration with universities is closely linked to the question of why firms engage in publishing activities. These two lines of inquiry are intertwined, as firms frequently engage in collaborations with universities with the intent of publishing jointly. In a comprehensive systematic literature review, Rotolo et al. (2022) formulated a conceptual framework elucidating five underlying factors motivating such actions. These include accessing external knowledge and resources, improving the firm's reputation, supporting commercialization and IP strategies, and attracting and retaining researchers. Given the interconnections between collaborating with universities and engaging in publishing activities, it is reasonable to posit that the incentives for publishing are also relevant to the original query.

Table 2.1, below, summarizes motivations driving academic scholars to collaborate with industry and, conversely, the motivations prompting industry to seek collaboration with academics, as discussed above.

Table 2.1. Motivations for university–industry collaborations: a comparison.

Direction	Motivation	Explanation
Academia → Industry		
	Leveraging complementary expertise	Engaging in collaborative efforts with industry partners facilitates access to complementary domain expertise and specialized knowledge resources.

[6] See Ankrah and Al-Tabbaa (2015) and Vick and Robertson (2018) for two thorough reviews.

	Utilizing state-of-the-art infrastructure	Collaboration enables researchers to utilize cutting-edge facilities and advanced equipment, augmenting their research capabilities.
	Securing research funding	Collaboration with industry provides opportunities to secure additional research funding and resources for scientific investigations.
	Advancing societal impact	Collaborations allow researchers to contribute to societal progress by addressing real-world challenges and advancing technological solutions.
	Assessing practical applicability	Collaborative projects offer the opportunity to evaluate the practical applicability of research findings in real-world industrial settings.
	Sustaining pedagogical excellence	Collaborations help academics stay updated with industry trends, enriching their teaching content and ensuring the relevance of educational programs.
	Navigating academic competition	Collaboration may be driven by the competitive nature of academia, especially concerning tenured positions, with researchers seeking to distinguish themselves in a crowded academic landscape.
Industry → Academia		
	Enhancing and leveraging human capital	Collaboration with academia enables industrial professionals to develop (and leverage) their human capital by gaining access to complementary knowledge and expertise. This access helps enrich their skills and competencies.
	Accessing cutting-edge resources	Industry partners collaborate with universities to access state-of-the-art facilities and advanced equipment, providing them with technological advantages and research capabilities.
	Expanding social capital	Engaging in partnerships with academia allows industrial researchers to increase their social capital by accessing new research networks and fostering connections with experts in various fields.
	Capitalizing on innovation	Industrial researchers engage with universities to leverage the emergence of groundbreaking inventions/innovations that offer significant returns on investment and increased economies of scale.
	Navigating global competition	Industry seeks collaboration with academic institutions to address the intensifying competition within the global marketplace. This is driven by factors such as reduced transportation costs, diminished communication expenses, and streamlined search processes.
	Improving the firm’s reputation	Partnerships (or publishing) with universities can boost a firm’s reputation, showcasing its commitment to cutting-edge research and innovation.
	Attracting and retaining employees (or researchers)	Engaging in partnerships with academia can make firms more attractive to talented employees (or researchers), aiding in the recruitment and retention of top-tier talent.

2.1.3 Individual characteristics of researchers as antecedents to academic engagement

Throughout the 21st century, there has been a notable upsurge in the perceived significance of academic engagement within the realm of research scholars. This trend is evident in the plethora of studies dedicated to exploring various pivotal factors influencing the antecedents of academic engagement. An overview of the aspects and the cited studies within this section can be found in Table 2.2, below. After the table, a more comprehensive discussion of these aspects is provided.

Table 2.2. Antecedents of academic engagement: factors discussed and cited research papers.

Focus	Authors
Scientific achievements	Aschhoff & Grimpe, 2014; Bekkers & Freitas, 2008; Ding & Choi, 2001; D'Este et al., 2019; Tartari et al., 2014; Zi & Blind, 2015
Academic engagement experience	D'Este & Patel, 2007; Lawson et al., 2016; Tartari et al., 2012
Non-academic experience	Aschhoff & Grimpe, 2014; Barbieri et al., 2018; Bruneel et al., 2010; Gulbrandsen & Thune, 2017; Johnson et al., 2017; Lawson et al., 2016; Tartari & Breshi, 2012; Tartari et al., 2012, 2014
Type of research	Abreu & Grinevich, 2017; Aschhoff & Grimpe, 2014; Lawson et al., 2019; Schuelke-Leech, 2013; Tartari & Breshi, 2012
Gender	Abreu & Grinevich, 2017; Blind et al., 2018; Gaughan & Corley, 2010; Gulbrandsen & Thune, 2017; Kongsted et al., 2017; Lawson et al., 2019; Link et al., 2007; Tartari & Salter, 2015
Biological age	Blind et al., 2018; Giuliani & Arza, 2009; Giunta et al., 2016; Iorio et al., 2017; Lawson et al., 2019; Link et al., 2007; Tartari & Breshi, 2012
Academic age and rank	Aschhoff & Grimpe, 2014; Boardman & Ponomariov, 2009; D'Este et al., 2019; Lawson et al., 2019; Link et al., 2007; Tartari & Breschi, 2012; Tartari et al., 2014
National and ethnic origin	Edler et al., 2011; Lawson et al., 2019; Tartari et al., 2012, 2014; Trippl, 2013

Scientific achievements

The research achievements of scholars serve as indicators of their human capital. These achievements encompass the number of publications, the number of citations received by these publications, and the reputation of the journals in which they appear. University-affiliated scientists who amass considerable citations, denoted high article impact, and who contribute to esteemed journals, denoted top journal reputation, and/or exhibit high publication activity within a given timeframe, denoted high research productivity, can plausibly be deemed more appealing as prospective collaborators from an industrial standpoint, all other factors being equal. However, an alternate perspective posits that university scientists possessing these attributes, particularly those with substantial article impact who frequently publish in esteemed journals, might exercise selectivity, opting to collaborate solely with other (academic) researchers aligned with their own impact and/or journal reputation, potentially limiting interactions with industrial researchers who might be fewer in number.

Regarding empirical findings, we turn first to article impact. The evidence suggests that it does not have a significant influence on the likelihood of conducting academic engagement. This holds true whether we measure article impact by the cumulative citations an individual scholar accrues (Ding & Choi, 2001; Tartari et al., 2014) or approximate article impact using the number of articles featured among the top 1% of most cited articles (D’Este et al., 2019). Shifting focus to journal reputation, empirical research in this realm is less abundant. A notable study discovered that university scientists who publish in highly reputed journals are less inclined to contribute to the establishment of industry standards, in contrast to those publishing in journals of a more technical or industry-oriented nature (Zi & Blind, 2015).

Turning to research productivity, the findings indicate a positive correlation between the number of articles published by university-affiliated scientists and the probability of their engagement in academic projects. This trend holds across diverse national contexts, such as the U.K. (Tartari et al., 2014), Germany (Aschhoff & Grimpe, 2014), the Netherlands (Bekkers & Freitas, 2008), and Spain (D'Este et al., 2019). In summary, it seems that research productivity exerts a favorable effect on the likelihood of academic engagement, while article impact appears to exert a neutral effect and journal reputation a detrimental effect on the likelihood of academic engagement.

Academic engagement experience

As discussed above, prior experience in academic engagement can signal to industrial researchers that the involved academic scholar possesses a firm grasp of their function and responsibilities within the context of academic engagement. Research indicates that this holds true; specifically, having academic engagement experience substantially enhances the likelihood of engaging in future academic projects (D'Este & Patel, 2007; Lawson et al., 2016; Tartari et al., 2012). To be more precise, Lawson et al. (2016) demonstrated that individuals with academic engagement experience are more than one and a half times as likely to participate in future academic engagement.

Non-academic experience

There are at least two compelling reasons why non-academic experience, such as industry experience, patenting involvement, and/or entrepreneurial ventures, can significantly influence the propensity of university scientists to engage with industry in the pursuit of knowledge creation and transfer. Primarily, having non-academic experience, particularly in the industrial sector, fosters a heightened comprehension of the intrinsic motives behind firms' inclination to collaborate. Consequently, this heightened understanding can either augment the willingness of academics to participate in collaborations or, conversely, diminish it, contingent on the specific context and origins of the non-academic experience. However, the acquisition of non-academic experience inherently serves as a demonstrative certification, a specific type of human capital that corporations might regard as valuable. Besides this, non-academic experience increases the social capital of the university scientist. This increase in social capital subsequently reinforces the likelihood of collaborative engagement between the university scientist and the specific firm.

The literature regarding industry experience is notably coherent and supports the observation that exposure to the industrial sector substantially magnifies the probability of future university–industry collaboration (Abreu & Grinevich, 2017; Gulbrandsen & Thune, 2017; Tartari et al., 2012, 2014). It is evident that industry experience exerts a favorable impact in terms of alleviating barriers associated with research orientation, although it does not necessarily reduce transaction-related barriers (Bruneel et al., 2010; Tartari et al., 2012). Here, orientation-related barriers refer to conflicts about the orientation of research with industry partners, while transaction-related barriers pertain to conflicts over intellectual property (IP) and dealing with university administration.

In contrast, the body of research on patenting experience presents a slightly more inconsistent stance, suggesting either a neutral effect (Aschhoff & Grimpe, 2014; Gulbrandsen & Thune, 2017) or even a positive effect (Tartari & Breshi, 2012) on the probability of future university–industry collaboration.

The influence of entrepreneurship experience on university–industry collaboration is more nuanced. Empirical investigations posit a moderately positive correlation between entrepreneurship experience and the likelihood of future academic engagement. Notably, Lawson et al. (2016) underscored that UK-based academics with prior involvement in commercial activities exhibited substantially higher propensities for future academic engagement than did their non-engaged counterparts. Similarly, Johnson et al. (2017) found that Scottish university scientists with prior entrepreneurial experience manifested a modestly positive, but statistically non-significant, influence on the likelihood of future academic engagement. Analogous to industry experience, entrepreneurship experience primarily serves to diminish orientation-related barriers, while transaction-related barriers remain largely unaffected (Barbieri et al., 2018; Tartari et al., 2012). Building on these findings, insights from Barbieri et al. (2018) indicate that founding a startup could potentially yield a reduction in the number of corporate entities the university scientist collaborates with. This phenomenon is attributed to the observed tendency of entrepreneurial university scientists to redirect their collaborative endeavors from external entities toward their own ventures.

On the whole, the evidence suggests a positive effect, or at the very least, a neutral effect, of non-academic experience on the likelihood of future academic engagement.

Type of research

Not all research endeavors are the same; rather, they diverge in their primary objectives. Some research endeavors aim to expand the understanding of fundamental phenomena within a scientific domain, commonly defined as basic research, while others are driven by their relevance to societal needs and applications, commonly denoted applied research (Niiniluoto, 1993; Stokes, 1997). Consequently, it is reasonable to anticipate that applied research would hold greater appeal from a firm's perspective. Corporations engage with university scientists to deepen their understanding of certain phenomena that possess direct utility and applicability, thereby offering avenues for commercialization.

This notion finds empirical validation in the research landscape, with findings consistently indicating that academic engagement is more prominent in the applied research domain (Abreu & Grinevich, 2017; Aschhoff & Grimpe, 2014; Lawson et al., 2019; Schuelke-Leech, 2013; Tartari & Breshi, 2012).

Gender

There are at least two valid reasons why gender can influence the likelihood of a university scientist engaging with industry for the purpose of creating and/or transferring knowledge. First, it is now well established in the psychological literature that there are personality differences between males and females. Large-scale meta-analyses have revealed that men, on average, exhibit greater risk-taking tendencies (Byrnes et al., 1999) as well as higher levels of assertiveness and self-esteem (Feingold, 1994) than do women. Holding other factors constant, this suggests that men are more inclined to initiate contact and embrace the associated risks linked with collaborating with industry, than are females.

Second, males are overrepresented in the engineering field (Hill et al., 2010; Yoder, 2012), and evidence also indicates that men dominate the highest ranks within academia. In other words, there are more male professors than female professors (Abreu & Grinevich, 2017; Madison & Fahlman, 2020). Again, under similar circumstances, males are more likely to form collaborations with their male counterparts, as outlined by homophily theory, which posits that individuals of similar characteristics (e.g., gender, race, and ethnicity) tend to interact more frequently than those with dissimilar attributes (Lazersfeld & Merton, 1954). Notably, this is not exclusive to gender but rather a broader phenomenon, one that can affect various aspects beyond gender, as this dissertation will further elucidate. In summary, there exist theoretical arguments favoring the notion that males are more likely to engage with industry to foster the creation and transfer of knowledge.

Empirical evidence generally corroborates this view (Abreu & Grinevich, 2017; Gaughan & Corley, 2010; Kongsted et al., 2017; Link et al., 2007; Tartari & Salter, 2015), although several studies have reported non-significant effects (Blind et al., 2018; Gulbrandsen & Thune, 2017). Even in more comprehensive models that incorporate personal and professional backgrounds, men still exhibit significantly greater involvement with industry (Abreu & Grinevich, 2017; Gaughan & Corley, 2010). Moreover, men seem to participate in a wider range of activities, encompassing both domestic and international academic engagement projects (Lawson et al., 2019). The predominant factors underlying the gender disparity in academic engagement are certain traits, including academic rank, research specialization, and industry experience. In particular, Abreu and Grinevich (2017) argued that the gender gap could be elucidated by the observation that academic engagement is most prevalent among professors in applied fields, often with prior industry exposure, which is less common among female academics.

Furthermore, differentiating among various forms of academic engagement reveals additional insights. For instance, Abreu and Grinevich (2017) found that men display greater involvement with industry in four out of five types of academic engagement (i.e., advisory board participation, public lectures, contract research, and informal advice), the exception being participation in exhibitions. Similarly, Tartari and Salter (2015) noted that men are more prone to forming new joint research agreements and contract research agreements, yet no gender disparity was evident in attending conferences where participants from both academia and industry are present. These findings suggest that female academics tend to engage with industry to a similar extent as men in less demanding activities, while exhibiting relatively lower engagement levels in more resource-intensive endeavors.

Biological age

The impact of biological age on the involvement of university scientists in academic engagement is subject to theoretical arguments on both sides of the coin. On one hand, a rationale supporting a positive correlation between age and academic engagement asserts that age is inherently linked with increased human and social capital. Specifically, older individuals have had more time to accumulate human capital and nurture social connections, all else being equal. Consequently, older age could augment the probability of academic engagement, as industrial researchers presumably seek collaboration with the most knowledgeable and seasoned university scientists. However, the nature of experience must align with this assumption for it to hold true. Conversely, a contrasting perspective suggests that young academics might be more focused on career development. Consequently, they might be inclined to invest additional time and resources in academic engagement to propel their career trajectories. In contrast, established academics may have already solidified their careers and might exhibit reduced enthusiasm for academic engagement. Furthermore, generational differences play a role, as younger individuals have grown up in a society that emphasizes the legitimacy of academic engagement. In contrast, older individuals were raised in an era when academic engagement was (at least more) discouraged, as universities primarily centered on teaching and research.

The interplay of these opposing factors contributes to the complexity of the relationship between biological age and academic engagement. As such, research findings on this topic are varied: studies indicate that age can yield either a positive effect (Giunta et al., 2016), no effect (Blind et al., 2018; Giuliani & Arza, 2009; Iorio et al., 2017; Link et al., 2007), or a negative effect on the likelihood of academic engagement (Giuliani & Arza, 2009; Tartari & Breshi, 2012). Furthermore, Lawson et al. (2019) introduced a non-linear dimension, revealing an inverted U-shaped relationship between age and the breadth of interaction with industry. Specifically, the middle-aged group exhibited the highest levels of academic engagement, underscoring a nuanced relationship between age and the breadth of academic engagement.

Academic age and rank

The same theoretical arguments that were stated to explain how biological age can influence the likelihood of a university scientist engaging in academic engagement can similarly be applied to academic age, which pertains to the number of years since a researcher obtained their doctoral degree. As discussed in the previous section, these arguments can yield both positive and negative effects on the likelihood of academic engagement. However, in the case of academically older researchers, not only does their background include being raised in a society that was less supportive of academic engagement, but they might also potentially hold negative opinions about academic engagement due to having pursued their doctoral education during a period when such activities were viewed in a negative light (Bercovitz & Feldman, 2008).

Consequently, similar to the literature on biological age, the literature on academic age also presents a mixed perspective, as concluded in the review article by Perkmann et al. (2021). For example, Tartari et al. (2014) discovered that academic age had a detrimental impact on academic engagement likelihood among academics in the UK. In contrast, Aschhoff and Grimpe (2014) found a significant and positive association between academic age and academic engagement likelihood for researchers based in Germany.

Turning to the dimension of academic rank, the same arguments used to elucidate a potential negative correlation between biological/academic age and academic engagement likelihood can also be partially extended to academic rank. This is because achieving the highest academic rank of professor generally requires several years of experience. However, there is a stronger theoretical basis supporting a positive correlation between higher academic rank and academic engagement likelihood. A higher academic rank serves as a signal of high human capital, which, in turn, could increase the propensity for academic engagement. Industrial researchers likely seek collaboration with the most knowledgeable and experienced university scientists, enhancing their likelihood of engagement. Building on these considerations, one might anticipate a more positive correlation between academic rank and academic engagement likelihood compared with biological/ academic age.

On examination of the empirical evidence, research on academic rank aligns coherently with these assumptions, affirming that greater seniority is associated with increased engagement with industry to foster knowledge creation and transfer. This pattern holds true for academics in various countries, including the USA (Boardman & Ponomariov, 2009; Link et al., 2007), the UK (Lawson et al., 2019; Tartari et al., 2014), Italy (Tartari & Breschi, 2012), and Spain (D'Este et al., 2019).

National and ethnic origin

As previously mentioned, homophily extends its influence to various characteristics, including national and ethnic origins (Lazersfeld & Merton, 1954), driven in part by the divergence in languages and cultural values across different regions of the world (Schwartz, 1999). This dynamic implies that, all else being equal, academic engagement is more likely to transpire between researchers sharing the same national and/or ethnic background. While empirical studies concerning the impact of national origin on academic engagement are somewhat limited, the available research corroborates this notion, indicating that native-born university scientists are involved in a wider range of intranational academic engagement. Notably, the magnitude of disparity in intranational academic engagement breadth increases when comparing native-born academics with newly relocated, non-English-native-speaking foreign-born academics, while foreign-born university scientists tend to engage in a broader range of international academic engagement projects (Lawson et al., 2019).

Similarly, in the context of ethnic origin, completing a doctoral degree in the same nation where the academic operates is linked to higher overall academic engagement (Tartari et al., 2014). Correspondingly, this aspect appears to enhance the scope of intranational academic engagement while concurrently diminishing the breadth of international academic engagement (Lawson et al., 2019). There is further evidence implying that highly mobile (star) university scientists conduct similar levels of both intranational and international academic engagement (Edler et al., 2011; Trippl, 2013); however, what seems to be of the highest importance is not the frequency of visits but rather their duration (Edler et al., 2011).

Moreover, it appears that completing a doctoral degree in the same nation where the academic functions reduces barriers associated with research orientation, including research alignment and incentives with industry partners. However, it does not significantly alleviate transaction-related barriers, such as potential IP and regulatory conflicts between the academic institution and industry (Tartari et al., 2012). Taken together, these findings suggest that the duration spent in a particular nation plays a pivotal role in intranational academic engagement projects, while international origin and/or experience emerge as key drivers of international academic engagement projects.

2.1.4 Key takeaways from Section 2.1

- While the academic engagement literature is extensive, there exist related areas requiring further research, for example, analysis of the consequences of academic engagement in terms of research impact and quality.
- The focus of this dissertation centers on the individual level, specifically, that of academic researchers, as they are the ones who engage in collaborations, not their employers.
- Given that the previous literature emphasizes the individual characteristics of well-established researchers, the chosen study population for this research consists of professors. The rationale behind this choice is further elaborated on in Section 4.1.
- Similarly, this study concentrates on one scientific discipline, namely, electrical engineering, which is an applied field with a high probability of university–industry collaboration. See Section 3.1 for more information.

2.2 Universities' role in the knowledge economy

Various literature streams discuss the role of knowledge in society. This section aims to demonstrate how some previous conceptualizations of the knowledge economy in economics and innovation studies enhance our comprehension of academic engagement as a phenomenon.

2.2.1 Defining the knowledge economy in this literature

Even before Menger famously stated that "nothing is more certain than that the degree of economic progress of mankind will still, in future epochs, be commensurate with the degree of progress of human knowledge" (Menger, 1871, p. 74), society began to gradually become a "knowledge economy." Menger was by no means the only influential scholar to argue for the importance of human capital (i.e., human knowledge). For instance, Schumpeter (1934, 1942) argued that the human capital that originates within a specific type of individual—the entrepreneur—plays a key role in stimulating the economy via introducing new products and new procedures, invading new markets, and creating new organizational forms, and Romer (1990) proposed that the accumulation of human capital dictates the pace of economic growth.

While it is widely believed that Drucker (1969) coined the term "knowledge economy" in his influential book *The Age of Discontinuity: Guidelines to Our Changing Economy* (Drucker, 1969), it is important to note that the term was initially articulated by the Austrian-American economist Machlup (1962) in his seminal work—*The Production and Distribution of Knowledge in the United States*—seven years prior to Drucker's publication. Currently, the term enjoys widespread recognition and finds frequent usage in both academic and industrial contexts, despite facing criticism for its lack of clarity (Smith, 2002). Nevertheless, for the purpose of this dissertation, "knowledge economy" refers to the "production and services based on knowledge-intensive activities that contribute to an accelerated pace of technical and scientific advance, as well as rapid obsolescence" (Powell & Snellman, 2004, p. 199).

As outlined by Powell and Snellman (2004), a fundamental element of a knowledge economy involves the transition from static comparative advantage, which hinges on a nation's intrinsic physical inputs and/or natural resources, as initially explained by Ricardo (1817) and further examined by other academic scholars such as Bernhofen and Brown (2018), to a dynamic comparative advantage rooted in intellectual capabilities. This dynamic advantage is cultivated within a nation through investments aimed at enhancing the human capital of its citizens, as discussed by Lucas (1988) and Romer (1990). In this context, human capital can be viewed to encompass "the knowledge, information, ideas, skills, and health of individuals" (Becker, 1993, p. 1).

Therefore, generally speaking, a nation's comparative advantage no longer primarily arises from its physical inputs or natural resources. Instead, it predominantly stems from strategic investments in the accumulation of human capital, thereby fostering the generation and management of knowledge-intensive innovations (Antonelli, 2012; Audretsch & Aldridge, 2009). Theoretically, this transformation leads to intensified global competition, as nations now compete based on their intellectual capabilities rather than the extent of their natural resources. Empirical research lends support to this shift (e.g., Friedman, 2005; Nelson, 1993).

To clarify, while the national dimension remains pertinent, its underlying significance has evolved from proximity to valuable physical inputs or natural resources to proximity to knowledge (Audretsch & Aldridge, 2008). Another fundamental reason for the importance of the national dimension can be attributed to the positive effects of clusters, which involve the agglomeration of firms in cities. This agglomeration results in several advantageous conditions, such as a larger base of local skilled labor supply, a reduced price of transaction-based knowledge, and a decreased cost of ordinary purchases (Karlsson, 2008; Karlsson & Johansson, 2006).

In essence, according to some streams of literature, geographical proximity to knowledge plays a pivotal role in facilitating the transfer of knowledge (Balland et al., 2015; Boschma, 2005; Storper & Venables, 2004), thereby enabling knowledge spillovers to occur (Anselin et al., 1997; Audretsch & Feldman, 1996; Jaffe et al., 1993). Here, knowledge spillover is defined as "a prototypical externality, by which one or a few agents investing in research or technology development will end up facilitating other agents' innovation efforts (either unintentionally, as it happens when inventions are imitated, or intentionally, as it may happen when scientists divulge the results of their research)" (Breschi & Lissoni, 2001, p. 975).

Researchers agree that knowledge spillover stimulates dynamic externalities (Karlsson & Johansson, 2006); however, there is no consensus on the precise manner in which it stimulates these dynamic externalities. One perspective, known as the Marshall-Arrow-Romer (MAR) externalities, posits that only intra-industry knowledge spillovers foster innovation (Glaeser et al., 1992), while an alternative viewpoint, termed Jacobs' (1969) externalities, argues that inter-industry knowledge spillovers foster innovation.

2.2.2 Impact of the innovation system literature in highlighting the importance of universities

The literature pertaining to the knowledge economy attracted significant attention toward the end of the 20th century, particularly from policy- and decision-makers (Sharif, 2006). They are interested in this literature because of "the comprehensive and crucial macroeconomic consequences of innovation" (Edquist, 1996, p. xiv). Consequently, numerous nations embraced a national innovation system (NIS) approach, manifested in the establishment of, for example, governmental innovation agencies. These entities aimed to strengthen national competitiveness (Lundvall, 1992; Nelson & Rosenberg, 1993). According to this perspective, a nation's competitive advantage hinges primarily on the ability of its firms, with the technological capabilities of these firms being pivotal sources of their competitive strength. These capabilities possess a certain national character and can be nurtured through collective national efforts.

Nelson and Rosenberg (1993) moreover stated that the term "system" refers to "a set of institutions [e.g., university laboratories, government laboratories, and firms] whose interactions determine the innovative performance … of national firms" (p. 4). This implies that universities play a significant role in a nation's competitive landscape. In essence, the NIS perspective contends that a nation competes through the technological capabilities of its firms, and that these capabilities result from the interplay between institutions, encompassing both public (e.g., universities) and private (e.g., firms) sectors.

In today's increasingly globalized and interconnected world, certain scholars contend, based on the regional innovation system (RIS) theory, that regions themselves, not just nations, engage in competition (Autio, 1998; Johansson et al., 2009). However, it is crucial to underscore that the very same scholars acknowledge that NIS and RIS theories are not mutually exclusive (Autio, 1998; OECD, 1999). More precisely, the argument can be made that there are still enough factors tied to the national level—such as governmental innovation agencies and national policies—to keep the NIS framework applicable. Simultaneously, the argument can be made that innovation-related factors specific to contextual settings lend applicability to the RIS framework.

2.2.3 Universities' changing identity

We have compelling theoretical arguments, supported by empirical evidence, indicating the significance of inter-organizational collaborations, such as university–industry collaborations, in driving economic progress (e.g., Lundvall, 1992; Nelson & Rosenberg, 1993). The mechanisms through which university–industry collaborations contribute to this progress have been investigated in existing research. According to McKelvey and Ljungberg (2017), who term it "collaborative research," university–industry collaborations have a positive impact on the innovation capabilities of participating firms through two distinct avenues. These avenues are direct enhancement via commercialization, and indirect enhancement through academic engagement, subsequently augmenting the competitive advantage of innovative firms. This activity is depicted in Figure 2.3, below.

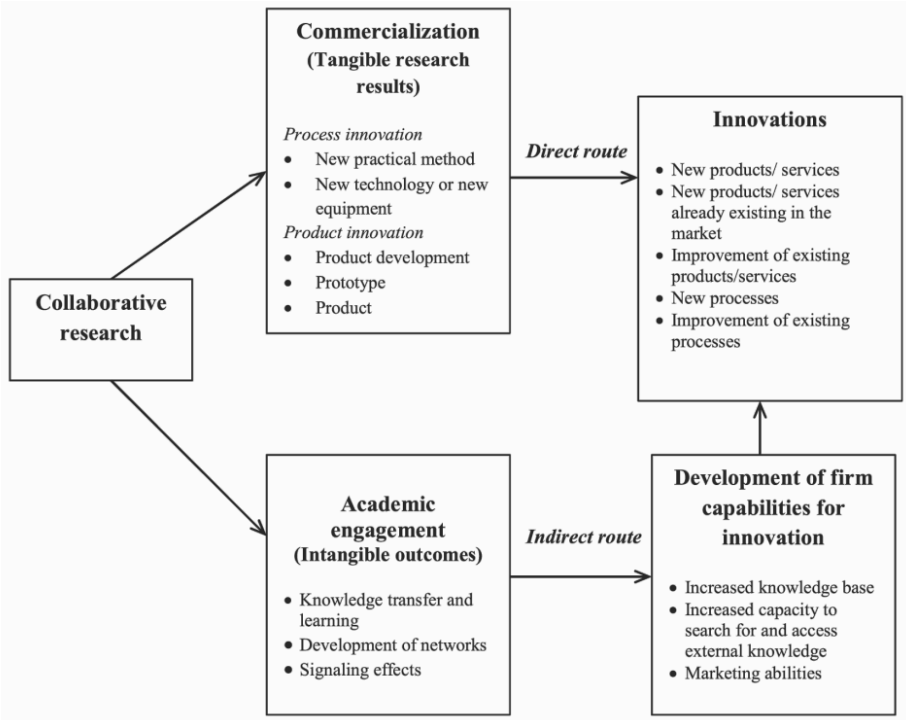

Figure 2.3. Conceptual framework of how collaborative research between universities and firms can influence firm innovation (McKelvey & Ljungberg, 2017).

In greater detail, McKelvey and Ljungberg (2017) contend that the direct pathway, referred to as commercialization, has the potential, if successful, to directly yield innovations in products and/or processes. In contrast, the indirect pathway—denoted academic engagement—has the potential, if successful, to indirectly yield innovations in products and/or processes through facilitating knowledge transfer and learning, stimulating positive signaling effects such as collaborating with a prominent university, and nurturing social capital. Here, social capital refers to "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit" (Nahapiet & Ghoshal, 1998, p. 243). Other studies provide further empirical evidence for McKelvey and Ljungberg's (2017) theoretical framework. For example, university–industry collaborations have been found to both directly amplify firm innovativeness through commercialization (e.g., González-Pernía et al., 2015) and indirectly augment firm innovativeness through academic engagement (e.g., Berg & McKelvey, 2020).

As stated above, the perceived positive impacts of university–industry collaborations have not gone unnoticed. Policy- and decision-makers have asserted that universities could enhance their contributions to the economy by intensifying their collaborative efforts with industry and strengthening their involvement in entrepreneurial and business-oriented activities. These activities include academic patenting, licensing, and the establishment of academic start-ups. This led a number of member nations within the Organisation for Economic Co-operation and Development (OECD) to extend the two traditional missions of universities (first mission: education; second mission: research) to encompass a third mission, explicitly focusing on these types of undertakings (Gulbrandsen & Slipersæter, 2007). This expansion was partially a response to such developments and was also influenced by various other factors (elaborated on below). As a result of these dynamics, the engagement of universities in third-mission activities witnessed substantial growth in numerous OECD member nations toward the end of the 20th century/beginning of the 21st century (Benner & Sörlin, 2015; Bercovitz & Feldman, 2008; Jankowski, 1999; Lissoni et al., 2008, 2011; Vincent-Lancrin, 2006). More recent empirical findings, derived from two surveys of university scientists in the UK (conducted in 2008–2009 and 2015), suggest that the prevalence of activities associated with the third mission has remained stable (Hughes et al., 2016; Lawson et al., 2016). This suggests that the prevalence of third-mission activities has reached a state of equilibrium, a phase that should not be viewed negatively but rather signifies the enduring presence and significance of these activities within the university landscape.

The upsurge in university–industry collaboration in recent decades can also be attributed to a combination of factors influencing both universities and firms. From the universities' perspective, at the organizational level, two noteworthy global trends emerged toward the close of the 20th century that "forced" universities to engage more extensively with the private sector. The first trend manifested as a relative reduction in funding from governmental sources, while the second trend saw a greater proportion of government funds being allocated through contract research arrangements, rather than relying on fixed funding allocations based on previous years' distributions. In other words, the financial landscape for universities underwent an unfavorable transformation. These trends were prevalent across most OECD member nations (Heyman & Lundberg, 2002; Jankowski, 1999; Vincent-Lancrin, 2006).

Managing and evaluating such interaction is no simple task, given the distinct contexts in which university scientists and industrial researchers operate—the former within academic institutions and the latter within corporate entities (Bruneel et al., 2010; Perkmann et al., 2011). This distinction has significance, as these two types of organizations are driven by divergent primary objectives: universities are oriented toward knowledge (generation, transfer, and diffusion), while firms prioritize profitability (Friedman, 1962; Merton, 1973; Nightingale, 1998). In essence, one could posit that university scientists perceive the creation of knowledge as their primary aim, with solving business challenges serving as a means to achieve that objective. On the other hand, industrial researchers regard capitalizing on resolving business issues as their primary goal, viewing knowledge as a tool to attain that goal. This difference has given rise to several barriers, including disputes over the distinction between public and private knowledge (Bruneel et al., 2010; Murray & O'Mahony, 2007) and conflicts concerning IP rights (Bruneel et al., 2010; Hall et al., 2001). Overcoming these barriers is essential for the successful realization of university–industry collaborations.

In the context of the dynamics surrounding university–industry collaboration, a profound shift has become apparent in the roles assumed by higher education institutions. This transformation has partly been prompted by the emergence of the third mission and the changing financial landscape. These developments have significantly reshaped the essence and function of universities.

According to some scholarly perspectives, universities, traditionally seen as institutions dedicated to "developing new areas of knowledge through research for use in future decades—and of widening the societal base of knowledge through teaching and diffusion of students" (Deicaco et al., 2009, p. 301), have undergone a notable transformation. This shift has led them to adopt a more competitive stance, positioning themselves as active players in the realm of knowledge dissemination. Their primary objective has evolved to that of producing knowledge that immediately addresses the needs of students, businesses, and society at large (Deicaco et al., 2009; McKelvey & Holmén, 2009).

Another group of scholars emphasizes a different dimension of change in the evolution of universities' roles. Initially, universities engaged in activities specifically tailored to compete with corporate entities. These activities ranged from offering targeted solutions to specific problems to capitalizing on these solutions through strategies such as patenting and licensing. Over time, this role expanded to encompass a broader range of endeavors aimed at enhancing individual competencies within the knowledge-driven economy. Specifically, these include fostering thinking, developing effective leadership skills, and promoting initiatives designed to bolster entrepreneurial capital (Audretsch, 2014; Audretsch et al., 2014).

It is worth restating that each of these viewpoints concerning the evolution of universities' roles offers only a partial view of the broader perspective. As a result, these theories do not inherently contradict one another. What can be noted is that a prominent theme arises from these dialogues, and that is the overarching notion of increased collaboration between universities and corporate entities. This collaborative effort leads to a collective impact on the broader societal context.

2.2.4 Key takeaways from Section 2.2

- The current literature on academic engagement is rooted in the fields of the economics of innovation and innovation studies. These fields have a primary focus on the development and diffusion of knowledge and its impact on the economy.
- Scholars in these and related streams of research have actively engaged with policymakers, advocating for increased university involvement with society and industry to promote economic growth.
- In the present day, universities and their researchers are involved in three core activities: teaching, research, and the “third mission,” which encompasses academic commercialization and various forms of academic engagement. These activities result in a range of outcomes and in impacts on both the academic and economic landscapes.

2.3 Redefining academic engagement analysis: knowledge network and knowledge creation insights

This section provides an account of the literature relating to knowledge networks and knowledge creation. This section consists of two parts: part one relates to core concepts and approaches, while part two concentrates on knowledge networks mainly in science but also in technology.

2.3.1 Core concepts and approaches

This section begins by taking a step backwards and defining knowledge and knowledge networks. Subsequently, it outlines research pertaining to the sociocentric and egocentric perspectives. The former encapsulates and directs its attention toward the entire network, whereas the latter revolves around a central actor within the network, commonly referred to as the ego (Marsden, 2002).

Defining knowledge and knowledge networks

Information is an artifact, built on data, that can yield knowledge, and it can be identified as a flow of messages (Nonaka, 1994), or as a signal (Dretske, 1981), that carries information. Information only becomes knowledge when it is obtained through cognitive efforts and integrated into people's minds (Davenport & Prusak, 1998; Nonaka, 1994; Stonier, 1990), so knowledge is, in that sense, personal (Dretske, 1981; Nonaka, 1994; Polanyi, 1958). One can also say that knowledge is therefore a hierarchal concept (Smith, 2002).

What knowledge entails, and especially whether it must be absolutely true or not, has been the subject of philosophical debate for millennia—dating back to the famous Greek philosophers (cf. Ayer, 1956; Chisholm, 1977; Dutant, 2015; Gettier, 1963). Further elaborating, more than 2000 years ago Plato famously argued in his dialogue *Theaetetus* that knowledge can be defined as "true belief" (Chappell, 2019). This was recently echoed by Ayer (1956), who concluded that the "necessary and sufficient conditions for knowing that something is the case are first that what one is said to know be true, second that one be sure of it, and third that one should have the right to be sure" (p. 34). However, this is in stark contrast to other philosophers, such as Gettier, who have argued that knowledge does not need to be true in the absolute sense (Gettier, 1963; see also Chisholm, 1977; Dutant, 2015).

Although this debate is still ongoing, this dissertation adopts the definition of knowledge as rational justified belief, following Gettier (1963) and Chisholm (1977). Rational justification, which replaces the notion that knowledge must be, in its absolute sense, true, suggests that knowledge may, in some circumstances, turn out to be false; however, it is still defined as knowledge, as long as it was based on rational justification such as empirical findings suggesting that it was true. This working definition is furthermore closely aligned with the views of Karl Popper, who argued that all knowledge is provisional/hypothetical in the sense that we can never truly prove our scientific theories; rather, we can merely provisionally confirm them, or ultimately, conclusively refute them (Popper, 1935, 1965).

Before proceeding to the next section, it is arguably also important to distinguish two types of knowledge, namely, explicit knowledge and tacit knowledge. According to Polanyi (1958, 1966), explicit knowledge refers to knowledge that is objective and structured, making it easier to communicate and document. Tacit, or implicit, knowledge, on the other hand, represents knowledge that is subjective and possesses a personal quality, rendering it more challenging to formalize and communicate or document. Numerous empirical studies have been undertaken to support this theory (e.g., Edmondson et al., 2003; Hansen, 2002; Levin & Cross, 2004; Reagans & McEvily, 2003; Zander & Kogut, 1995).

In this Ph.D. dissertation, the term "knowledge network" is adopted according to the perspective of Phelps et al. (2012). Per their definition, a knowledge network is "a set of nodes—individuals or higher level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge—interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge" (Phelps et al., 2012, p. 1117). In a knowledge network, nodes (such as individuals) participate in collaborations aimed at acquiring, sharing, and generating knowledge. These collaborations, symbolized by edges within the network, contribute to the accumulation of human capital at individual nodes. In the realm of science and technology, knowledge networks represent a concept that encapsulates the intricate web of knowledge-related interactions among diverse elements within a system. In this context, the outcomes of these endeavors, such as scientific publications and technological patents, are viewed as manifestations of knowledge networks. Within this framework, authors and inventors function as nodes, while publications and patents act as the connecting edges between them.

In their comprehensive literature review on knowledge networks, Phelps et al. (2012, p. 1119) argued that four main types of properties affect knowledge outcomes (with knowledge outcomes referring to "knowledge creation, knowledge transfer and learning, and knowledge adoption"): structural properties, nodal properties, relational properties, and knowledge properties.

Structural properties refer to research examining how the structure of the network influences knowledge outcomes (e.g., the overall knowledge network's density and the nodes' centrality in the knowledge network).

Nodal properties refer to research examining how different node characteristics and traits affect knowledge outcomes (e.g., the nodes' level of education).

Relational properties refer to research examining how the relationships between nodes affect knowledge outcomes (e.g., the strength of the relationships between nodes).

Knowledge properties refer to research examining how different kinds of knowledge influence knowledge outcomes (e.g., the type of knowledge being transferred or created).

The various properties of a knowledge network are interconnected (Borgatti & Cross, 2003; Kossinets & Watts, 2009; Reinholt et al., 2011). This implies that to accurately analyze a knowledge network, one must consider not only the structure of the network but also the attributes of the nodes, the relationships among them, and the type of knowledge being transmitted and/or created. Comprehending these dynamics is of paramount importance in grasping knowledge creation, transfer, learning, and adoption—cornerstones of economic growth (Lucas, 1988; Menger, 1871; Romer, 1990).

Sociocentric approach

The structure of the entire network has an impact on knowledge outcomes (Phelps et al., 2012). Typically, the network structure is assessed by its density, which informally quantifies the extent to which individuals within the network are connected (Knoke & Yang, 2020; Koschützki et al., 2005). This fundamental measure was originally introduced by Proctor and Loomis in 1951, as documented by Koschützki et al. (2005).

At one extreme, if no individuals are connected, it implies that all knowledge creation occurs in isolation, with no sharing of created knowledge among individuals. As previously argued in this dissertation, this scenario is far from ideal. Conversely, at the opposite extreme, if all individuals are interconnected, it indicates that at least some aspects of knowledge outcomes are shared among every individual within the network. For a large network, this seems unattainable and highly ineffective; thus, there seems to be a "sweet spot" with regard to overall connectedness that supports productive and successful knowledge outcomes.

The underlying conceptual foundation for why higher density can positively affect knowledge outcomes is that density increases both the amount of information an individual can receive and the levels of obligations, expectations, trustworthiness, and coordination among individuals, as argued by Coleman (1988, 1990). However, excessive density can theoretically, in the long run, negatively affect knowledge outcomes due to the redundancy of old information and the lack of novel information (Burt, 1992; Granovetter, 1973). In his famous article, "The strength of weak ties," published more than 50 years ago, Granovetter (1973) examined the concept of "weak ties," which has since become foundational in the field of social network analysis. His groundbreaking work challenged traditional assumptions about the role of strong ties (i.e., close relationships) versus weak ties (i.e., more distant acquaintances) in the diffusion of information and social influence within networks. In short, his findings suggest that weak ties are important for bridging social distance and allowing the spread of information beyond one's immediate circle of contacts.

Empirical research investigating this phenomenon and knowledge outcomes indicates that higher overall connectedness is positive for knowledge outcomes, and this has been found to be true in several settings, such as U.S. patent data (Singh, 2005), small- to medium-sized enterprises (SMEs) in China (Cong et al., 2017), and the chemicals, automotive, and pharmaceutical industries (Gilsing et al., 2008); however, excessive density has been shown to have a detrimental effect on knowledge outcomes (Gilsing et al., 2008), as theorized.

Egocentric approach

The egocentric perspective places a focal actor (i.e., the ego) at its core. This perspective has two fundamental dimensions: network positions and roles. Network position pertains to an actor's placement within the broader network, signifying their location relative to other actors within the network. Conversely, the concept of roles is rooted in the specific interactions and relationships an actor maintains within their immediate network. In other words, "having a definition of role is not the same as having a definition of position. Positions can be thought of as specific locations in a particular social structure; roles, in contrast, should provide a way of classifying positions across any number of distinct social networks, or within different parts of the same network" (Winship & Mandel, 1983–1984, p. 316).

The relationship between network position and network role is thus twofold. To start with, different network positions can be categorized into distinct network roles, for example, using betweenness centrality scores to define intermediaries among actors in the network who have scores above the 75th percentile. By way of contrast, specific network roles diverge from network positions in that the former focus on identifying unique roles within the network based on connection patterns within an actor's immediate set or sets of contacts, while the latter focus on identifying an actor's position relative to all other actors in the network (Koschützki et al., 2005; Lerner, 2005).

What follows is a review on these two aspects, starting with network positions.

Network positions

The specific position within a network can influence knowledge outcomes (Phelps et al., 2012). This effect arises from the fact that distinct positions within the network are exposed to different quantities and qualities of information, with more central positions generally considered advantageous (Borgatti, 2005; Ebadi & Utterback, 1984; Freeman, 1978/1979).

It is crucial to acknowledge, however, that the concept of centrality possesses some degree of ambiguity, as it pertains to various conceptual foundations (Borgatti, 2005; Freeman, 1978/1979). In essence, centrality encompasses multiple meanings. Therefore, when discussing centrality, it is imperative not merely to allude to "centrality" in general terms but rather to specify the particular type of centrality under consideration. Over the years, numerous centrality measures have been developed.[7]

[7] For example, the CINNA package in R has 49 different centrality measures (Ashtiani et al., 2023).

This dissertation will concentrate on three of the most prominent ones, i.e., degree centrality, eigenvector centrality, and betweenness centrality, each of which emphasizes distinct and critical aspects of centrality.

The concept of degree centrality focuses on connectedness, specifically referring to the number of direct collaborators an actor possesses (Freeman, 1978/1979). Although this measure is intuitively understandable, it is essential to briefly delve into its underlying conceptual foundation to mitigate any potential ambiguities.[8] On one hand, a higher degree centrality corresponds to greater exposure to information, leading other actors in the network to perceive individuals with higher degree centrality as major channels of information (Freeman, 1978/1979). On the other hand, a point not addressed by Freeman (1978/1979) is that higher degree centrality is also more time-consuming (Coleman, 1988, 1990) and may result in redundant information (Burt, 1992; Granovetter, 1973). This suggests that an optimal degree centrality exists, contingent on various factors such as the time commitment of each collaborator and the novelty of the information they possess.

Extensive research has explored this phenomenon, consistently supporting the outlined concepts. Specifically, numerous studies have identified a positive correlation between degree centrality and knowledge outcomes across various settings, including the chemical industry (Ahuja, 2000), the pharmaceutical industry (McKelvey & Rake, 2016), a multinational electronics company (Hansen, 2002), and a Swedish information and technology company (Björk & Magnusson, 2009). Conversely, excessive degree centrality has been found to be detrimental, as it demands excessive time and energy (Hansen, 2002; McFadyen & Cannella Jr., 2004). Consequently, it appears that the number of collaborators an individual

[8] In fact, when the specific measure was first introduced by Shaw, he did not even bother discussing its conceptual foundation (Shaw, 1954).

possesses and the knowledge outcomes from collaboration with them follow a well-established U-shaped curve.

The concept of the eigenvector centrality model underscores the influence and prestige of actors within their immediate network by focusing not on the quantity of connections but on their quality. It specifically quantifies the number of direct collaborators an actor has, with their contributions being weighted by their eigenvector centralities (Bonacich, 1972, 1987). The foundational idea behind this measure is the notion that individuals connected to highly influential actors, who in turn exert significant influence over other actors (who, in their own right, influence additional actors), also possess influence, even if their degree centrality is low (Borgatti, 2005). In other words, individuals with high eigenvector centrality gain exposure to more information because their collaborators are exposed to high levels of information, not merely due to having numerous collaborators, as is the case with degree centrality. Furthermore, these individuals exert a greater impact on the network, assuming they can influence highly connected individuals, who subsequently influence a multitude of others. Put plainly, an individual's influence is not solely determined by their degree centrality (Cook & Emerson, 1978).

On one hand, hypotheses have been formulated, and empirically supported with data on the Korean semiconductor industry, suggesting that high eigenvector centrality positively affects knowledge outcomes (Kim, 2019). This positive effect is argued to result from the individual's connections to influential and prestigious figures who are exposed to extensive knowledge flows. On the other hand, in the U.S. pharmaceutical industry, hypotheses have been proposed and supported contending that high eigenvector centrality exerts a negative influence on knowledge outcomes (Dong & Yang, 2016). This negative effect is attributed to connections with influential and prestigious individuals who primarily possess well-established knowledge, which has a diminished potential to generate subsequent knowledge outcomes. In contrast, other research in the pharmaceutical industry suggests that eigenvector centrality has a non-significant effect on knowledge outcomes (McKelvey & Rake, 2016).

As an interim conclusion, it is apparent that being connected to influential individuals plays a pivotal role in knowledge outcomes, although it may come at the cost of limited exposure to novel information.

The concept of betweenness centrality focuses on the intermediary role, referring to the extent to which one individual appears on the shortest path connecting other actors in the network (Freeman, 1977, 1978/1979). While Freeman is arguably the one who popularized the concept as we know it today, it was first introduced by Anthonisse (1971) as flow centrality. According to Burt (e.g., 1992, 1997), betweenness centrality is a common measure for detecting whether an individual spans structural holes, which are defined as the "relationship of nonredundancy between two contacts" (Burt, 1992, p. 18). Nonredundancy refers to contacts that are either directly disconnected (i.e., there is no direct contact [edge] between them) or indirectly disconnected (i.e., the contacts' knowledge network consists of different actors).[9] One can clearly see how individuals with high betweenness centrality span many structural holes.

The structural hole theory postulates that individuals spanning multiple otherwise poorly connected (knowledge) networks may benefit from transferring diverse information between these networks. This gives rise to specific information benefits, such as access to new information and/or control benefits, such as controlling the flow of new information (Burt, 1992, 1997; Freeman, 1977, 1978/1979).

[9] Burt (1992) referred to the former, directly disconnected contacts, as redundancy by cohesion, and the latter, indirectly disconnected contacts, as redundancy by structural equivalence.

Importantly, one underlying assumption of this theory is that different knowledge networks provide different information. Therefore, individuals connected to several different knowledge networks know about, have a hand in, and exercise control over more opportunities.

Assuming that the theory holds true, there are at least two downsides to having too high a betweenness centrality (i.e., spanning too many structural holes). First, the information an individual receives via collaborations that span a structural hole is more difficult to assimilate because it is different—it is novel. This is true because an individual's capacity to assimilate information is largely a function of prior related knowledge (Cohen & Levinthal, 1990). A second drawback is that trust development between collaborators is inhibited due to lower levels of obligations (Coleman, 1988, 1990).

Regarding empirical findings, the results are mixed. High levels of structural holes (or betweenness centrality) have been found to positively affect knowledge outcomes (Rost, 2011; Ter Wal et al., 2016), have no effect on knowledge outcomes (McKelvey & Rake, 2016), or negatively affect knowledge outcomes (Ahuja, 2000; Gilsing et al., 2008; Ter Wal et al., 2016). When analyzing these papers more deeply, it further seems that whether or not spanning structural holes is positive for an individual depends on the structure of cognitive proximity and/or the strength of the relationship between collaborators.

Specifically, Ter Wal et al. (2016) found that spanning structural holes is positive when the cognitive proximity between collaborators is high, meaning they have a more similar knowledge base; conversely, it was negative when they had low cognitive proximity. Ahuja (2000) found that spanning a structural hole is positive when the relationship between collaborators spanning that structural hole is strong and negative when their relationship is weak.

In conclusion, these findings imply that whether spanning structural holes is positive or negative for knowledge outcomes mainly depends on the collaborators' cognitive proximity and how well they know each other.

Roles

One can conceptualize different network roles as unique structural signatures, as observed in network analysis (Skvoretz & Faust, 2002). This line of research thus rests on the foundational premise that various "social roles begin from a structural foundation in simple commonalities in behavior" (Gleave et al., 2009, p. 2), meaning that different structural positions (or signatures) within the network correspond to distinct behaviors.[10]

To illustrate this concept, consider the example presented in Figure 2.4, below, which depicts three ego networks. These networks differ in the pattern of connections among neighbors while maintaining a consistent number of neighbors for each ego. Specifically, the ego's degree centrality remains constant while the number of edges among the ego's contacts varies. In this example, the key network metric is the local clustering coefficient, defined as the ratio of observed connections among an actor's neighbors and the total possible connections among an actor's neighbors (Watts & Strogatz, 1998).[11]

In Case A, this coefficient equals 0/10, in Case B, 5/10, and in Case C, 10/10. As previously elucidated, the ego in Network A is relatively more likely to receive novel

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[10] The broader idea of *social roles* is a well-established and central idea within sociology (e.g., Merton, 1968; Parsons, 1951). For a broader and more thorough discussion of roles, I recommend the *Handbook of Sociological Theory*, Ch. 11 by Stryker (2001) and Ch. 12 by Turner (2001).

[11] Mathematically, this equals $\frac{\text{\# of observed connections}}{(\frac{k(k-1)}{2})}$ for an undirected network, where *k* is the number of neighbors (Watts & Strogatz, 1998).

information from their diverse neighbors, albeit at the expense of lower levels of obligations, expectations, trustworthiness, and coordination. In contrast, the ego in Network C is predisposed, over the long term, to encounter redundant information and a lack of novel insights (cf. Burt, 1992; Coleman, 1988, 1990; Granovetter, 1973). To summarize this straightforward yet, hopefully, enlightening example, roles can be attributed to the distinct egos, particularly distinguishing A from C. The ego in Network A assumes the role of a coordinator, whereas the ego in Network C assumes the role of a team player.

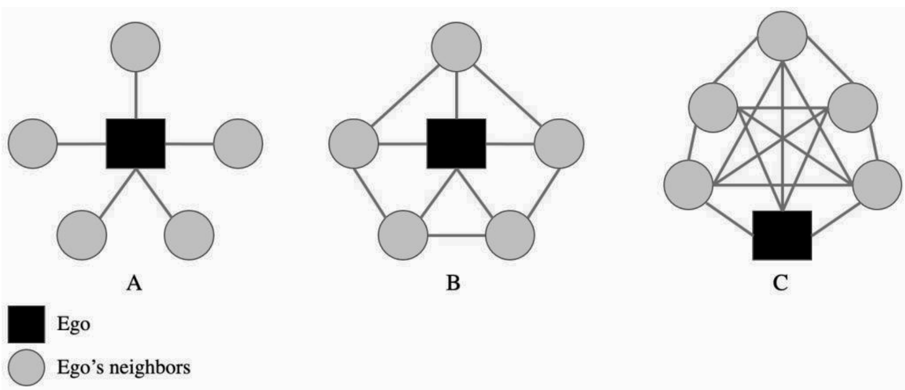

Figure 2.4. Different neighbors' behavior suggest different ego network roles.

The role that has attracted the most attention in the scientific literature is that of the knowledge network broker. As mentioned in the previous discussion, betweenness centrality is often considered a proxy measure of brokerage. Nevertheless, some scholars argue for the importance of distinguishing between proxies of brokerage, such as betweenness centrality, and the distinct role of serving as a knowledge network broker. This differentiation arises because betweenness centrality computes the shortest paths connecting other actors within the network, while "long paths do not seem, either empirically or intuitively, to play a very important role in purposive social interaction" (Gould & Fernandez, 1989, p. 95).

Taking these considerations into account, Gould and Fernandez (1989) formulated an original theoretical framework delineating various brokerage roles, which they referred to as "brokerage behaviors," for actors within transaction networks. Their work introduced a typology consisting of five distinct roles, as depicted on the left-hand side of Figure 2.5, below. The figure illustrates these roles, with the first type being the coordinator, also known as the local broker. This role involves facilitating communication among actors belonging to the same group as the coordinator. The second type is the itinerant, also known as the cosmopolitan, which entails facilitating communication among actors from different groups than that of the itinerant. The third type is the gatekeeper, responsible for enabling communication from an actor in a different group to an actor in the same group as the gatekeeper. The fourth type is the representative, facilitating communication from an actor in the same group to an actor in another group, acting as a representative. Lastly, the fifth type is the liaison, aiding communication from an actor in one group to an actor in a third group, operating as a liaison. In parallel with betweenness centrality serving as a proxy for being an intermediary, the distinct network roles elucidated above are not absolute measures of an actor's degree of engagement in that role; instead, they offer approximations of an actor's potential to fulfill such a role (Gould & Fernandez, 1989).

Expanding on this foundational work, Lissoni (2010) adapted the concept of brokering roles to better suit their analysis of academic inventors affiliated with Italian universities, with a particular focus on their activities related to patents. Lissoni's refined categorization of four brokerage positions is depicted on the right-hand side of Figure 2.5. Academic researchers assume the role of brokers when they engage in collaborations between two industrial researchers. They take on the role of gatekeepers when they participate in collaborations between an academic researcher and an industrial researcher. The role of liaison emerges when they collaborate between an academic student and an industrial researcher. Finally, they serve as coordinators when facilitating collaborations between two other academic researchers.

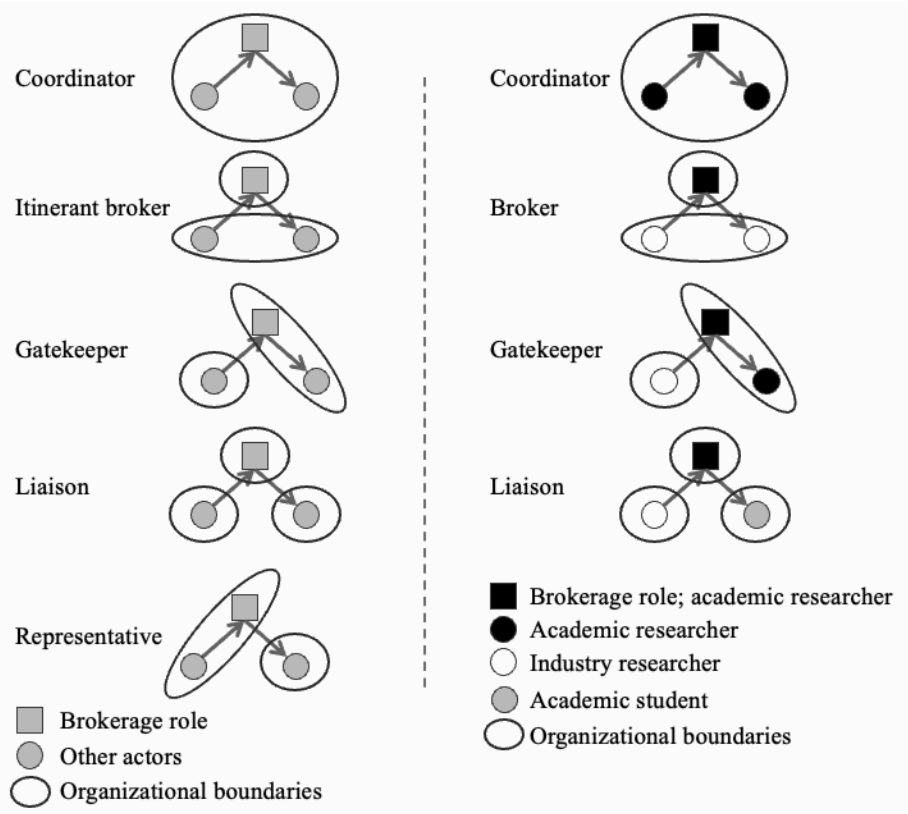

Figure 2.5. Different brokerage behaviors/types according to Gould and Fernandez (1989; left) and Lissoni (2010; right).

Employing a negative binomial model, Lissoni (2010) conducted an analysis showing that "only a minority of academic inventors play important brokerage roles, and that scientific productivity, intensity of patenting activity, and the type of patent assignees (companies vs. universities or individuals) are all correlated to such roles" (p. 844). Distinctions were also found among these roles. Specifically, Lissoni identified noteworthy correlations between the number of university-owned patents signed by academic researchers and high brokerage scores for gatekeepers, coordinators, and liaisons. However, no significant effects were observed for the broker role. Conversely, negative correlations were noted between the number of individually owned patents signed by academic researchers and high brokerage scores for brokers and gatekeepers, while no significant effects were found for the coordinator and liaison roles.

These findings align well with the nature of the different roles. For instance, the broker role inherently involves an academic researcher collaborating between two industrial researchers; consequently, the negative correlation with individually owned patents is unsurprising, given the expectation that firms often hold patent ownership. Lissoni (2010) also effectively highlighted the fact that actors can simultaneously occupy multiple roles to varying extents. This insight underscores the unsurprising notion that actors possess multiple structural signatures contingent on how the network is examined.

Building on the original work of Gould and Fernandez (1989), Llopis and D'Este (2022) conducted a large-scale study of biomedical scientists. They applied a cost–benefit perspective (see Dahlander et al., 2016) to examine the importance of facilitating innovation through various broker roles. The cost–benefit perspective results from the interplay of two opposing forces: the non-redundant knowledge provided by network contacts and the costs associated with integrating that knowledge from the network. Llopis and D'Este distinguished between balanced triadic structures and unbalanced ones. The former denotes collaborations characterized by mutual cooperation and positive relationships among members, which tend to be more stable and avoid relational tensions; in contrast, the latter are less stable and can lead to stress and discomfort among their members.

In line with Gould and Fernandez's terminology, Llopis and D'Este (2022) focused on four roles: gatekeeper, itinerant, liaison, and coordinator. They classified gatekeeper and itinerant roles as balanced because two out of the three members belong to one organization, resulting in a favorable balance between accessing new information and ease of integrating said information. On the other hand, liaison and coordinator roles were associated with unbalanced triadic structures, where either all members come from the same organization or none do. This configuration results in limited access to knowledge or difficulties in assimilating that knowledge.

Their findings are aligned with their theoretical framework. Specifically, balanced open triads, represented by gatekeepers and itinerants, played a more crucial role in facilitating individual innovativeness than did unbalanced open triads, which included coordinators and liaisons.

2.3.2 Knowledge networks in science and technology

The driving force behind the growing importance of knowledge-related collaborations lies in the continuous expansion of the total volume of knowledge worldwide, which far surpasses an individual's capacity to comprehend it.[12] As a result, the process of generating new knowledge becomes progressively more challenging, as individuals need to acquire a greater amount of knowledge before they can effectively contribute to new knowledge. This highlights the necessity of collaborative efforts, in which individuals can pool their knowledge and expertise to collectively advance the frontiers of knowledge.

The importance of understanding research collaborations is further supported by various studies that examine the age at which researchers achieve significant milestones in their careers. For example, studies analyzing the age at which researchers publish their first article in prestigious journals (Brendel & Schweitzer,

[12] Here, the term "collaboration" broadly refers to "social processes whereby human beings pool their human capital for the objective of producing knowledge" (Bozeman et al., 2013, p. 3).

2019) and the age of Nobel Prize laureates (Jones, 2010) demonstrate a trend of knowledge advances being achieved by individuals at later stages of their careers. In the context of publishing research articles, Brendel and Schweitzer (2019) exclusively focused on the field of mathematics. Their findings revealed that the average age at which authors publish their first article in a top-ranked mathematics journal had increased by five years over a span of 64 years. In greater detail, the average age rose from 28.3 years in 1950 to 33.3 years in 2013, suggesting that researchers are achieving significant research contributions at later stages of their careers.[13] These empirical findings validate the necessity of collaborative efforts in research.

To stay at the forefront of knowledge in a particular domain, specialization is essential (Brendel & Schweitzer, 2019; Smith, 1776). One consequence of specialization is that knowledge becomes heterogeneously distributed within society, increasing the need for collaboration. During the 20th century, researchers began addressing this "burden of knowledge" by adopting the division of labor, specializing, and transitioning from individual work to teamwork, as mentioned above. For instance, Wuchty et al. (2007a, 2007b) analyzed over 13 million scientific papers published in science and engineering-related journals. They found that in 1955, approximately 50% of these papers were published by teams, while in 2000, the proportion exceeded 80%.

Furthermore, there is evidence indicating that this shift from individual to team-based research has predominantly involved teams with three or more members, while the prevalence of working in pairs has remained relatively stable (Kuld & O'Hagan, 2018; WIPO, 2019; Wuchty et al., 2007a). Additionally, research collaborations are

[13] Similar findings have been made in relation to the age at which inventors file their first patent (e.g., Jones, 2009).

increasingly global in nature (Adams, 2013; Adams et al., 2005; Carayannis & Laget, 2004; Kuld & O'Hagan, 2018; Larivière et al., 2015; Vincent-Lancrin, 2006; WIPO, 2019), indicating a significant reduction in the costs associated with collaboration, for example, due to technological advances (Agrawal & Goldfarb, 2008; Cairncross, 2001; Forman et al., 2018) and decreased travel expenses (Catalini et al., 2016; Perry, 2014).

Regarding the specialization within actual research collaborations, evidence suggests that teams as a whole are not becoming more specialized over time. Empirical studies focusing on interdisciplinary research, which involves the integration of knowledge, techniques, and perspectives from multiple disciplines, indicate that research collaborations are moving toward greater integration of diverse knowledge and expertise, rather than specialization and isolation within specific disciplines (Noorden, 2015; Porter & Rafols, 2009). For instance, Noorden (2015) observed significant growth in interdisciplinary research in the natural sciences and engineering between 1980 and 2010. Similarly, Porter and Rafols (2009) found a comparable trend, although less pronounced, in their study of the engineering, electrical, and electronic fields from 1975 to 2005. These findings suggest a shift toward interdisciplinary collaboration, emphasizing the importance of integrating diverse perspectives and knowledge across disciplines in research collaborations.

Maximizing the potential for knowledge outcomes within collaborations presents a multifaceted challenge. To effectively address this challenge, one must consider various factors, including (but not limited to) team size, team familiarity, the unique human capital each member contributes, the similarity of their knowledge bases, and their geographic proximity (Bozeman et al., 2013; Phelps et al., 2012). According to the framework proposed by Phelps et al. (2012), these components can be sorted into two categories: nodal properties and relational properties; academic rank exemplifies a nodal property, while relationship strength exemplifies a relational property.

The remainder of this section will delve into the literature on nodal and relational properties, emphasizing the following four dimensions: team size and its implications, the impact of knowledge-related diversity in the team, the longevity of the team's collaboration, and the geographical proximity of team members. These are identified as four aspects that the research on academic engagement should consider more explicitly.

Team size

Team size—which straightforwardly refers to the number of collaborators in a collaboration—is a critical factor in collaborative endeavors. One reason why teams are superior in terms of knowledge creation to working solo is that all collaborators, in this case, researchers, bring unique human capital derived from their prior experiences, including their education and work backgrounds. By pooling individuals' human capital and facilitating the exchange of information and ideas, knowledge outcomes are enhanced (Becker & Murphy, 1992; Bozeman et al., 2013; Katz & Martin, 1997; Phelps et al., 2012; Powell & Grodal, 2006). However, the merits of larger teams must be weighed against potential drawbacks, such as greater management and coordination complexities (Becker & Murphy, 1992; West & Anderson, 1996) and the elevated risk of "groupthink" (Janis, 1982; Whyte, 1998).

The current era is characterized by a fragmented knowledge domain due to the division of labor (McDowell & Melvin, 1983), underscoring the relevance of collaborative teamwork. This approach not only promotes the efficient distribution of tasks based on individual proficiencies but also minimizes redundant efforts, a notion posited by Becker and Murphy as early as 1992: "A more extensive division of labor raises productivity because returns to the time spent on tasks are usually greater to workers who concentrate on a narrower range of skills" (p. 1157).

In line with this perspective, both teams enriched by members possessing substantial human capital and larger teams appear superior to their smaller counterparts in terms of both knowledge outcomes and productivity, given their potentially greater cumulative human capital and task division benefits, all else being equal. Nonetheless, the caveats associated with larger teams, including the conjectured challenges of effective management and coordination (Becker & Murphy, 1992; West & Anderson, 1996) as well as the vulnerability to groupthink (Janis, 1982; Whyte, 1998), mandate the determination of optimal team size. This optimal size is contingent on the intricacy of the collaborative endeavor.

Empirical investigations have identified the pivotal influence of collaborating with individuals having greater human capital in terms of scientific knowledge, approximated either through indicators such as having a doctoral degree or publishing in esteemed journals, or through the accomplishment of superior scientific and knowledge outcomes (Anderson & Richards-Shubik, 2019; Gruber et al., 2013; Schilling & Green, 2011). In more detail, research reveals that elevated prior average journal impact factor (JIF) scores are positively linked to future higher JIF scores (Anderson & Richards-Shubik, 2019), and greater prior article impact increases the likelyhood of generating future high article impact papers alongside fostering innovation (Schilling & Green, 2011). Notably, losing the possibility of collaborating with a star scientist has also been found to negatively affect subsequent scientific outcomes (Azoulay et al., 2010).

Furthermore, empirical data underscore the role of teams in ensuring both the novelty of research and its overall scientific impact. Regarding novelty, one study revealed that co-authored papers were, on average, 38% more likely to introduce novel insights than were single-authored papers (Uzzi et al., 2013). Additionally, another study found that the inclusion of an extra collaborator increased the likelihood of creating a novel article by 10% on average (Carayol et al., 2019).

While teams seem to be superior to working alone, overly large teams may hinder the development of novelty. To elaborate, Wu et al. (2019) conducted an extensive analysis of over 24 million research papers spanning the years 1954 to 2014. Their findings suggest that, within this timeframe, smaller teams were more likely to introduce innovative ideas and opportunities, whereas larger teams tended to concentrate on the advancement of existing ones. Additionally, a similar pattern emerged in the realm of technology, encompassing patents and software. Figure 2.6, below, provides additional detail of the relationship between team size and two critical metrics: median citations and average disruption percentile.

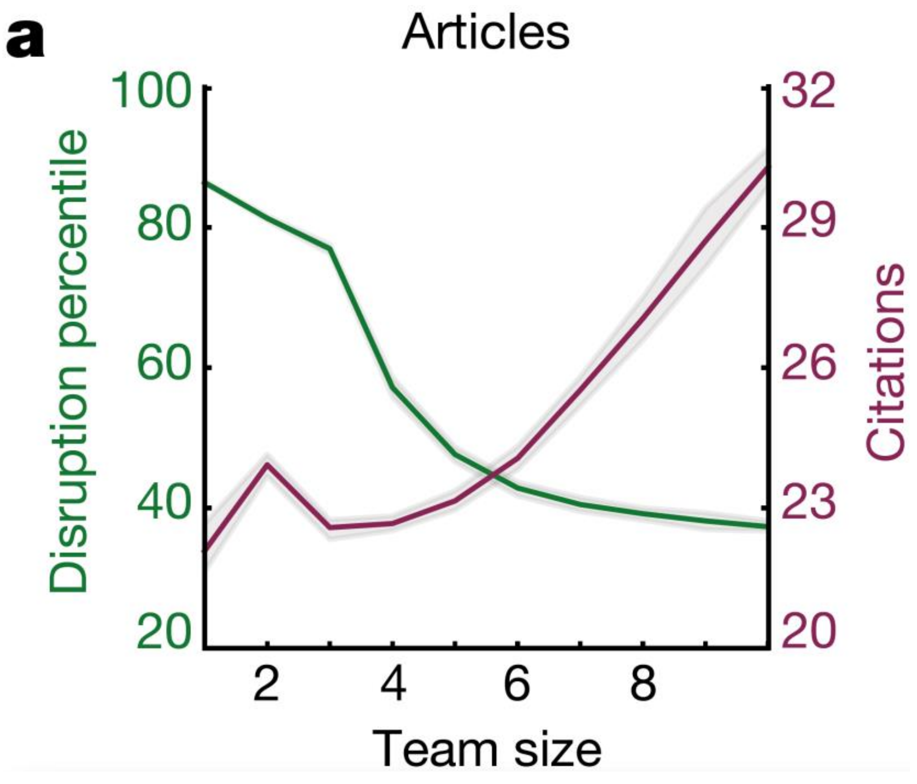

Figure 2.6. Smaller teams disrupt, whereas larger teams develop (Wu et al., 2019).

The paper by Wu et al. (2019) supports the benefits of teamwork in terms of increasing the article impact of publications. In addition to that study, two other studies have demonstrated that co-authored papers receive, on average, approximately 110% more citations than do their single-authored counterparts (Gazni & Didegah, 2011; Wuchty et al., 2007a). An additional study has shown that papers authored by teams consisting of two to four members receive, on average, 30–90% more citations than do single-authored papers (Kuld & O'Hagan, 2018). It is worth noting that multi-authored papers consistently exhibit higher article impact, in terms of citation rates, even when accounting for self-citation biases (Larivière et al., 2015).

Research productivity also encounters a positive stimulus from collaborative endeavors (Anderson & Richards-Shubik, 2019; Ductor, 2014, 2015; Hollis, 2001; Lee & Bozeman, 2005); however, when discounting for the number of collaborators, the findings are more ambiguous. Some findings indicate positive effects (Ductor, 2014, 2015), while others indicate negative effects (Hollis, 2001; Lee & Bozeman, 2005). There is further evidence suggesting that partnering with productive co-authors positively affects an individual's subsequent scientific outcomes (Ductor et al., 2014), and that collaborations with highly educated individuals (Gruber et al., 2013) and successful co-authors (Stuart, 2000) similarly have positive effects on knowledge outcomes.

Knowledge-related team diversity

Team diversity encompasses various dimensions, such as job-relevant diversity and background-related diversity (Hülsheger et al., 2009). In this dissertation, however, the focus pertains to the similarity of collaborators' knowledge bases. This concept will be referred to as knowledge-related team diversity, or as team members' cognitive proximity, more in line with the terminology used by Boschma (2005) and Nooteboom (2007).

Considering the arguments established earlier, it is plausible to assume that individuals ideally prefer collaborators who are as knowledgeable as humanly possible, especially in domains where their own expertise is limited. This suggests a desire for highly unique human capital among collaboration partners, vis-à-vis the relevant phenomena. Analogous to the premise of larger teams having greater collective human capital, greater knowledge-related team diversity should theoretically translate to heightened combined human capital, implying that teams characterized by increased knowledge-related diversity should yield superior knowledge outcomes, all else being equal (Schilling & Green, 2011).

Nevertheless, as previously highlighted, the potential challenges inherent to diversity must be acknowledged, such as difficulty in comprehending one another because an individual's capacity to assimilate information is largely a function of prior related knowledge (Cohen & Levinthal, 1990). Consequently, collaborators with highly dissimilar knowledge bases might face hindrances in effective communication and knowledge exchange, whereas completely similar knowledge bases also impede meaningful knowledge transfer.

This suggests that there exists an optimal level of knowledge-related team diversity, i.e., an ideal cognitive distance somewhere between these two extremes (Boschma, 2005; Nooteboom et al., 2007). In the realm of knowledge creation, particularly in contexts involving substantial tacit knowledge, a team that is more homogeneous concerning knowledge bases is advocated, given the challenges in conveying tacit knowledge (Nonaka, 1994; Polanyi, 1958, 1966). It is essential to note that not all team members are required to possess a substantial common knowledge base. Some members may serve as knowledge brokers, acting as facilitators to enable effective knowledge transfer among a diverse team of individuals (Leifer & Delbecq, 1978; Tushman, 1977; Tushman & Scanlan, 1981). Detailed discussions of the significance of various roles have been previously addressed in Section 2.3.1.

Empirical investigations pertaining to knowledge-related team diversity underscore its significance for knowledge outcomes (Bercovitz & Feldman, 2010; Broekel & Boschma, 2012; Lane & Lubatkin, 1998; Nooteboom et al., 2007; Rodan & Galunic, 2004). Additionally, findings suggest an inverted U-shaped relationship between cognitive proximity and knowledge outcomes, implying that excessive cognitive proximity can be counterproductive (Broekel & Boschma, 2012; Nooteboom et al., 2007).

In greater detail, Nooteboom et al. (2007) conducted a quantitative analysis to examine the contrasting impacts of small and large cognitive distances on the cognition of firms engaged in technology-based alliances. They explored the implications of this combined effect on firm performance in terms of explorative and exploitative innovation in the chemicals, automotive, and pharmaceutical industries. In this context, exploitation pertains to the refinement and extension of existing technologies, while exploration involves experimentation with novel alternatives. The key finding of the study was that the cognitive distance between firms exhibited an inverted U-shaped effect on innovation performance, irrespective of whether the innovation was explorative or exploitative. However, the positive impact on firms was significantly greater when they engaged in more radical and explorative alliances than more exploitative alliances, aligning with the anticipated outcomes. Consequently, it appears "there is a trade-off to be made between the opportunity of novelty value and the risk of misunderstanding" (Nooteboom et al., 2007, p. 1030).

Furthermore, research exploring job-related diversity, characterized by variances in job- or task-related attributes, corroborates the importance of cognitive team diversity (Adams, 2013; Hülsheger et al., 2009; Larivière et al., 2015). Besides these findings, empirical investigations indicate that boundary spanners play a crucial role in facilitating knowledge creation (Conway, 1995; Cross & Prusak, 2002; Curseu & Pluut, 2018; Patriotta et al., 2013; Tushman, 1977; Tushman & Scanlan, 1981).

For instance, Curseu and Pluut (2018) conducted an experiment involving bachelor students, revealing that knowledgeable boundary spanners compensated for the group's limited absorptive capacity. This underscores the indispensable role of boundary spanners, particularly when collaborators possess disparate knowledge bases. Moreover, Patriotta et al. (2013), drawing on a case study of a global organization, found that a critical managerial role is to act as a "higher-level intermediary": this involves providing "coordination across functional and geographical boundaries by making knowledge sources available, connecting the parties to the transfer, and generating opportunities for knowledge exchange" (p. 515). Simply put, the absence of these roles in an organization leads to a less favorable outcome.

Team longevity

Team longevity, denoting the duration of a collaboration or multiple collaborations over time, hinges on the underlying assumption that it corresponds to the strength of relationships among team members—i.e., the older the team, the more robust the relationships. Research suggests that prolonged collaborations offer several advantages. For instance, over time, team members cultivate enhanced trust and deeper mutual understanding of their diverse incentive structures, objectives, strengths, and weaknesses (Bruneel et al., 2010; Kunttu & Neuvo, 2019), which in turn facilitates efficient task allocation and improved productivity. Additionally, extended collaboration durations empower team members to delve deeply into business-related inquiries (Rivera-Huerta et al., 2011).

Nevertheless, long-lived collaborations also harbor potential drawbacks. A potential risk is that shared experiences within long-standing teams could lead to a convergence of human capital and make them less inclined to challenge the status quo, reducing the likelihood of having innovative ideas (Guimerá et al., 2005; Katz, 1982; West & Anderson, 1996).

Empirical investigations lend credibility to the notion that extended collaborations augment researchers' productivity (Garcia et al., 2020; Rivera-Huerta et al., 2011) and enhance knowledge outcomes (Crescenzi et al., 2017; Kachra & White, 2008; Reagans & McEvily, 2003; Rost, 2011). However, some research suggests that the effect on knowledge outcomes might not be statistically significant (Hülsheger et al., 2009; West & Anderson, 1996). Weaker relationships inherent in new collaborations could also foster more novel information exchanges, a critical factor for long-term knowledge outcomes (Levin & Cross, 2004).

Team members' geographical proximity

Team members' geographical proximity refers to the spatial or physical distance between collaborating researchers, i.e., individuals (Boschma, 2005). Given that knowledge transfer, particularly of tacit knowledge, thrives through face-to-face interactions (Nonaka, 1994; Storper & Venables, 2004), geographical proximity holds significance. It minimizes transportation costs and times, rendering face-to-face interactions more accessible and economical (Boschma, 2005, 2014). However, advances in technology and increased competition have increased the ease of collaborating through digital means (Agrawal & Goldfarb, 2008; Forman et al., 2018), alongside falling communication and travel costs (Agrawal & Goldfarb, 2008; Catalini et al., 2016; Forman et al., 2018; Perry, 2014). This raises the question of whether geographical proximity's importance has diminished due to the greater ease of digital collaboration and cheaper transportation.

Some researchers posit that permanent geographical proximity might not be crucial; instead, the ability to attain temporary geographical proximity as needed is vital (Torre, 2008; Torre & Rallet, 2006). Extreme proximity might also hinder access to the external world, i.e., the amount of external knowledge spillover (Boschma, 2005; Boschma & Frenken, 2009), prompting the idea that relationships among parties geographically distant from one another could "span geographical holes," analogous to Burt's structural hole theory (Bell & Zaheer, 2007). Notably, in relation to disseminating knowledge outcomes, various geographical locations provide immediate audiences, potentially enhancing outcomes such as article impact (Lancho Barrantes et al., 2012).

Empirical findings regarding geographical proximity are, in some respects, contradictory. Nonetheless, when distinguishing between scientific and knowledge outcomes, the results are more aligned. Article impact research indicates that collaborations spanning national borders yield significantly higher impact (Frenken et al., 2010; Glänzel & Schubert, 2001; Lancho Barrantes et al., 2012; Larivière et al., 2015). Moreover, involving a greater number of institutions is associated with higher impact (Bercovitz & Feldman, 2010; Larivière et al., 2015). In the context of novelty, international collaborations appear to be positively correlated with greater novelty (Carayol et al., 2019; Wang et al., 2017), although one study presented opposing findings (Wagner et al., 2019).

Regarding broader knowledge outcomes, the empirical consensus suggests that geographical proximity fosters such outcomes, that is, being located spatially close facilitates knowledge outcomes (Balachandran & Hernandez, 2018; Bell & Zaheer, 2007; Broekel & Boschma, 2012; Škerlavaj et al., 2010; Torre, 2008). However, spatial distance can also yield positive knowledge outcomes (Balachandran & Hernandez, 2018; Bell & Zaheer, 2007; Bercovitz & Feldman, 2010). For instance, Balachandran and Hernandez (2018) revealed that intranational collaborations are conducive to innovation volume (i.e., productivity), while international collaborations are conducive to producing more radical innovations.

2.3.3 Key takeaways from Section 2.3

- In the knowledge economy, the continuous expansion of the total volume of worldwide knowledge demands greater specialization and collaboration.
- The extensive literature on knowledge networks encompasses numerous studies of science and technology. These studies indicate that individuals with diverse competencies and different types of organizations engage in collaborative research, which is the form of academic engagement studied here.
- Applied research, such as the engineering sciences, frequently involves teams that increasingly comprise members from different organizations and spanning larger geographical areas.
- Publications having at least one author affiliated with a university and one author affiliated with a firm are considered indicative of prior academic engagement through collaborative research.
- Drawing insights from the knowledge network literature, two key properties have been identified that could enhance the existing academic engagement literature, particularly in the context of the present research focus. These properties are team size and roles (e.g., brokerage and team leadership).

2.4 Outcomes and impacts of academic engagement

2.4.1 Publications as an outcome of academic engagement

As stated above, various forms of academic engagement exist, such as collaborative R&D, providing informal advice, and delivering (public) lectures. According to Cantner et al. (2022), university–industry collaborations yield three major outcomes: scientific outcomes, commercializable outcomes, and follow-up cooperation. Scientific outcomes refer to newly generated knowledge resulting from collaborative activities, "(usually) codified in publicly available publications" (Cantner et al., 2022, p. 6). Commercializable outcomes encompass the potential economic applications of the acquired knowledge, which can be either tacit, codified in patents, or embedded in prototypes. Follow-up cooperation signifies an outcome that indicates potential to generate scientific or economic results in subsequent interactions, either by further exploiting previously achieved collaborative outcomes or by exploring new research directions. Based on survey data from researchers in Germany, this study reveals that scientific outcomes are the most prevalent, followed by follow-up cooperation, with commercializable outcomes being the least common.

The above finding underscores that engagements resulting in publications are common, and it is posited that those publications represent significant achievements valued by all participating parties. For this reason, publications resulting from academic engagement are regarded as a reliable, albeit partial, measure of successful scientific knowledge creation by university scientists collaborating with industrial researchers (Perkmann et al., 2011; Tijssen, 2009). This proxy measure has been extensively employed to investigate this phenomenon, as is evident when reading the subsequent section, which features numerous references underscoring this point.

2.4.2 Impacts of publications resulting from academic engagement

In the scientific enterprise, authorship provides a basis for peer recognition, allowing researchers to be acknowledged for their work (Merton, 1973; Moed, 2005).[14] Several types of impacts result from publications, including scientific impact, technological impact, and broader societal impact, as shown in the *Springer Handbook of Science and Technology Indicators*, edited by Moed and Thelwall (2019).

[14] The International Committee of Medical Journal Editors, commonly referred to as the ICMJE, outlines the Vancouver criteria for authorship: making substantial contributions to the work's conception, design, data analysis, or interpretation; drafting or critically reviewing the content; granting final approval for publication; and taking responsibility for investigating and resolving integrity-related questions (ICMJE, 2023). See Appendix A for further details.

This dissertation primarily concentrates on two types of impacts that exhibit a clear connection to economic progress, which is particularly relevant within the chosen empirical context of electrical engineering: scientific impact and technological impact. It is noteworthy that in recent years, there has been increasing interest in the quantitative measurement of the broader societal impact of research. This field, often referred to as the analysis of altmetrics or alternative metrics of impact, has attracted considerable attention. However, it is crucial to emphasize that a significant portion of these efforts is dedicated to scrutinizing the quality, limitations, and challenges associated with this approach (e.g., Bornmann, 2014; Fleerackers et al., 2022; Haustein, 2016).

Scientific impact

In Chapter 5 of this dissertation, a more comprehensive exploration of the concept of scientific impact will be provided. Therefore, at this stage, a concise overview of the interpretation of this concept will be provided. The notion of scientific impact in the context of publications is twofold. That is, from my perspective, when assessing the scientific impact of an individual research paper, the impact primarily encompasses two key dimensions: article impact and journal reputation.

Article impact is approximated by analyzing the number of scientific citations a publication receives, while journal reputation is assessed by analyzing the impact factor of the journal in which the publication was published.[15] Furthermore, when examining scientific impact over an extended timeframe rather than on a per-document basis, publication productivity also assumes significance. This is because

[15] As a consequence of the aforementioned operationalization, it is possible to measure article impact across all scientific publications, encompassing journal articles, conference proceedings, book chapters, and more, while measuring journal reputation is restricted to journal articles, since conferences generally lack an associated journal impact factor.

a researcher who publishes more papers is more likely to garner visibility within the scientific community and to obtain a higher total number of citations, all else being equal.

While empirical research on academic engagement's scientific outcomes predominantly addresses research productivity (Perkmann et al., 2021), it has paid less attention to article impact and journal reputation. That said, studies of these topics do exist, and discussion of several such studies will occur in this section.

In terms of article impact, some empirical evidence suggests that academic engagement has either a neutral (Frenken et al., 2010; McKelvey & Rake, 2020) or negative impact (Bekkers & Freitas, 2008; Frenken et al., 2010). Notably, McKelvey and Rake (2020) focused solely on the pharmaceutical industry, whereas Bekkers and Freitas (2008) restricted their analysis to the Netherlands. Frenken et al. (2010) compared several scientific domains, finding that the publications resulting from academic engagement had high article impact in the fields of biotechnology, organic fine chemistry, and analysis measurement and control technology (with "high" meaning similar to that of articles published by academics only), but lower article impact in other fields, such as agriculture and food chemicals and IT (Frenken et al., 2010).

Concerning journal reputation, empirical findings in the context of the pharmaceutical industry indicate a slight positive or neutral effect (McKelvey & Rake, 2020). Conversely, an alternative approach, focusing on all academic researchers in a single nation (i.e., Italy) spanning various scientific disciplinary sectors, revealed similar journal reputation outcomes compared to publications involving academics exclusively, with no significant effects observed (Abramo et al., 2009).

Numerous factors may account for these dissimilar findings, including the nature of knowledge recombination, the involvement of boundary spanners in collaborative efforts, and the specific research topics under examination. Since the chief focus of Chapter 5 is to empirically analyze the outcomes associated with scientific impact, it is sensible to postpone the comprehensive examination of how this impact might manifest itself within the engineering sciences. Essentially, this section is an introduction to the interpretation of the concept of scientific impact and a presentation of various empirical studies of the subject, with the conceptual aspect to be elaborated on in Chapter 5.

Although none of the empirical investigations in this dissertation prioritizes research productivity as its primary focus, it is still valuable to provide a succinct overview of the literature in this domain as it offers additional insights into the nature of academic engagement. Research productivity relative to academic engagement intensity displays ambiguous and curvilinear patterns in three studies (Banal-Estanol et al., 2015; Rentocchini et al., 2014; Rivera-Huerta et al., 2011). Banal-Estanol et al. (2015) found an inverted U-shaped relationship between academic engagement and research productivity among UK engineering scientists. Rentocchini et al. (2014) revealed decreasing research productivity as academic engagement intensity increased for Spanish engineering scientists, while Rivera-Huerta et al. (2011) identified a similar trend for agriculturally related sciences in Mexico.

A possible explanation is that high academic engagement levels correlate with high research productivity when research is conducted with few actors, allowing for more profound analysis and research. This hypothesis finds support in a recent study by Garcia et al. (2020), indicating a positive relationship between long-term academic engagement and research productivity among Brazilian university scientists. Furthermore, Bikard et al. (2019) observed that articles resulting from academic engagement tend to stimulate more subsequent research articles than do those initiated by individual university scientists. They proposed an additional explanation, noting that "when collaboration bridges institutions, the differences in the skills and objectives of individuals across the institutional boundary can open the door to an efficient distribution of tasks and responsibilities, potentially leading to net gains in productivity" (Bikard et al., 2019, p. 442). In summary, it seems that collaborating with firms benefits academics in terms of research productivity up to a certain extent, and that this advantage holds true under most conditions.

Technological impact

At this juncture, a concise overview of my interpretation of the concept of technological impact will be provided, while a more comprehensive exploration is presented in Chapter 6. Similar to the assessment of article impact, technological impact primarily concerns the quantification of citations received. However, in this context, the focus shifts from citations within the scientific domain to citations coming from the technological domain, specifically from patents.

The overarching assessment of a publication's technological impact can be categorized into three distinct types of impacts: individual technological impact, organizational technological impact, and knowledge spillover. The first category emphasizes author–inventor pairs, i.e., citations coming from a patent for which at least one author of the cited publication is also an author of the patent. This type of impact emphasizes the personal dimension of knowledge transfer and dissemination. The second category, organizational technological impact, shifts the spotlight to affiliation–assignee pairs, meaning that it accounts for citations for which one of the affiliations on the publication is an assignee on the patent. This highlights the intricate process of knowledge transfer occurring within the confines of organizational boundaries. The third and final construct, knowledge spillover, emphasizes the dissemination of knowledge outside the immediate sphere of the original research, essentially delving into the phenomenon of knowledge "spilling over" to external actors. This construct underscores the broader industrial implications of published work, demonstrating its capacity to influence a wider range of stakeholders.

There is a notable lack of studies analyzing the technological impact of papers resulting from academic engagement, as shown in the systematic literature review by Perkmann et al. (2021) but also emphasized in other studies, such that by Petruzzelli and Murgia (2020). To the best of my knowledge, no paper investigates the technological impact of science while focusing on the similarities and differences between academic engagement and academic projects and also distinguishing different pathways of technological impact.

Nevertheless, valuable related studies do exist. One particularly noteworthy investigation is that by McKelvey and Ljungberg (2017), who analyzed 66 collaborative research projects between universities and firms in the Swedish food industry. They found that these 66 research-based projects resulted in several process and product innovation outcomes. Specifically, these projects yielded 23 new practical methods, nine new technologies (including equipment), 14 new product developments, ten new prototypes, and five new products. Furthermore, their study highlighted that these collaborations could indirectly enhance firm capabilities for innovation, as previously mentioned in this chapter.

Another related paper examined joint patents, with a specific emphasis on the conditions under which university–industry collaborations produce innovations whose spillovers are then leveraged by other international firms in their own innovation processes (Petruzzelli & Murgia, 2020). There also exist papers that investigate the technological impact of research. Two such recent biblio-metric examples assessed the technological impact of biomedical research, with a focus on novelty and basicness (Ke, 2020) and on interdisciplinary research (Ke, 2023).

While the studies by McKelvey and Ljungberg (2017) and Petruzzelli and Murgia (2020) lack a control group, meaning they do not compare university collaborations with university–industry collaborations, the papers by Ke (2020, 2023) do not distinguish among papers published by universities, industry, or both types of actors. Consequently, while these papers are intriguing and contribute to our understanding of what drives impact, they provide limited insights into how university–industry collaborations influence technological impact compared with similar collaborations that involve only one type of actor. These, and other related papers, will be subjected to more comprehensive scrutiny in Chapter 6, where hypotheses will be formulated pertaining to the effect of academic engagement on technological advancement.

2.4.3 Key takeaways from Section 2.4

- This dissertation focuses on a singular scientific outcome, i.e., publications, which are a result of previous collaborative research endeavors between academia and industry.
- The concept of scientific impact centers on two key aspects: the quantity of scientific citations acquired by publications (referred to as article impact) and the reputation of the journals in which these publications appear (referred to as journal reputation).
- Empirical studies analyzing the impact of academic engagement on research productivity have been more prevalent, and reveal a clearer picture, than do those examining how the publications resulting from academic engagement affect article impact and journal reputation.
- The concept of technological impact is assessed through quantifying the patent citations received by publications. This impact can be further divided into three pathways, comprising an individual pathway, an organizational pathway, and an external pathway (i.e., knowledge spillover).
- There is a substantial need for research examining the technological impact of publications resulting from academic engagement, as most existing studies

primarily concentrate on their scientific impact, which, as previously argued, is somewhat ambiguous or limited in scope to begin with.

2.5 Theoretical framework

In this chapter, we have explored numerous scholarly works, aiming to foster a comprehensive understanding of the phenomenon under investigation. Expanding on this, Figure 2.7 presents a theoretical framework that visually represents the most central concepts and their interconnections while also adding insights into the empirical setting of this dissertation and providing a guide to the forthcoming chapters.

While heavily influenced by Perkmann et al.'s (2021) framework, this version incorporates a notable change. It not only considers individual characteristics but also incorporates knowledge network properties, capturing the essence of academic engagement as a multifaceted concept intertwined with concepts from the broader knowledge network literature. In other words, the figure illustrates the idea that the analysis of academic engagement can be enhanced or redefined by incorporating concepts and theories from the broader literature on knowledge networks and knowledge creation. This proposition is founded on the belief that the knowledge network literature offers a relevant perspective by considering co-authored publications as manifestations of knowledge networks, in which authors from both the academic and industrial sectors act as nodes, and co-publications serve as connections (i.e., edges) between them.

Specifically, the framework highlights three such properties: team size, boundary spanner, and the team leader. These properties are identified as key elements that could enhance the existing academic engagement literature, particularly in the context of collaborative research. The framework further demonstrates that the organizational and institutional context has an impact on the knowledge network properties as well as on the form of academic engagement, in line with Perkmann et al.'s (2021) framework. It also depicts the chosen empirical setting in terms of individual characteristics (professors), the organizational context (five universities: Chalmers University of Technology, Lund University—Faculty of Engineering, KTH Royal Institute of Technology, Linköping University, and Uppsala University), the institutional context (electrical engineering in Sweden), and the form of academic engagement (collaborative research). Lastly, it also illustrates the impacts of interest, i.e., scientific impact and technological impact, providing insights into the interpretation of how to measure those.

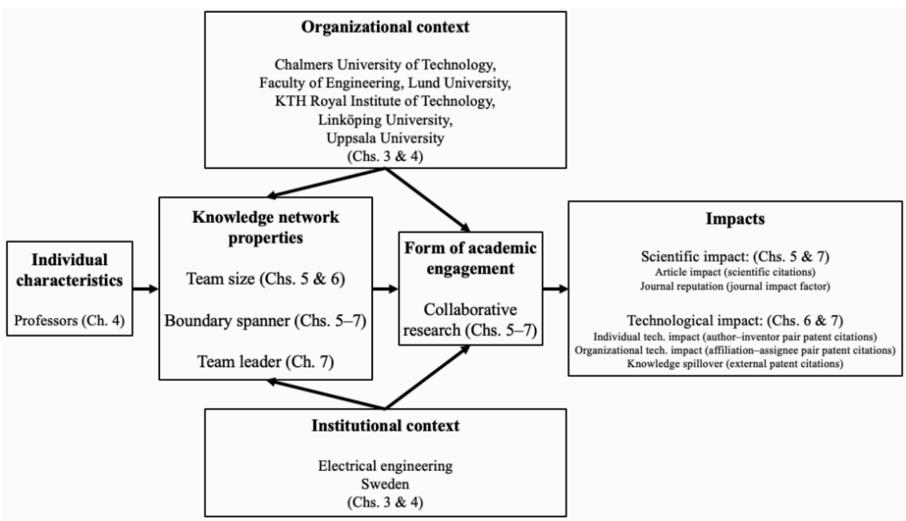

Figure 2.7. Theoretical framework.

Furthermore, the above framework highlights the specific areas in the academic engagement literature to which the three empirical studies primarily aim to contribute. Chapter 5 is dedicated to investigating the impact of team size and boundary spanners on scientific outcomes in the context of academic engagement. In contrast, Chapter 6 delves into the same variables but in the context of technological outcomes. Chapter 7 builds on the findings of Chapters 5 and 6 while introducing a noteworthy factor: the type of affiliations of the lead author and their influence on both the scientific and technological impacts.

It is important to note that while this framework is comprehensive, it does not encompass all areas or variables of interest. As mentioned previously, it focuses on the core aspects of the research. For instance, as discussed in Section 2.3.2, the geographical proximity of team members often plays a significant role in influencing collaboration outcomes. While this aspect is examined to some extent in the empirical analyses, it is not the central focus of the study and, consequently, is not included in the framework.

3 EMPIRICAL SETTING

The objective of this chapter is, clearly and concisely, to describe the specific empirical context where the analyses have taken place.[16] The chapter begins by defining and discussing three related concepts: engineering, science, and technology. A description of Sweden's academic setting is then provided, focusing on the electrical engineering sciences. Following that, the chapter describes the academic context with respect to university–industry collaboration. The chapter concludes by explaining a certain national institutional regime known as the teachers' exemption and professors' privilege, and by discussing what implications related legislation might have had in Sweden.

3.1 Engineering, science, and technology

Engineering, science, and technology are related concepts that need to be differentiated as they represent somewhat separate but parallel processes.

A useful conceptualization for this Ph.D. dissertation, and one that is widely recognized, can help clarify the scope of engineering sciences. Stokes (1997) developed a 2-by-2 matrix of different types of scientific research, arguing that the engineering sciences can be characterized as "use-inspired basic research" (p. 73). According to this classification, the engineering sciences encompass a combination of basic and applied knowledge. These fields aim to enhance the understanding of fundamental phenomena within a scientific domain (i.e., basic) while simultaneously being motivated by societal needs and practical applications (i.e., applied). This

[16] Tracing the history of the Swedish higher education system up to the present, encompassing its structure and reforms, falls beyond the scope of this chapter. For readers seeking a comprehensive understanding of this, I recommend the works of Berit Askling and Sverker Sörlin.

classification distinguishes the engineering sciences from pure basic research, which focuses solely on advancing scientific knowledge, and from pure applied research, which solely pursues practical objectives.

A visual representation of Stokes's 2-by-2 matrix can be found in Figure 3.1, below.

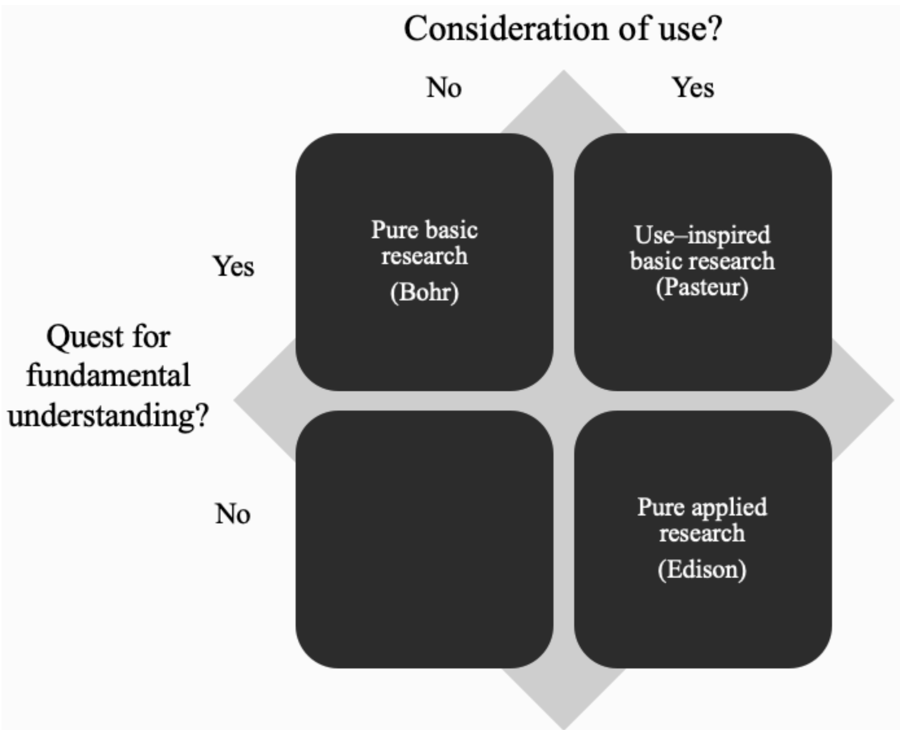

Figure 3.1. Stokes's (1997) quadrant model of scientific research (own representation).

Use-inspired basic research is a useful initial conceptualization, as the term suggests that we should consider both science and technology as different aspects of engineering. This stands in stark contrast to other scientific disciplines, such as the more basic disciplines that originated from philosophy (Niiniluoto, 1993). Applied sciences generate new knowledge with the specific objective of enhancing the effectiveness of human activities, while basic (or fundamental) research involves the scientific community's pursuit of new scientific knowledge. According to Rosenberg and Nelson (1994), it is crucial to define basic research based on the quest for fundamental understanding, rather than focusing solely on the absence of practical applications. Consequently, in the applied sciences, such as the engineering sciences, some research is, in fact, oriented toward fundamental understanding at a very basic level.

Engineering, or more precisely "standard engineering," according to Arthur (2009), encompasses the collective activities undertaken by engineers when embarking on new projects. These activities include the development of methods, the design and construction of artifacts, and testing, all aimed at advancing our understanding of the phenomena under consideration. Accordingly, new projects are initiated when there is a need for novel inventions or for the exploration of existing ones. Consequently, all new projects primarily revolve around problem-solving. Moreover, as Arthur (2009) also pointed out, engineers complete projects by synthesizing various elements in a specific manner that aligns with the project's objectives, resulting in innovative solutions. In essence, engineering is fundamentally focused on problem-solving: every new project presents new challenges, and the ultimate outcome is always a solution (Arthur, 2009). According to this way of thinking, standard engineering has a long history spanning millennia.

However, the engineering sciences have a more recent history. If one delimits engineering sciences to include all scientific fields pertaining to technology, these fields emerged at universities in the 19th century, primarily due to the industrial revolution (Banse & Grunvald, 2009). For example, the Massachusetts Institute of Technology (MIT) introduced its first electrical engineering course in 1882 and awarded its first doctorate in the subject in 1885 (Rosenberg & Nelson, 1994).

The main distinction between standard engineering and the engineering sciences lies in their methodologies. In the past, engineering innovations were often achieved through a trial-and-error approach. However, with advances in computational capabilities and instrumentation, engineering has evolved, leading to the development of more comprehensive frameworks and categories (Arora & Gambardella, 1994). As defined here, the engineering sciences are understood to have emerged through the process of applying scientific principles to standard engineering practices.

To enrich our understanding of engineering sciences, an alternative description of the fields is that they can be characterized as "sciences of action," as defined by Banse and Grunvald (2009, p. 158). According to their definition, these fields are concerned with supporting human endeavors (or actions) through technology, whether by offering technological solutions or by providing the essential knowledge and knowhow required to engage with technology effectively. The scientific part of their definition refers to the systematic investigation and analysis of the conditions essential for successful outcomes and to expanding the realm of actionable possibilities. These authors' view of the engineering sciences concisely captures its fundamental nature, encompassing its multifaceted role in shaping and advancing our world and underscoring its profound influence on human progress.

Similar to Stokes, Banse and Grunvald (2009; see also König, 2006) argued that the engineering sciences have two equally important fundamental objectives: a cognitive (or epistemic) aim and a practical aim. The cognitive aim primarily concerns generating new knowledge, encompassing understanding technological systems as well as building knowledge pertaining to physical and chemical processes. Moreover, the practical aim primarily revolves around the anticipation and creation of technology that is saleable, purchasable, acceptable, and feasible. Put differently, the cognitive goal of the engineering sciences is to pursue scientific excellence and to legitimize standard engineering, with the primary criterion for success being the "truth of knowledge." Conversely, the practical goal aims for a high degree of societal relevance, with the primary criterion for success being "usefulness to society."

Banse and Grunvald (2009) further argued that the coherence of the engineering sciences stems from their particular connection between theory and practice. The duality of goals is a distinct and noteworthy characteristic of these sciences, setting them apart from the natural sciences. Specifically, in contrast to the natural sciences, which move from the real world to increasingly abstract models, the engineering sciences directly target practical objectives in the real world.

Here, it is important to note that technology is synonymous with the applied sciences; there are several instances in which technology appeared before the science that explains it (Nightingale, 2014). For example, the innovation of flush riveting in American aircraft manufacturing during the 1930–1950s was developed "without science" (Vincenti, 1984). Instead, technology concerns the products of human action, i.e., the artifacts (Bijker, 2010; Nightingale, 2014; Orlikowski, 1992). The ontological questions pertaining to technology, such as the inquiry into the meaning of technology within constructivist technology studies, are beyond the scope of this dissertation (see Bijker, 2010). However, the straightforward definition of technology proposed by Arthur (2009) is advocated, which views technology as a means to carry out a human purpose, as this ultimately represents its fundamental function in society:

> For some technologies—oil refining—the purpose is explicit. For others—the computer—the purpose may be hazy, multiple, and changing. As a means, a technology may be a method or process or device: a particular speech recognition algorithm, or a filtration process

> in chemical engineering, or a diesel engine. It may be simple: a roller bearing. Or it may be complicated: a wavelength division multiplexer. It may be material: an electrical generator. Or it may be nonmaterial: a digital compression algorithm. Whichever it is, it is always a means to carry out a human purpose. (Arthur, 2009, p. 11)

In conclusion, for this Ph.D. dissertation, the definition used is that the engineering sciences encompass all scientific fields pertaining to technology. The engineering sciences studied here may thus include researchers who work at universities as well as those who work at firms. The concept of engineering, as used here, incorporates elements of both science and technology as concepts used in the innovation management literature. This means that, on one hand, the technological problems addressed in engineering may be more general in terms of mathematics or may be oriented toward users and applications in industry. On the other hand, identifying and solving these technological problems will often involve a scientific approach to methods and research. This Ph.D. dissertation will therefore explore both the scientific impact and the technological impact of collaborative research projects in engineering.

3.2 Universities in Sweden involved in electrical engineering

In total, Sweden has 17 universities and 13 university colleges. The key distinguishing factor between these two types of institutions is that only universities have been granted general degree-awarding powers at third-cycle levels (i.e., doctoral degrees), whereas university colleges must apply for specific entitlements (UKÄ, 2020).

In Sweden, the landscape of electrical engineering research is predominantly shaped by five prominent institutions: Chalmers University of Technology (hereafter "CTH," according to the university's Swedish name: Chalmers Tekniska Högskola);

Faculty of Engineering, Lund University (hereafter "LTH," according to the Swedish name of the university's faculty of engineering: Lunds Tekniska Högskola);[17] KTH Royal Institute of Technology (hereafter "KTH," according to the university's Swedish name: Kungliga Tekniska Högskola); Linköping University (hereafter "LiU" according to the university's Swedish name: Linköpings Universitet); and Uppsala University (hereafter "UU" according to the university's Swedish name: Uppsala Universitet).

Currently, all these universities are state-owned institutions, with the exception of CTH, which has been privately owned by a foundation since 1994 (CTH, 2004). According to a report from CTH (2004), the distinctions between publicly owned Swedish universities and CTH may not be as substantial as one might presume. Specifically, many of the legislative frameworks that affect publicly owned Swedish universities also extend their influence over CTH. It is noteworthy that CTH continues to primarily rely on funding from the Swedish government. The most pronounced disparity between these two categories perhaps stems from CTH's governance through a foundation, endowing it with greater autonomy relative to state-controlled universities. Furthermore, KTH and CTH are situated in Sweden's two largest cities, while UU and LiU are positioned in the nation's third and fourth largest cities. LTH, in contrast, is located in Sweden's 12th largest municipality (SCB, 2020a).

Table 3.1 shows an overview of these Swedish universities in 2019, highlighting not only their ownership status and urban locations, but also revealing similarities in a few key metrics. These metrics include the average number of employees, total student enrollment, total article publications in peer-reviewed journals, and average

[17] Note that the analysis of LTH exclusively concerns LTH, rather than the whole Lund University, as LTH operates to a very large extent as an independent organization.

number of publications per employee. It is worth emphasizing the need for caution when interpreting these data, as the table is derived from aggregated averages and should not be used to draw definitive conclusions. Specifically, these data do not reflect the diversity in staff engagement with research activities, as some may dedicate a significant portion of their time to research, while others are primarily involved in administrative or teaching roles, which affects the results. Despite this caveat, the data suggest the universities' foci seem to exhibit some variations, particularly visible through the average number of publications in peer-reviewed journals per average number of employees. This difference implies varying emphases, with certain universities emphasizing educational pursuits (e.g., LiU), while others place a stronger emphasis on research endeavors (e.g., LTH).

Table 3.1. Key metrics of sampled universities, 2019.

University	Ownership	City (population) [rank]	No. of employees	No. of students	No. of Ph.D. students	No. of journal articles	No. of journal articles per employee
CTH	Private	Gothenburg (579,281) [#2]	3372	9744	811	3011	0.89
KTH	Public	Stockholm (974,073) [#1]	5044	12,442	964	3153	0.63
LiU	Public	Linköping (163,051) [#5]	4043	17,907	606	2121	0.52
LTH	Public	Lund (124,935) [#12]	1487	6508	459	1979	1.33
UU	Public	Uppsala (230,767) [#4]	7265	26,045	1240	5167	0.71

Sources: annual reports (CTH, 2020; KTH, 2020; LiU, 2020; UU, 2020); data from SCB for city populations and rankings (SCB, 2020a); LTH's university website, where necessary, as the university's annual report is for the whole university, rather than specifically for LTH (LTH, 2020); and ownership information for CTH (CTH, 2004).

3.3 University–Industry collaboration in Sweden

Swedish universities have a longstanding tradition of collaborating with industry, a fact documented by multiple scholars (Benner & Sörlin, 2015; Pettersson, 2012; Talerud, 2002). For instance, in the 1970s and 1980s, Sweden introduced a new category of professors known as “adjunct professors” (Fagrell et al., 2015). These adjunct professors are individuals simultaneously employed by both a firm and a university, in accordance with Swedish practice and legislation (Arbetsgivarverket, 2011; SFS, 1993:100). This introductory development underscores Sweden’s perceived emphasis on establishing strong ties with industry. In this dissertation, this type of professor is referred to as a dual-affiliated professor.

At the turn of the 21st century, a number of pivotal events and trends further catalyzed these activities. Foremost among these was the inception of the third mission in 1998, an event of considerable consequence (Benner & Sörlin, 2015; Eklund, 2007). This third mission encompasses the commitment of universities to actively address societal challenges, promote innovation and entrepreneurship, and enhance the economic and social well-being of their surrounding communities. Simultaneously, Swedish universities, mirroring their counterparts in other OECD member nations (Heyman & Lundberg, 2002; Jankowski, 1999; Vincent-Lancrin, 2006), underwent profound financial transformations. Specifically, their fiscal landscape saw a dual transformation: a relative decrease in funding from the Swedish government, and an increased reliance on contract research (Askling, 2000; Heyman & Lundberg, 2002; Vincent-Lancrin, 2006). The third landmark event occurred in 2001 with the establishment of the Swedish Governmental Agency for Innovation Systems—Vinnova, a strategic move aimed at bolstering Sweden’s competitive edge (Eklund, 2007; Vinnova, 2020).

Empirical findings concerning the demographic profile of university scientists involved in university–industry collaborations in Sweden align with empirical investigations based on other countries. In greater detail, a survey sent in 2007 to 20,000 university scientists affiliated with Swedish higher education institutions (52% response rate) suggests that "the group [that engages in university–industry collaborations] consists of senior academics with Ph.D.s, with a larger share of faculty members from mathematics, natural science, medicine and dentistry … the group consists predominantly of male researchers" (Wigren-Kristoferson et al., 2011, p. 490).

3.4 Teachers' exemption

In 1949, the Swedish Patent Act was altered. The changes included the introduction of a new principle granting researchers/educators in universities, colleges, and other educational institutions within the national framework the rights to their own inventions (SFS, 1949:345). The efficacy of this legislative change has been subject to intense debate in recent decades (Benner & Sörlin, 2015; SOU, 2005:95; Vinnova, 2003), and its existence even came into question during the NYFOR investigation in 1996. However, the outcome of this investigation recommended the retention of the legislation, a recommendation that has endured (Riksarkivet, 1996:SE/RA/324648).

The debate surrounding this matter was fueled, in part, by the misconception that university scientists in Sweden, as well as other nations, patented only a fraction of what their U.S. counterparts did. Contrary to this misconception, it was revealed that the patenting activities of university scientists in Sweden were comparable to those of U.S. scientists with regard to academic patents as a proportion of the total patents of domestic inventors (Lissoni et al., 2008, 2011). Here, an academic patent refers to a patent filed by at least one university scientist. This erroneous belief emerged due to comparisons between the patent holdings of universities across different countries, overlooking critical distinctions in legislation. For instance, nations like the U.S.A. possessed a significantly higher patent count than did countries like Sweden. However, such a comparison rests on a flawed premise, as countries like Sweden retain the teachers' exemption legislation, while others, like the U.S.A., have adopted alternative regulations, such as the Bayh–Dole Act. This newer legislation, the Bayh-Dole Act, assigns universities the rights to their scientists' inventions.

A shift in perspective, focusing on the individual level rather than the university level, reveals a more accurate picture: nations upholding the teachers' exemption legislation – like Sweden – exhibit substantially greater patenting activity than initially assumed. Figures 3.2 and 3.3, below, illustrate this point, highlighting the similarities and differences in academic patent ownership among the U.S.A., France, Italy, and Sweden, as well as the contribution of academic patents to the overall patent landscape in these nations. Notably, while Sweden and the U.S.A. exhibit comparable levels of academic patenting (Figure 3.2), they diverge in terms of ownership distribution. In Sweden, firms hold 82.1% of all patents, with universities owning merely 3.9%, while, in contrast, the U.S.A. sees universities owning 68.7% of all patents, with firms holding 24.2% (Figure 3.3).

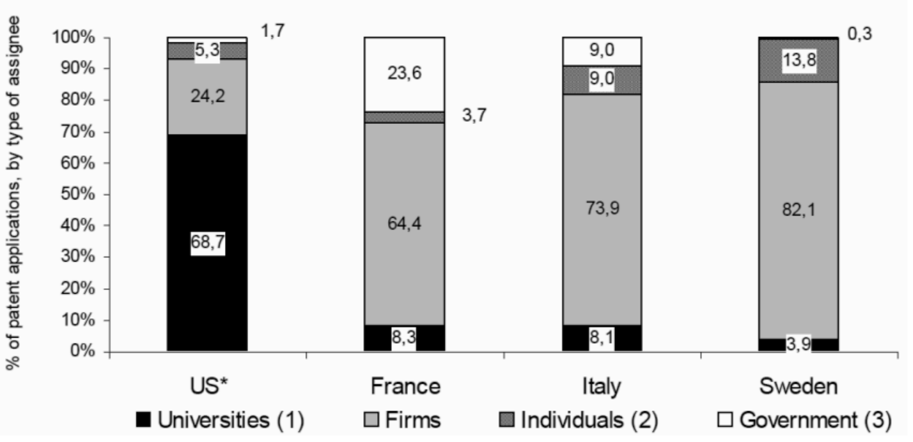

Figure 3.2. Ownership of granted academic patents by domestic inventors in France, Italy, Sweden, and the U.S.A., 1994–2001 (Lissoni et al., 2008).

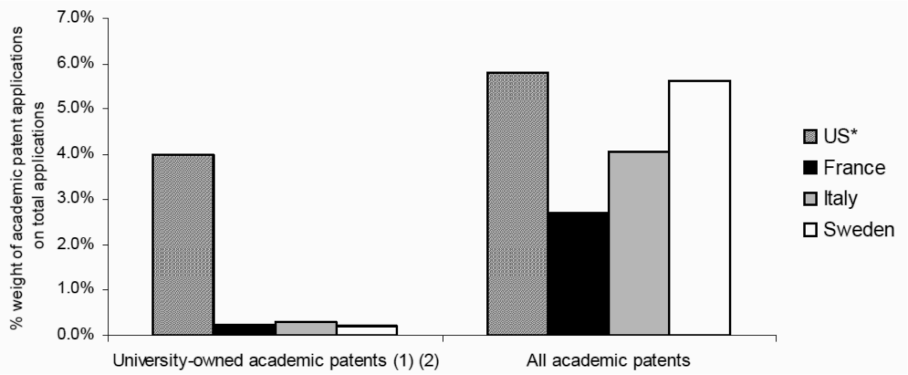

Figure 3.3. Granted academic patents as a proportion of total patents by domestic inventors, by nation and type of ownership, 1994–2001 (Lissoni et al., 2008).

As evident from the preceding discussion, over 80% of academic patents in Sweden find ownership within corporate entities. Empirical research moreover suggests that firms predominantly engage in collaboration with university scientists in fields closely aligned with the firms' technological core, rather than in marginal fields (Ljungberg & McKelvey, 2012). Core fields denote areas where a firm possesses a substantial patent portfolio and wields a notable technological edge, while marginal fields denote areas with fewer patents and negligible technological dominance (Granstrand et al., 1997; Patel & Pavitt, 1997).

Consequently, one would anticipate academic patents within a firm's core fields to bear heightened significance for the firm, considering their prevalence. This conjecture is supported by empirical data, with research indicating that academic patents situated in core fields generally yield a more pronounced technological impact than do their counterparts in non-core fields (Ljungberg et al., 2013). It is imperative to note, however, that a contrasting pattern emerges when scrutinizing academic and non-academic patents within the same category. Specifically, academic patents in core fields exhibit comparatively less technological impact than do non-academic patents in corresponding categories. Conversely, academic patents in marginal fields display more technological impact than do non-academic counterparts in similar domains (Ljungberg & McKelvey, 2012). This suggests a greater relative significance for firms to collaborate with university scientists in non-core/marginal fields as opposed to core fields.

The core rationale behind recognizing the implications of the teachers' exemption hinges on the possible differences in attitudes exhibited by collaborating researchers, particularly in comparison with scenarios in which universities retain rights to potential inventions. It could be that university scientists affiliated with Swedish institutions may be more motivated to engage in collaborative endeavors with firms due to financial incentives stemming from their ownership of invention rights; however, empirical evidence derived from university scientists in Sweden largely contradicts this (Wigren-Kristoferson et al., 2011). Conversely, an alternative perspective posits that firms may be more predisposed to engage in collaboration with university scientists due to the relative ease of negotiating rights for potential inventions directly with the researchers, as opposed to navigating negotiations with the broader university entity—a process that arguably entails greater complexity.

4 SAMPLE, DATA, AND DESCRIPTIVE STATISTICS

This chapter provides an overview of the data utilized in this dissertation, along with a detailed explanation of the preprocessing methodologies applied. The first section of the chapter focuses on the sample examined in the dissertation. Following that, the subsequent section outlines the data employed in the dissertation. This includes a comprehensive elucidation of the preprocessing procedures conducted prior to analysis, accompanied by a critical assessment of the data quality. The concluding section of the chapter presents descriptive statistics, which offer valuable insights into the data and the sample.

Historically, the practice of detailing data management has not been commonplace among researchers. However, we have started to witness an increased awareness of the ethical dimensions of research, coupled with an increased vulnerability to IT/data breaches, which arguably have prompted the shift toward the greater prevalence of such reporting. In response to these evolving considerations, proactive measures were taken, resulting in a data management plan (DMP) in late 2020, drawing inspiration from the checklist offered by the Swedish National Data Service (SND, 2017). Subsequently, this DMP has been periodically revised and is also accessible upon request.

4.1 Sample

Selection criteria for the academic scientists analyzed were based on several requirements. The process of sample selection hinges on considerations encompassing field, country, university, and the academic positions held by the individuals. Progressing from the macro to the micro, the rationale behind these prerequisites can be delineated as follows.

First, as argued in this dissertation, the engineering sciences was chosen because these disciplines can be characterized by two equally important fundamental aims, namely, a cognitive (i.e., scientific) and a practical (i.e., technological) aim (Banse & Grunvald, 2009; Stokes, 1997). Furthermore, a focused and in-depth analysis of a specific research field is warranted, as opposed to broader findings across multiple fields. This approach is informed by the understanding that "different policies would be required to increase knowledge transfer in different research fields… [as a consequence of] certain variables [that] only contributed to an increased transfer in specific research fields" (Landry et al., 2007, p. 562, 586).

More specifically, this dissertation focuses on electrical engineering, which plays a pivotal yet often overlooked role in technological advancement (Arthur, 2007). This field involves collaborations among a diverse array of stakeholders, including universities, MNEs, and KIE firms (Berg, 2019; Ljungberg et al., manuscript to be submitted for publication). Building on two semi-structured interviews conducted in June 2020 with an electrical engineering expert (a professor of electrical engineering since 2006), along with supplementary email correspondence, the decision was reached to center on four distinct sub-fields of electrical engineering: biomedical, communication, control, and signal processing.

These fields were selected to achieve a desirable level of heterogeneity among the sampled academic scientists' research foci and to allow more robust results. Specifically, the interviews with the electrical engineering professor illuminated the distinct nature of these sub-fields within electrical engineering: biomedical and communication engineering inherently addresses specific applications; signal processing engineering provides a foundational toolbox of generic techniques applicable across various domains (e.g., to biomedical engineering); while control engineering engages with more abstract matters tied to the tools and algorithms used to solve practical problems. It is moreover noteworthy that these sub-fields of electrical engineering play pivotal roles as enabling technology, underpinning the success of some of Sweden's best-known corporations, including AstraZeneca, Ericsson, Volvo Cars, and Volvo AB.

Second, instead of focusing on engineering in a global context, I have chosen a country where universities have a rich historical tradition of engagement with industrial partners (Benner & Sörlin, 2015; Pettersson, 2012; Talerud, 2000) and where engineering companies have a high level of R&D investment and technological capabilities—Sweden.

Third, the insights obtained from the semi-structured interviews guided the process of selecting universities and specific departments/units to be included in the study. It was deemed appropriate to focus on five prominent Swedish universities renowned for their contributions to electrical engineering: CTH, KTH, LiU, LTH, and UU. The guidance provided by the expert was instrumental in pinpointing the suitable department(s) and/or unit(s) from each university to incorporate into the dissertation framework. Upon identifying the designated departments/units from each university, employment data were obtained from all the selected institutions. These data facilitated the identification of academic researchers affiliated with the targeted departments/units. It is important to clarify that some of the surveyed universities underwent organizational changes during the analyzed timeframe (2000–2018; see subsequent section). In instances in which uncertainties arose due to these changes, the expert was consulted to mitigate any resulting ambiguities.

Fourth, the decision was made to exclusively sample university scientists who held the position of professor during the analyzed period. This strategic emphasis on sampling professors was supported by several rationales. Initially, it was evident that professors, being entrusted with the pivotal responsibility for advancing scientific knowledge and shaping the research trajectory of their respective departments or units, held a crucial role meriting inclusion in the dissertation. Furthermore, in light of insights obtained from the expert and corroborated by the research undertaken by my former Ph.D. student colleague, Karin Berg (2023), it became apparent that professors often engage in collaborative publication endeavors with their doctoral students. Consequently, by targeting professors in the sampling process, a substantial proportion of publications authored by junior academics, such as doctoral candidates, could be effectively captured. Second, the decision to focus solely on professors resulted in a high degree of homogeneity within the sample. This uniformity stemmed from the intrinsic emphasis that professors place on scientific output, which may not be uniformly echoed across all academic ranks. Third, attaining the rank of professor should necessitate a significant and impactful contribution to the realm of scientific inquiry, resulting in a rich dataset. Fourth, due to the relatively lower frequency of employer changes among professors at Swedish universities than among other occupations (Askling, 2001), there arises the opportunity to analyze their activities over extended periods of time while maintaining a consistent employer variable. Lastly, empirical evidence, as elucidated by Boardman and Ponomariov (2009), Lawson et al. (2019), and Tartari et al. (2014), among others, substantiates that professors are more prone to engaging in academic interactions when juxtaposed with their counterparts occupying lower ranks within the academic hierarchy. This propensity for academic engagement increases the significance of investigating professors' roles and activities. It is noteworthy that this methodological approach—centering explicitly on professors—is quite common among scholars investigating academic engagement and/or academic commercialization (e.g., Bianchini et al., 2016; Callaert et al., 2015; Slavtchev, 2013).

To conclude, the thoughtful selection of parameters—encompassing distinct sub-fields of electrical engineering, specific departments/units across prominent Swedish universities, and a deliberate emphasis on professors—has resulted in a final sample comprising 184 unique professors. In 2018, 146 of the sampled professors were employed, constituting approximately 85% of Sweden's professorial force in the selected field. Data from Statistics Sweden (SCB) on behalf of the Swedish Higher Education Authority (UKÄ) indicate that, at that time, Sweden had 172 professors in electrical engineering and electronics (Haglund & Nyström, 2019). It is worth noting that this number (85%) is slightly exaggerated, as UKÄ and SCB report their numbers as "full-time equivalents," and this study does not control for that factor. Nevertheless, this approximation provides insight into the sample's size relative to the entire population of electrical engineering and electronics professors employed in Sweden, offering compelling evidence for the robustness and credibility of the results.

4.2 Bibliometric data

To test the hypotheses and ultimately answer the research questions, various types of data is used, excluding the previously mentioned semi-structured interviews and employment data. Three types of data have been utilized: scientific documents from Web of Science, patents from OECD REGPAT, and patent-to-article citations from Reliance on Science in Patenting. Additionally, data on professors' gender was gathered by examining their names along with profile photos from university websites, The Institute of Electrical and Electronics Engineers,[18] and/or LinkedIn profiles when necessary.

Evidently, all data utilized for the analyses, except for the gender information, fall within the realm of bibliometric data. Bibliometric data, often referred to as bibliometrics, pertain to the quantitative assessment of bibliographic information for

[18] The Institute of Electrical and Electronics Engineers is the "world's largest technical professional organization dedicated to advancing technology for the benefit of humanity" (IEEE, 2020).

analytical objectives (Broadus, 1987; Garfield et al., 1978). The primary data in all three empirical chapters are derived from scientific documents such as journal articles and conference proceedings. In contrast, patent data assume a role more akin to that of an influential control variable. In the context of two of the empirical chapters (Chapters 6 and 7), the data concerning patent-to-article citations assume a central position.

The analyses conducted in this dissertation encompass a time span exceeding two decades of published scientific documents (1995–2021) authored by the sampled professors. The initial five-year period (1995–1999) was designated a pre-analysis window, with the primary analyses being conducted during the period spanning from 2000 to 2018. Subsequently, the concluding three years (2018–2021) constitute a post-analysis window. Notably, the dataset includes only the years when professors held their positions and an additional year following the conclusion of their professorships (to accommodate potential publication delays). To illustrate, if a professor attained the rank of professor in 2003 and retained that status until 2018, the compilation encompasses their scientific documents from 1998 to 2018. For another example, if a professor became a professor in 2010 and departed from the university in 2012, their scientific output would be collated from 2005 to 2013. It is important to clarify that the professors' scientific output during the five-year period preceding the actual analysis was employed to control for their preceding scientific impact. The treatment of patent data adhered to the same rationale.

The choice of the main analysis period (2000–2018) is underpinned by three principal rationales. Perhaps most pivotal, the selection ensures that the sample size is sufficiently robust for statistical analyses. Research addressing sample size within the context of quantitative bibliometric analysis suggests that a range of 30 to 50 observations can be considered the minimal sample size for approximating attributes such as mean distribution normality (Glänzel & Moed, 2013), while a minimum of

200 articles is a reasonable sample size for gauging citation impact (Rogers et al., 2020). The proposed analysis period of 2000–2018 meets these criteria. A second pragmatic rationale is associated with the challenge of identifying, without access to comprehensive employment data, all professors within the sampled universities. Given that many Swedish universities transitioned to digital records at the end of the 20th century, the earliest year for which access to the pertinent employment data across all institutions was 2000. The third rationale takes into account the imperative to accurately account for the scientific impact of each document. To capture the scientific impact of each article in a good enough manner—specifically, its number of forward citations within a defined period—the analysis must conclude a few years prior to the most recent year for which citation data are available, which was 2020. Conforming to established practice (e.g., Beaudry & Kananian, 2013; Bellucci & Pennacchio, 2015; McKelvey & Rake, 2020), this mandates that the analysis must end no later than 2018, allowing for a three-year citation window (2018–2020; pertaining to articles published in 2018).

It is worth noting that robustness checks have been carried out with a five-year citation window for all scientific documents published before 2017. The adoption of a lengthier citation window for control purposes is particularly advantageous, as it offers a more precise approximation of the impact exhibited by novel articles (Garfield, 1980; Stephan et al., 2017; Veugelers & Wang, 2019; Wang et al., 2017). Nevertheless, the extension of the time window results in a reduction in the sample size. Consequently, a decision was made to employ a three-year citation window for the principal analyses, allowing for more optimal sample size. Subsequently, the more expansive five-year citation window was reserved for the purpose of conducting robustness tests.

4.2.1 Scientific data

Three of the most widely recognized and frequently utilized tools for collecting scientific data are Web of Science, Scopus, and Google Scholar. Web of Science was utilized for collecting all the scientific data, for several reasons. [19]

First and foremost, combining databases is discouraged due to a few associated drawbacks. Merging databases leads to articles within the combined database possessing metadata from disparate sources, including variations in citations from different databases. Such discrepancies in citations have been empirically demonstrated (Harzing & Alakangas, 2016; Martín-Martín et al., 2018a, 2018b), ultimately leading to skewed results. Thus, to ensure the integrity of the analyses, a singular database needs to be the foundation, necessitating the reliance on one of the aforementioned databases.

There exist at least three compelling reasons for excluding Google Scholar as the sole data source: (1) Google Scholar exhibits a relatively elevated occurrence of duplicates compared with Web of Science (Haddaway et al., 2015; Harzing & Alakangas, 2016); (2) Google Scholar somewhat frequently lacks vital metadata such as author affiliation and funding details (Martín-Martín et al., 2018a); and (3) many of the unique citations in Google Scholar might originate from lower-quality citing documents, potentially diminishing the viability of using citations as a reliable proxy for scientific impact (Martín-Martín et al., 2018a).

Upon reviewing recent comparative studies of Web of Science and Scopus, and considering the prevalence of these databases in the fields of innovation and entrepreneurship, I arrived at four reasons for choosing Web of Science while

[19] Web of Science was originally produced by the Institute for Scientific Information (ISI), but is currently maintained by Clarivate Analytics (Cision, 2016).

acknowledging one rationale for not choosing it. The four reasons for favoring Web of Science were: (1) Web of Science surpasses Scopus in addressing duplicate entries, exhibiting fewer duplicates (Valderrama-Zurián et al., 2015; van Eck & Waltman, 2019); (2) Web of Science offers the inclusion of "keyword plus" in addition to "author keywords," a feature not provided by Scopus (which offers only "author keywords"), and "keyword plus" is recognized as a superior source for topic analysis, according to certain scholars (Zhang et al., 2015); (3) as of 2016, Scopus' expansion to pre-1996 articles was still in progress, posing a risk of limited coverage for articles preceding 1996 (Harzing & Alakangas, 2016); and (4) in the fields of innovation and entrepreneurship, Web of Science is the predominant choice for articles containing empirical analyses, lending a degree of enhanced credibility to its usage. Contrarily, the rationale for selecting Scopus stems from its broader coverage of proceedings in comparison to Web of Science (Martín-Martín et al., 2018a).

A comprehensive evaluation of the merits and limitations inherent in each database led to the choice of Web of Science as the preferred option, a sentiment mirrored by bibliometric scholars (e.g., Aria et al., 2020). Scientific document data were collected from the Web of Science from February to March 2021. Employing Web of Science's "Author SearchBETA," each university scientist in the sample was identified. Subsequently, for each identified researcher, their "Full Record and Cited References" along with the corresponding "Citation Report" were obtained.

4.2.2 Patent data

Four databases were initially considered for collecting patent data, i.e., the databases of the Swedish Intellectual Patent Office (PRV), the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the World Intellectual Property Organization (WIPO). The EPO, as accessed through the OECD REGPAT database, emerged as the optimal resource for obtaining patent-related information, for several reasons.

Both geographical extremes, PRV and WIPO, were excluded as top choices due to geographical limitations. PRV's downside is that professors' collaborations extend beyond Swedish borders, potentially resulting in patent applications from other countries. WIPO covers international patent applications under the Patent Corporation Treaty involving 156 contracting states (WIPO, 2023). However, seeking worldwide patents for inventions limited to a few countries can be overly costly: it makes little to no sense to apply for a worldwide patent when the patented invention is limited to just one or a few countries given that broader applications are generally more expensive.

EPO and USPTO, the two remaining databases, have two notable differences (cf. Akers, 2000; Criscuolo & Verspagen, 2008; Franzoni & Giuseppe, 2010). The first difference is that US patent law follows the "duty of candor," requiring inventors to disclose all prior art relevant to patentability; EPO does not follow this system. The duty of candor refers to the fact that inventors (and attorneys, if applicable) have the obligation to inform of all prior art deemed relevant to the patentability of the application in question. The benefit of this is that it minimizes cherry-picking, which is counterbalanced by inventors citing even remotely related references: "rather than running the risk of filing an incomplete list of references, they tend to quote each and every reference even if it is only remotely related to what is to be patented" (Michel & Bettels, 2001, p. 192). The second, less known dissimilarity is that USPTO allows a "grace period" of around 12 months for filing after public idea disclosure; EPO denies such rights. The grace period is the window of time during which an inventor may submit a patent application after disclosing his or her idea to the public.

Ultimately, patent applications were collected from the EPO through the OECD REGPAT database, specifically from the July 2020 edition (OECD REGPAT, 2020). This decision stemmed from several factors. Notably, the selection of professors for sampling was based on their affiliation with Swedish institutions, within a European

Union Member State. Furthermore, the precedent of prior empirical investigations conducted in Sweden, exemplified by studies such as those conducted by Bourelos et al. (2017), Ljungberg and McKelvey (2012), and Tur et al. (2022), lends support to the usage of this database.[20] Moreover, this choice was reinforced by the EPO's distinctive capacity to closely align patents with pre-existing art, resulting in a reduction of noise in the dataset (Finardi, 2011).

4.2.3 Patent-to-article data

The publicly available dataset Reliance on Science in Patenting developed by Marx and Fuegi (2020, 2022), which matches full-text USPTO and EPO patents to scientific publications in Microsoft Academic Graph, served as the cornerstone of this dissertation.[21] This dataset encompasses citation linkages across all USPTO patents granted from 1836 to 2020 and all EPO patents granted from 1978 to 2020.

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[20] In addition, other studies not sampling Sweden, as such, have also chosen to collect patent data from the EPO database (e.g., Czarnitzki et al., 2007; Finardi, 2011).

[21] The reader might correctly note that Microsoft Academic Graph was not discussed in the above "Scientific data" section, and that is because Microsoft Academic Graph is not yet that well known. This warrants a condensed review here. Hug and Brändle (2017) found that Microsoft Academic Graph surpasses Web of Science and Scopus in covering book-related documents and conference proceeding items, although it falls slightly behind Scopus in covering journal articles. They furthermore found that the overall and unique coverage of Zurich Open Archive and Repository (2008–2015) publications was 52.5% for Microsoft Academic Graph, 52.0% for Scopus, and 47.2% for Web of Science. Note, however, that the coverage in Engineering and Technology is much, much higher: Microsoft Academic Graph 95.4%, Scopus 96.9%, and Web of Science 95.0%. In a follow-up paper published in 2021, Martín-Martín et al. found that Microsoft Academic Graph had higher coverage than either Scopus or Web of Science in the fields of engineering and computer science, although it did not match the coverage of Google Scholar. To conclude, these two findings clearly suggest that Microsoft Academic Graph , even though it is relatively new, is a reliable source of citation data. For a more general overview of Microsoft Academic Graph, please see Sinha et al. (2015).

Notably, the dataset includes over 160 million papers published since 1800, meticulously captured by Microsoft Academic Graph. Several compelling reasons underpin the selection of this dataset.

First, the dataset aligns with the temporal scope of this research. Second, this dataset takes into consideration, and distinguishes, front-page citations and in-body citations. The significance of this is underscored by findings of Bryan et al. (2020) and Marx and Fuegi (2022) demonstrating that including in-body citations in the analysis yields meaningful insights. This stands in contrast to prior investigations often based solely on front-page citations. For instance, a compelling illustration of this is the study conducted by Marx and Fuegi (2022), which replicated Ahmadpoor and Jones' (2017) study. The outcome revealed that patents exhibit a proximity to the academic–industry interface that is approximately 40% greater than that reported by Ahmadpoor and Jones (2017) using a front-page-only approach. Third, the authors have seemingly done an excellent job building the dataset by combining machine-learning techniques developed by de Rassenfosse and Verluise (2020) with fine-tuned heuristics developed in house. Fourth, even though it is a relatively new dataset, a Web of Science search in September 2022 suggested that no fewer than seven published papers had already utilized the Reliance of Science in Patenting database. This clearly indicates that the scientific community finds the recently disclosed database to be of high value, validity, and reliability.

4.3 Data preprocessing

The harsh truth is that bibliometric data require extensive preprocessing, including cleaning and structuring, before analysis can be conducted. Aside from some manual patent-related data cleaning executed in Excel, all preprocessing was accomplished using R. This language stands as one of the most prevalent and potent tools for statistical computing. This section outlines the approaches taken to preprocess the different types of bibliometric data.

4.3.1 Scientific data

The challenge of erroneous results, especially encompassing both false positives and false negatives pertaining to author names (Tang & Walsh, 2010), was effectively mitigated through the utilization of Web of Science's "Author SearchBETA" feature.[22] By leveraging this function, the risk of inaccuracies at both the individual and article levels was minimized, owing to its built-in author disambiguation algorithm as well as by allowing researchers to claim ownership of articles and maintain their own profiles via Publons.

A noteworthy proportion of the professors possessed authenticated profiles, which significantly facilitated the process of pinpointing the accurate professor in cases of multiple individuals sharing identical names. However, it is important to acknowledge that this was not without errors. In instances in which the outcomes of the author search yielded ambiguity—for example, presenting several individuals named Prof. Smith without clear differentiation—the universities' websites were consulted to identify articles definitively published by the "correct" Prof. Smith and then used those articles to correctly identify the right individual.

Following the download of the sampled professors' "Full Record and Cited References" reports along with their corresponding "Citation Reports" from Web of Science, two R packages were employed to extract valuable insights from the

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[22] A false positive refers to an instance when something is wrongly assigned as *true*, and a false negative refers to an instance when something is wrongly assigned as *false.* In other words, a false positive occurs when an attribution is made to an author (or inventor) for publishing an article (or applying for a patent), yet in actuality, another individual sharing the same or a similar name is the true author (or inventor). Conversely, a false negative arises when an article (or patent) is ascribed to a different individual with a matching or similar name, even though the actual rightful attribution should pertain to the individual under consideration.

amassed articles. The first package was “bibliometrix,” an R tool tailored for comprehensive science mapping (Aria & Cuccurullo, 2017). The second package was “refsplitr,” an R package used for processing, organizing, and visualizing reference records from Web of Science (Fournier et al., 2020).

Subsequently, an exhaustive examination and cleaning of the data was undertaken—in R—with a specific emphasis on modifying organization names to ensure uniformity. This measure was necessitated by the lack of standardized formats in the bibliometric data, among other factors, such as (human) reporting errors. The following steps detail the actions undertaken to achieve this essential objective.

First, a frequency table was generated, documenting the prevalence of each distinct organization. The contents of this comprehensive table were then sorted in descending order based on the frequency of occurrence. Second, a systematic approach was adopted by directing the attention toward organizations with the most frequent occurrences. The primary objective during this phase was to ascertain the existence of similar variants of a given organization, such as “Chalmers University of Technology,” “Chalmers Technology University,” and “Chalmers University.” This analysis yielded a clear pattern in which organizations with higher numbers of entries also exhibited higher numbers of variations. Consequently, as the third and concluding step, an extensive harmonization process was initiated. More than 200 organizations were systematically homogenized, with a specific focus on those exhibiting the highest frequencies.

A coherent methodology was implemented throughout the process of organization name standardization. Each entity was attributed to its highest hierarchical level. For instance, all units or departments of a university were aligned with the corresponding parent university. In a similar vein, subsidiary firms were linked to their parent companies. In cases involving hospitals, university hospitals were aligned with their respective universities. Table 4.1, below, clearly demonstrates the importance of prioritizing the cleaning of organization names with the most entries. This is exemplified through a comparative analysis of the organization name with the most entries, "LUND UNIV," in its pre-cleaning state, against the 100th most frequent organization, namely, "UNIV VALLADOLID." The table further presents the frequency of each distinct variant, its name before standardization, and its harmonized name following the standardization process.

Table 4.1. Organizational names before and after adjustment, for the leading and the 100th most common organizations' versions.

No. of entries	Name before adjustment	Name after adjustment
3294	LUND UNIV	LUND UNIV TECH
178	LUND INST TECHNOL	LUND UNIV TECH
173	UNIV LUND HOSP	LUND UNIV TECH
32	UNIV LUND	LUND UNIV TECH
7	LUND UNIV HOSP	LUND UNIV TECH
3	LUND TECH UNIV	LUND UNIV TECH
3	SKANE UNIV HOSP LUND	LUND UNIV TECH
2	LUND UNIV AND HOSP	LUND UNIV TECH
2	LUND UNIV EKONOMIHGSK	LUND UNIV TECH
2	LUND UNIV LTH	LUND UNIV TECH
1	C LUND UNIV	LUND UNIV TECH
1	LUND UNIV MAPCI	LUND UNIV TECH
1	TECH UNIV LUND	LUND UNIV TECH
1	UNIV HOSP LUND	LUND UNIV TECH
1	UNIV LUND TECHNOL	LUND UNIV TECH
32	UNIV VALLADOLID	UNIV VALLADOLID
1	UNIV VALLADOLID IBGM UVA	UNIV VALLADOLID

Following data preprocessing, distinguishing publications resulting from academic engagement was addressed. In journal articles and conference papers, few research scholars delve into the intricacies of their method for accomplishing this task. Hence, after engaging in meaningful conversations with multiple researchers, it was concluded that two principal approaches could be utilized to this end, each with its trade-offs: one approach risks including false positives, while the other risks omitting true positives.

Delving deeper into these strategies, the first approach, characterized by its inclusion of false positives, revolved around the identification of authors affiliated with universities and/or other public institutions (e.g., schools and institutes). All other organizations were categorized as firms. This method hinged on recognizing any name and abbreviation of the sought-after institutional types within the author's stated affiliation.

Conversely, the second strategy, prone to omitting true positives, operated in the inverse direction. Here, the focus was on identifying firm affiliations, while designating the remaining affiliations as universities (public institutions). This was primarily executed through the identification of abbreviations and acronyms associated with various legal firm forms (e.g., AB, CORP, PLC, and LLC), drawing from an exhaustive compilation of such forms provided by the European Central Bank (ECB, 2020) and the U.S. Small Business Administration (SBA, 2020), as well as a more specific list encompassing Swedish forms (Bolagsverket, 2020).

For the sake of transparency, this comprehensive pursuit encompassed the search for approximately 150 distinct firm forms. However, in hindsight, it is noteworthy that over 90% of articles resulting from academic engagement could be effectively captured by utilizing the 10% most prevalent firm abbreviations and acronyms.

The decision was to proceed with the second strategy due to its stronger mathematical appeal, primarily because the academic engagement group holds central significance in this context. A hypothetical example is provided to elucidate why the second strategy was mathematically more compelling: Let us initially assume a sample of 1000 publications, comprising 90% academic publications and

10% academic engagement publications (McKelvey & Rake, 2020, in their analysis of the pharmaceutical industry, found that 6.4% of all publications resulted from academic engagement projects, so utilizing 10% for a more technical field was reasonably justified). Additionally, let us posit that each of the two strategies yields 5% errors.

The first strategy (the one focusing on identifying publications resulting from academia only) erroneously categorizes 5% of the publications as stemming from academic engagement projects. That is, the first approach entails that the academic engagement group incorporates false positives. Interpreted from the academic engagement group's perspective, this accounts for 45 false positives. In contrast, the second strategy (the one focusing on identifying publications resulting from academic engagement) wrongly labels 5% of the publications as originating from academic projects. In other words, the academic collaboration group contains 5 false positives.

4.3.2 Patent data

The patent data underwent thorough cleaning procedures primarily based on the aforementioned heuristics at the name level. However, a notable departure from the aforementioned approach was adopted. In addition to prioritizing the validation of the researchers' names and assignees (i.e., affiliations), careful attention was directed toward the inventor-provided addresses and their corresponding technological domains. This approach facilitated the identification and elimination of well-defined anomalies, i.e., false positives.

Let me illustrate this refined methodology with an example. One of the sampled professors had multiple patents exhibiting a coherent pattern: matching technological domains, identical organization affiliations, and consistent regional addresses. However, this cohesive pattern was disrupted by a singular patent in an adjacent technological domain, accompanied by an altered address situated in another region. Notably, this patent was filed between the other patents, thereby eliminating the possibility that the professor had relocated. Consequently, this patent was deduced to originate from another individual who happened to share the same name as the sampled professor.

4.3.3 Patent-to-article data

The data preparation process involved the following steps. First, all publications with digital object identifiers (DOIs) and/or PubMed identifiers (PMIDs) was identified. Subsequently, these identified publications was cross-referenced with the "Reliance on Science in Patenting" dataset developed by Marx and Fuegi (2020, 2022). This allowed the identification all patents citing my sample of publications, constituting the third step. The fourth step encompassed the retrieval of patent-related information for these patents from Espacenet, an esteemed and widely adopted patent database.[23] The fifth step involved a cleaning process. Specifically, patents lacking pivotal information, including instances of inventors' details being absent (33 patents), instances of incomplete surnames or first names (45 patents), and instances of non-English patents (13 patents), were excluded. The sixth phase was marked by harmonization aimed at ensuring consistency in the representation of inventor names. This was achieved by standardizing the structure to match that of the scientific publications (surname followed by initials), and similarly, aligning assignee names with their corresponding affiliations. This task was accomplished using the above-mentioned heuristics and manual work. In the seventh and final step, a matching

[23] If the focal objective of Chapter 6 was to delve into the analysis of the technological impact of the patents themselves, then the utilization of more detailed databases such as PATSTAT would indeed be preferable. It is noteworthy, however, to underscore that the specific area of interest in this endeavor is examining the inventors and assignees involved, resulting in the aforementioned databases, Espacenet and PATSTAT, becoming less distinguishable and the choice between them less germane.

process was undertaken, linking authors with inventors and affiliations with assignees.

4.4 Data quality

The quality of the bibliometric data utilized in this dissertation merits thorough examination. While a bibliometric approach allows for an objective and reliable approach to analyzing quantitative data (Diodato & Gellatly, 1994; Subramanyam, 1983), it is also widely acknowledged that these data possess inherent limitations.

Previously, two limitations were addressed: first, the absence of a comprehensive global bibliometric repository encompassing all articles and patents; second, the prerequisite for disambiguating, cleaning, and structuring the bibliometric data, as outlined in Sections 4.2.1 and 4.2.2.

A third constraint associated with the employed bibliometric data pertains to their representation of outcomes, specifically, the resultant articles and/or patents, rather than directly reflecting the underlying activities themselves (Bozeman et al., 2013; Katz & Martin, 1997). Furthermore, this analysis solely considers successful article submissions and patent applications, instead of all applications. Consequently, this means that all conclusions made in this dissertation are grounded on analyses of those collaborative research projects resulting in at least one scientific paper, rather than the entirety of collaborative research projects.

A fourth limitation is the equal weighting assigned to each citation. However, this practice does not accurately reflect the varying significance of citations in academic discourse (e.g., Giuffrida et al., 2019). Citations differ in their value and implications; for instance, a study might be cited to challenge its conclusions rather than to support them.

A fifth limitation pertains to potential bias toward firms that prioritize publication, thereby causing overrepresentation in the analytical framework (Tijssen, 2009). This bias indicates that the conclusions drawn within this dissertation predominantly align with the characteristics of firms featured in the sample. Comparable reasoning is also relevant to the analysis of patents (Griliches, 1990).

Despite these overarching limitations, bibliometric data are still considered to provide a reliable, although partial, measure of successful scientific and technological knowledge creation (Griliches, 1990; Perkmann et al., 2011; Ponomariov & Boardman, 2016; Tijssen, 2009). Research scholars have moreover argued that patent-to-article data can be viewed as a similar type of measure, that is, a reliable, although partial, measure (Callaert et al., 2006; Roach & Cohen, 2013).

Furthermore, bibliometric data remain a cornerstone in quantitatively analyzing academic interactions (as seen in references within Perkmann et al., 2013, 2021), research collaborations (as seen in references in Bozeman et al., 2013), and knowledge networks (as seen in references in Phelps et al., 2012). Their significance lies in their ability to provide a substantial and credible resource for addressing the complexities inherent in measuring broader conceptions of knowledge creation, knowledge transfer, and knowledge diffusion.

4.5 Descriptive statistics

Figure 4.1 shows the geographical distribution of the sampled universities in Sweden. It presents the total number of sampled professors from each university during the studied period, categorized into two groups: “academic professors,” encompassing full-time professors, guest professors, and emeritus professors, and “adjunct professors.”

Additionally, the figure shows the number of publications generated by the sampled professors per university, along with the proportion of publications attributed to academic engagement. Finally, the gender distribution at the universities is presented.

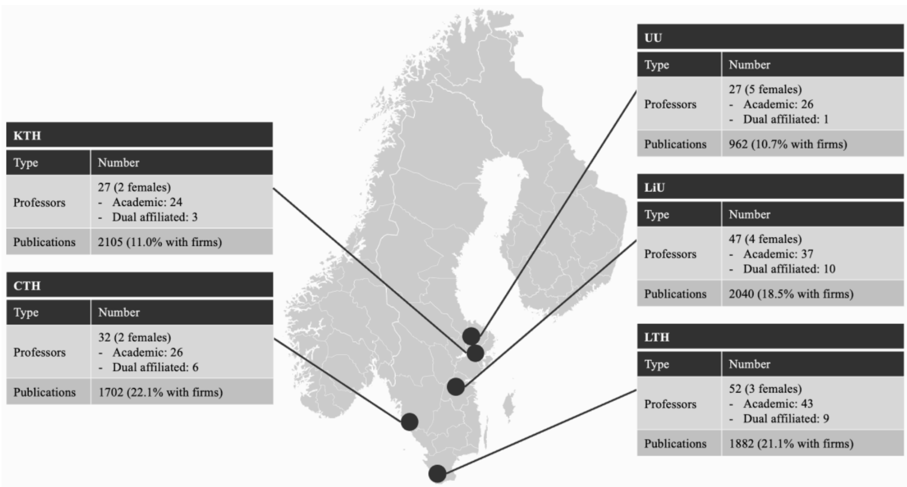

Figure 4.1. The number, type, and gender of the sampled professors, from each university.

Note: The figure indicates that the total number of sampled professors is 185. However, one of the professors was sampled at two universities, which means that the true number of uniquely sampled professors is 184.

It is evident that the largest number of professors was sampled from LTH (52), closely followed by LiU (47), and then CTH (32), KTH (27), and UU (27). In terms of the share of adjunct professors, LiU exhibited the highest percentage at 21%, followed by CTH at 19%, LTH at 17%, KTH at 11%, and UU at 4%. Furthermore, the figure shows that CTH had the largest portion of publications resulting from academic engagement (22.1%), closely followed by LTH (21.1%). Subsequently, LiU accounted for 18.5%, followed by KTH at 11.0% and UU at 10.7%.

As expected, males are overrepresented among professors; however, the extent to which they are overrepresented is striking. Only 8.7% of all professors are females (16 out of 184), which contrasts with the fact that more than 20% of all new doctoral degree holders in the engineering sciences, in both Sweden and the U.S.A. at the beginning of the 21st century, were females (Hill et al., 2010; SCB, 2020b; Yoder, 2012). In greater detail, 18.5% of all professors at UU (five professors), 8.5% at LiU (four professors), 7.4% at KTH (two professors), 6.3% at CTH (two professors), and 5.8% at LTH (three professors) were female.

5 THE SCIENTIFIC OUTCOMES AND IMPACTS OF COLLABORATIVE RESEARCH AS ONE FORM OF ACADEMIC ENGAGEMENT

5.1 Introduction

In the literature on the knowledge economy, the university, as an organization, and science, as an activity, are both considered pivotal in stimulating broader processes involving technology, economic growth, job generation, and societal goals (Lundvall, 1992; Nelson & Rosenberg, 1993; Owen-Smith & Powell, 2004). However, the impact resulting from collaborative research involving universities and firms is not yet well understood, and there have been calls for further research to disentangle this relationship (e.g., Bozeman et al., 2013; Perkmann et al., 2021).

This chapter focuses chiefly on analyzing the scientific impact of one form of academic engagement, i.e., collaborative research, in comparison with similar research not involving firms, i.e., academic projects. That is, the primary objective of this chapter is to address this gap in the existing literature. Specifically, the focus is on addressing the first research question of this Ph.D. dissertation:

How does the scientific impact of publications resulting from academic engagement projects differ from that of publications resulting from academic projects?

This inquiry has significant merit as it endeavors to enhance our comprehension of the factors contributing to scientific impact. By gaining deeper insights into this matter, we stand poised to establish a climate in which such collaborations become more common, ultimately fostering greater scientific and technological advances. In other words, the crucial importance of elucidating this phenomenon is underscored by the obvious connection between certain scientific domains and the progress of technology (Ahmadpoor & Jones, 2017; Jaffe et al., 1993; Narin et al., 1997).

Within this framework, the engineering sciences emerge as a fitting empirical context, owing to their intrinsic relevance to industrial development. Drawing on prior research in this empirical domain, it is anticipated that collaborative efforts are more likely to yield indirect benefits for the participating firms, including knowledge transfer, learning, network development, and signaling effects in the market regarding the use of advanced science and technology (Berg, 2022; Berg & McKelvey, 2020; Hemberg, 2023; McKelvey & Ljungberg, 2017).

This interpretation combines two opposing views of how science and technology facilitate the search for new combinations. On one hand, Fleming and Sorensen (2004) proposed that technology search occurs more locally, through incremental steps of independent components, whereas science guides the search, providing advantages for distant search (e.g., for more breakthrough inventions). On the other hand, Kaplan and Vakili (2015) argued that breakthrough inventions may require both a narrow recombination of application areas and a more distant search. In the engineering sciences, in which knowledge developments are relevant to industrial development, these two views may be combined.

Specifically, while not all science leads to radical breakthrough results stemming from distant searches and combining knowledge from multiple fields, not all engineering science is solely related to specific applications of technical knowledge in firms. Thus, the engineering sciences in Sweden provide a strong empirical context in which to study scientific outcomes, particularly scientific impact. It is important to note that publications resulting from academic engagement are compared and contrasted with those publications involving only academics in universities within the same group of professors, i.e., university academics.

The remaining sections of this chapter are structured as follows: The subsequent section discusses related literature, ultimately resulting in the formulation of four hypotheses. Following this, the presentation includes details about the data employed and the methods applied in this study. Descriptive findings are then provided, followed by econometric results, a comprehensive discussion, and, ultimately, conclusions.

A more specialized iteration of this chapter has been submitted to the special issue entitled "Micro Processes in Science–Industry Interaction: Actors, Channels, and Impacts" of the *Journal of Industry and Innovation*, as detailed in Table 1.1. It is important to clarify that that paper, co-authored by Ström, McKelvey, and Gifford, is distinct from this chapter, which is solely the work of the author of this dissertation, Ström.

5.2 Theory and hypotheses

This section aims to expand on the empirical works introduced in Section 2.4 by exploring how the inclusion of firms in collaborative research processes can influence the scientific impact of the resulting papers in the context of electrical engineering. Before delving into the specifics of how this influence may manifest itself, it is essential to more thoroughly discuss the actual meaning and components of the concept of scientific impact.

5.2.1 The concept of scientific impact

As briefly discussed earlier in this dissertation, the interpretation of scientific impact in the context of publications, based on the literature presented below, encompasses two key dimensions: article impact and journal reputation.

Article impact pertains to the number of scientific citations a paper receives, reflecting the extent to which the scientific community found the paper valuable.

Through forward citations, research scholars acknowledge prior scientific work (Merton, 1973; Moed, 2005). A large number of citations suggests that members of the scientific community have actively used the publication to inform their own research, indicating a high article impact. Citations are not limited to the assessment of papers; they can also be employed at the individual level to validate a researcher's work. Among the best-known and most widely used measures (or indexes) for assessing researchers' productivity and citations of their published works is the h-index, developed by Hirsch in 2005, formally defined as "the number of papers with citation number ≥h" (Hirsch, 2005, p. 16569).

Aksnes et al. (2019) have argued that citations reflect two aspects of research quality, namely, scientific impact and relevance, although with important limitations. One limitation of citations, as raised by Aksnes et al., is that they do not reflect other aspects of research quality, such as solidity and plausibility, which are virtues related to the research being well-founded, based on sound scientific methods, and yielding convincing results. This viewpoint aligns with the arguments raised by Waltman et al. (2013), who found support in a simulation model suggesting that citation impact should be distinguished from researchers' overall scientific impact.

The process of publishing an article in an academic journal is a rigorous one, especially in higher-impact journals, in which under 10% of all submitted articles are accepted (Shaikh, 2016). This implies that journals have varying quality requirements and prestige. Hence, publications in top-tier journals have undergone rigorous peer scrutiny, indicating that they are well-founded, based on sound scientific methods, and produce convincing results. Similar to citations indicating the extent to which the scientific community values a paper, publishing in top-tier journals serves as an indicator of the reputation gained by the author.

The impact of journals is quantified through their journal impact factor (JIF) score, which, in a given year, is calculated as the number of citations the journal has received in the previous two years divided by the number of articles published in that journal in the same two years (Garfield, 1999, 2006; see also Garfield, 1955, when he first proposed the idea). However, it is important to note that JIF has been widely criticized as a proxy for measuring the article impact of individual papers, primarily because it is an aggregate measure intended to assess the prestige and influence of a journal (Amin & Mabe, 2000; Lozano et al., 2012; Seglen, 1997).

For instance, Lozano et al. (2012) noted that "since 1990 the overall proportion of highly cited papers coming from highly cited journals has been decreasing, and the proportion of highly cited papers not coming from highly cited journals has been increasing" (p. 2140), implying that the use of JIF is not very accurate for measuring the article impact of individual papers. However, while the JIF score is not a precise proxy for article impact, it is a suitable proxy for the scientific rigor and quality of an article, as academic scholars tend to associate JIF with a journal's reputation and quality (McKiernan et al., 2019). Additionally, Mahmood (2017) conducted a meta-analysis investigating whether perception-based rankings (e.g., expert surveys) and citation-based rankings (e.g., journal impact factor) correlated with regard to their evaluation of journal quality, finding an overall clear positive correlation.

Together, these two measures represent two distinct aspects of scientific impact. Article impact reflects the value attributed to a publication by the scientific community, while journal reputation conveys the reputation associated with the publication. This comparison underscores two crucial distinctions between the two aspects. First, while journal reputation inheres in an article from the moment of publication, article impact is something that accumulates over time. Second, researchers have more control over the journal reputation associated with their articles, as they decide where to publish (or, at least, where not to publish), but they cannot compel other scholars to cite their work.

The questions concerning the operationalization of these two aspects of scientific impact and the extent to which they correlate with each other will be discussed in Section 5.3.1.

5.2.2 Understanding the scientific impact of collaborative research

Previous research has investigated the involvement of firms in scientific publications, yielding mixed empirical findings regarding the scientific impact of these publications. Some of this research has focused on science-based industries. Notably, in the pharmaceutical industry, it has been observed that firm participation in scientific publications can enhance either the article impact or journal reputation of the resulting scientific work, contingent on specific conditions (McKelvey & Rake, 2016; Rake, 2021).

Frenken et al. (2010) conducted a comparative study of various scientific domains and found that publications resulting from academic engagement exhibited high article impact in fields such as biotechnology, organic fine chemistry, and analysis measurement and control technology, with “high” indicating a level of impact similar to that of publications involving academics alone. However, in other fields, such as agriculture and food chemicals and IT, the article impact of such publications was comparatively lower.

Some researchers have applied a national perspective, as demonstrated by Abramo et al. (2009), who examined all academic researchers in one nation (i.e., Italy) operating in numerous scientific disciplinary sectors. Their findings indicated that publications resulting from academic engagement had similar journal reputations as did publications involving academics exclusively.

It is noteworthy that few such studies have specifically examined engineering in depth. Therefore, this discussion will explore all possible outcomes, to reduce the risk of partiality toward a single cause/explanation (Chamberlain, 1965), starting with the case of why publications resulting from academic engagement may lead to higher or lower article impact.

The interplay between academic engagement and article impact within the engineering sciences

As previously mentioned, the field of engineering sciences serves a dual purpose, encompassing both cognitive and practical aims (Banse & Grunvald, 2009). This duality implies that publications resulting from academic engagement projects in this field could possess both commercial relevance and academic significance, potentially leading to higher article impact, especially when these publications are conceived as collaborative research outputs involving similar but diverse knowledge bases (see, e.g., Boschma, 2005; Nooteboom, 2000; Nooteboom et al., 2007).

To frame this differently, high article impact is likely to characterize a publication based on engineering science, which comprises two critical constructs. First, it incorporates deep application knowledge essential for practical problem-solving, often represented by the participating firms. Second, it involves a more abstract and distant search in the realm of engineering science, where there is a high alignment and synergy between the scientific and technological components of the paper. Consequently, such publications are more likely to attract a broader audience interested in the findings, as they offer a valuable fusion of different knowledge bases. This combination of diverse knowledge sources represents a potential source of superior knowledge outcomes (Schilling & Green, 2011), provided that the individuals involved possess adequate prior related knowledge to effectively interact.

The fact that industrial researchers belong to different knowledge networks implies that they have an alternative channel for disseminating their findings, enhancing the visibility and potential impact of their publications (Spencer, 2001). Similarly, larger teams are likely to expand the readership of their publications. Larger teams should theoretically also have the potential to improve the overall outcome because when a larger number of individuals pool their knowledge bases, they create an environment where information and ideas can be exchanged at a larger scale, facilitating the emergence of beneficial combinatory knowledge outcomes (Becker & Murphy, 1992; Bozeman et al., 2013; Katz & Martin, 1997; Phelps et al., 2012). Such a scenario is particularly relevant to academic engagement, as it involves a more extensive mix of knowledge bases and logics. However, it is important to acknowledge that there are limits to the diversity and size of groups involved in collaborative research.

It is also conceivable that some authors may have dual affiliations, simultaneously employed in both academia and industry, serving as knowledge brokers. The literature suggests that not all team members need to have an optimal cognitive distance from one another. Instead, one team member, who is cognitively proximate to the others (i.e., the knowledge broker), can serve as a conveyer and translator of the diverse knowledge, indirectly facilitating knowledge transfer (Gertner et al., 2011; Leifer & Delbecq, 1978; Meyer, 2010; Tushman, 1977; Tushman & Scanlan, 1981). For example, Gertner et al. (2011) noted that "the recruitment of an appropriate associate [who has dual membership in the university and industry communities] with excellent cross-cultural and boundary-spanning skills may well be crucial to the success of international KTPs" (p. 641), with "KTPs" standing for knowledge transfer partnerships, i.e., government-sponsored collaborative projects between academia and industry. This underscores the vital role that individuals with dual affiliations can play in the success of academic engagement projects.

In contrast, a higher measure of article impact may also be attainable by exclusively academic projects, resulting in reduced article impact for academic engagement projects. Despite the proximity of science and technology in the engineering sciences, the technical challenges addressed through these collaborations may closely align or even overlap with the specific needs of the companies, potentially failing to generate any significant interest in the broader academic community. Furthermore, it is noteworthy that industrial researchers generally possess less experience in publishing than do their university counterparts (Arora et al., 2015; Godin, 1996; Hicks, 1995; Hicks & Katz, 1996; McKelvey & Rake, 2020). From a knowledge network perspective, the involvement of a diverse and extensive cohort of authors can lead to heightened tensions and coordination costs (Becker & Murphy, 1992; West & Anderson, 1996), potentially resulting in reduced novelty within the research findings and diminished overall impact. In such circumstances, it is reasonable to anticipate that the article impact will be higher for academic projects.

This discussion thus offers arguments favoring both higher and lower scientific impact for publications resulting from academic engagement projects, leading to the formulation of two contradictory hypotheses:

H5.1a

Publications originating from academic engagement collaborations are associated with higher article impact.

H5.1b

Publications originating from academic engagement collaborations are associated with lower article impact.

The interplay between academic engagement and journal reputation within the engineering sciences

Publishing in academic journals entails a series of substantial investments, encompassing high desk rejection rates, multiple rounds of revisions, and extended lead times. On one hand, publications stemming from academic engagement projects have the potential to be featured in esteemed academic journals. The reason is similar to that articulated above, that these projects produce unique results of a particularly irreplicable nature, results that rely on collaboration with industry and offer relevance to the academic community. Furthermore, firms may prioritize publishing in highly reputable journals as part of their overall strategy (Rotolo et al., 2022), and task key employees with this responsibility. At an individual level, co-authors from within the firms, many of whom likely hold Ph.D. degrees, may be motivated by career advancement and personal fulfillment (Roach & Sauermann, 2010), prompting them to actively pursue publication in prestigious journals.

Conversely, publications arising from purely academic projects might be more likely to achieve a higher journal reputation. When a project becomes excessively firm centric, it might not sufficiently align with the academic requirements necessary for publication in top-tier journals. At the organizational level, firms are primarily inclined toward leveraging technology to address business challenges. Consequently, one could argue that authors employed by these firms are primarily interested in the act of publishing itself rather than in placing articles specifically in high-ranking journals. The regular work duties of firm employees may not involve targeting high-ranked journal publications, and given the difficulties associated with publishing in these journals, they may not have the time or resources to invest in such endeavors, while those involved in purely academic projects have more incentives to do so, for career advancement.

As in the preceding section, this discussion presents arguments supporting both higher and lower scientific journal reputations for articles stemming from academic engagement projects, resulting in the formulation of the final two contradictory hypotheses to be tested in this chapter:

H5.2a

Journal articles originating from academic engagement collaborations are associated with higher journal reputation.

H5.2b

Journal articles originating from academic engagement collaborations are associated with lower journal reputation.

5.2.3 Key takeaways from Section 5.2

- Scientific impact encompasses two key dimensions: article impact and journal reputation. Article impact reflects the value attributed to a publication by the scientific community, whereas journal reputation pertains to the associational reputation the article gains from the journal in which it appears.
- The conceptual framework, grounded in the literature, does not provide a straightforward answer as to whether one should anticipate higher or lower article impacts and journal reputations for publications resulting from academic engagement projects versus academic projects.
- This ambiguity primarily arises from the inherent nature of the engineering sciences, which encompass both fundamental and applied research, and is further complicated by the presence of conflicting institutional logics.
- Consequently, the literature offers support for arguments favoring both higher and lower scientific impacts for publications resulting from academic engagement projects, leading to the formulation of contradictory hypotheses (Figure 5.1).

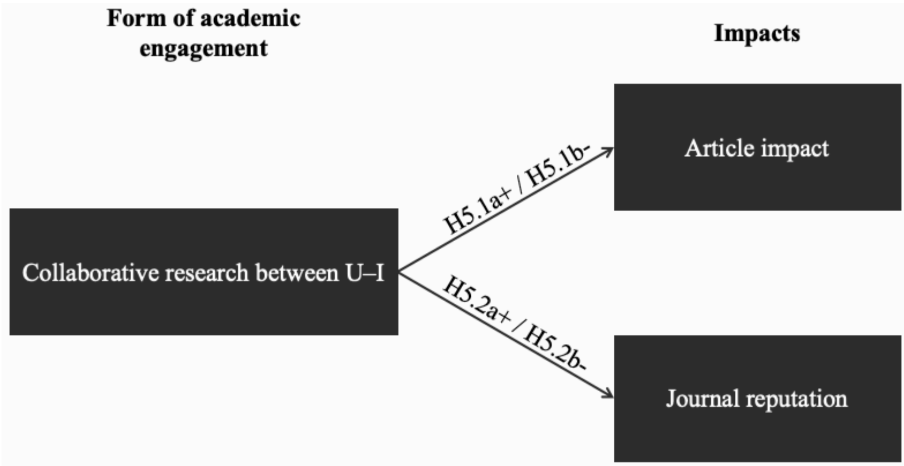

Figure 5.1. Conceptual model for understanding the hypothesized impact of academic engagement on article impact and journal reputation.

5.3 Data and method

This section outlines the data and methods used in conducting the research and analyses: the first part presents the data; the second part relates to the operationalization of variables; and the last part addresses the methods used, including presenting a detailed account of the reasons underlying the empirical strategy.

5.3.1 Data

In this undertaking, all publications and all EPO patents published by the 184 sampled engineering professors between the years 1995 and 2018 have been utilized. Furthermore, data on the number of citations received by each publication annually during the first three years after publication were collected. For example, an article published in 2010 would encompass citations from 2010, 2011, and 2012.

Operationalization of variables

For ease of reading, this section has been divided into three parts according to the three types of variables, namely, dependent variables, independent variables, and control variables.

Dependent variables

Two dependent variables have been operationalized, namely, *Article_impact* and *Journal_reputation*. These dependent variables aim to measure the two aspects of scientific impact.

Article impact has been approximated by counting the total number of forward citations a scientific document received in the first three years after publication (*Article_impact*). The choice of a rolling time window based on the article's publication date, rather than a fixed window irrespective of the publication year, is motivated by the desire to more equally capture the article impact of each publication (Amin & Mabe, 2000). For instance, in the context of this study, which spans the 2000–2018 period, a fixed, static measure would employ a window from 2000 to 2021 to gauge the number of forward citations, regardless of when an article was published during the analysis period. In contrast, a dynamic, rolling measure tailors the window to each article based on its publication date. For instance, an article published in 2000 would have a window of 2000–2002 for measuring forward citations, while an article published in 2010 would have a window of 2010–2012. This approach results in a more justifiable estimation of the article impact of each publication.

The selection of a three-year rolling time window is based on existing research, as it has been shown that the number of forward citations tends to peak within this period (Amin & Mabe, 2000). Furthermore, it is a commonly employed operationalization in the field (e.g., Beaudry & Kananian, 2013; Bellucci & Pennacchio, 2016;

McKelvey & Rake, 2020; Poege et al., 2019). Nevertheless, longer time windows, such as five years (Callaert et al., 2015), seven years (Wang et al., 2017), and even ten years (Fontana et al., 2020), are also utilized due to their ability to offer a more precise measure of the article impact of certain novel publications—notably, publications with a delayed article impact, which are often referred to as "sleeping beauties" (see, e.g., Garfield, 1980; van Raan, 2004, 2021; Wang et al., 2017). However, it is imperative to acknowledge that using longer time windows results in a shorter analysis period and, consequently, a reduced dataset. Therefore, a three-year rolling time window is preferred. To ensure the robustness of the analysis, a five-year rolling time window is used as a robustness test (see Section 5.4.3).

Inspired by prior research that operationalizes articles published in journals belonging to the top 5% of the total JIF distribution as having high journal reputation (Lozano et al., 2012; McKelvey & Rake, 2020), this study differentiates the top 15% from the remaining articles in my sample. This choice of a 15% threshold is based on quantile plotting of the variable, supported by basic quantile regression modeling, and because it aligns well with the top 5% threshold of the overall JIF distribution. In essence, although the outcome would have been similar regardless of the approach chosen, it makes more sense to focus on the journals in my sample, given that many of the journals with the highest JIF distributions are from different fields. Therefore, this is a binary variable, taking the value of 1 for all articles with the top 15% highest JIF scores, and 0 otherwise (*Journal_reputation*). While this is the main specification, it is important to note that various cutoff points are employed in robustness testing (see Section 5.4.3).

The 2018 Web of Science Journal Citation Report was chosen as it is the final year of the analysis period, consistent with the approach employed by McKelvey and Rake (2020). Additionally, with article impact as the dependent variable, this variable is included in the regressions as a control variable, as previous research has indicated a correlation between the journal of publication and an article's impact (e.g., Garfield, 1999, 2006; Lozano et al., 2012).

Figure 5.2, below, presents a scatterplot of article impact (*x*-axis) and the journal impact factor scores on which the second independent variable is based (*y*-axis). The line representing the ordinary least square (OLS) model indicates a correlation between the two variables, as expected. However, it also provides evidence that they represent two distinct aspects of scientific impact, as publications with the highest article impact are not necessarily published in journals with the highest journal impact factor scores. Similarly, articles published in top-scoring journals do not consistently achieve notably high article impact.

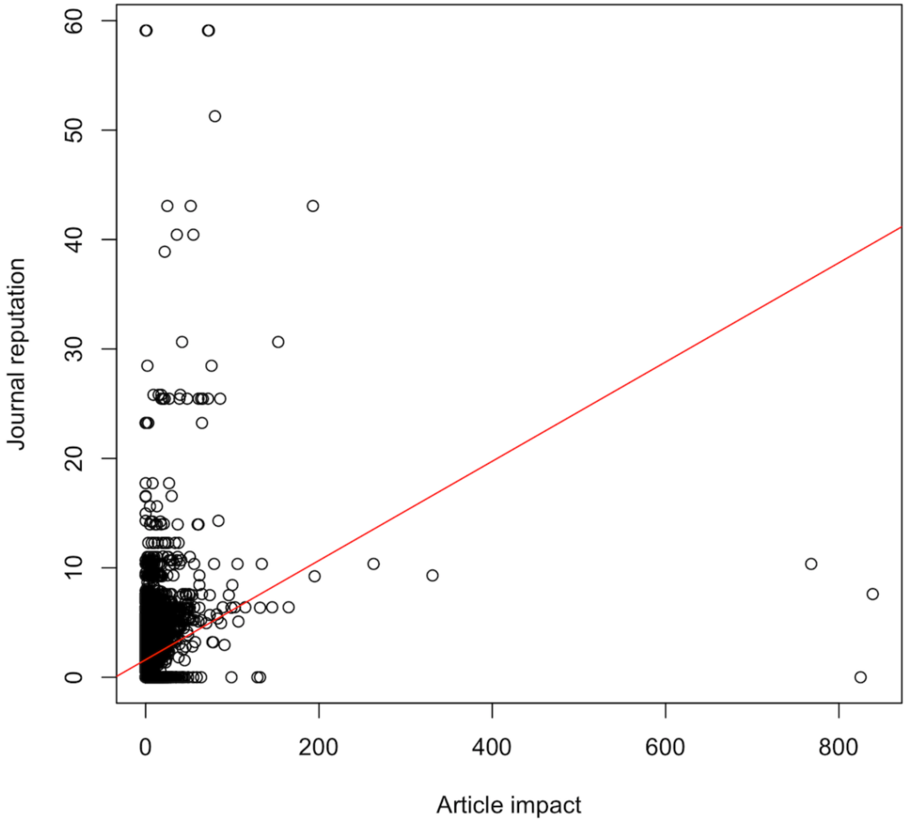

Figure 5.2. Scatterplot of article impact vs. journal reputation (journal impact factor scores).

Independent variables

Three independent variables have been operationalized, namely, *Academic_engagement*, *Academic_engagement:Number_authors*, and *Academic_engagement:Dual_affiliated_professor*.

Publications resulting from academic engagement projects are approximated by examining the affiliations reported by the authors of an article. Articles that include any reported firms are defined as products of prior collaborative research projects between academics and firms (*Academic_engagement*). These are distinguished from academic collaboration publications, which are authored exclusively by one or more academic scholars (for further details on the methodology used to identify firm publications, please see Chapter 4).

While it is also possible to detect publications resulting from academic engagement projects by scrutinizing university-unit funding data, as mentioned by Perkmann et al. (2011), this approach primarily identifies the organizations providing funding rather than the individuals involved in the project; hence, this method was not employed here.

Analyzing the resulting publications offers a reliable, albeit partial, indicator of successful collaborative research projects between university researchers and firms (Perkmann et al., 2011; Tijssen, 2009). In accordance with the literature, such as the papers by Frenken et al. (2010) and McKelvey and Rake (2020), the first independent variable is a binary variable, taking a value of 1 when any firm is included in the reported affiliations, and 0 otherwise.

The number of authors per paper is a crucial variable to consider, as numerous empirical studies have indicated that larger team sizes have a positive impact on the scientific output of collaborations (see, e.g., Hollis, 2001; Uzzi et al., 2013; Wu et al., 2019; Wuchty et al., 2007a). These observations find further support in the descriptive statistics pertaining to this dissertation's dataset, as presented in Figure 5.3, below.

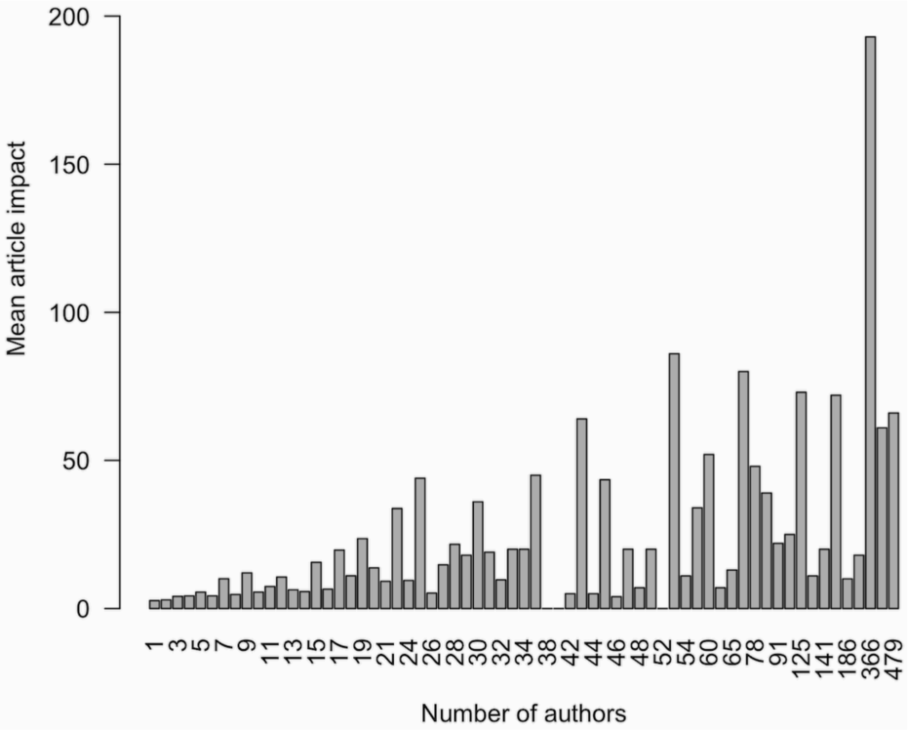

Figure 5.3. Mean article impact by the number of authors of the paper.

Overall, the figure suggests an increase in the mean article impact per publication with an increase in the number of authors. It is noteworthy that nearly all bars representing the article impact of publications with more than 30 authors are based on a single publication, contributing to large variance in mean article impact. To mitigate the impact of papers with extreme numbers of authors but with limited observations, all publications with nine or more authors were grouped into one bin. The decision to set the cut-off point at nine authors was based on the notably lower frequency of papers with nine or more authors. Table 5.1, below, displays the frequency of the modified variable. Consequently, the first interaction combines academic engagement with the number of authors per paper (*Academic_engagement:Number_authors*). It is important to note that this variable serves as a control variable when not included in the interaction.

Table 5.1. Frequency distribution of publications based on the *Number_author* variable.

Number_authors	**Frequency**
1	217
2	1443
3	2043
4	1673
5	895
6	787
7	276
8	437
9+	684

The second interaction combines academic engagement with the presence of any of the sampled dual-affiliated professors among the authors of the paper (*Academic_engagement:Dual_affiliated_professor*). This interaction is motivated by the insights of the literature reviewed above (Section 5.2.2). It is important to emphasize that publications resulting from dual-affiliated professors are only considered an outcome of prior academic engagement when these papers list at least one firm as an affiliation.

Control variables

In addition to the dependent and independent variables, several control variables have also been included in the models, namely, *Prior_article_impact*, *Prior_patenting*, *Prior_coauthors*, *Top_university*, *Number_universities*, *Number_nations*, *Number_fields*, *Article*, *Female*, *University_dummies*, *Field_dummies*, and *Year_dummies*.

Put succinctly, it is advisable to control for prior article impact as it is a fairly good predictor of future article impact (Acuna et al., 2012; Anderson & Richards-Shubik, 2019; Penner et al., 2013; Schilling & Green, 2011). Following the work of Schilling and Green (2011), the effect of a sampled university scientist's prior impact on the scientific outcomes of the collaboration has been approximated for every published scientific article by counting the total number of forward citations the sampled university scientist has received in the five years preceding the publication of the focal article (*Prior_article_impact*). Along the lines of Schilling and Green (2011), if more than one of the sampled university professors authored an article, the article impact score of the most impactful professor is used.

In addition to controlling for prior article impact, controlling for whether the authors have recently applied for a patent is also essential. Previous empirical research suggests a positive correlation between patenting and article impact (Balconi & Laboranti, 2006; Bourelos et al., 2012, 2017; Czarnitzki et al., 2007) as well as a positive correlation between patenting and scientific productivity (Czarnitzki et al., 2007; Haeussler & Colvyas, 2011). Consequently, this variable was estimated by analyzing whether any of the sampled university scientists had applied for a patent from the EPO in the seven years preceding the publication of the focal article (*Prior_patenting*).

The influence of network effects on the scientific outcomes of a collaboration has been approximated for every published article by counting the number of co-authors the sampled university scientists have had in the seven years preceding the publication of the article in question (*Prior_coauthors*). This means that the third independent variable is a count variable. Furthermore, following Schilling and Green (2011), if more than one of the sampled university scientists authored an article, the highest value is used (i.e., the value of the most highly cited researcher is used). For consistency and equality in my proxies, a rolling time window of seven was chosen rather than a fixed or open-ended window. By doing so, this study closely follows Ductor et al.'s (2014) approach to capturing researchers' prior degree centrality (they used a five-year long rolling time window). It is also possible to capture the researchers' network centrality according to other network measures, such as their betweenness centrality (see, e.g., Ductor et al., 2014; McKelvey & Rake, 2016; MingJi & Ping, 2014; Mirc et al., 2017); however, considering that the professors and not all authors are sampled, degree centrality is considered a more fitting measure since it is based on the researchers' direct number of edges rather than on the whole network (as betweenness centrality is based on). Although this measure likely includes a certain level of redundant information (Burt, 1992; Granovetter, 1973), it is still a good proxy for overall access to information (Freeman, 1978/1979; Granovetter, 1973), and has commonly been used in recent empirical studies (see, e.g., Ductor et al., 2014; McKelvey & Rake, 2016; MingJi & Ping, 2014; Mirc et al., 2017).

The analysis moreover controls for articles in which at least one of the top 50 universities worldwide is reported among the authors' affiliations (*Top_university*), according to the Academic Ranking of World Universities 2018, commonly referred to as the ShanghaiRanking (ARWU, 2018).[24] This factor, too, is important to take into account, as different universities arguably have different degrees of prestige, both within and outside the scientific community, as the academic university rankings are based on metrics such as the number of forward citations and the number of Nobel laureates (Rauhvargers, 2011); accordingly, authors from more prestigious universities are more likely to have their work acknowledged, all else being equal.

Numerous studies have examined the impact of authors' geographical diversity on the scientific outcomes of collaborations. These investigations reveal that such

[24] The 2018 rankings were chosen because the analysis period ended in 2018.

diversity can significantly influence the results of a publication (Bercovitz & Feldman, 2010; Carayol et al., 2019; Frenken et al., 2010; Glänzel & Schubert, 2001; Lancho Barrantes et al., 2012; Larivière et al., 2015; Wagner et al., 2019; Wang et al., 2017). To account for this factor, this study includes two controls: one estimating the number of universities among the authors' affiliations (*Number_universities*) and another measuring the variety of nations represented in the authors' affiliations (*Number_nations*) for each article.

Interdisciplinary research has garnered significant attention in the scientific community (Larivière et al., 2015; Wang et al., 2015; Yegros-Yegros et al., 2015). In response, this study introduces a control variable to gauge a publication's level of specialization or breadth. This control involves a count variable representing the total number of scientific fields categorized by the Web of Science encompassed by the document (*Number_fields*).

Since different types of scientific publications—e.g., journal articles versus conference proceedings—have been found to attract different levels of citations (Michels & Fu, 2014), this study controls for whether the publication was a journal article (*Article*).

The difference in the inclination to participate in academic engagement between males and females, as discussed in Section 2.1.3, and the imbalanced representation of male and female professors in the sample necessitate the inclusion of a control variable. This variable is assigned a value of 1 if any professor listed on the focal scientific document is female, and 0 otherwise (*Female*).

This study also controls for the sampled universities by which the authors of an article were employed when the article was published, by analyzing which organizations are reported among the authors' affiliations (*University_dummies*:

CTH, *KTH*, *LiU*, *LTH*, *UU*). Controlling for this factor is important as, all else being equal, the different universities are located in different sized cities, have different geographical proximities to different firms, have different amounts of industrial funding, and therefore have different experiences of, and inclinations toward, academic engagement projects, all of which can influence the scientific outcome of collaboration (cf. Aschhoff & Grimpe, 2014; Bishop et al., 2011; D'Este & Patel, 2007; Martin & Moodysson, 2013; Ponomariov, 2008; Tartari et al., 2014).

Following similar papers (e.g., Abramo et al., 2009; Bekkers & Freitas, 2008; Callaert et al., 2015; McKelvey & Rake, 2020), this study also controls for differences between research fields and between years. First, it controls for different fields in accordance with the field(s) to which an article was assigned by Web of Science (2020). In greater detail, a simple analysis of the frequencies of the different subject areas Web of Science had assigned to all articles revealed that three fields were substantially more common than the rest, so three control variables were established for these fields (*Field_dummies*: *Computer_science*, *Telecommunications*, and *Automation_and_control_systems*). Second, a variable controlling for the publication year of each paper was included (*Year_dummies*).

Variable summary

Table 5.2, below, provides an overview of all variables, including name, type of variable, and operationalization.

Table 5.2. Summary of the regression variables used in Chapter 5.

Name	**Type**	**Description**
Article_impact	DV	A count variable representing the total number of scientific citations received by a publication in the three years after its release
Journal_reputation	DV, CV	A binary variable with a value of 1 if an article was published in a journal belonging to the top 15% of the 2018 Journal Impact Factor distribution with regard to my sample, and 0 otherwise

Academic_engagement	IV	A binary variable with a value of 1 if a firm is reported among the authors' affiliations on the publication, and 0 otherwise
Dual_affiliated_professor	CV	A binary variable with a value of 1 when at least one of the sampled dual-affiliated professors is listed as an author of the publication, and 0 otherwise
Number_authors	CV	A categorical variable indicating the number of authors of each publication, categorized into groups of 1–8 authors and 9 or more authors
Prior_article_impact	CV	A count variable representing the total number of scientific citations received by a sampled professor in the five years preceding the release of the publication; if more than one of the sampled professors authored the publication, the highest value is used
Prior_patenting	CV	A binary variable with a value of 1 if any of the sampled professors authoring a publication applied for a patent in the five years preceding the release of the publication, and 0 otherwise
Prior_coauthors	CV	A count variable indicating the total number of co-authors the sampled professor had in the five years preceding the release of the publication; if more than one of the sampled professors authored the publication, the highest value is used
Top_university	CV	A binary variable with a value of 1 if any of the top 50 universities worldwide is reported among the authors' affiliations on the publication, according to the 2018 Academic Ranking of World Universities, and 0 otherwise
Number_universities	CV	A count variable indicating the total number of unique university addresses reported among the authors' affiliations on the publication
Number_nations	CV	A count variable representing the total number of unique nation addresses reported among the authors' affiliations on the publication
Number_fields	CV	A count variable indicating the total number of fields in which the publication has been categorized by Web of Science
Article	CV	A binary variable with a value of 1 if the publication is classified as an article, according to Web of Science, and 0 otherwise
Female	CV	A binary variable with a value of 1 if any of the sampled professors on the publication is female, and 0 otherwise
University_dummies	CV	Five similar dummy variables, each with a value of 1, if the sampled university is reported among the authors' affiliations on the publication, and 0 otherwise; the universities are CTH, KTH, LiU, LTH, and UU
Field_dummies	CV	Three similar dummy variables, each with a value of 1, if Web of Science has assigned the publication to the specific subject areas of "Computer Science," "Telecommunications," or "Automation and Control Systems," and 0 otherwise

Year_dummies	CV	A factor variable representing the year in which the publication was released; the possible years are 2000–2018

5.3.2 Empirical strategy

The overall objective of the empirical strategy is to distinguish academic engagement projects from academic projects, and subsequently, to quantitatively analyze the outcomes of the two types of collaborations with regard to article impact and journal reputation. The objective is also to explicitly analyze the influence exerted by dual-affiliated professors as well as to analyze the interplay between academic engagement and the number of authors of a paper concerning its scientific impact.

Following studies with similar data characteristics (e.g., Blind et al., 2018; Carayol et al., 2019; D'Este & Iammarino, 2010; Frenken et al., 2010; McKelvey & Rake, 2020), the first dependent variable (*Article_impact*) was estimated using a (generalized) negative binomial regression model, since the overdispersion test developed by Cameron and Trivedi (1990) suggested overdispersion (Equation 5.1). Put differently, the observed conditional variance of the response was statistically greater than the variation implied by the distribution used in fitting the model, that is, the variance was statistically greater than the mean. According to several authors (Cameron & Trivedi, 1998; Fox & Weisberg, 2018; Hilbe, 2011; Lawless, 1987; Venables & Ripley, 2002), negative binomial regression is an effective model for dealing with this type of frequency data as it accommodates between-individual variability via introducing a random subject effect (α), which can have different values for different subjects. The model can furthermore be viewed as a mixture of two distributions, as the number of observations (y_i) is assumed to follow a Poisson distribution but the dispersion is assumed to follow a gamma distribution.

Mathematically, a negative binomial regression model for observation *i* is commonly expressed as:

Equation 5.1. The negative binomial regression model.

$$P(Y = y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}$$

where y_i is the observed number of counts for some identified event (here, the observed number of forward citations); $i = 1, 2, \dots, n$ is the number of observations; $\mu_i = \exp(x\beta)$ is the conditional mean (or the rate or intensity parameter) of *y* given the values of $x\beta$, where x and β are the model-independent variables and parameters, respectively ($x\beta = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$); α is the individual random subject effect; and Γ is the gamma function. Importantly, this means that the dependent variable (*y*) is a random variable, whereas the independent variables (the *x*s) are nonrandom. The model moreover assumes the independent variables to be independent and to have low correlation among one another.

This dependent variable was furthermore estimated using generalized linear models (GLMs), which extend linear models in that they allow for normal and non-normal distributions such as Gaussian, binomial, Poisson, and gamma distributions (Fox & Weisberg, 2018; McCullagh & Nelder, 1989; Venables & Ripley, 2002). Additionally, it was estimated using Huber–White robust standard errors, in line with research (McKelvey & Rake, 2020).

The other commonly used approach for dealing with overdispersed data is to employ a quasi-Poisson regression (Fox & Weisberg, 2018; Hilbe, 2011; Ver Hoef & Boveng, 2007; Wedderburn, 1974; Wooldridge, 1997, 2012). According to these authors, the difference between the models is that the variance in a negative binomial model is a quadratic function of the mean, while in the quasi-Poisson model, it is a linear function of the mean. Put differently, the negative binomial model accommodates overdispersion by setting the variance to be a multiple of the mean, while the quasi-Poisson model accommodates overdispersion by specifying the relationship between the variance-mean through a dispersion parameter. This difference can have an effect on how well the model fits the data; however, one consequence of the fact that the quasi-Poisson model is characterized only by its mean and variance (and thus does not necessarily have a distributional form) is that one cannot use formal, scientifically proven methods, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), to assess how well the two different models fit the data. While the negative binomial model was the preferred choice, since it is the most widely used model in this context, the quasi-Poisson model serves as a good robustness check.

Because the second dependent variable (*Journal_reputation*) is a binary indicator that distinguishes high-journal-reputation papers from those of lower journal reputation, it has been estimated using a generalized probit model, with Huber–White robust standard errors (Equation 5.2). This is in line with existing studies such as the one by McKelvey & Rake (2020). Put differently, given an outcome (*Y*) and a vector of independent variables (***X***), the probit model estimates the probability of publication in a highly reputed journal.

Mathematically, the model is normally expressed as:

Equation 5.2. The probit model.

$$P(Y = 1|X_i) = \emptyset(\beta_0 + X\beta)$$

5.4 Results

In this section, the findings of the first empirical study are presented. Prior to engaging in the econometric analysis, and thereby addressing the hypotheses, interesting descriptive findings are presented and briefly discussed. The chapter concludes by examining the robustness of the aforementioned results.

5.4.1 Descriptive findings

The total number of published documents over the analyzed period (2000–2018) was 8455, for an average of 4.0 publications per year per professor. Of the 8458 publications, 4118 (48.7%) were classified as proceedings papers, 4056 (48.0%) as articles, and the remaining 281 (3.3%) as other types (e.g., meeting abstracts, editorial material, and book chapters).

Figure 5.4, below, shows that there was a clear trend for publications resulting from both academic engagement projects and academic projects to increase throughout the analyzed period. Notably, it shows that publications arising from academic engagement exhibited more rapid growth, signifying a greater prevalence of academic engagement throughout this timeframe. Furthermore, the prevalence of academic engagement started at 11.0% in 2000 and culminated at 23.8% in 2018. This difference is statistically significant at the 1% level according to a two-proportion z-test. Moreover, when distinguishing among the sampled universities, we note that the professors affiliated with the different universities published with firms to varying extents. With respect to z-testing, professors employed in CTH and LTH published significantly more with firms than did the professors affiliated with KTH, LiU, and UU.

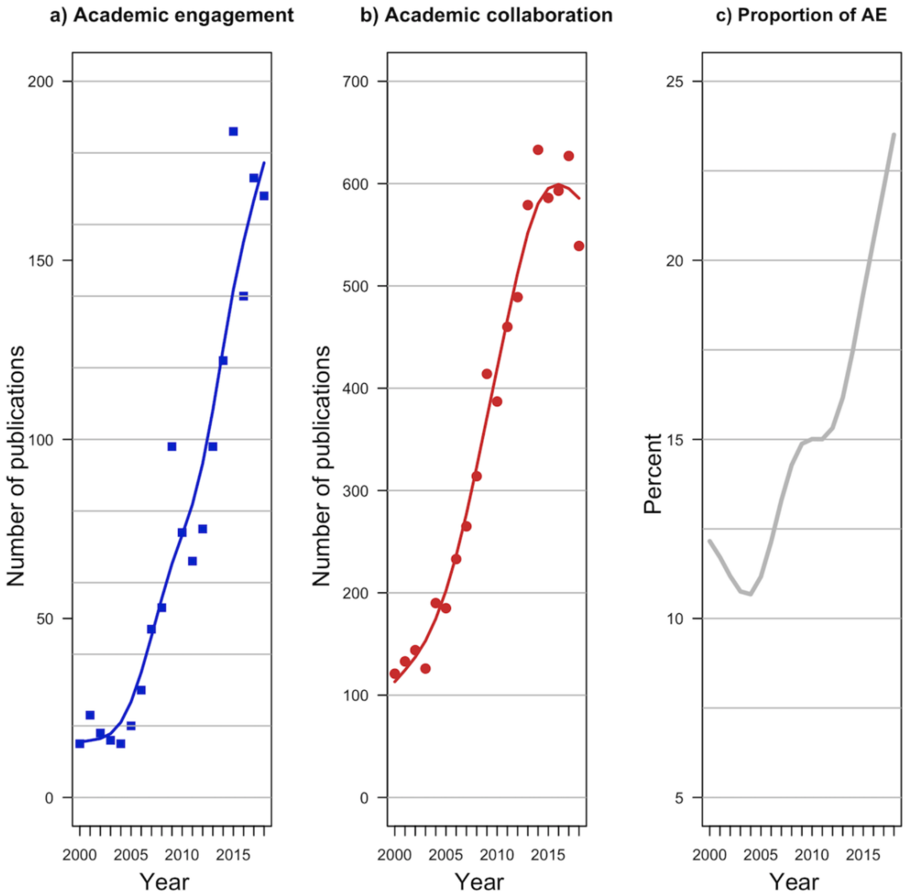

Figure 5.4. The number of publications resulting from academic engagement (left), academic collaboration (middle), and the proportion of publications resulting from academic engagement (right).

To gain deeper insight into the collaborative patterns of the sampled professors, we can examine firms that appear in their publications more than ten times over the entire period, and assess the degree to which these publications are associated with the sampled universities (Table 5.3, below). It becomes evident that the sampled professors most frequently engage in collaborations with industrial researchers employed by multinational enterprises (MNEs). Additionally, it is apparent that certain firms collaborate with several universities (e.g., Ericsson and Nokia), while others predominantly or exclusively collaborate with a single university (e.g., Oticon and Sony). In cases in which multiple universities are linked to publications with a given firm, more of the sampled professors tend to be co-authors of these publications. Conversely, when collaborations are more exclusively linked to one of the sampled universities, the number of sampled professors contributing to the co-authored publications tends to be lower (e.g., one of the sampled professors is a co-author of all 82 publications linking LiU with Oticon). By summing the values in a given row and comparing it with the "total" value for the same row, we can gauge the extent to which publications with a particular firm involve more than one of the sampled universities. Notably, out of 18 firms, 12 have never published any papers involving more than one of the sampled universities, while only three firms have done so more than 5% of the time (i.e., Nokia: 20.0%, Volvo Cars: 16.9%, ABB: 9.8%).

Table 5.3. Number of publications affiliated with the sampled universities and firms with ten or more documents.

		University					
		CTH	KTH	LiU	LTH	UU	Total*
Firm	Ericsson	67	68	45	86	10	267
	Oticon	0	0	82	0	0	82
	Volvo Cars	61	1	9	10	2	71
	AstraZeneca	18	0	0	34	3	55
	Huawei Technologies	21	26	3	3	0	52
	SAAB	12	0	15	25	2	52
	ABB	0	15	24	13	4	51
	Scania Group	0	24	15	0	1	40
	Nokia	15	5	13	7	8	40
	Volvo Group	10	3	2	10	0	25
	Mitsubishi Electric Corporation	5	0	0	17	0	22
	Sony	1	1	0	20	0	22
	Bluetest	19	0	0	0	0	19
	Qamcom	18	1	0	0	0	19
	Perimed	0	0	14	0	0	14
	QualTech	11	0	0	0	0	11
	Infineon	0	1	10	0	0	11
	Intel	2	1	6	2	0	11

* Total represents the total number of occurrences per firm, and this is not necessarily equal to the sum of the numbers in the cells to the left in each row (multiple universities can be affiliated with the same publication).

Given the established significance of conference proceedings papers in the field of engineering sciences (e.g., Michels & Fu, 2014), the average article impact, covering both journal articles and conference proceedings, is presented in Figure 5.5, below. It is evident that it is through journal articles that professors primarily receive recognition for their contributions, even though proceedings papers were slightly more common. Additional analysis (results not shown) revealed that a mere 11.5% of all published articles resulted in zero article impact, meaning that they had received zero citations within three years of publication. In stark contrast, a substantial 57.8% of all proceedings papers failed to accumulate any article impact.

The somewhat unexpected anomaly in 2018, regarding article impact, can be plausibly attributed to two key factors. First, it is possible that some of the distinguished senior professors, known for their high-impact contributions, had reduced their publication output from the peak of their careers. Consequently, this reduction in output may have contributed to lowering the average article impact. Second, there may exist a lag in the citation process within Web of Science. To elaborate, the number of citations was collected three years after publication; thus, all documents released in 2018 were subjected to a citation window extending from 2018 to 2020. As the data for all citations were compiled in February/March 2021, some of the documents published in 2018 could conceivable have been inaccurately assessed or underrepresented in the citation count.

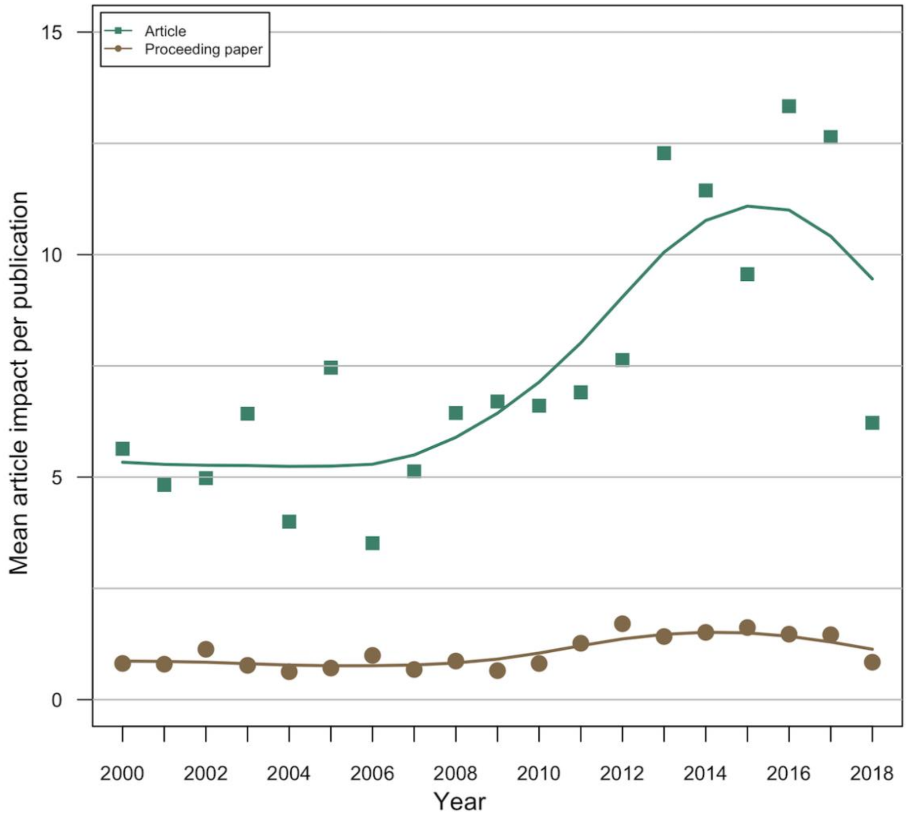

Figure 5.5. The mean article impact of proceedings papers and articles.

In relation to publications resulting from academic engagement versus academic projects, the trend lines depicted in Figure 5.6, below, imply that publications resulting from academic engagement had an article impact premium over those resulting from academic projects. When investigating the mean article impact for all articles, the mean article impact for those resulting from academic engagement was 7.9, whereas it was only 4.2 for those resulting from academic collaboration. This offers tentative support for Hypothesis 5.1a. However, it is noteworthy that academic engagement has fewer observations, meaning that outliers have a larger effect on the mean (e.g., in 2014, one of the documents resulting from academic engagement had 839 citations).

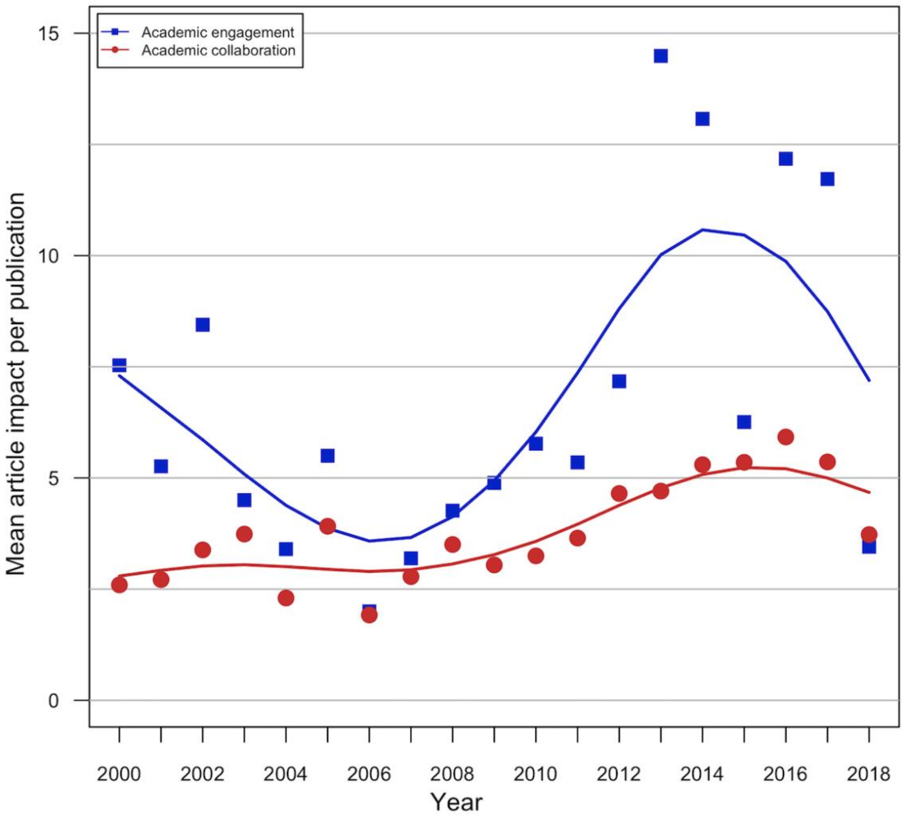

Figure 5.6. The mean article impact of publications resulting from academic engagement and academic collaboration.

Examining the journal reputation of articles published in journals listed in the Web of Science Journal Citation Reports, as shown in Figure 5.7, below, reveals that the mean journal reputation per published article by the sampled professors has remained stable throughout the observed period.[25] Furthermore, this figure provides a comparative perspective, showcasing the median journal reputation of the sampled professors in contrast to the median journal reputation of all journals categorized under “Engineering, Electrical & Electronic” in the Web of Science database. This comparison underscores a substantial disparity, revealing that the sampled

[25] Over 90% of all published articles were published in journals included in the Web of Science Journal Citation Reports.

professors' journal reputations significantly surpass those of the broader fields in which they operate.

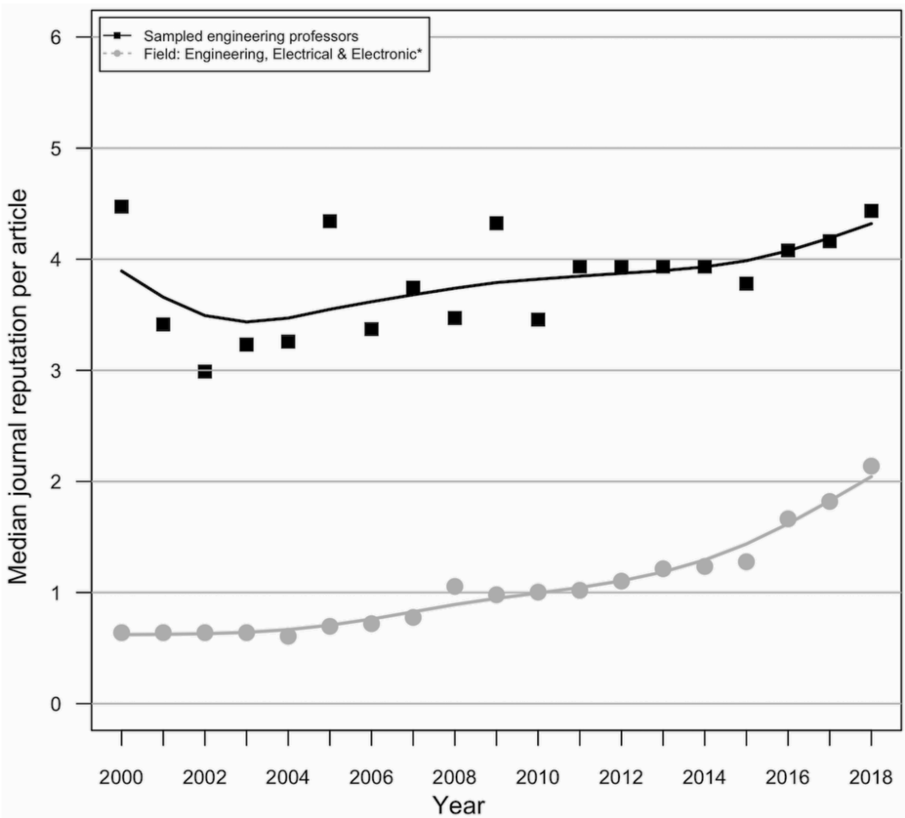

Figure 5.7. The median journal reputation per article by the sampled professor and that for the whole electrical/electronic engineering field as defined by the Web of Science.

Focusing on comparing and contrasting the publications resulting from academic engagement and those arising from academic collaboration, Figure 5.8, below, implies that journal articles from academic engagement, on average, exhibit journal reputations similar to those of articles from academic collaborations. In greater detail, the mean journal reputation for all articles resulting from academic engagement was 4.8, whereas it was 4.4 for those resulting from academic collaboration. The statistical significance of these differences remains unclear, indicating that neither Hypothesis 5.2a nor 5.2b is conclusively supported by the data.

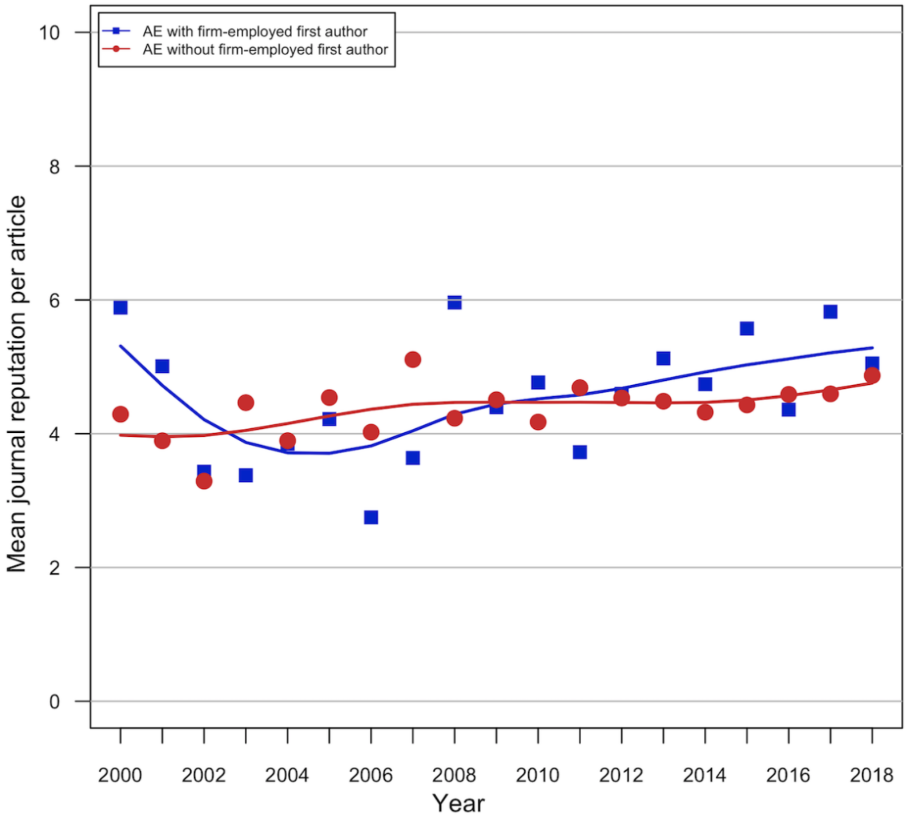

Figure 5.8. The mean journal reputations of articles resulting from academic engagement and academic collaboration.

Appendix A presents additional descriptive statistics indicating the differences among the sampled universities and most common subfields in relation to article impact and journal reputation. Noteworthy observations include a higher mean article impact for publications centered on telecommunication, coupled with a lower likelihood of being featured in top-ranked journals, in contrast to papers focusing on automation and control systems as well as computer science. These statistics were moved to Appendix A as they do not constitute the primary focus of this study.

5.4.2 Regression analyses

Table 5.4 presents descriptive statistics for all variables included in the models, providing information such as variable names, counts of observations, means, standard deviations, minimum and maximum values, ranges, skewness, and kurtosis. Due to the extensive number of variables in the dataset, individual comments on each will not be provided. Readers are encouraged to review the table thoroughly. Specific variables and correlations that warrant special attention will be discussed.

The descriptive statistics table shows that the skewness and kurtosis values for one of the dependent variables (*Article_impact*) are remarkably high, meaning that the distribution of that variable is asymmetric and peaked—in other words, non-normal (D'Agostino et al., 1990; DeCarlo, 1997). This justifies the decision to employ a negative binomial GLM when analyzing that dependent variable. Three other variables also displayed high skewness and kurtosis, i.e., *Number_authors*, *Number_universities*, and *Number_nations*: the first variable was handled by modifying it to form a categorical variable, as mentioned before, and the other two were handled by logging those in the regression analysis.

The pairwise correlational matrix, located in Appendix B, provides preliminary evidence that multicollinearity may not be a significant concern, as the pairwise correlations are generally in the low to moderate range. It is crucial to note, however, that "not all collinearity problems can be detected by inspection of the correlation matrix: collinearity can exist even if no pair of variables has a particularly high correlation" (James et al., 2013, p. 101). Therefore, further analyses are necessary. Subsequent analyses, specifically variance inflation factor (VIF) assessments conducted on the primary model specification, confirm that multicollinearity is not a primary concern. All variables of interest have VIF values below 3, well below the commonly accepted threshold of 10 commonly recognized as indicating multicollinearity (James et al., 2013; see also Wooldridge, 2012).

Table 5.4. Descriptive variable statistics, Chapter 5.

Variable	*No.*	mean	SD	median	min	max	range	skew	kurtosis
Article_impact	8455	4.85	18.70	1	0	839	839	30.5	1253.9
Journal_reputation	3414	0.17	0.38	0	0	1	1	1.7	1.0
Academic_engagement	8455	0.17	0.38	0	0	1	1	1.8	1.1
Number_authors	8455	5.06	9.99	4	1	479	478	30.3	1203.4
Dual_affiliated_professor	8455	0.06	0.23	0	0	1	1	3.9	13.0
Prior_article_impact	8455	282.5	488.26	109	0	3925	3925	3.9	18.3
Prior _patenting	8455	5.01	22.31	0	0	391	391	10.6	138.9
Prior_coauthors	8455	66.67	104.54	45	0	1516	1516	8.7	99.6
Top_university	8455	0.08	0.27	0	0	1	1	3.1	7.4
Number_universities	8455	1.80	3.75	1	1	184	183	33.0	1370.0
Number_nations	8455	1.48	1.10	1	1	36	35	10.3	212.0
Number_fields	8455	1.88	0.83	2	1	7	6	1.1	2.9
Article	8455	0.45	0.50	0	0	1	1	0.2	–2.0
Female	8455	0.04	0.20	0	0	1	1	4.6	19.4
CTH	8455	0.20	0.40	0	0	1	1	1.5	0.2
KTH	8455	0.25	0.43	0	0	1	1	1.2	–0.7
LiU	8455	0.24	0.43	0	0	1	1	1.2	–0.5
LTH	8455	0.22	0.42	0	0	1	1	1.3	–0.2
UU	8455	0.11	0.32	0	0	1	1	2.4	3.9
Computer_science	8455	0.24	0.43	0	0	1	1	1.2	–0.5
Telecommunications	8455	0.24	0.43	0	0	1	1	1.2	–0.6
Automation_and_control_systems	8455	0.21	0.41	0	0	1	1	1.4	0.0
Year_dummies	8455	2012	4.70	2013	2000	2018	18	–0.7	–0.4

Table 5.5, below, displays the regression results with article impact as the dependent variable. Model 1 incorporates all control variables but no independent variables. Model 2 introduces the first independent variable, i.e., academic engagement. Model 3 encompasses an interaction term between academic engagement and the number of authors of the paper, while Model 4 incorporates an interaction term between academic engagement and dual-affiliated professors.

Table 5.5. Regression results with article impact as the dependent variable.

Results

	Dependent variable: *Article_impact*			
	(1)	(2)	(3)	(4)
Academic_engagement		0.143^{***}	–0.048	0.124^{**}
		(0.054)	(0.130)	(0.059)
Academic_engagement:Number_authors			0.037	
			(0.023)	
Academic_engagement:Dual_affiliated_professor				0.400^{**}
				(0.172)
Number_authors	0.013	0.006	–0.001	0.008
	(0.014)	(0.015)	(0.016)	(0.014)
Dual_affiliated_professor	–0.124			$–0.385^{***}$
	(0.092)			(0.133)
Journal_reputation	0.954^{***}	0.948^{***}	0.941^{***}	0.955^{***}
	(0.098)	(0.097)	(0.095)	(0.097)
Prior_article_impact	0.0003^{***}	0.0003^{***}	0.0003^{***}	0.0003^{***}
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Prior_patenting	–0.0002	–0.001	–0.001	–0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	$–0.0004^{**}$	$–0.0004^{**}$	$–0.0004^{**}$	$–0.0004^{**}$
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.282^{***}	0.275^{***}	0.277^{***}	0.274^{***}
	(0.084)	(0.084)	(0.084)	(0.084)
log(*Number_universities*)	0.283^{***}	0.297^{***}	0.296^{***}	0.298^{***}
	(0.088)	(0.090)	(0.090)	(0.089)
log(*Number_nations*)	0.206^{***}	0.189^{***}	0.184^{***}	0.180^{***}
	(0.058)	(0.058)	(0.057)	(0.057)
Number_fields	$–0.060^{**}$	$–0.060^{**}$	$–0.058^{**}$	$–0.061^{**}$
	(0.030)	(0.030)	(0.029)	(0.030)
Article	1.342^{***}	1.334^{***}	1.335^{***}	1.339^{***}
	(0.050)	(0.051)	(0.051)	(0.051)

Female	–0.248**	–0.239**	–0.232**	–0.231**
	(0.100)	(0.101)	(0.101)	(0.100)
University_dummies	Yes	Yes	Yes	Yes
Field_dummies	Yes	Yes	Yes	Yes
Year_dummies	Yes	Yes	Yes	Yes
Constant	–0.051	–0.052	–0.012	–0.032
	(0.222)	(0.216)	(0.204)	(0.217)
Observations	8455	8455	8455	8455
Log likelihood	–19,307.05	–19,302.86	–19,300.94	–19,295.95
Akaike inf. crit.	8658.10	38,649.72	38,647.87	38,639.89

Robust standard errors in parentheses.

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Model 2 illustrates a statistically significant correlation, indicating that publications resulting from academic engagement projects are associated with higher article impact. Consequently, this model supports Hypothesis 5.1a, suggesting that publications resulting from academic engagement have a higher article impact than do those arising solely from academic projects. As a result, it rejects Hypothesis 5.1b, which predicted the opposite correlation.

In Model 3, no statistically significant effect is observed for the first interaction term (*Academic_engagement:Number_authors*). However, the p-value is relatively low (0.12). Further insights into this relationship are provided in Figure 5.9, below, suggesting that academic engagement with a small number of authors (below four) has a negligible effect on article impact, while collaboration with a larger number of authors positively influences article impact. This finding necessitates additional analyses, which will be presented and discussed in the following section focusing on robustness tests.

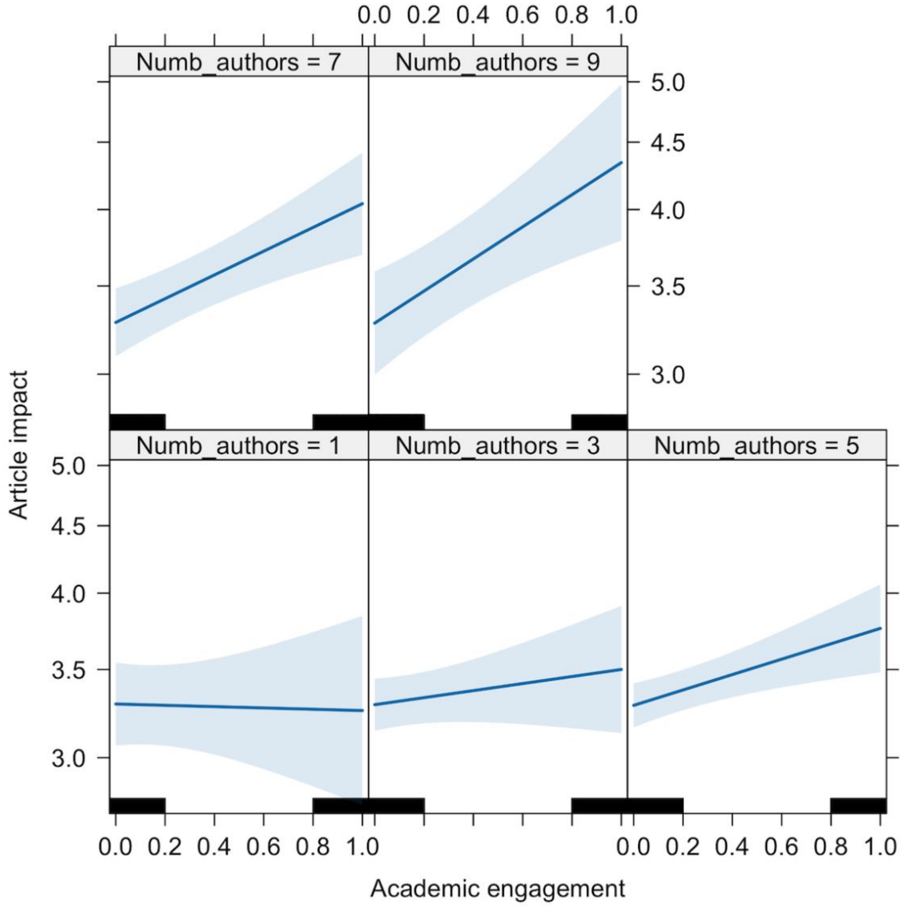

Figure 5.9. The relationship between academic engagement, number of authors, and article impact.

Model 4 found a significant difference for the final interaction term (*Academic_engagement:Dual_affiliated_professor*), suggesting that including dual-affiliated professors positively influences the article impact of the resulting publications.

Concerning the control variables, a few of them correlated with higher article impact, namely, publishing in top-ranked journals, at least one author having recent superior article impact, at least one author being affiliated with any of the top 50 ranked universities worldwide, publishing with researchers from various universities and/or countries, and publishing scientific articles. Three of the control variables were also correlated with lower article impact, namely, at least one author recently publishing papers with many different authors, publications addressing many different topics, and publications involving the sampled female professors.

Continuing the established format, Table 5.6, below, presents the regression results with journal reputation as the dependent variable.

Table 5.6. Regression results with journal reputation as the dependent variable.

Results

	Dependent variable: *Journal_reputation*			
	(1)	(2)	(3)	(4)
Academic_engagement		–0.118*	–0.377*	–0.110
		(0.072)	(0.197)	(0.076)
Academic_engagement:Number_authors			0.047	
			(0.033)	
Academic_engagement:Dual_affiliated_professor				–0.198
				(0.244)
Number_authors	0.005	0.010	0.001	0.009
	(0.015)	(0.016)	(0.017)	(0.016)
Dual_affiliated_professor	0.120			0.237
	(0.125)			(0.167)
Prior_article_impact	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior_patenting	0.002**	0.003***	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.190**	0.194**	0.194**	0.198**
	(0.089)	(0.089)	(0.090)	(0.089)
log(*Number_universities*)	0.233***	0.226***	0.221***	0.227***

	(0.065)	(0.065)	(0.065)	(0.065)
log(*Number_nations*)	0.198***	0.211***	0.206***	0.213***
	(0.073)	(0.073)	(0.073)	(0.073)
Number_fields	0.303***	0.302***	0.305***	0.304***
	(0.041)	(0.040)	(0.040)	(0.040)
Female	0.083	0.097	0.099	0.057
	(0.166)	(0.170)	(0.170)	(0.167)
University_dummies	Yes	Yes	Yes	Yes
Field_dummies	Yes	Yes	Yes	Yes
Year_dummies	Yes	Yes	Yes	Yes
Constant	24.104*	23.765*	23.593*	23.287*
	(12.600)	(12.604)	(12.594)	(12.638)
Observations	3414	3414	3414	3414
Log likelihood	–1341.38	–1340.53	–1339.34	–1339.47
Akaike inf. crit.	2722.76	2721.06	2720.68	2722.94

Robust standard errors in parentheses.

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The findings corroborate Hypothesis 5.2b, showing that publications resulting from academic engagement collaborations are associated with lower journal reputation (i.e., they are more likely to be published in less-reputed journals than those resulting from academic projects, all else being equal). It is worth pointing out that the statistical relationship is weakly significant with a *p*-value of 0.098, meaning that this finding is not as robust as that in relation to the first set of hypotheses. The proof can be seen in Model 2, which shows that publications resulting from academic engagement are weakly statistically significantly correlated with lower journal reputation. This relationship is also observed in Model 3, which incorporates the interaction term involving the number of authors, while Model 4, which incorporates the interaction term involving dual-affiliated professors, found no statistically significant relationship (*p*-value = 0.146).

Finally, Models 3 and 4 suggest that the journal reputation of the papers resulting from academic engagement is not statistically significantly affected by the number of authors or the presence of at least one dual-affiliated professor, respectively.

With respect to the control variables, many of the usual factors seem to positively affect journal reputation. These include having a larger number of authors, having at least one author affiliated with one of the top 50 ranked universities globally, having at least one author with recent superior article impact and/or with a substantial number of patent applications, and engaging in research collaborations that involve multiple universities and/or countries.

5.4.3 Robustness tests

To ensure the robustness of the results, several robustness tests were conducted. This section primarily focuses on describing those tests and their implications. All referenced regressions can be found in Appendix C.

To further investigate the relationship between academic engagement and the number of authors of a paper, in relation to article impact, the number of authors variable was categorized in three relatively equal-sized bins: one to three authors, four or five authors, and six or more authors. The aim of this is to distinguish the papers for which there seemed to be no significant interaction effect, the first bin, from the rest, while also separating papers with a medium number of authors from those with a large and very large number of authors. Figure 5.10, below, provides insights into this relationship, indicating that academic engagement with a small number of authors (three or fewer) has a negligible effect on article impact, while collaboration with a larger number of authors (above three) positively influences article impact. Here, there was a significant effect for the medium-sized bin (four or five authors).

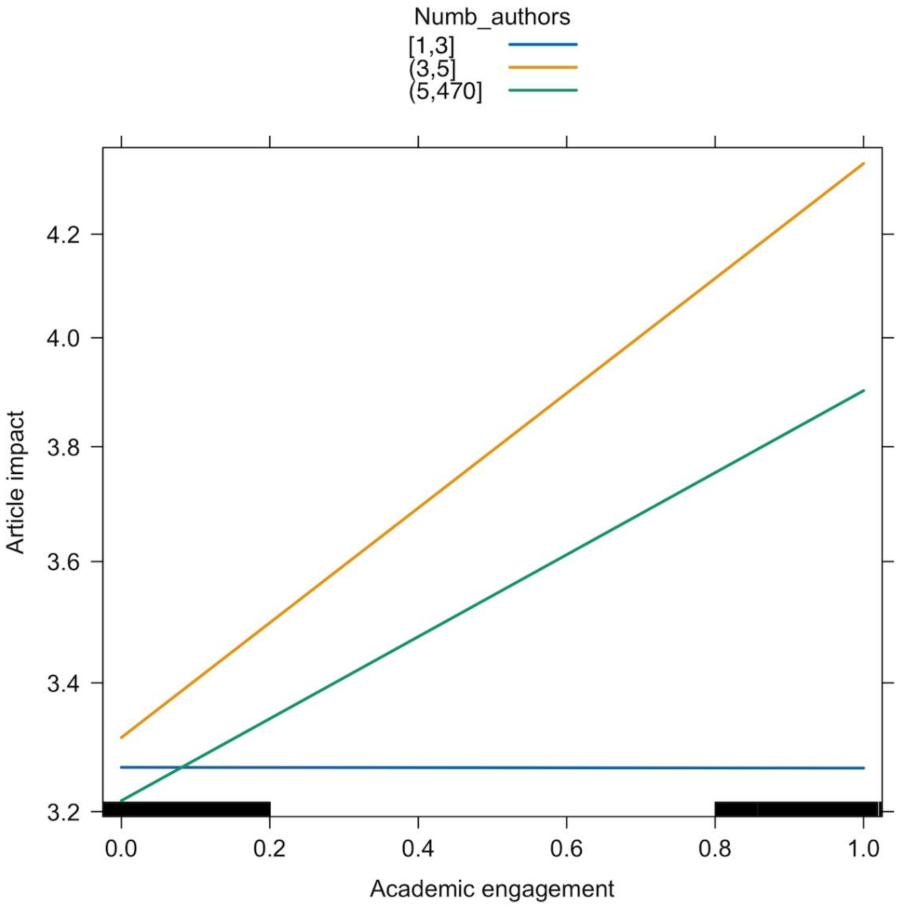

Figure 5.10. The relationship between academic engagement, number of authors (three bins), and article impact.

In another test, the article impact rolling time window was extended from three to five years to accommodate delayed article impact (e.g., van Raan, 2004, 2021). Additionally, in accordance with Slavtchev (2013), the main regressions were performed with a transition from Huber–White robust standard errors to author-clustered standard errors to account for intragroup correlation. All negative binomial GLMs were also re-run, utilizing a quasi-Poisson estimation, which offers a viable approach to handling overdispersed count data (e.g., Ver Hoef & Boveng, 2007).

Regarding these adjustments, the outcomes and trends of the findings remained consistent, albeit with slightly diminished levels of statistical significance, transitioning, for instance, from a significance level below 0.05 to below 0.10. This reduction in significance is particularly noteworthy in the context of results pertaining to publications resulting from academic engagement co-authored by at least one of the sampled dual-affiliated professors. Consequently, the findings related to the dual-affiliated professors should be interpreted with caution.

To further test the robustness of the study, different cut-off points for the binary dependent variable (*Journal_reputation*) were implemented, i.e., 25% and 5% (vs. 15% in the main regression). These specifications indicate that there is a statistically significant difference when using the lower cut-off point, but not the highest. Specifically, this difference disappears when using the 5% cut-off points.

5.5 Discussion

Several noteworthy findings have been made, some of which corroborate and/or contradict previous comparable findings, and some of which offer more novel insights. This section is chiefly concerned with those findings and how they relate to the broader scientific field. Additionally, this section makes recommendations for future research work and outlines the limitations of this empirical study.

The first contribution involved examining the prevalence of academic engagement in the field of engineering. This undertaking revealed that, in Sweden, publications resulting from academic engagement projects exist in the context of electrical engineering. In fact, the results suggest a trend of increased co-authoring with firms, in contrast to the findings of Arora et al. (2018). While their research suggests the declining involvement of firms in scientific activities, this study indicates the opposite trend in the context of electrical engineering in Sweden.

More concretely, by offering some benchmark numbers, this study shows that the overall prevalence of documents resulting from academic engagement is higher than either Tijssen et al. (2016) found in their analysis of the 750 largest research-intensive universities (5.2%) or McKelvey and Rake (2020) found in their analysis of the pharmaceutical industry (6.4%). This seems reasonable considering that the engineering sciences are arguably closer to industry than are other fields, and that my sample consists of university scientists who were professors during the analysis period, both of which have been shown to be correlated with higher levels of academic engagement projects (cf. Abreu & Grinevich, 2017; Aschhoff & Grimpe, 2014; Boardman & Ponomariov, 2009; D'Este et al., 2019; Lawson et al., 2019; Link et al., 2007; Schuelke-Leech, 2013; Tartari & Breschi, 2012; Tartari et al., 2014). This analysis also revealed diversity among the partner firms and publications, both of which can be further analyzed.

The second contribution relates to article impact. According to the regressions, publications resulting from academic engagement have a higher article impact than do those resulting from pure university research. The logical interpretation of this finding is that resolving the differing institutional logics of firms and universities (Dasgupta & David, 1994; Sauermann & Stephan, 2013), and their related tensions, through creating so-called hybrid spaces (McKelvey et al., 2015; Perkmann et al., 2018; Thune & Gulbrandsen, 2011) enables both partners to benefit. It is plausible that publications resulting from academic engagement projects include elements of both distant searches as well as deep application knowledge, thereby benefitting authors from both firms and universities, likely through increased knowledge combination.

This finding is relevant to the debates about the relative impacts of science and technology (Fleming & Sorensen, 2004; Kaplan & Vakili, 2015). This finding arguably places academic engagement projects in a slightly different light, as it differs from some previous findings suggesting that publications resulting from academic engagement projects have a relatively neutral or negative effect on article impact, as compared with publications involving only one or more university scientists (Bekkers & Freitas, 2008; Frenken et al., 2010).

In relation to the knowledge network, the strongest effect in terms of academic engagement occurs when the number of authors is larger than three, especially when it is in the "sweet spot" of four or five co-authors. Different interpretations of this result could reflect an optimized cognitive distance between co-authors (Nooteboom et al., 2007) and/or that it indirectly captures the pooling of unique knowledge, which can lead to better outcomes (Becker & Murphy, 1992; Bozeman et al., 2013; Katz & Martin, 1997; Phelps et al., 2012), simultaneously as the cost of collaboration is kept under control (Becker & Murphy, 1992; West & Anderson, 1996). Dual affiliation in the context of academic engagement is positively associated with article impact. Therefore, having a cognitively proximal boundary spanner (Gertner et al., 2011; Leifer & Delbecq, 1978; Tushman, 1977; Tushman & Scanlan, 1981) as part of the co-author team may result in an on average higher article impact premium. Future research could further examine knowledge networks in academic engagement, by examining author team heterogeneity (i.e., team compositional properties) in more depth.

In addition to these insights, the results suggest that conference proceedings, including The Institute of Electrical and Electronics Engineers (IEEE) conference papers, do not overall receive many, if any, citations, recalling Michels and Fu's (2014) findings. However, two expert interviews conducted in this Ph.D. dissertation suggested that these conferences and associated publications are of high importance in the electrical engineering sciences for signaling, networking, and idea generation. Future research could explore this type of impact more thoroughly, as opposed to focusing predominantly on citations, as in this study.

The third contribution relates to journal reputation. The results indicate that academic engagement is negatively associated with journal reputation, as compared with having only academics at universities as authors, but this effect disappears when using a stricter operationalization of what counts as a top-reputed journal. In the context of academic engagement, the data moreover suggest that dual-affiliated professors and the number of authors of the paper do not significantly affect the probability of publishing in top-reputed journals. It is noteworthy, however, that the regression models do not directly assess the underlying motivations for the observed co-authoring, as it is an endogenous factor in the models. Motivations, such as wishing to be published in a journal of high reputation, can vary and have diverse effects on publishing aspirations. Higher-ranked journals typically apply a more rigorous peer review process, which may go beyond the scope of what some collaborations deem worth pursuing.

The conflicting results concerning the impact of academic engagement on both article impact and journal reputation—i.e., two ways of indicating scientific impact—call for further research in this area. This research should aim to delve into the underlying motivations and aspirations of the universities and firms involved in collaborative research, and how those affect scientific outcomes, as distinct from, but possibly interrelated with, commercial outcomes and follow-up collaboration, as identified by Cantner et al. (2022).

As with all empirical research, the research undertaken here is not without limitations. Specifically, at least two major limitations, plus an additional three secondary limitations, need to be noted regarding this study.

The first major limitation of this empirical undertaking is that the sampled university scientists' co-authors are treated as black boxes (e.g., the influence of certain factors of the industrial researchers, such as their prior article impact and prior degree centrality, is not controlled for). The other major limitation is the relatively small number of articles resulting from academic engagement projects involving dual-affiliated professors, as well as the fact that those articles are published by a somewhat small number of researchers (i.e., 11 dual-affiliated professors). These two limitations lower the validity of the findings, with validity referring to the extent to which something that has been studied can be said to have been accurately depicted (Carmines & Zeller, 1979).

Concerning the secondary limitations, a first limitation is the focus on the outcomes of academic engagement projects, rather than on analyzing the activities within these projects themselves. Related to this, a second limitation concerns the reliance on bibliometric data. Specifically, the study analyzes only published articles instead of all submitted articles, identifying academic engagement projects by examining the organizations listed by authors in the articles (see Section 4.4 for a detailed discussion). Essentially, this approach means that the analysis encompasses only those academic engagement projects that result in at least one published article. Although bibliometric data such as scientific articles are considered to provide a reliable, albeit partial, measure of successful scientific knowledge creation (Perkmann et al., 2011; Tijssen, 2009), and can be used to assess both the quantity and quality of work produced (Nederhof & Van Raan, 1992), the reliability of this approach—with reliability referring to the extent to which an instrument consistently yields accurate results (Carmines & Zeller, 1979)—remains high. However, a third limitation, which also constitutes one of the strengths/novelties of this study, is its empirical context. The research focuses specifically on one field and one nation (electrical engineering and Sweden, respectively), which limits the generalizability of the findings and related implications.

5.6 Conclusion

The primary aim of this empirical study was to elucidate the scientific impact of electrical engineering articles in terms of their article impact on the academic community and the reputation of the journals in which they are published. To achieve this objective, a dataset comprising 8455 publications was comprehensively analyzed. These articles were authored by 184 engineering professors affiliated with the five largest/most prominent universities in Sweden, with respect to their engineering departments and/or units. The central research question that guided this endeavor was as follows (which is also RQ1 of this Ph.D. dissertation):

How does the scientific impact of publications resulting from academic engagement projects differ from that of publications resulting from academic projects?

Relating to the research question, four hypotheses were proposed. Table 5.7, below, summarizes the conclusions drawn in relation to these hypotheses, followed by a concise discussion and concluding remarks. The implications of this undertaking are discussed in Chapter 8 of this dissertation.

Table 5.7. Hypotheses: empirical evidence for confirmation or refutation – Chapter 5.

Hypothesis	**Empirical findings**
5.1a. Publications originating from academic engagement collaborations are associated with higher article impact.	Supported
5.1b. Publications originating from academic engagement collaborations are associated with lower article impact.	Rejected
5.2a. Journal articles originating from academic engagement collaborations are associated with higher journal reputation.	Rejected
5.2b. Journal articles originating from academic engagement collaborations are associated with lower journal reputation.	Supported*

* Reduced statistical power (i.e., the *p*-value is between 0.1 and 0.05).

To summarize the main results, the findings reported in this empirical study suggest that there was a significant difference between articles resulting from academic engagement projects and those resulting from academic collaboration, with respect to both article impact and journal reputation. Specifically, academic engagement had a seemingly positive effect on the resulting publications' article impacts, although they were more likely to be published in less-reputed journals. Examining the data more closely revealed that the premium in article impact can be attributed to those collaborations having more than three authors, and especially to those with a moderate number of authors (i.e., four or five). The presence of dual-affiliated professors improved the outcome. Concerning journal reputation, the findings suggest that papers resulting from academic engagement are less likely to be published in top-reputed journals, although this finding loses significance with stricter operationalization of the dependent variable. The number of authors of the resulting publications and the presence of dual-affiliated professors moreover had no significant influence on the likelihood of publication in top journals.

6 THE TECHNOLOGICAL IMPACTS OF COLLABORATIVE RESEARCH AS ONE FORM OF ACADEMIC ENGAGEMENT

6.1 Introduction

This chapter examines the technological impact of science, specifically comparing the technological impact of collaborative research as one form of academic engagement versus research carried out solely by academics. While Chapter 5 examined different forms of scientific outcomes and scientific impacts, this chapter explicitly examines technological impacts.

This chapter thus examines how science may also lead to technological impacts, and is related to a tradition in economics of innovation and innovation studies. There is a long history of debates on—and studies of—the relationship between science and technology. Ample research has demonstrated the importance of science for subsequent technological inventions seen explicitly as patents (e.g., Ahmadpoor & Jones, 2017; Jaffe et al., 1993; Narin et al., 1997). While it is true that some technology is developed without science, such as the innovation of flush riveting in American airlines from the 1930s to 1950s (Vincenti, 1984), many studies published over decades have shown the importance of science to subsequent technological inventions (e.g., Ahmadpoor & Jones, 2017; Jaffe, 1989; Jaffe et al., 1993; Narin et al., 1997; Scandura, 2019; Tijssen, 2001, 2002). Other research has shown the effects of science and technology on industrial dynamics (McKelvey et al., 1996) and on economic growth more broadly (Mansfield, 1991; Rosenberg, 1974). Note that this chapter does not tackle the broad impacts; instead, it follows the tradition in this literature of considering technology as proxied by patents and science as proxied by publications.

Moreover, it is essential to acknowledge that not all fields of science hold equal significance for technological progress. Even though the distinction is not without its limitations, the more applied sciences tend to be more directly relevant to technological advances, as articulated by Tijssen (2002): “Clearly, all technical inventions are based to some extent on research, in the least on (applied) engineering research of some sort, but sometimes also on inputs from scientific and engineering research of a more fundamental nature” (p. 511). This study of engineering accordingly stands at the intersection of science and technology, providing an interesting and relevant empirical context. While prior, related research has suggested that science affects technology (e.g., Hemberg, 2023; McKelvey & Ljungberg, 2017), the nature of the relationship between the two is multifaceted and needs to be unpacked.

Indeed, universities are a type of organization in which science and technology interact. The literature suggests that technological impact can occur either directly through interaction between individuals and organizations or more indirectly through spillovers. Because universities are repositories of ample and diverse scientific knowledge, firms are likely to collaborate with them to develop inventions and ultimately introduce them to the market (Rotolo et al., 2022). Research suggests that collaborative research between universities and firms can benefit the collaborating firm via the development of capabilities valuable for creating technology usable in future innovations (McKelvey & Ljungberg, 2017). Furthermore, indirect impacts are also worth considering. External firms can benefit from knowledge spillovers (Messeni Petruzzelli & Murgia, 2020), which refer to the phenomenon in which investments in research or technology development by one or a few agents intentionally or unintentionally facilitate the innovation efforts of other agents (Breschi & Lissoni, 2001).

This chapter will address the following research question (which is also RQ2 of this Ph.D. dissertation):

How does the technological impact of publications resulting from academic engagement projects differ from the impact of those resulting from academic projects?

This comparison aims to help us disentangle the relative technological value of collaborative research projects between universities and firms, especially in the engineering sciences where the applied and basic aspects of research can be difficult to distinguish. Patents and publications give us a way to explicitly examine the relationships between more basic research and the impacts in terms of technological inventions. Few studies have investigated whether collaborative research between universities and firms is more or less valuable from a technological viewpoint as compared with similar research conducted solely by researchers at public research institutions and universities. Notably, Messeni Petruzzelli and Murgia (2020) emphasized the need for more comprehensive assessment of the industrial impact of university–industry collaboration. This call for future research on these topics has been confirmed in the latest article by Perkmann et al. (2021), providing a conceptual framework for and structured literature review on academic engagement.

To address the research question, the subsequent sections will propose two distinct pathways through which science can lead to technological impacts relevant to academic engagement. These pathways represent different mechanisms for the development, application, and utilization of scientific knowledge in technology: an individual approach and an organizational approach. Additionally, it is important to note that the remainder of this chapter will focus on technology in relation to patents and on science in relation to publications. The aim is to extend the analysis beyond merely studying scientific outcomes and impacts. By examining these dimensions, the research aims to shed light on the extent of technological impact resulting from academic research in the engineering sciences. This investigation has the potential to inform policymakers, researchers, and industry practitioners, thereby facilitating evidence-based decision-making and promoting effective collaborations that drive technological innovation.

The remainder of this chapter is structured as follows: The next section delves into theories related to technological impact. This is succeeded by a detailed outline of the research design and empirical methodology. The chapter then presents and discusses the findings. It ends by outlining relevant conclusions.

6.2 Theory and hypotheses

Following a longstanding tradition in the study of innovation (e.g., Nelson & Winter, 1982; Schumpeter, 1934), technological invention is conceptualized as a process of striving for the reconfiguration of existing combinations or for the combination of existing components in a novel manner. A view of technology as resulting from the fundamental nature of inventors' activities, as proposed by Fleming and Sorenson (2004), is thus useful for this study. They suggested that the fundamental mechanism in play appears to be that "science alters inventors' search processes, by leading them more directly to useful combinations, eliminating fruitless paths of research, and motivating them to continue even in the face of negative feedback" (Fleming & Sorenson, 2004, p. 909).

The literature on search processes for innovation suggests that firms benefit from combining local and non-local (i.e., exploratory) search (Laursen, 2012; Savino et al., 2017). Given the abundance of diverse scientific knowledge contained within universities, firms are likely to seek collaborations with these institutions to enhance their (non-local) search processes, ultimately accelerating the development and eventual market introduction of innovations (Rotolo et al., 2022). The absorptive capacity generated by firms' internal research influences their ability to leverage connections to external knowledge sources, that is, firms engaged in research are better equipped to search for and identify new opportunities (Fabrizio, 2009). Consequently, the expectation is that collaborative research, as one form of academic engagement, should yield a higher technological impact than specifically academic projects because firms engaged in these endeavors not only intend to develop technological inventions but also possess the capacity to do so, including the ability to identify opportunities in the first place.

The next sub-section will delve into the literature concerning the linkages between patents and publications in the context of technological impacts. Consistent with the research design, the primary reference in this literature review will be to scenarios in which patents serve as proxies for technology (sometimes technological inventions), while publications are used as proxies for science.

6.2.1 Studies of technological impact through patents and publications

Determining the precise extent to which technology relies on science is challenging, mainly due to variations over time among disciplines and in estimation methods. As a point in case, there are two notable approaches that rely on bibliometric data, namely, the indirect and direct approaches.[26]

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[26] This research omits one notable approach, that of relying on survey data (e.g., Tijssen, 2002). While data from surveys, which normally ask respondents about their prior activities and subjective opinions, have their merits, they are not well suited for this particular type of study. This is because the fundamental interest of this research lies in determining whether and why scientific publications resulting from the sample of engineering professors influence future technological inventions. Simply put, the sampled professors may not be aware of the extent to which their research has influenced subsequent technological inventions outside their immediate knowledge network.

In the indirect approach, one investigates to what extent research papers are cited as prior art in technological patents (e.g., Marx & Fuegi, 2022). Similar to how researchers use citations in science to acknowledge previous work (Merton, 1973; Moed, 2005), inventors use citations in patented technology to inform us, especially the examiners, about prior art (Akers, 2000; Criscuolo & Verspagen, 2008; Trajtenberg, 1990). "Prior art" refers to the evidence for why a technological invention is novel to the world and why it is not already known. This suggests that recognition is due to the work on which the focal invention is building.

In a recent study employing an indirect approach, researchers investigated the extent to which technological patents cite scientific articles, revealing that approximately 25% of technological inventions are connected to prior research (Marx & Fuegi, 2022). The significance of relying on more recent research is underscored by advances in computing power and improved estimation techniques. Previous reports often relied on smaller datasets, limited their scope to front-page citations, and employed less sophisticated identification methods. In contrast, Marx and Fuegi (2022) based their study on a comprehensive analysis of all USPTO patents granted from 1836 to 2020 and all EPO patents granted from 1978 to 2020. Their analysis incorporates advanced extraction techniques, including machine learning.

Regarding the direct approach, Coward and Franklin (1989) reported that, in a dataset of 2452 patents, 238 constituted true patent–paper pairs, accounting for 9.7% of the total. In contrast, Magerman et al. (2015) found that in an analysis of 88,248 EPO and USPTO patents, only approximately 0.66% exhibited a direct link to scientific research.

Disregarding the consequences of employing different methodological approaches, let us shift focus to the factors that can influence the potential to shape technology. Chapter 5, which examined scientific outcomes and impacts, argued that one plausible explanation for the elevated article impact of publications arising from academic engagement lies in the unique combination of in-depth applied knowledge and more abstract and distant exploration (i.e., search). The positive and significant correlation between papers resulting from academic engagement and their article impact suggests the likelihood of a corresponding technological impact premium, as previous related research indicates.

For instance, an extensive bibliometric analysis of 32 million research papers and 4.8 million patents revealed that publications directly cited by patents have a higher likelihood of receiving substantial citations from other research papers (Ahmadpoor & Jones, 2017). This implies that the publications deemed crucial for subsequent research also have significant value for future technological innovations. Supporting evidence was provided by Poege et al. (2019), who found a strong correlation between the technological impact of patents that cite highly impactful research articles. Poege et al. (2019, p. 1) asserted that "what is considered excellent within the science sector also leads to outstanding outcomes in the technological and commercial realms."

Papers like these may also result in higher technological impact because the combination of deep application knowledge with a more abstract and distant search is advantageous from a technological standpoint. According to Walsh et al. (2016), collaborations between universities and industries can lead to higher-quality inventions because academic scholars can bring cutting-edge scientific knowledge to the collaboration group. Further support for this idea was provided by McKelvey and Ljungberg (2017), who found that many collaborative research projects between universities and firms in the Swedish food industry resulted in both product and process innovations.

Additionally, several studies have explored the characteristics of scientific publications that increase their technological impact. In this context, Ke (2020) analyzed citation links among nearly 3.8 million biomedical papers published between 1980 and 1999 and all granted USPTO utility patents from 1976 to 2012. He found that both basic and novel papers exhibited high patent citation intensity. More specifically, in terms of novelty, the findings revealed that moderately and highly novel papers received 3.4% and 13.5% more patent citations, respectively, than did their non-novel counterparts. This finding aligns with an earlier similar discovery of Veugelers and Wang (2019), who found that moderately and highly novel papers were 22% and 43% more likely, respectively, to have a greater technological impact than non-novel papers.

Regarding the fundamental nature of publications, Ke (2020) determined that moderately and highly basic papers garnered 14.9% and 11.8% more patent citations, respectively, than did non-basic papers of a similar nature. This led Ke to conclude that the most likely recipients of patent citations were those papers that encompass both basic science and clinical medicine components. This observation aligns closely with the prior argument that the types of knowledge being recombined in collaborative research constitute one form of academic engagement, in engineering. This leads to the formulation of the first hypothesis to be tested in this endeavor, which is also visually represented below (Figure 6.1):

H6.1

Publications originating from academic engagement collaborations are associated with higher technological impact.

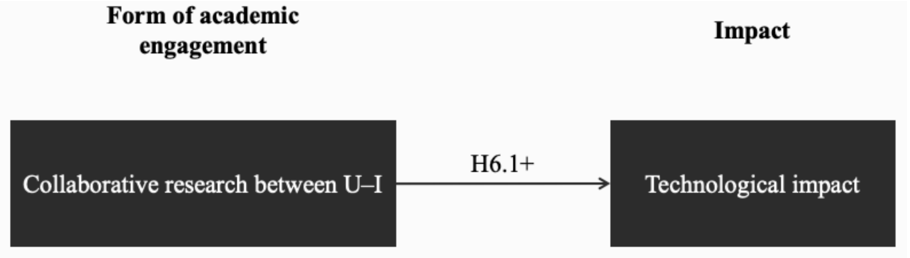

Figure 6.1. Conceptual model for understanding the hypothesized impact of academic engagement on technological impact.

This technological impact can manifest through three distinct pathways: individual technological impact, organizational technological impact, and knowledge spillover. While this chapter has so far concentrated on the individual and organizational pathways, as they pertain to the actors involved in the collaborations, information concerning knowledge spillover can be found in Section 6.4.3 focusing on robustness tests.

6.2.2 Individual and organizational technological impact

Individual technological impact involves researchers engaging in both scientific research and the development of innovations derived from that research. This personal pathway relies on the individualized nature of knowledge, as discussed by Dretske (1981), Nonaka (1994), and Polanyi (1958), positing that knowledge cultivated in one specific context can be effectively applied in another.

Research suggests that boundary spanners, i.e., individuals who have a deep understanding of both science and technology, are especially valuable in this context. For instance, a study conducted by Baba et al. (2009) examining the advanced material industry suggests that "Pasteur scientists," referring to university scientists who have contributed to numerous patent applications in addition to publishing numerous high-article-impact publications, offer greater value to firms' R&D productivity than do researchers lacking such experience, even those considered star scientists. The underlying argument is that researchers engaged in collaborative research between universities and firms are more likely to collectively exhibit the characteristics of Pasteur scientists. This is particularly true due to factors such as prior commercialization experience and non-academic work experience, which are identified as key determinants associated with future academic engagement, as highlighted by Perkmann et al. (2021) in their systematic literature review.

The second pathway, known as organizational technological impact, involves researchers focusing solely on scientific endeavors, while one or more of their colleagues within the same organization leverage the insights gained from that research to create technological innovations.

This technological impact pathway is closely associated with the idea that transferring knowledge within the boundaries of an organization differs fundamentally from knowledge transfer that crosses organizational boundaries, defined as knowledge spillover. This perspective aligns with the work of Kogut and Zander (1992) and Nahapiet and Ghoshal (1998). For example, Kogut and Zander (1992) argued that knowledge is not only held by individuals but is also expressed in routines by which colleagues cooperate within an organization, allowing firms to more effectively share and transfer knowledge among colleagues than is possible in the market, outside organizational boundaries.

From the perspective of the participating firm, the potential efficiency and significant contribution of employees engaged in scientific activities to technological advances hinges on the nature of the field under investigation. When the boundaries between science and technology are blurred, the individual pathway may emerge as preferred. In this context, a single individual possesses the capability to advance technological frontiers by leveraging the insights and expertise gained from their scientific endeavors. This approach is deemed resource efficient as it does not rely on the effective transfer of knowledge from the researcher(s) to the inventor(s). Conversely, if science and technology are too different, optimal efficiency is achieved by assigning distinct individuals to each activity, due to a greater division of labor. In other words, in this scenario, researchers focus solely on conducting research and they disseminate their insights to their colleagues involved in development, who can then leverage this information in the creation of new technologies.

In the empirical context, characterized by researchers pursuing both academic and practical aims (Banse & Grunvald, 2009) and in which collaboration between universities and firms is prevalent (Chapter 5), it is anticipated that the individual pathway will be utilized more frequently than the organizational pathway. This forms the basis for the second hypothesis to be tested in this chapter:

H6.2

Individual technological impact is more prevalent than organizational technological impact.

6.2.3 Key takeaways from Section 6.2

- Technological invention is conceptualized as striving to reconfigure existing combinations or assemble components in a novel manner, with science guiding inventors toward useful combinations.
- Internal research enhances firms' absorptive capacity, enabling more effective exploratory search processes by tapping into academic scholars' expertise.
- Existing research in conjunction with prior analysis (Chapter 5) implies that publications arising from academic engagement valuably combine in-depth applied knowledge and a more abstract and distant search, likely resulting in a technological impact premium.
- Technological impact from publications can manifest itself through three distinct pathways: individual technological impact involves researchers

engaging in both scientific research and the development of innovations from their findings; organizational technological impact entails researchers focusing on scientific endeavors, while colleagues from the same organization leverage those insights for technological innovations; and knowledge spillover emphasizes the technological impact of publications on external individuals and organizations.

- The conceptual framework suggests that firms commonly utilize the individual technological pathway, as science and technology are closely intertwined, while the organizational pathway is less prevalent.

6.3 Data and method

This section explains the data used in this research as well as the techniques employed to analyze those data. The data are presented in the first section. The operationalization of variables is covered in the second section. The final section covers the techniques employed, including giving a thorough explanation of the underlying causes guiding the choice of empirical strategy.

6.3.1 Data

This chapter relies on the same data as did the prior empirical chapter as well as on the patent-to-article dataset—Reliance on Science in Patenting—developed and published by Marx and Fuegi (2020, 2022). The Reliance on Science in Patenting dataset compiles citation linkages between full-text patents and scientific publications. This dataset contains noteworthy improvements compared with earlier datasets, such as including, and distinguishing, front-page citations and in-text citations, whereas most earlier research is based only on front-page citations (e.g., Ahmadpoor & Jones, 2017). As Bryan et al. (2020) pointed out, in-text citations should "better measure the real knowledge inventors use to motivate and construct their inventions" (p. 1) because that part of the patent is frequently written in large part by the inventors themselves, as opposed to patent attorneys who concentrate on the more legally significant claims and prior art disclosure. See Section 4.2 for a more thorough explanation of the respective datasets, including how the data were prepared for analysis.

The final number of scientific publications attributed to the 184 sampled professors was 8455. Of these, 5143 had a digital object identifier (DOI) number and/or a PubMed identifier (PMID) through which the two datasets were matched. The vast majority (96%) of the publications that did not have a DOI or PMID number were proceeding papers (note, however, that 946 proceeding papers had a DOI and/or PMID number). Put differently, whereas the preceding empirical chapter (Chapter 5) was based on the final number of scientific publications attributed to the sampled professors ($n = 8455$), this chapter is based on all scientific publications attributed to the sampled professors that had a DOI and/or PMID number ($n = 5143$).

Operationalization of variables

This section elaborates on how the concepts used in this undertaking have been operationalized. To clarify, this section is divided into three parts according to the three types of variables, namely, dependent variables, independent variables, and control variables.

Dependent variables

This study has operationalized three dependent variables to be used in the main regression: *Total_tech_impact*, *Individual_tech_impact*, and *Organizational_tech_impact*. In addition to these variables, a fourth dependent variable used in a robustness test is also presented, *Knowledge_spillover*; it is presented in this section rather than in the robustness test section as it relates to these dependent variables and some of the descriptive statistics include this variable.

In accordance with Veugelers and Wang (2019) as well as Ke (2020), the first dependent variable, the total technological impact (*Total_tech_impact*), that is, to what extent a scientific publication has had a meaningful influence on any technological inventions, has been approximated by investigating the total number of citations the focal publication received in granted patents before 2021.[27]

A noteworthy limitation of this operationalization is its potential to underestimate the technological impact, primarily because it excludes patents applied for before the public disclosure of the research, even when the research has partially contributed to these patents. This limitation is likely most notable in the context of collaborative research involving universities and firms, in which case it is plausible that mutual agreements may enable researchers employed by the firm, or their colleagues, to secure patent filings before public disclosure. Empirical research supports this assertion, demonstrating that technological inventions precede related publications arising from academic engagement, attributable to the patentability criterion that mandates absolute novelty (Chang et al., 2017).

The second and third dependent variables follow the same logic as the first dependent variable but focuses on the different pathways of technological impact. Specifically, the second dependent variable measures the number of citations the focal publication has received in patents granted before 2021, defined as those publications and technological patents in which at least one of the authors (scientific publications) and inventors (technological patents) are the same (*Individual_tech_impact*). These citations are referred to as author–inventor pair citations.

[27] An alternative measure involves counting the number of forward citations to create a binary (i.e., dummy) variable that differentiates between patents/publications receiving the greatest number of citations and all others (e.g., Ahmadpoor & Jones, 2017; Uzzi et al., 2013). Nonetheless, the use of a count variable is considered advantageous as it accommodates a greater degree of variance.

The third dependent variable measures the number of citations the focal publication has received by patents granted before 2021, defined as those publications and technological patents in which at least one of the organizations listed as affiliations of the authors and patent assignees listed by the inventors are the same, but all the authors and inventors are different individuals (*Organizational_tech_impact*). These citations are referred to as organization–affiliation pair citations.

Lastly, the final pathway of technological impact, knowledge spillover, is simply defined as the number of citations the focal publication has received in patents granted before 2021 from external parties, i.e., the total technological impact of the publication minus the individual technological impact and the organizational technological impact (*Knowledge_spillover*). The aim of this variable is to capture those citations that have "spilled over" to other actors by excluding all author–inventor and affiliation–assignee citations. This variable is used as a robustness test.

The indirect approach was chosen as the preferred method after a thorough review of the two approaches. Even though citations have received criticism for not being an indicator that captures all knowledge transfer from science to technology or as a "noisy" indicator (e.g., Criscuolo & Verspagen, 2008; Jaffe et al., 1998; Meyer, 2000; Tijssen, 2001), it is a well-accepted indicator that has been used for decades (e.g., Arora et al., 2022; Narin & Noma, 1985; Popp, 2017; Roach & Cohen, 2013).[28] Moreover, when investigating the technological impact of technology (as opposed to investigating the technological impact of science, as done here), citation counts are also commonly measured (e.g., Fleming & Sorenson, 2001, 2004; Messeni Petruzzelli & Murgia, 2020; Verhoeven et al., 2016).[29]

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[28] To my knowledge, Narin and Noma were the pioneers in using this method, as evidenced in their 1985 study entitled "Is technology becoming science?"

[29] Numerous indicators exist to measure technological impact and the related measure of value; for an extensive discussion of this topic, refer to van Zeebroeck (2011).

As reasoned by Callaert et al. (2006), when reviewing prior literature, scientific references in patents, commonly referred to as non-patent literature (NPL) citations, should not be seen as science unidirectionally and directly influencing technological inventions; rather, the citations reflect a more general indicator of the interaction between science and technology. Callaert et al. (2006) further argued that their findings allow for the conclusion that "developing recurrent, robust indicators based on these references is plausible. Such indicators can depict the extent to which technology development is situated within the vicinity of scientific findings, and they offer multiple possibilities for mapping and analyzing technological activity along this dimension" (p. 16).

Several limitations are associated with the direct approach, which contributed to the decision to employ the indirect approach here. First, it arguably necessitates expert judgment when establishing potential linkages, as demonstrated by Coward and Franklin (1989) and Woltmann and Alkærsig (2018).[30] Second, matching is usually based on the abstracts of publications (e.g., Magerman et al., 2010, 2011, 2015; Woltmann & Alkærsig, 2018), primarily due to the practical difficulties and time constraints associated with acquiring the full texts of all papers, posing obvious drawbacks.[31] Furthermore, the direct identification of linkages is exceedingly rare. For instance, Magerman et al. (2015) reported that only approximately 0.66% of the

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[30] Although Woltmann and Alkærsig (2018) based their study on publication–website pairs rather than patent–paper pairs, their methodology for identifying the pairs is believed to be the same, making it a credible reference despite its not being strictly aligned with the patent–paper pair definition.

[31] It is furthermore common for similar natural language processing studies analyzing *only* patents to rely on abstracts (see, e.g., Arts et al., 2018, 2021). This can be explained as follows: "While text mining may be relevant for natural language documents, only titles and abstracts are widely and easily available for patents and publications (large sets of full-text documents are difficult or expensive to obtain)" (Magerman et al., 2010, p. 295).

sampled patents exhibited a direct scientific link. This low number suggests that it may be too narrowly defined as a proxy for this research endeavor. Finally, linguistic disparities exist between scientific publications and patents, as reported by Xu et al. (2021). These disparities make the successful implementation of natural language processing techniques based on the link between publications and patents challenging.

As explained in Chapter 5, it is true that a rolling time window based on when the article was published, rather than a fixed, static window regardless of what year the article was published, is sounder because a rolling time window more equally captures the scientific and technological impact of each article (cf. Amin & Mabe, 2000; Branstetter & Ogura, 2005).[32] However, after examining the descriptives of the data, such as the time lags between publication and patent linkage, the decision was made to employ a longer, fixed time window. This approach was deemed more appropriate due to its ability to capture a greater number of linkages and thus more data. Consistent with established research (Fleming & Sorenson, 2004; Popp, 2017), the approach to controlling for censoring involved the inclusion of fixed year effects in the regressions, incorporating a factor variable representing the publication year in all regression models.

Inspiration for the operationalization of the second and third dependent variables comes mainly from the study by Coward and Franklin (1989), but to a lesser extent also from other papers, such as the one by Bonaccorsi and Thoma (2007). Coward and Franklin (1989) investigated three possible types of patent–paper pairs:

- Individual name matches between paper authors and patent inventors

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[32] As stated by van Zeebroeck (2011, p. 39), "the effect of time increases the probability for any patent to have been cited by subsequent patents. The easiest remedy to this censoring issue consists of counting citations received by patent applications within a given period of time (e.g., within the first 5 years from their publication)."

- Institutional name matches between organizations listed as affiliations by authors and patent assignees
- Examiner-cited literature references found in patents

They found that the first two approaches—i.e., author–inventor pairs and affiliation–assignee pairs—yielded better results, and that the first approach—i.e., author–inventor pairs—performed the best. Arguably directly or indirectly inspired by Coward and Franklin's (1989) paper, author–inventor pairs have attracted a lot of attention (e.g., Breschi & Catalini, 2010; Meyer, 2003; Noyons et al., 1994; Zhang et al., 2019), whereas less emphasis had been put on affiliation–assignee pairs.

Independent variables

One independent variable has been operationalized, which is the same as in Chapter 5.

More specifically, publications resulting from collaborative research as one form of academic engagement project have been approximated by investigating the affiliation(s) that an article's authors report. Articles reporting any affiliated firms are defined as academic engagement projects (*Academic_engagement*), as distinguished from academic collaboration projects, which are scientific publications reporting no affiliated firms, that is, articles authored only by one or more academic researchers. Thus, closely following similar previous literature (e.g., Frenken et al., 2010; McKelvey & Rake, 2020), the first and only independent variable is a binary variable taking the value of 1 when any firm is reported among the affiliations, and 0 otherwise. For more information about the methodology employed to identify publications with at least one firm included in the affiliations, see Section 4.3.

The reason to not interacted this variable with the number of authors of a paper or with whether any dual-affiliated professor is listed as an author is due to the sample sizes became too small. In greater detail, there were 795 scientific papers with any technological impact; of these, 156 were defined as author–inventor pairs. Of these 156 scientific publications, 14 were defined as resulting from academic engagement in which at least one dual-affiliated professor was listed as an author. Besides, of these 14 scientific publications, nine were a result of one dual-affiliated professor. This suggests that any conclusions drawn as to the interaction effect between academic engagement and dual-affiliated professors will be a result mostly of a single dual-affiliated professor rather than of the full sample of dual-affiliated professors.

Control variables

In addition to the dependent and independent variables, the same control variables as used in Chapter 5 is also included: *Prior_article_impact, Prior_patenting, Prior_coauthors, Top_university, Number_universities, Number_nations, Number_fields, Article, Female, University_dummies, Field_dummies, and Year_dummies.* For detailed information regarding these, see Section 5.3.

Variable summary

Table 6.1, below, provides an overview of all variables, including name, type of variable, and how they have been operationalized.

Table 6.1. Summary of the regression variables used in Chapter 6.

Variable	Type	Description
Total_tech_impact	DV	A count variable indicating the total number of technological (patent) citations received by the publication before 2021
Individual_tech_impact	DV	A count variable corresponding to the total number of technological author–inventor pair citations the publication received before 2021
Organizational_tech_impact	DV	A count variable corresponding to the total number of technological affiliation–assignee pair citations the publication received before 2021

Knowledge_spillover	DV (RT*)	A count variable corresponding to the total number of technological citations not defined as author–inventor or affiliation–assignee pair citations the publication received before 2021
Academic_engagement	IV	A binary variable with a value of 1 if a firm is reported among the authors' affiliations on the publication, and 0 otherwise
Journal_reputation	CV	A binary variable with a value of 1 if the article was published in a journal belonging to the top 15% of the 2018 Journal Impact Factor distribution with regard to my sample, and 0 otherwise
Dual_affiliated_professor	CV	A binary variable with a value of 1 when at least one of the sampled dual-affiliated professors is listed as an author on the publication, and 0 otherwise
Number_authors	CV	A categorical variable indicating the count of authors for each publication, categorized into groups of 1–8 authors and 9 or more authors
Prior_article_impact	CV	A count variable representing the total number of scientific citations received by the sampled professor in the five years preceding the release of the publication; if more than one of the sampled professors has authored the publication, the highest value is used
Prior_patenting	CV	A binary variable with a value of 1 if any of the sampled professors on a publication applied for a patent in the five years preceding the release of the publication, and 0 otherwise
Prior_coauthors	CV	A count variable indicating the total number of co-authors the sampled professor had in the five years preceding the release of the publication; if more than one of the sampled professors has authored the publication, the highest value is used
Top_university	CV	A binary variable with a value of 1 if any of the top 50 universities worldwide is reported among the authors' affiliations on the publication, according to the 2018 Academic Ranking of World Universities, and 0 otherwise
Number_universities	CV	A count variable indicating the total number of unique university addresses reported among the authors' affiliations on the publication
Number_nations	CV	A count variable representing the total number of unique nation addresses reported among the authors' affiliations on the publication
Number_fields	CV	A count variable indicating the total number of fields in which the publication has been categorized by Web of Science
Article	CV	A binary variable with a value of 1 if the publication is classified as an article, according to Web of Science, and 0 otherwise
Female	CV	A binary variable with a value of 1 if any of the sampled professors on the publication is female, and 0 otherwise

University_dummies	CV	Five similar dummy variables, each with a value of 1, if the sampled university is reported among the authors' affiliations on the publication, and 0 otherwise; the universities are CTH, KTH, LiU, LTH, and UU
Field_dummies	CV	Three similar dummy variables, each with a value of 1, if Web of Science has assigned the publication to the specific subject areas of "Computer Science," "Telecommunications," or "Automation and Control Systems," and 0 otherwise
Year_dummies	CV	A factor variable representing the year in which the publication was released; the possible years are 2000–2018

* RT = Robustness test

6.3.2 Empirical strategy

The overarching objective of this undertaking is to better understand whether and, if so, how the technological impact of scientific publications resulting from collaborative research, as a form of academic engagement, differs from that of scientific publications resulting from collaborations only among academics.

All three dependent variables (*Total_tech_impact*, *Individual_tech_impact*, and *Organizational_tech_impact*) are count variables, focusing on the intensity of the impact. These variables were estimated using generalized negative binomial regression models, since the overdispersion test developed by Cameron and Trivedi (1990) suggests overdispersion. As stated in Chapter 5, overdispersion means that the observed conditional variance of the response was statistically larger than the variation implied by the distribution used in fitting the model, that is, the variance was statistically larger than the mean. According to several authors (Cameron & Trivedi, 1998; Fox & Weisberg, 2018; Hilbe, 2011; Lawless, 1987; Venables & Ripley, 2002), negative binomial regression is an effective model for dealing with this type of frequency data as it accommodates between-individual variability via introducing a random subject effect (α), which can have different values for different subjects. This is also the option preferred by researchers handling similar types of data (Fleming & Sorenson, 2001, 2004; Popp, 2017; Verhoeven et al., 2016). Moreover, the model can be viewed as a mixture of two distributions, as the number of observations (y_i) is assumed to follow a Poisson distribution but the dispersion is assumed to follow a gamma distribution.

6.4 Results

The results of this undertaking are detailed in this section. First, descriptive data pertaining to the variables of interest are presented and discussed. This section also addresses the second hypothesis. Subsequently, regression results are shown and discussed, shedding light on the first hypothesis. The chapter concludes by examining the robustness of the aforementioned findings.

6.4.1 Descriptive findings

As explained above, this study is based on a subset of the sampled publications, specifically all publications that had a DOI and/or a PMID (n = 5143). Of these, 795 publications (15.5%) had technological impact, that is, 795 publications were cited at least once in a technological patent before 2021.

Figure 6.2, below, depicts the number of scientific papers that had any technological impact five years after publication, the number of documents without technological impact five years after publication, and the proportion of documents with any technological impact.[33] Although the absolute number of documents with any technological impact five years after being published is increasing over time, the prevalence of papers with technological impact is decreasing. Interestingly, this is in contrast to the proportion of papers resulting from academic engagement, which became more common in relative terms.

[33] It is more intuitive to present the descriptives with a rolling time window even though the regression is not based on rolling time windows. As will be shown later, the clear majority (87.9%) of all papers with any technological impact achieved that impact within the first five years of publication (see Figure 6.5).

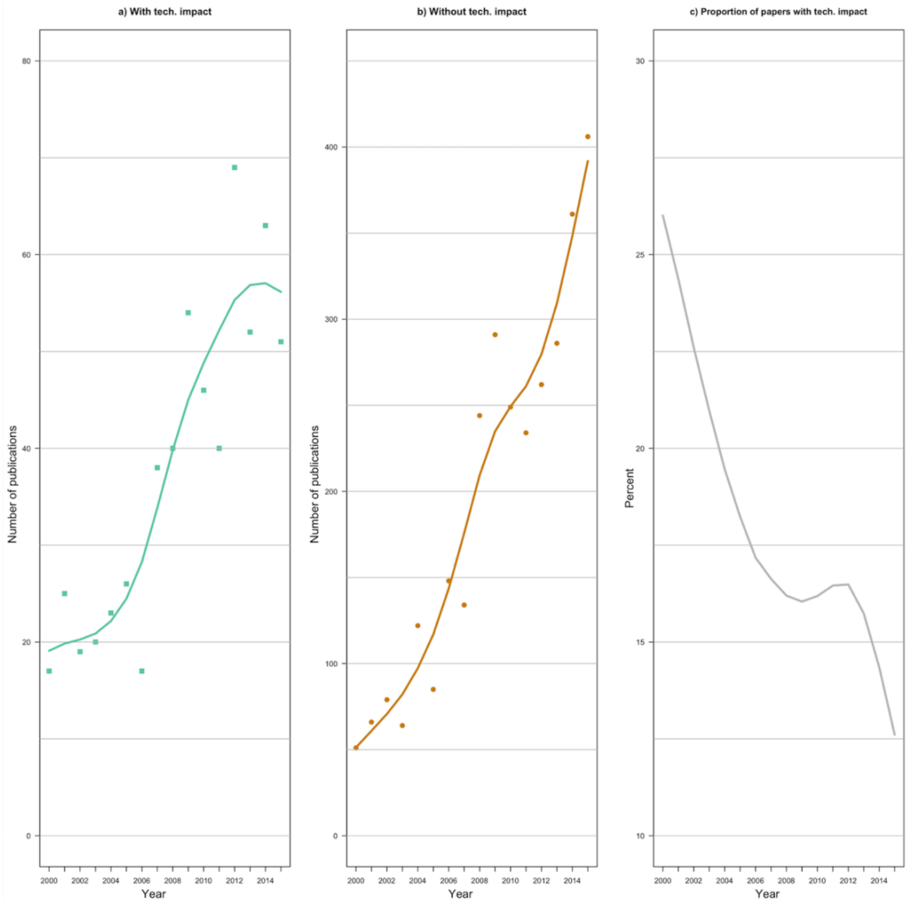

Figure 6.2. The number of publications published each year, 2000–2015, with any technological impact or without technological impact five years after publication (panels a and b, respectively), and the proportion of scientific papers with any technological impact (panel c).

Table 6.2, below, focuses solely on the subset of publications with technological impact (not limited to a five-year rolling time window). It depicts the minimum, 1st quartile, median, mean, 3rd quartile, and maximum number of citations these publications received. It furthermore depicts the same information for the different types of technological impact, namely, individual technological impact, organizational technological impact, and knowledge spillover. Interestingly, we note that knowledge spillover is by far the most common type of technological impact as well as the type that contributes the most to higher technological impact, on average. This suggests that the publications published by the sampled professors result in a significant degree of tangible knowledge spillover. The descriptives moreover show that individual technological impact had a relatively much higher mean score than did organizational technological impact. This suggests that organizations are more likely to involve the same employees in the two activities—publishing scientific papers and patenting technological inventions building on that knowledge—rather than separating those activities between employees/individuals. This finding gives support for Hypothesis 6.2 (see also Table 6.5, below).

Table 6.2. Descriptive statistics of technological impact.

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Total technological impact	1	1	2	5.6	5	181
Individual technological impact	0	0	0	0.4	0	13
Organizational technological impact	0	0	0	0.1	0	8
Knowledge spillover	0	1	2	5.0	4	172

Now, the focus shifts to comparing and contrasting papers resulting from academic engagement versus those resulting from academic projects, with regard to technological impact. Of the 5143 publications analyzed in this chapter, 998 (19.4%) were defined as resulting from academic engagement. As stated above, of these 5143 publications, 795 had technological impact. Of these 795 publications, 203 (25.5%) were defined as resulting from academic engagement. This simple comparison suggests that publications resulting from academic engagement are more likely to be cited in patents than are publications resulting from academic projects.

Figure 6.3, below, depicts the proportions of papers resulting from academic engagement and academic projects. This too indicates that scientific papers resulting from academic engagement are more likely to influence future technological inventions than are their academic counterparts. This pattern holds true across all sampled universities. It also reveals that both types of papers follow the same overarching trendline, i.e., a relative decrease in occurrence over time.

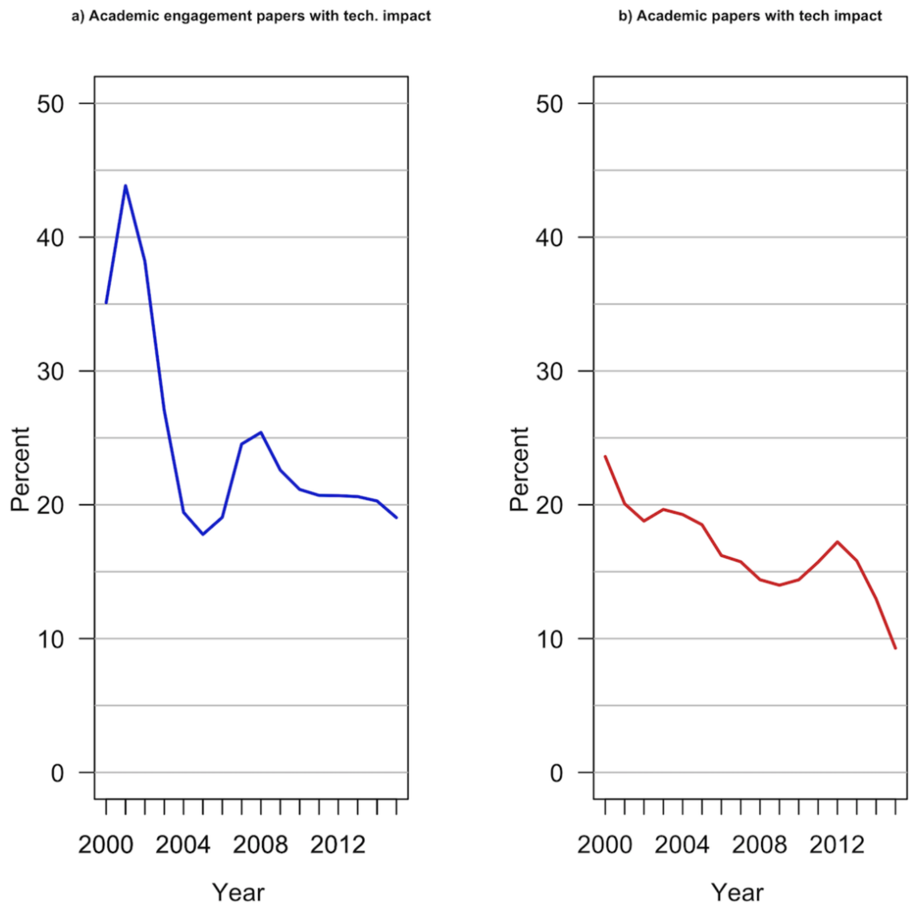

Figure 6.3. The percentage of scientific papers with any technological impact five years after publication resulting from academic engagement (panel a) and academic projects (panel b).

Tables 6.3 and 6.4, below, offer finer-grained insights. These tables depict the same type of information as does Table 6.2, above, but distinguish those papers resulting from academic engagement from those resulting from academic projects. The data presented in these tables suggest that publications resulting from academic engagement are, on average, more likely to have higher technological impact. This is at least partially driven by a few publications with very high impacts, as seen by their higher maximum technological impacts. Excluding the mean and maximum values, the only difference between the two tables is found in relation to individual technological impact and the third quartile, showing that relatively more publications resulting from academic engagement have individual technological impact.

Table 6.3. Descriptive statistics of technological impact: papers resulting from academic engagement.

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Total technological impact	1	1	2	6.3	5	181
Individual technological impact	0	0	0	0.7	1	13
Organizational technological impact	0	0	0	0.2	0	8
Knowledge spillover	0	1	2	5.4	4	172

Table 6.4. Descriptive statistics of technological impact: papers resulting from academic collaboration.

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Total technological impact	1	1	2	5.3	5	89
Individual technological impact	0	0	0	0.3	0	8
Organizational technological impact	0	0	0	0.05	0	7
Knowledge spillover	0	1	2	4.9	4	89

Table 6.5, below, provides more interpretable results regarding the prevalence of different pathways of technological impact. As previously demonstrated, the individual pathway surpasses the organizational pathway in terms of prevalence. Specifically, in the context of academic engagement projects, 28.6% of technological impact can be ascribed to the individual pathway, while only 10.8% can be attributed to the organizational pathway. The distinctions become more apparent in the context of academic projects, in which only 2.0% of all technological impact is linked to the organizational pathway, whereas 16.6% is associated with the individual pathway. This also suggests that, while academic engagement projects exhibit higher overall technological impact, with elevated relative levels of individual and organizational technological impact, academic projects have a greater prevalence of knowledge spillover. As stated before, this supports Hypothesis 6.2.

Table 6.5. Descriptive statistics of the different types of technological impact: academic engagement projects versus academic projects.

Variable	Academic engagement project	Academic project
Total technological impact	203	592
Individual technological impact	58 (28.6%)	98 (16.6%)
Organizational technological impact	22 (10.8%)	12 (2.0%)
Knowledge spillover	123 (60.6%)	506 (85.5%)

Concerning the time lag of technological impact (see Figure 6.4, below), note the following insights. According to the Reliance on Science in Patenting database, some citation linkages (3.6%) have a negative time lag difference. This implies that some patents that cite scientific papers were filed before the associated papers were published. This confusion is simply explained by the fact that there was a lag between the time when the assignees filed for the patent and the actual grant date, implying that the assignees or the examiner added the citation after the first filing.[34] It could also be that publications were available as forthcoming and later were assigned final publication dates when they were included in issues. The two histograms in the figure also indicate that the vast majority of a scientific paper's earliest technological impact occurs almost immediately (i.e., within one year of publication), whereas most citations appear one to three years after publication, on average.

[34] For example, the shortest time lag is negative five years (to be exact, 60 months). The focal publication entitled "Hybrid Digital–Analog Source–Channel Coding for Bandwidth Compression/Expansion" (DOI: 10.1109/TIT.2006.878212) was published in The Institute of Electrical and Electronics Engineers in September 2006. The citing publication entitled "Fixed, variable and adaptive bit rate data source encoding (compression) method" (patent number: US7236640) thus has its earliest priority date in September 2000 (i.e., exactly five years before the paper was published); however, the patent was first granted in June 2007 (that is, nine months after the paper was published). In this case, it was the applicant who added the citation, and the citation is only found on the front page of the patent.

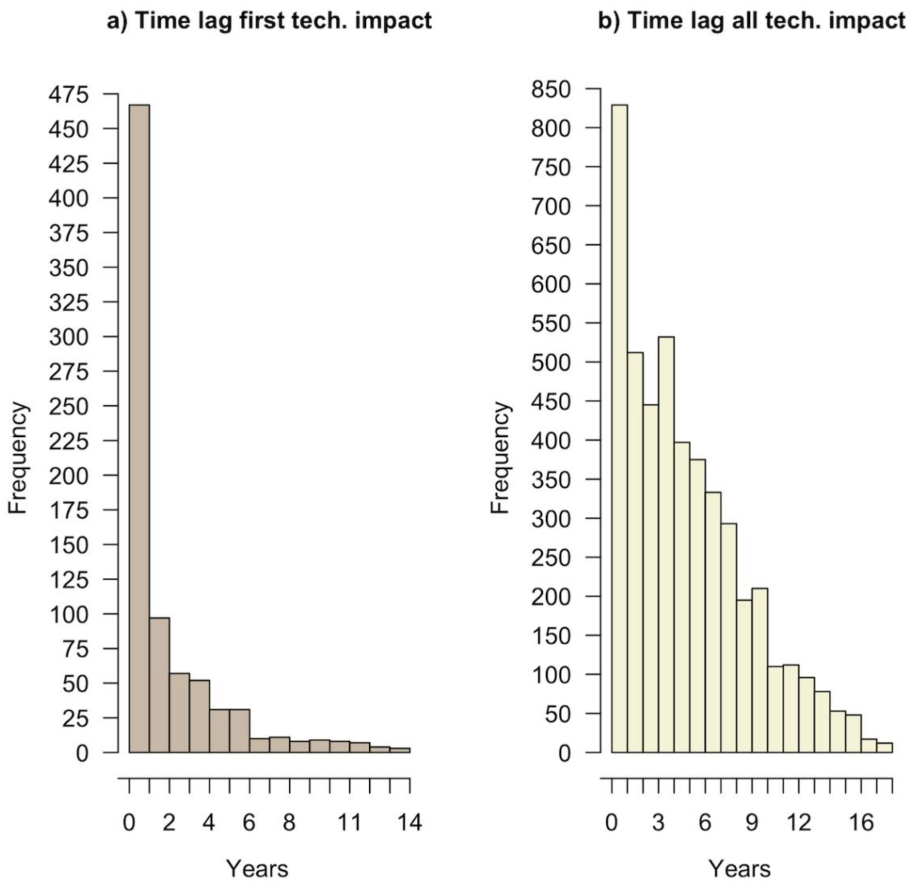

Figure 6.4. Histogram of the time lag for all publications' first technological impact (TI) (panel a) and all their TI (panel b).

Table 6.6, below, gives the specifics regarding time lag, showing that the median lag for the first technological impact is one year after publication, whereas the same number when taking into account all technological impacts is five years. Additionally, the table reveals more insights, for example, that the longest period between a publication and its first technological impact is approximately 14 years.

Table 6.6. Descriptive statistics of time lag (years).

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Time lag, first technological impact	0	0	1	2.0	3	14
Time lag, all technological impact	0	2	5	5.3	8	18

As above, let us now compare academic engagement and academic projects with regard to the time lag of their technological impact. Consequently, Figures 6.5 and 6.6, below, depict the same information as does Figure 6.3, above, with the caveat that they concentrate on academic engagement and academic projects, respectively. Clearly, we can see that the curves are similar overall, suggesting that papers resulting from academic engagement projects and academic projects affect technology in a similar way.

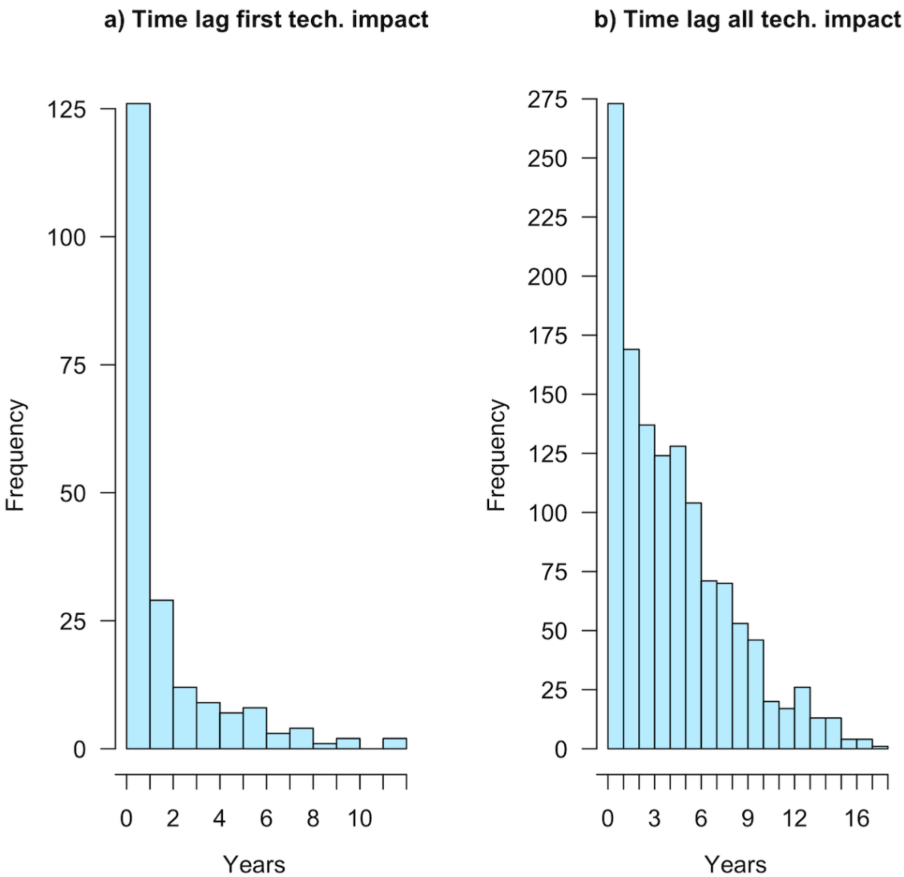

Figure 6.5. Histogram of the time lag for all publications resulting from academic engagement: first technological impact (panel a) and all their technological impact (panel b).

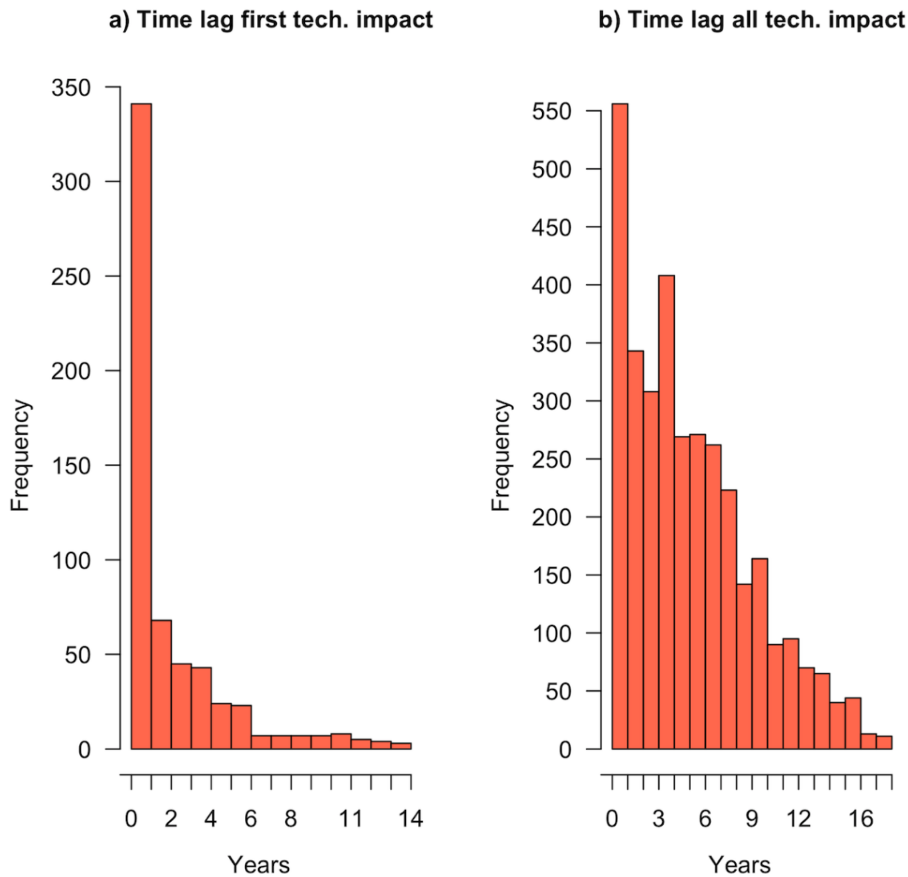

Figure 6.6. Histogram of the time lag for all publications resulting from academic collaboration: first technological impact (panel a) and all their technological impact (panel b).

However, as Tables 6.7 and 6.8 show, there are some minor differences. Most notable is that the time lag for the first and for all technological impact for papers resulting from academic engagement is slightly lower for several statistics, including the median, mean, and third quartile. If anything, this implies two things: first, academic engagement has a negative effect on the time lag; second, academic engagement has a negative effect on the longevity of their usefulness. Regressions are needed to disentangle this, bearing in mind that the key focus in this study is on the time lag in relation to the papers' first technological impact.

Table 6.7. Descriptive statistics of time lag (years): academic engagement.

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Time lag, first technological impact	0	0	0	1.7	2	12
Time lag, all technological impact	0	2	4	4.6	7	18

Table 6.8. Descriptive statistics of time lag (years): academic collaboration.

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Time lag, first technological impact	0	0	1	2.1	3	14
Time lag, all technological impact	0	2	5	5.5	8	18

This analysis will now briefly examine the most common firms that cite my sample of publications (Table 6.9, below), and consider whether these are the same as the most common co-publishing firms (Table 6.10, below). Quite interestingly, several of the top citing firms are not the same as the top co-authoring firms, with only Ericsson and Huawei being found on both lists. This comparison also reveals that five of the ten most common co-authoring firms (i.e., AstraZeneca, SAAB, ABB, Scania, and Volvo Group) only cite my sample of publications a handful of times. To be clear, this does not automatically establish that these firms are any worse at capitalizing on the co-developed knowledge; rather, it informs us that there is a large discrepancy between which firms co-publish with the sampled professors and which firms cite their findings.

Although the most common industry for the co-authoring and citing firms is the same, i.e., telecommunications, that field is more overrepresented among the citing firms. There are also some other differences; for example, the professors publish to a relatively larger degree with several motor vehicle manufacturing firms (i.e., Volvo Cars, Scania Group, and Volvo Group), but only one is found on the citing side (i.e., Ford Global Technologies, which is the R&D subsidiary of Ford Motor Company).

Table 6.9. The ten most common citing firms.

Firm	Industry/description	No. of citations
Rearden	Telecommunications	201
Ericsson	Telecommunications	156
Life Technologies	Biotechnology research	117
FloDesign Sonics	Biotechnology research	111
Gapwaves	Telecommunications	96
Qualcomm	Telecommunications	92
Huawei Technologies	Telecommunications	83
Prognosys Medical Systems	Medical equipment Manufacturing	80
Ford Global Technologies*	Motor vehicle manufacturing	72
Sony Corporation	Electronics	64
Cohere Technologies	Telecommunications	61

* R&D subsidiary of Ford Motor Company

Table 6.10. The ten most common co-authoring firms.

Firm	Industry/description	No. of citations
Ericsson	Telecommunications	201
Oticon	Medical equipment manufacturing	14
Volvo Cars	Motor vehicle manufacturing	13
AstraZeneca	Pharmaceutical manufacturing	2
Huawei Technologies	Telecommunications	83
SAAB	Defense and space manufacturing	1
ABB	Electrical equipment manufacturing	5
Scania Group	Motor vehicle manufacturing	4
Nokia	Telecommunications	34
Volvo Group	Motor vehicle manufacturing	0
Mitsubishi Electric Corporation	Electrical equipment manufacturing	36

With regard to citation-specific statistics, there are two elements worth investigating. The first element concerns who added the citation, distinguishing applicant-added citations from examiner-added citations. The second element has to do with where the citation was located in the technological patent, distinguishing whether the citation was found only on the front page, only in the body of the patent, or in both places.

According to Bryan et al. (2020), in-text citations should "better measure the real knowledge inventors use to motivate and construct their inventions" (p. 1), because that part of the patent is frequently written in large part by the inventors themselves, as opposed to by patent attorneys who concentrate on the more legally significant claims and prior art disclosure. Marx and Fuegi (2022) also found that in-text scientific citations are less likely to cite articles authored by the inventors. Table 6.11, below, presents these results.

As we can see in Table 6.11 below, the applicant added 75.8% and the examiner added 24.2% of all citations. For publications defined as resulting from academic engagement, the proportions are 79.9% for the applicant and 20.1% for the examiner; for academic projects, the proportions are slightly lower, i.e., 73.9% for the applicant and 26.1% for the examiner. The clear majority of the citations, 86.1%, were found on the front page only, whereas 6.9% were found in the body only and 7.0% both on the front page and in the body. For academic engagement (academic projects), 84.0% (86.8%) of all citations were found on the front page only, 6.5% (7.1%) in the body only, and 9.5% (6.1%) both on the front page and in the body.

Table 6.11. Patent citation characteristics.

Variable	**All publications with technological impact**	**Academic engagement publications with technological impact**	**Academic publications with technological impact**
Who added the citation?			
Applicant	2382 (75.8%)	817 (79.9%)	1565 (73.9%)
Examiner	759 (24.2%)	205 (20.1%)	554 (26.1%)
Where was the citation located?			
Front page only	2703 (86.1%,)	864 (84.0%)	1839 (86.8%)
Body only	217 (6.9%)	67 (6.5%)	150 (7.1%)
Both front page and body	221 (7.0%)	91 (9.5%)	130 (6.1%)

Additional descriptive statistics located in Appendix A illustrate the similarities and differences among the sampled universities and prevalent subfields concerning technological impact. Two interesting findings are that the publications of the sampled professors from LTH exhibit the highest probability of affecting technological inventions as well as the highest mean technological impact, as compared with the publications of professors from the other sampled universities. These statistics, although noteworthy, were put in Appendix A as they do not constitute the primary focus of this study.

6.4.2 Regression analyses

Table 6.12, below, depicts descriptive statistics for all variables included in the models, including variable name, number of valid cases, mean, standard deviation, minimum, maximum, range, skewness, and kurtosis. A correlation table of the variables included in the analysis can be found in Appendix B. Consistent with Chapter 5, variables exhibiting high skewness and kurtosis have been addressed in accordance with econometric theory. Although correlations exist between certain variables (as in Chapter 5), these do not exceed acceptable thresholds. Consequently, the analysis will proceed directly to the subsequent part of this section (for further details, see Section 5.4.2).

Table 6.12. Descriptive variable statistics, Chapter 6.

Variable	***No.***	**mean**	**SD**	**median**	**min**	**max**	**range**	**skew**	**kurtosis**
Total_tech_impact	5143	0.86	5.08	0	0	181	181	15.9	393.8
Individual_tech_impact	5143	0.07	0.51	0	0	13	13	12.3	199.3
Organizational_tech_ impact	5143	0.01	0.23	0	0	8	8	22.3	586.0
Academic_engagement	5143	0.19	0.40	0	0	1	1	1.5	0.4
Number_authors	5143	5.62	15.31	2	1	479	478	25.0	729.0
Dual_affiliated_professor	5143	0.07	0.25	0	0	1	1	3.5	10.3
Journal_reputation	5143	0.11	0.31	0	0	1	1	2.5	4.2
Prior_article_impact	5143	267.1	452.71	106	0	3925	3925	4.1	21.9
Prior_patenting	5143	4.64	21.76	0	0	391	391	11.2	152.5

Prior_coauthors	5143	71.91	127.24	45	0	1516	1516	7.6	70.0
Number_universities	5143	2.09	4.75	1	1	184	183	26.5	868.7
Top_university	5143	0.09	0.29	0	0	1	1	2.8	5.9
Number_fields	5143	1.80	0.83	2	1	7	6	1.3	3.3
Number_nations	5143	1.55	1.30	1	1	36	35	9.8	173.6
Female	5143	0.05	0.21	0	0	1	1	4.3	16.5
Computer_Science	5143	0.18	0.38	0	0	1	1	1.7	0.8
Automation_and_Control_Systems	5143	0.19	0.39	0	0	1	1	1.6	0.5
Telecommunications	5143	0.19	0.39	0	0	1	1	1.6	0.5
CTH	5143	0.18	0.39	0	0	1	1	1.6	0.7
KTH	5143	0.22	0.41	0	0	1	1	1.4	-0.1
LiU	5143	0.26	0.44	0	0	1	1	1.1	-0.8
LTH	5143	0.24	0.43	0	0	1	1	1.2	-0.5
UU	5143	0.13	0.33	0	0	1	1	2.3	3.1
Year_dummies	5143	2012	4.77	2013	2000	2018	18	-0.6	-0.5

The outcomes of the econometric regression analyses are outlined in Table 6.13, below. The regression models adhere to the following logic: uneven numbered models include the control variables, while even numbered models include the control variables plus the independent variable. For example, Models 1 and 2 focus on the total technological impact of the publications (DV = *Total_tech_impact*), with Model 1 including only the control variables and Model 2 adding the independent variable (*Academic_engagement*).

Table 6.13. Regression results with total technological impact, individual technological impact, and organizational technological impact as the dependent variables.

Results

	Dependent variable: Models 1 and 2: *Total_tech_impact* Models 3 and 4: *Individual_tech_impact* Models 5 and 6: *Organizational_tech_impact*					
	(1)	(2)	(3)	(4)	(5)	(6)
Academic_engagement		0.529^{***}		0.976^{***}		2.784^{***}
		(0.150)		(0.230)		(0.686)
Number_authors	0.362^{**}	0.271^{*}	0.501^{***}	0.384^{*}	0.143	–0.235
	(0.150)	(0.142)	(0.173)	(0.197)	(0.406)	(0.629)
Dual_affiliated_professor	-0.665^{**}	-0.820^{***}	–0.405	-0.917^{***}	2.128^{***}	0.881
	(0.271)	(0.302)	(0.308)	(0.299)	(0.527)	(0.676)
Prior_article_impact	0.0005^{***}	0.001^{***}	–0.00001	0.0001	–0.00003	0.0005
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.001)	(0.0003)
Prior_patenting	0.007^{***}	0.006^{***}	–0.004	–0.004	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Prior_coauthors	–0.0001	–0.0001	0.002^{***}	0.002^{***}	0.001	0.002^{***}
	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
Journal reputation	0.865^{***}	0.865^{***}	0.985^{***}	1.000^{***}	1.344	1.641
	(0.228)	(0.227)	(0.302)	(0.285)	(1.208)	(1.065)
Top_university	0.180	0.182	0.518^{*}	0.490	1.261^{**}	2.492^{***}
	(0.203)	(0.202)	(0.297)	(0.308)	(0.628)	(0.638)
log(*Number_universities*)	–0.067	–0.040	–0.026	–0.016	–0.313	–0.359
	(0.131)	(0.133)	(0.201)	(0.197)	(0.570)	(0.762)
log(*Number_nations*)	–0.139	–0.208	–0.217	–0.246	0.205	–0.432
	(0.176)	(0.182)	(0.275)	(0.276)	(0.628)	(0.613)
Number_fields	–0.013	–0.002	–0.010	–0.048	–0.222	–0.216
	(0.073)	(0.074)	(0.113)	(0.119)	(0.344)	(0.503)
Female	–0.279	–0.168	-1.060^{**}	-0.980^{*}	0.417	–0.558
	(0.335)	(0.340)	(0.536)	(0.521)	(1.527)	(2.230)
University_dummies	Yes	Yes	Yes	Yes	Yes	Yes
Field_dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year_dummies	Yes	Yes	Yes	Yes	Yes	Yes

Constant	409.551***	420.425***	164.356***	178.203***	312.946***	383.522***
	(22.206)	(23.088)	(34.259)	(34.625)	(86.429)	(81.034)
Observations	5143	5143	5143	5143	5143	5143
Akaike inf. crit.	7800.7	7788.3	1788.8	1776.6	515.01	494.79

Robust standard errors in parentheses.

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

First, we note that the overarching dependent variable, which is the sum of the three pathways of technological impact, is significant in Model 2. This suggests that there is a difference between scientific papers resulting from academic engagement and those resulting from academic projects when it comes to the intensity of their technological impact. Consequently, this finding lends support to Hypothesis 6.1.

Delving deeper into the analysis, the data reveal that those papers resulting from academic engagement exhibit both greater individual technological impact (Model 4) and greater organizational technological impact (Model 6). This suggests that the authors of publications stemming from academic engagement, along with the organizations they list as their affiliations, cite these papers more frequently than comparable research originating from academic projects.

In this series of regression models, several control variables exhibit significant effects. The variables associated with the professors' prior accomplishments and activities all demonstrate noteworthy positive impacts. This implies that publications stemming from the sampled professors with a high prior article impact, a substantial number of prior patent applications, and a significant number of prior co-authors all contribute to an increase in at least one form of technological impact. Furthermore, publications characterized by numerous co-authors, published in top-tier journals, and involving a researcher from any of the world's top 50 global universities are also correlated with heightened technological impact.

In contrast, dual-affiliated professors appear to exert a somewhat negative influence on technological impact. However, this effect lacks clarity and significance when the variable representing academic engagement is taken into account. It is notable, though, that the presence of dual-affiliated professors demonstrates a significant positive impact on organizational technological impact when the independent variable is excluded (Model 5), suggesting that these authors serve as knowledge translators within the firm.

6.4.3 Robustness tests

In summary, several robustness tests have been conducted, and their overall outcomes support the findings presented in the main regression analysis. Further elaboration on these tests is provided below, while all referenced regression analyses can be found in Appendix C.

As a first robustness test, all dependent variables were modified from count variables to binary variables. These new dependent variables represent whether or not the publications have been cited by at least one patent. This operationalization is in line with earlier research, such as that of Veugelers and Wang (2019) and Ke (2020). These regressions supported the main specifications. They also gave evidence that not only do the papers resulting from academic engagement have greater technological impact, but they are also more likely to be meaningfully useful for at least one future patented technology, as compared with similar publications written solely by academics.

As a second test, the dependent variable was modified to measure knowledge spillover. These regressions indicated that the academic engagement variable coefficient is also statistically significant in a positive direction. This signifies that external organizations, particularly firms, cite papers resulting from academic engagement more frequently than they cite research stemming from academics.

As a third robustness check, the dependent variables were altered to count only the citations originating from the applicant(s), rather than all citations. Unlike scientific publications that only have references inserted by the co-authors, technological patents can have citations added by both the inventors (including patent attorneys) and the patent examiners. Research suggests that examiners add a relatively large share of the citations in technological patents (e.g., Alcácer et al., 2009); however, Lemley and Sampat (2012) also suggested that those references are predominantly to prior patents rather than the non-patent literature. Although this suggests that the examiners' impact on which scientific publications are cited is low to negligible, it is worthwhile investigating whether the aforementioned findings are biased due to the examiners. This is the third robustness test. Specifically, this test modified the dependent variables so that they count only the applicant citations rather than all citations (i.e., applicant + examiner citations). This did not meaningfully change any of the interpretations made in the prior section.

As a final test, all main regressions were executed with author-clustered standard errors (as in Chapter 5), which account for intragroup correlations, instead of relying on robust standard errors. This robustness test did not change the interpretation of the aforementioned findings in any noteworthy way.

6.5 Discussion

In the previous section, several noteworthy discoveries emerged. The aim of this section is to examine these findings in relation to the relevant literature. This discussion will also encompass an exploration of the study's limitations and, in connection with this, propose avenues for future research projects.

According to the data, 20.3% of all papers resulting from academic engagement had some technological impact, whereas only 14.3% of all papers resulting from academic projects had any technological impact. This relationship, that is, that publications resulting from academic engagement are more likely than those resulting from academic collaboration to have any technological impact, is true for all sampled universities and for the most common subfields when analyzing them separately.

The share of publications valuable for technological inventions seems rather high, although it is important not to confuse these percentages with the percentages of patents that cite science (e.g., as done by Magerman et al., 2015; Marx & Fuegi, 2022; Tijssen, 2002), as they do not reflect the same phenomenon. To clarify, this study investigates to what extent publications made by the sampled professors are cited by patents, while the other stream focuses on to what extent patents cite scientific publications. Therefore, what can be stated regarding these findings is that they indicate that Swedish-employed electrical engineering professors conduct research that is highly valuable for firms, adding more empirical evidence for the notion that "sciences of action," such as electrical engineering, truly influence technology (see, e.g., Ahmadpoor & Jones, 2017; Jaffe et al., 1993; Narin et al., 1997).

The descriptives show some evidence that those scientific papers resulting from academic engagement had higher individual technological impact and organizational technological impact than did those papers resulting from academic projects. The regression analyses supported this finding, giving support to Hypothesis 6.1, as stated in the preceding section. These findings corroborate prior findings stating that academic engagement can indirectly lead to firm inventions/innovations as firms are the type of organization that most often applies for patents (McKelvey & Ljungberg, 2017; Walsh et al., 2016).

Descriptive statistics clearly indicate that organizations (i.e., firms) exhibit a greater propensity to employ the individual technological impact pathway over the organizational technological impact pathway (supporting Hypothesis 6.2). From a broader perspective, these findings suggest that the focal employee involved in the research has acquired the requisite knowledge to apply these insights in alternative settings (i.e., technological development), aligning closely with the personal dimension of knowledge (Dretske, 1981; Nonaka, 1994; Polanyi, 1958). This discovery lends support to the idea that the specific context under investigation can be accurately characterized as a science of action, serving the dual purpose of advancing both science and technology (Banse & Grunvald, 2009). This dual purpose may account for the ability of universities and firms to resolve their conflicting logics, allowing predominantly universities to disseminate the findings through publications and firms to leverage that knowledge via patents, most likely via hybrid spaces (Perkmann et al., 2018).

Robustness tests further suggest that publications arising from academic engagement are more likely to yield tangible knowledge spillovers. This not only implies recognition of the research's value by the parties involved but also underscores the appreciation of its significance by external actors, predominantly firms. This supports the proposition that these papers have great technological value and are not merely the byproducts of prior activities but are actively utilized for their intrinsic technological merit. This is likely the result of a greater combination of knowledge bases (Schilling & Green, 2011), including a combination of deep application knowledge essential for practical problem-solving and a more abstract and distant search in the realm of engineering science (see Chapter 5).

Concerning the time lag of the technological impact, the descriptives suggest that there is little to no difference between the papers resulting from academic engagement and those resulting from academic projects. Regression analyses (not shown) also support this claim. However, in relation to time lag, we may have only half the picture. For example, it is conceivable that the collaborators have prearranged agreements allowing researchers employed by the firm (or their colleagues) to pursue a patent prior to the public disclosure of the research—a proposition substantiated by empirical investigations (Chang et al., 2017; see also Hemberg, 2023; McKeveley et al., 2015). This type of patent is not accounted for in this analysis, nor is it included in the other regressions, as already mentioned.

Even though those patents applied for before the research is made public are not included in the analysis, the lead time from science to technology in was found to be lower than reported in other papers (median one year, mean two years). For example, some research into biotechnology (Finardi, 2011), nanoscience, and nanotechnology (Murray & Stern, 2007) informs us that the most common lead time from scientific research to technological invention is around three to four years. In the large-scale analysis of 32 million research papers and 4.8 million patents brought up earlier, Ahmadpoor and Jones (2017) found the average time lag to be around six to seven years. This is viewed as further evidence of the closeness of foci between science and technology within the electrical engineering field in Sweden.

Focusing on which firms actually use these publications most in patented technology, we first note that they are not the same as the firms that these professors collaborate with the most (cf. Tables 6.9 and 6.10). Specifically, only two of the ten most common co-authoring firms are also found among the ten most common citing firms (i.e., Ericsson and Huawei Technologies). Although this could be deduced from the fact that knowledge spillover was much more prevalent than individual technological impact and organizational technological impact combined, this is an interesting observation.

Moreover, when focusing on the firms that co-publish the most with my sample of professors, they vary greatly in the extent to which they use that knowledge for technological inventions. There are several possible explanations for the latter remark. One explanation is simply that they simply do not utilize this knowledge in the best way possible. The contradictory explanation is that they do utilize the insights from the research in a (near-)optimal way but not via technological patents. For example, research suggests that firms have divergent strategies when it comes to patenting and that different types of inventions are differently appropriate to patent (Griliches, 1990). A third explanation is that the firms allow their scientifically interested employees to publish, but that falls outside the scope of their other work-related tasks, in line with the belief that some employees are driven by a "taste for science" (Roach & Sauermann, 2010, p. 422).

Naturally, this undertaking is not without limitations. Some limitations were brought up in Chapter 5 (see Section 5.5), including concerns about treating co-authors as black boxes, the small number of articles resulting from academic engagement projects, limited generalizability due to focusing on one field and one nation, analyzing outcomes rather than collaborations, and the reliance on bibliometric data.

In addition to these, there are at least two other notable limitations. First, the chosen methodological approach does not account for patents that were applied for before the research was submitted to a journal, but that originated from the collaboration. By definition, these patents cannot be included in the analysis due to the novelty criterion for patentability. Although existing research suggests that such cases are rare and constitute a very small percentage of the total (Magerman et al., 2015), it is important to better understand their significance for our overall understanding of the technological impact of collaborative research.

Second, the regression models do not consider the researchers' prior employment, which likely has an effect (Ljungberg et al., manuscript to be submitted for publication). For example, if a close R&D colleague of a firm employee involved in collaborative research leaves the firm shortly after a publication and subsequently incorporates the insights of that research into their new invention, which is referenced in a patent application, these instances are defined as external knowledge spillover, despite the obvious link between the research and the patent.

Further research is warranted to explore these aspects in greater depth. It is particularly recommended to begin with qualitative studies that investigate the underlying characteristics of these findings, adopting a dyadic approach that equally emphasizes the perspectives of both academic and industrial researchers. Additionally, there are great possibilities to build on this work through quantitative investigations. At the individual level, further quantitative work should pay more attention to all authors, while at the paper level, proxies for other aspects of the publications should be taken into account, proxies such as the level of appliedness and novelty. For researchers interested in classifying publications based on their applied or basic nature, the paper by Boyack et al. (2014) is highly recommended. For those focusing on novelty, the paper by Wang et al. (2017) offers valuable insights.

6.6 Conclusion

This chapter builds on the previous investigation into the scientific impact of academic engagement by shifting the focus to examining technological impact stemming from collaborative research between universities and firms. Although the academic engagement field is relatively new, it is a fast-growing research field covering several different focus areas (Perkmann et al., 2013, 2021). As of today, little research exists investigating the (technological) impact of publications resulting from academic engagement, as argued by Messeni Petruzzelli and Murgia (2020) and also highlighted in the review by Perkmann et al. (2021).

Consequently, this study set out to remedy this gap in the literature. That is, the overall purpose of this empirical undertaking has been to better understand the technological value of academic engagement projects, distinguishing three pathways of impact—individual technological impact, organizational technological impact, and knowledge spillover. The exact research question—which is also RQ2 of this Ph.D. dissertation—that has guided this undertaking is stated below, as well as the hypotheses and whether the findings have supported or rejected them (Table 6.14). That is followed by a few more expanded concluding remarks.

How does the technological impact of publications resulting from academic engagement projects differ from the impact of those resulting from academic projects?

Table 6.14. Hypotheses: empirical evidence for confirmation or refutation – Chapter 6.

Hypothesis	**Empirical findings**
6.1. Publications originating from academic engagement collaborations are associated with higher technological impact.	Supported
6.2. Individual technological impact is more prevalent than organizational technological impact.	Supported

To the best of my knowledge, no similar research exists that analyzes this phenomenon in equal detail; hence, this study makes a number of contributions to the relevant literature streams. The two most significant are mentioned below.

First, the findings, as demonstrated above, support the hypothesis that collaborative research, as a form of academic engagement, positively influences the intensity of technological impact. This implies that publishing with firms is not only advantageous from a scientific impact standpoint (Chapter 5), but also offers benefits from a technological impact perspective. The juxtaposition of these findings is intriguing, indicating that collaborative research, as one form of academic engagement, generates outcomes valued by both the scientific and technological communities. The underlying explanation for this outcome is argued to mainly be a result of the integration of diverse knowledge bases and practices.

Second, the results further support the hypothesis, indicating more utilization of the first pathway (i.e., the individual technological pathway) than the second pathway (i.e., the organizational technological impact). This discovery has significance as it provides insights into the empirical context, supporting the inherent proximity of science and technology—an integral conjecture derived from the literature at the initiation of this Ph.D. undertaking.

7 THE IMPACT OF THE LEAD AUTHOR IN COLLABORATIVE RESEARCH AS ONE FORM OF ACADEMIC ENGAGEMENT

7.1 Introduction

As shown in previous chapters, collaboration among researchers is widely acknowledged as a fundamental element of the modern scientific enterprise (Shen & Barabási, 2014; see also Wuchty et al., 2007a). The increasing significance of research collaboration can be attributed to the continuous expansion of the global knowledge base, which far exceeds any individual's capacity for comprehension. Consequently, the process of generating new knowledge has become increasingly challenging, as individuals must acquire a substantial amount of knowledge before they can effectively contribute to it. This underscores the essentiality of collaborative efforts, in which team members combine their knowledge and expertise to collectively advance the frontiers of knowledge.

There is further empirical evidence suggesting that researchers have employed a division of labor to manage the "burden of knowledge" (Brendel & Schweitzer, 2019; McDowell & Melvin, 1983), and there is a trend toward larger research teams (Kuld & O'Hagan, 2018; Wuchty et al., 2007a). This implies, supported by empirical research, that researchers take on distinct roles in collaborations, with all researchers in a collaboration having different responsibilities (Corrêa Jr. et al., 2017; Wren et al., 2007). Studies indicate that the perception of the authors' contributions is significantly influenced by the order of the authors listed on a paper, known as the byline order (Bhandari et al., 2014; Nylenna et al., 2014). For instance, while the sequencing of authors on a byline in multi-authored research papers may vary across fields, countries, and years (Yu & Yin, 2021), the first author is generally considered the lead author, having made the most significant contribution (Bhandari et al., 2014;

Corrêa Jr. et al., 2017; Nylenna et al., 2014; Wren et al., 2007), and is often the corresponding author, especially in the engineering sciences (Yu & Yin, 2021).

Despite the perceived importance of the lead author, particularly in the engineering sciences, there is a notable lack of research studying differences in authorship roles and the associated contributions. Notable exceptions addressing this research gap include a recent publication by Thelwall et al. (2023) suggesting that highly cited first authors are regarded as more important than highly cited teams when it comes to publishing in journals with higher journal reputations, that is, journals with higher impact factor ratings. This has resulted in a limited understanding of how authorship order can affect the impact of research papers, as argued by Kohus et al. (2022a).

The key objective of this research is to address one aspect of this knowledge gap by quantitatively analyzing the influence exerted by the lead author on both the scientific and technological impacts of the publications resulting from academic engagement, specifically examining how their type of affiliation shapes the overall outcomes. In line with the rest of this dissertation, I distinguish among three types of affiliations: academic, industrial, and dual-affiliated (i.e., first authors affiliated with both university and industry simultaneously). The question guiding this endeavor is the third research question of this dissertation, formulated as follows:

How does the scientific and technological impact of the papers resulting from academic engagement depend on the affiliation of the lead author?

The lead author's affiliation(s) are emphasized because universities and firms follow competing institutional logics when developing science and technology, with firms prioritizing capitalizing on the developed knowledge and universities prioritizing disseminating that knowledge (Dasgupta & David, 1994; Sauermann & Stephan, 2013). This influential role is likely to exert a significant influence on the collaboration's outcomes, particularly in terms of its scientific and technological impact. In line with the competing institutional logic argument, the most straightforward ex ante surmise is that publications resulting from academic engagement having lead authors affiliated with industry would have a higher technological impact but a lower scientific impact, although there are several conflicting arguments regarding the manifestation of this effect.

In essence, understanding how the affiliation of the lead author influences research outcomes provides valuable insights for various stakeholders, including practitioners, researchers, funding agencies, universities, and firms. These insights can inform decision-making processes regarding collaboration structures and support. In other words, by shedding light on the influence of authorship order and affiliation on collaboration outcomes, this research has the potential to contribute to the development of effective approaches for promoting and facilitating successful academic engagement collaborations. Ultimately, the present findings may drive positive changes in the way collaborative research involving universities and firms is conducted, benefiting the scientific community and society as a whole.

The remainder of this chapter is organized as follows: The subsequent section explores essential theories pertaining to the roles of authors in scientific and technological collaborations. This is followed by an outline of the research design and empirical strategy. The chapter concludes with a presentation of the findings, an in-depth analysis of these findings, and the formulation of relevant conclusions.

7.2 Theory and hypotheses

This section aims to analyze how authorship order may influence the scientific and technological impacts of publications. While research on this matter is scarce, there is a broad literature from various disciplines studying the order of authors in academic publications. Before delving into the specifics of how this influence may manifest itself, a broader discussion of authorship is provided.

7.2.1 Studies of authorship

In the scientific enterprise, authorship provides a basis for peer recognition, allowing research scholars to be acknowledged for their work (Merton, 1973; Moed, 2005). Consequently, it is essential to accurately attribute symbolic credit where it is due, especially when it is considered the main currency in academic publishing (Bourdieu, 1975; see also Desrochers et al., 2018). Accurately attributing credit to authors is not easy, however, as credit results from the premises that authors take on distinct roles when collaborating and that their contributions are not equally valued (e.g., Bhandari et al., 2014; Corrêa Jr. et al., 2017; Nylenna et al., 2014; Wren et al., 2007).

To address this issue, academic journals have clarified the criteria for authorship, and research scholars have proposed various co-authorship credit allocation models. These models include the fractional counting model (Price, 1981), the proportional counting model (Van Hooydonk, 1997), and the harmonic counting model (Hagen, 2008). The evolution of credit allocation models has transitioned from solely crediting the first author to giving equal credit to all authors and, more recently, to emphasizing the importance of the authors' positions in the byline, with the first author generally receiving the largest credit allocation. It is important to note that the researchers themselves determine the order of authors on a paper. Hence, the purpose of credit allocation models is to retrospectively assign appropriate credit to all authors based on their contributions. Readers interested in a more detailed discussion of authorship and how seven prominent credit allocation models distribute credit to authors are referred to Appendix D.

Furthermore, certain journals, notably those published by the Public Library of Science (known as PLOS journals), have implemented contributorship statements (Allen et al., 2014) to enhance the transparency of the scientific process. These statements are intended to more precisely attribute credit to co-authors and ensure accountability among scholars for their work, especially in instances of scientific misconduct. Regrettably, scientific misconduct, such as ghost authorship (Wislar et al., 2011), remains a genuine concern (Nylenna et al., 2014). In light of these contributorship statements, and assuming that the contributions are fairly honestly listed, the potential for issues such as ghost authorship should be mitigated. There have also been calls to transition from co-authorship to contributorship (e.g., Smith, 2012; Vasilevsky et al., 2021; Zauner et al., 2018), and scholars have recommended that journals adopt common and transparent standards of authorship, such as the Contributor Roles Taxonomy (known as CRediT) distinguishing 14 different contributor roles (Holcombe, 2019; McNutt et al., 2018).[35] This addition to scientific papers has prompted empirical research, including studies examining patterns of contributorship in scientific manuscripts (Corrêa Jr. et al., 2017), contributorship and division of labor (Larivière et al., 2016), and contributorship-based credit allocation models (Ding et al., 2021; Yang et al., 2022).

Although contributorship statements have the potential to enhance our understanding of how different collaboration processes influence outcomes, they have not yet become widely adopted. The alternative approach is to look at an individual author's byline position in the paper as well as to examine who the corresponding author is. Apart from the aforementioned paper by Thelwall et al. (2023), this limited stream of research has mainly focused on the country of origin of the first and/or corresponding author (e.g., Grácio et al., 2020; Kohus et al., 2022a; de Moya-Anegón et al., 2018).

[35] The 14 contributor roles are: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing (original draft), and writing (review & editing) (CRediT, 2023).

For example, Kohus et al. (2022a) analyzed the relationship between the byline positions of affiliated and non-affiliated authors and the normalized article impact of research articles published by European universities in the field of medical science. The affiliated group comprised all papers in which the first, last, and/or corresponding author was affiliated with the sampled/focal university, whereas the not-affiliated group comprised all other publications, that is, all research articles in which the first, last, and corresponding authors had no affiliation with the sampled/focal university. The study suggests that institutions generally benefit from the inclusion of non-affiliated authors in the first, last, and corresponding byline positions in terms of article impact.

In a similar study, de Moya-Anegón et al. (2018) analyzed the relationships between the corresponding author, international publication, and normalized article impact. Among other things, they found that the article impact of a country's papers in which the corresponding author was from that country was lower than that of the country's papers in which the corresponding author was not for all 40 nations included in the analysis except for the USA. This finding has been corroborated by other papers, such as that by Chinchilla-Rodríguez et al. (2019).

While these studies offer valuable insights, the understanding of the specific relationship with respect to the research question of this chapter remains limited. Instead, they inform us that the first/corresponding author can significantly influence the scientific impact of a collaboration. However, the precise mechanisms driving this influence remain largely unknown. Is this influence a consequence of authorship order, potentially resulting from increased visibility, or does it stem from the nature of the collaborative research, possibly influenced by the diversity of research questions addressed?

Given the scarcity of empirical evidence, the following section will leverage related theory-inspired and logic-based reasoning to deepen our comprehension of the phenomenon.

7.2.2 Understanding how first authorship may influence the scientific and technological impacts of collaborative research

When engaging in collaborative research between firms and universities, all parties typically have distinct objectives. When firms engage in collaborative research with universities, their primary objective is to enhance their innovation capacity, either directly or indirectly (e.g., McKelvey & Ljungberg, 2017). Consequently, if a firm representative assumes the role of the first author of a scientific paper, which entails making the most significant contribution to the research project and leading the team of co-authors toward achieving the desired end goal, it is reasonable to assume that they are steering the project in a manner that maximizes the firm's chances of capitalizing on the work.

In successful cases, these collaborations are likely to yield substantial individual and/or organizational technological impacts. Given their perceived value to the firms, it is plausible that they hold significance for other organizations as well. Supporting evidence for this is derived from the aforementioned study by Messeni Petruzzelli and Murgia (2020), who examined 772 joint patents involving universities and firms in the pharmaceutical, biotechnology, and medical technology sectors. Their findings indicated that local university–industry collaborations, which are common in my sample, had a positive and statistically significant impact on knowledge spillover. While this investigation focused on patents, a parallel mechanism likely operates in the context of collaborative research in the field of engineering, owing to the intertwined nature of science and technology in this discipline.

Similarly, one can argue that the firm may prefer to steer publications toward journals with smoother publication procedures. This preference is rooted in the desire to minimize the resources required for publication, consequently increasing the likelihood of having publications in journals of lower ranking but with more streamlined publication processes.

However, it is crucial to acknowledge the limitations of this perspective, as certain companies may adopt a business strategy that also places a premium on conducting world-class research. In other words, their research endeavors are geared not only toward maximizing their technological impact but also toward maximizing their scientific impact, and they allocate the necessary resources accordingly. It is also conceivable that the publication process might be driven by the firm employees' "taste for science" (Roach & Sauermann, 2010, p. 422), and some employers may grant their research employees complete autonomy over their research, allowing them to prioritize maximizing their academic achievements.

From the perspective of academic researchers, similar arguments, but with contrasting viewpoints, can be formulated. As previously mentioned, it is primarily through forward citations that research scholars receive recognition for their work (Merton, 1973; Moed, 2005), implying that they generally strive to guide collaborative research endeavors in a manner that optimizes their scientific impact. This may entail focusing on topics or questions they believe are highly likely to generate substantial scientific interest and aiming to publish their work in top-reputed journals. Furthermore, it is plausible that some highly impactful papers may also exert a substantial influence on the technological domain, given that all technological innovations are, to some extent, grounded in research (Tijssen, 2002).

Finally, from the perspective of dual-affiliated lead authors, the perceived influence they exert on a collaboration is that they have the ability to conceptualize papers that have a high probability of attracting significant interest from both the scientific and technological communities.

This ability is attributable to their profound understanding of both the scientific community and the firm engaged in the collaboration, as they maintain affiliations with both simultaneously. As previously mentioned, these researchers are considered boundary spanners, facilitating the translation of diverse knowledge among the collaboration's members. When assuming a leadership role within the collaboration, it is plausible that their contributions may lead to advantageous conceptualizations that hold value for both communities. This belief is underpinned by prior research, discussed at length earlier in this dissertation, highlighting the beneficial role played by boundary spanners (e.g., Conway, 1995; Gertner et al., 2011).

Furthermore, there is also relevant literature on gatekeepers (e.g., Llopis & D'Este, 2022; Ter Wal et al., 2017; Tortoriello & Krackhardt, 2010). While these studies often empirically focus on innovations, it is reasonable to assume that similar dynamics apply to research, especially in the field of engineering, where science and technology are intertwined. In a more comprehensive examination of gatekeepers, Llopis and D'Este (2010) observed that collaborations involving a gatekeeper, defined as an individual belonging to the same group as one of the contacts being brokered, while the other contact belongs to a different group, tend to strike a favorable balance between accessing new information and the ease of integrating said information.

It is important to acknowledge that all collaborations in the context of academic engagement having three or more authors meet this criterion. However, the argument being made is that when one of the members is affiliated with both organizations, he or she can function as a gatekeeper in both directions. Similarly, Tortoriello and Krackhardt (2010) argued that the presence of common third-party ties around a central bridge profoundly alters the nature of the bridging relationship through which knowledge flows. Notably, they found that when individuals engaged in boundary-spanning relationships shared third-party ties, they were more likely to generate innovations than in situations in which such shared third-party ties were absent. In the presence of a dual-affiliated lead author, shared third-party ties are arguably more likely.

Having said this, the findings presented in Chapter 5 indicate that dual-affiliated professors exhibited a reduced likelihood of publishing in highly reputed journals. This implies that, despite generating considerable interest within the scientific community, papers from this cohort may not achieve the same level of publication in top-tier journals as those originating from academic-led academic engagement projects.

This discussion concludes in the formulation of five hypotheses to be tested in this endeavor:

H7.1

Academic-led publications originating from academic engagement collaborations are associated with higher article impact.

H7.2

Academic-led journal articles originating from academic engagement collaborations are associated with higher journal reputation.

H7.3

Firm-led publications originating from academic engagement collaborations are associated with higher technological impact.

H7.4

Dual-affiliated-led publications originating from academic engagement collaborations are associated with higher article impact.

H7.5

Dual-affiliated-led publications originating from academic engagement collaborations are associated with higher technological impact.

The conceptual model relating to these hypotheses is visually represented below in Figure 7.1.

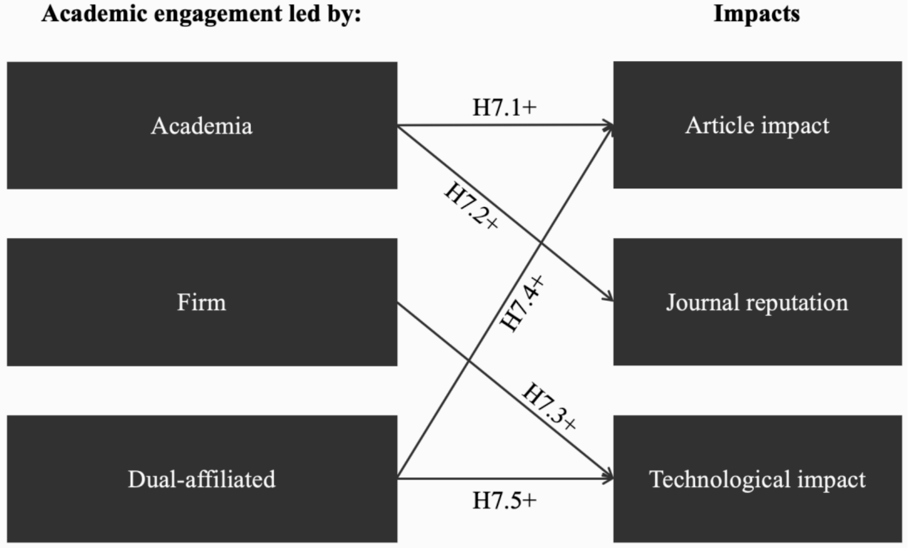

Figure 7.1. A conceptual framework for understanding the hypothesized differences between academic-led, firm-led, and dual-affiliated-led academic engagements and their respective scientific and technological impacts.

7.2.3 Key takeaways from Section 7.2

- The lead author influences the paper via major contributions, particularly in terms of conceptualization and ensuring the completion of the work.
- Publications resulting from academic engagement led by firms generally

contain a conceptualization perceived as highly valuable for the industry, including the involved firm but also other relevant actors (i.e., firms).

- Publications resulting from academic engagement led by academics generally contain a conceptualization perceived as highly valuable to the scientific community; in some rarer instances, it also proves very valuable to the technological sector.
- Publications resulting from academic engagement led by dual-affiliated researchers generally contain a conceptualization believed to offer valuable insights to both the scientific and technological communities; however, prior analyses (Chapter 5) suggest that dual-affiliated professors are less likely to publish in highly ranked journals.

7.3 Data and method

The data and methods utilized here largely replicate the approach employed in the previous two empirical chapters, with the incorporation of new key independent variables. Therefore, this chapter primarily provides a comprehensive explanation of these new variables and methods, while offering a concise summary of the data and methods employed in Chapters 5 and 6. Additional information pertaining to the data and methods can be found in Chapter 4, Sections 5.3 and 6.3.

7.3.1 Data

The dataset employed in this chapter combines the data used in Chapters 5 and 6. In other words, it encompasses all publications written by the sampled set of engineering professors and the numbers of citations those publications obtained from the scientific and technological communities.

Operationalization of the new independent variables

Since the aim of this undertaking is to analyze the influence of different types of first-author affiliation on the resulting academic engagement publications' scientific and technological impacts, the original academic engagement variable has been divided into three types: *Academic_led_AE*, *Firm_led_AE*, and *Dual_led_AE*.

The first of these variables (*Academic_led_AE*) was approximated by identifying publications resulting from academic engagement while excluding papers with a first author affiliated with a firm and papers with a first author affiliated with both a university and a firm. This independent variable is thus a binary variable, taking the value of 1 when there is at least one author affiliated with a firm other than the first author, who is an academic researcher, and 0 otherwise. This approach seems to align with related papers, such as those by Kohus et al. (2022a, 2022b). The same logic was applied to create the other two variables (*Firm_led_AE* and *Dual_led_AE*). It is important to note that while the number of papers attributed to a dual-affiliated lead author amounted to 97, only five of these (5.2%) involved one of the sampled dual-affiliated professors. Consequently, the previously used variable for dual-affiliated professors was included in the regressions as a control variable.

Variable summary

Table 7.1, below, provides an overview of all variables, including name, type of variable, and operationalization.

Table 7.1. Summary of the regression variables used in Chapter 7.

Variable	Type	Description
Article_impact	DV	A count variable representing the total number of scientific citations received by the publication within three years of its release
Journal_reputation	DV, CV	A binary variable with a value of 1 if the article was published in a journal belonging to the top 15% of the 2018 Journal Impact Factor distribution with regard to my sample, and 0 otherwise
Total_tech_impact	DV	A count variable indicating the total number of technological (i.e., patent) citations received by the publication before 2021
Academic_led_AE	IV	A binary variable with a value of 1 if a firm is reported among the authors' affiliations on the publication and if the first author is affiliated with at least one university but no firm, and 0 otherwise

Firm_led_AE	IV	A binary variable with a value of 1 if a firm is reported among the authors' affiliations on the publication and the first author is affiliated with at least one firm but no university, and 0 otherwise
Dual_led_AE	IV	A binary variable with a value of 1 if a firm is reported among the authors' affiliations on the publication and if the first author is affiliated with at least one university and at least one firm, and 0 otherwise
Dual_affiliated_professor	CV	A binary variable with a value of 1 when at least one of the sampled dual-affiliated professors is listed as an author on the publication, and 0 otherwise
Number_authors	CV	A categorical variable indicating the number of authors of each publication, categorized into groups of 1–8 authors and 9 or more authors
Prior_article_impact	CV	A count variable representing the total number of scientific citations received by the sampled professor in the five years preceding the release of the publication; if more than one of the sampled professors has authored the publication, the highest value is used
Prior_patenting	CV	A binary variable with a value of 1 if any of the sampled professors on a publication applied for a patent in the five years preceding the release of the publication, and 0 otherwise
Prior_coauthors	CV	A count variable indicating the total number of co-authors the sampled professor had in the five years preceding the release of the publication; if more than one of the sampled professors has authored the publication, the highest value is used
Top_university	CV	A binary variable with a value of 1 if any of the top 50 universities worldwide is reported among the authors' affiliations on the publication, according to the 2018 Academic Ranking of World Universities, and 0 otherwise
Number_universities	CV	A count variable indicating the total number of unique university addresses reported among the authors' affiliations on the publication
Number_nations	CV	A count variable representing the total number of unique nation addresses reported among the authors' affiliations on the publication
Number_fields	CV	A count variable indicating the total number of fields in which the publication has been categorized by Web of Science
Article	CV	A binary variable with a value of 1 if the publication is classified as an article, according to Web of Science, and 0 otherwise
Female	CV	A binary variable with a value of 1 if any of the sampled professors on the publication is female, and 0 otherwise
University_dummies	CV	Five similar dummy variables, each with a value of 1, if the sampled university is reported among the authors' affiliations on the publication, and 0 otherwise; the universities are CTH, KTH, LiU, LTH, and UU
Field_dummies	CV	Three similar dummy variables, each with a value of 1, if Web of Science has assigned the publication to the specific subject areas of "Computer

		Science," "Telecommunications," or "Automation and Control Systems," and 0 otherwise
Year_dummies	CV	A factor variable representing the year in which the publication was released; the possible years are 2000–2018

7.3.2 Empirical strategy

Two of the dependent variables (*Article_impact* and *Total_tech_impact*) are count variables. Because their data are overdispersed (Cameron & Trivedi, 1990), they have been estimated using generalized negative binomial regression models, in line with econometric theory (Cameron & Trivedi, 1998; Fox & Weisberg, 2018; Hilbe, 2011; Lawless, 1987; Venables & Ripley, 2002). These have been estimated using Huber–White robust standard errors. The remaining dependent variable (*Journal_reputation*) is a binary variable. Therefore, it was estimated using generalized Probit models, with Huber–White robust standard errors, in line with similar research (e.g., McKelvey & Rake, 2020).

7.4 Results

In this section, the results of the study are presented. Descriptive data are first provided before delving into the econometric analysis. The chapter concludes by examining the robustness of the findings presented.

7.4.1 Descriptive findings

The objective of this section is to analyze the data and extract descriptive information to better understand their characteristics. This section explicitly centers on statistics pertaining to the lead author, as plentiful statistics have already been presented.[36]

[36] See Sections 4.3, 5.3.1, and 6.3.1.

The total number of scientific papers resulting from academic engagement was 1437. Of these, 1226 have a lead author from academia (85.3%), 114 from a firm (7.9%), and 97 from a dual-affiliated lead author (6.8%). Among the firm and dual-affiliated lead authors, six individuals served as the lead author in more than two publications. Table 7.2, below, provides additional details about these authors. The table includes information pertaining to the type of affiliation listed on the focal publications, including whether the authors were affiliated solely with a firm or affiliated with both a firm and a university simultaneously. It also includes the names of the firms (and, in some cases, the universities) to which they belong, the type of firms they are associated with, and the specific industries in which these firms operate.

Table 7.2. Descriptive information on the affiliation(s) of the researchers with the highest number of publications as firm-employed or dual-affiliated lead authors.

Type of affiliation	**No. of times lead author**	**Firm (university)**	**Type of firm**	**Industry**
Firm	6	5× Sekvensa; 1× Teamster	KIE (both)	Automation (both)
Dual	4	Ericsson (KTH)	MNE	Telecommunications
Firm	3	IFEN		Aerospace
Dual	3	Saab Dynamics (LTH)	MNE	Defense
Firm	3	Saab Aerosystems	MNE	Aerospace
Dual	3	Ericsson (University of Gävle)	MNE	Telecommunications

The table shows that both firm and university affiliations are found. The first type of affiliation, affiliated solely with a firm, underscores the substantial contributions of researchers employed by various firms in advancing scientific knowledge. It is noteworthy that while these authors list only one firm on the focal papers, they have all published additional research papers with the sampled professors while being affiliated with one of the sampled universities, the same ones they collaborated with as firm-affiliated researchers. To put it differently, the firm researchers who listed only the firm either had an ongoing dual affiliation but listed only the firm, or had a prior affiliation (e.g., employment) with the firm. The firms listed in this category constitute a KIE firm and two MNEs. Collectively, these firms span a diverse range of industries, namely, automation, telecommunications, aerospace, and defense.

The second type of affiliation highlighted in the table involves authors who are dual-affiliated researchers, meaning they are affiliated with both a firm and a university simultaneously. This type of affiliation underscores the close linkages between academic institutions and firms, showcasing the synergy between theoretical knowledge and practical application. The table provides specific examples of such collaborations, featuring firms such as Ericsson, Saab Dynamics, and Saab Aerosystems, in conjunction with the universities KTH, LTH, and the University of Gävle. These collaborations encompass the fields of telecommunications, aerospace, and defense.

Due to the limited number of publications with firm and dual-affiliated lead authors, graphical representations are deemed inappropriate owing to the potential for misleading visualizations. Hence, descriptives pertaining to the dependent variable, in relation to the three independent variables, are presented in Table 7.3, below.

Table 7.3. Descriptive statistics for the dependent variables in relation to the three independent variables.

Variable	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum	SD
Academic_led_AE							
Article impact	0	0	2	8.5	3	839	37.6
Journal reputation	0.6	2.6	3.8	5.1	5.4	59.1	6.4
Technological impact	0	0	0	1.2	0	181	6.9
Firm_led_AE							
Article impact	0	0	1	3.7	5	33	4.9
Journal reputation	0.9	3.0	4.8	4.2	5.4	10.4	2.4
Technological impact	0	0	0	1.4	0	46	2.1
Dual_led_AE							
Article impact	0	1	4	5.2	6	50	7.6
Journal reputation	0.8	2.0	3.2	3.5	5.1	9.3	5.6
Technological impact	0	0	0	2.2	1	26	5.8

The highest mean (8.5) and median (2) for article impact are observed when the lead author was affiliated with a university, underscoring the wide range of impact in this context, with a significant maximum value of 839 and a high standard deviation. In contrast, when the lead author was affiliated with a firm, the mean article impact was lower (3.7), with a maximum value of 33. Publications in this category thus exhibit a lower but more consistent article impact profile. For publications resulting from dual-affiliated lead authors, there was an intermediate mean article impact (5.2) and a maximum value of 50.

Moving on to journal reputation, lead authors affiliated with universities had the highest mean (5.1), indicating a high journal reputation, supported by a maximum value of 59.1. For firm-affiliated lead authors, the mean journal reputation was 4.2, with a maximum value of 10.4, demonstrating a moderate level of journal reputation. In contrast, dual-affiliated lead authors exhibited a relatively lower mean journal reputation (3.5), with a maximum value of 9.3, highlighting a lower journal reputation.

Regarding technological impact, university lead authors demonstrated a relatively low mean (1.2) and a median of 0, suggesting that their technology-related contributions were somewhat limited. However, the presence of a maximum value of 181 indicates notable exceptions. In contrast, publications with a firm-affiliated lead author display a slightly higher mean technological impact (1.4), although with a lower maximum value of 46. Here, dual-affiliated lead authors exhibited the highest mean technological impact of 2.2 but the lowest maximum value of 26, indicating a somewhat stronger and more consistent technological focus.

In summary, the findings indicate intriguing patterns in article impact, journal reputation, and technological impact based on the lead author’s affiliation in the context of academic engagement. Publications resulting from lead authors affiliated with a university are associated with higher article impact and journal reputations but lower technological impact, although with occasional technological impact "home runs." These findings are in line with Hypotheses 7.1 and 7.22. Those publications resulting from a lead author affiliated with a firm yield more consistent, though lower, results in relation to article impact and journal reputation, albeit with higher values for technological impact, than do the academic-led and dual-affiliated-led publications. This lends tentative support for Hypothesis 7.3. Publications resulting from dual-affiliated lead authors had the lowest mean journal reputation, intermediate mean article impact, and the highest mean technological impact. This provides some basis for rejecting Hypothesis 7.4 while lending support for Hypothesis 7.5.

When examining the similarities and differences between the sampled universities, there are slight variations in the extent to which professors from the different universities published research papers with lead authors affiliated with firms and with dual-affiliated lead authors. In more detail, the proportions of publications resulting from academic engagement having a lead author having a firm affiliation are 13.0% for KTH, 9.6% for CTH, 7.7% for LiU, 5.8% for UU, and 4.8% for LTH. Interestingly, almost the exact opposite trend is evident for the dual-affiliated lead authors, with proportions of 16.5% for UU, 7.9% for LiU, 7.6% LTH, 4.5% for CTH, and .6% for KTH. In other words, the sampled professors from KTH and CTH relatively more commonly wrote papers in which a firm employee took the lead, while UU professors in particular more commonly wrote papers in which a dual-affiliated author took the lead.

In terms of the similarities and differences among the three most common subfields, notable differences were observed. In particular, in the field of automation and control systems, approximately one in six papers (17.5%) resulting from academic engagement had a lead author employed by a firm and around every 11th paper had a dual-affiliated lead author (9.0%). In the subfields of computer science and telecommunications, approximately one in every 10–12 papers had a lead author affiliated with a firm (9.6% and 8.5%, respectively); for papers with dual-affiliated lead authors, the proportions were much lower, at 4.4% and 2.9%. Interestingly, as shown in Chapter 5, computer science had the highest level of collaboration with firms, but as shown here, those papers relatively often had university-affiliated lead authors.

7.4.2 Regression analyses

This section mainly focuses on the econometric regression analyses related to the proposed research question. These regression models closely resemble those used in Chapters 6 and 7. Consequently, the regression results will be presented and discussed first, with a specific focus on the independent variables. In essence, the sole distinction in the models presented here, when juxtaposed with those presented in Chapters 5 and 6, lies in the inclusion of independent variables that capture the different types of lead-author affiliation (i.e., Academic_led_AE, Firm_led_AE, and Dual_led_AE). Hence, it is my belief that referencing the previously disclosed descriptive statistics and their corresponding pairwise correlations, as detailed in Sections 5.3.2 and 6.3.2, should suffice.

The results of the statistical analysis examining both the scientific and technological impacts of the publications are presented in Table 7.4, below.

Table 7.4. Regression results with article impact, journal reputation, and total technological impact as the dependent variables.

Results

	Dependent variable: Model 1: *Article_impact* Model 2: *Journal_reputation* Model 3: *Total_tech_impact*		
	(1)	(2)	(3)
Academic_led_AE	0.205^{***}	–0.055	0.550^{***}

	(0.058)	(0.080)	(0.166)
Firm_led_AE	–0.205	–0.418	0.931**
	(0.136)	(0.266)	(0.418)
Dual_led_AE	0.098	–0.530**	–0.130
	(0.162)	(0.223)	(0.333)
University_dummies	Yes	Yes	Yes
Field_dummies	Yes	Yes	Yes
Year_dummies	Yes	Yes	Yes
Additional control variables	Yes	Yes	Yes
Constant	–0.025	30.223**	429.782***
	(0.211)	(12.998)	(23.772)
Observations	8455	3414	5143
Log likelihood	–19,296.01	–1337.16	–3868.52
AIC	38,642.02	2720.31	7787.05

Robust standard errors in parentheses.

Significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

As demonstrated above, publications resulting from academic engagement having lead authors affiliated with universities exhibit a statistically significant increase in article impact (Model 1) and technological impact (Model 3), but no statistically significant increase in journal reputation (Model 2). This supports Hypothesis 7.1 while rejecting Hypothesis 7.2.

Shifting our focus to firm-led publications resulting from academic engagement, the results suggest that those led by firm employees have a technological impact premium (Model 3), while displaying no statistically significant effect in terms of the other two outcome variables (Models 1 and 2); this supports Hypothesis 7.3. It is essential to highlight that the technological impact of articles led by firm employees is nearly twice that of articles led by academic researchers, providing compelling evidence of their greater technological impact.

Finally, findings suggest that journal articles led by dual-affiliated authors seem to have a lower likelihood of publication in highly reputed journals (Model 2), while having no meaningful impact in terms of article and technological impacts (Models 1 and 3). This rejects both Hypotheses 7.4 and 7.5.

7.4.3 Robustness tests

Several robustness tests have been conducted, mirroring those carried out in previous chapters (Chapters 5 and 6). The collective results of these tests provide additional support for the conclusions drawn from the primary regression analysis.

As an additional robustness test, not focused on the regressions but rather on a key assumption, an analysis was conducted to assess the frequency of the corresponding author not being the first author in the sample. Specifically, an analysis of 25 randomly selected publications resulting from academic engagement plus 25 randomly selected publications resulting from academic collaborations showed that the first author served as the corresponding author in nearly all instances, with only 1 out of the 50 publications contradicting this pattern. To be clear, this is not a robustness test of the regressions but rather of the assumption that the first author also assumes the role of the corresponding author. As stated before, the underlying reason for this is that the perception of authors' contributions can also be influenced by who the corresponding author is (Bhandari et al., 2014; Wren et al., 2007).

7.5 Discussion

Readers should keep in mind that the purpose of this study is to illuminate the extent to which the scientific and technological impacts of publications resulting from academic engagement are influenced by the affiliation or affiliations of the lead author and how this influence is manifested. Subsequent qualitative research could yield valuable insights into the underlying mechanisms that this undertaking has revealed.

Comparing this study with previous research is challenging due to the absence of prior inquiries addressing this specific phenomenon. To the best of my knowledge, these findings are consistent with previous research demonstrating the significant influence the lead author can have on publication outcomes. For example, as previously mentioned, a recent study by Thelwall et al. (2023) found that first authors with high article impact counts play a crucial role in shaping project outcomes, particularly in terms of journal reputation, which served as their dependent variable.

Similarly, the findings reported here suggest that the type of lead-author affiliation can significantly affect the outcomes. Specifically, when controlling for additional variables, such as the professor's prior article impact, the journals in which they publish, and the topics their publications cover, these results suggest that researcher-led academic engagement is significantly associated with high article impact and technological impact. Papers led by a firm are notably linked to a very high technological impact premium, while those led by a dual-affiliated researcher are less likely to be published in top-tier journals. This undertaking shed additional light on the previous two empirical chapters, which found that academic engagement had a positive influence on article impact and technological impact, in that we know more about one key factor driving those outcomes.

The findings thus support, as hypothesized, the notion that publications led by academics are more tailored to the scientific community, while those led by firms are closer to the technological sphere. In my view, this is partially due to the lead author's major influence on the paper, especially relating to its conceptualization. What this means, for example, is that if a paper is led by a firm, those topics (or perhaps more accurately, the problems investigated) are in some sense closer to technology.

Papers resulting from dual-affiliated first authors were associated with a decreased probability of being published in highly reputable journals, but they exerted no statistically significant influence on the outcome concerning article impact and technological impact. One possible explanation for the lower journal reputation is that multiple types of dual-affiliated researchers exist, so some of their papers may be byproducts of master's thesis work for a company, as is known to occur in this field (Ljungberg et al., manuscript to be submitted for publication). In greater detail, in a more detailed quantitative analysis of 248 publications involving collaborations between firms and the Signals and Control Engineering group at CTH, it was observed that dual-affiliated authors can be categorized based on their primary employment affiliation, ranging from academia to industry (Ljungberg et al., manuscript to be submitted for publication).

In simpler terms, they were either dual-affiliated researchers with their main employment in academia or dual-affiliated researchers with their main employment in industry. Moreover, there are those with extensive experience, including dual-affiliated professors, and those with comparatively less experience, such as master's students engaged in collaborative work with a firm for their thesis, ultimately resulting in a publication where they share the status of being the (dual-affiliated) first author. Since only a small fraction of the papers resulting from dual-affiliated lead authors were part of my sample of dual-affiliated professors (5.2%), it is plausible that a larger share was an outcome of prior master thesis collaborations involving firms. It is moreover likely that some papers were the result of the work of industrial Ph.D. students, also found in this domain (Berg, 2022), who have more academic experience than do master's students, although less than other academic scholars with Ph.Ds.

A complementary explanation for the observed negative correlation between journal reputation and dual-affiliated-led papers, which is not mutually exclusive, is that those lead authors may intentionally target lower-reputed journals by choice, a factor not controlled for in the regressions.

These findings offer additional insights into the influence of boundary spanners and highlight the importance of distinguishing their different types. Different roles with regard to individual collaborations have been distinguished in several network-based empirical studies (e.g., Gould & Fernandez, 1989; Lissoni, 2010; Llopis & D'Este, 2022), but what is warranted is studies distinguishing different types of boundary spanners based on primary affiliation and/or different levels of experience.

The researchers with the highest number of publications as firm-affiliated lead authors and dual-affiliated lead authors also exhibited a noteworthy trend: they all had a prior link to the university with which they co-published. This connection manifested itself in various ways, including existing affiliations (dual affiliation), dual employment where only the firm was listed, or previous employment with the university followed by subsequent co-authorship.

These findings align with Ljungberg et al.'s (manuscript to be submitted for publication) previously mentioned study, which examined a smaller dataset but arrived at a similar conclusion. They demonstrated that ongoing or prior links to a university department play a crucial role in predicting ongoing co-publishing. Consequently, this result supports the notion that personal relationships are influential factors in fostering ongoing academic engagement—an aspect that appears to be valuable for these collaborations (Bruneel et al., 2010; Kunttu & Neuvo, 2019; Rivera-Huerta et al., 2011).

The limitations brought up in Sections 5.5 and 6.4 are present in this undertaking as well. Besides these, there is a limitation related to the independent variables. Specifically, this limitation is first associated with researchers possibly having different practices when reporting affiliations on a paper, possibly biasing the results in one way or another. Second, this limitation is associated with the assumption that all first authors occupy the same role in their research collaborations, which is most likely not entirely true in reality. This assumption may be particularly inaccurate considering that these publications are outcomes of prior academic engagement, an area in which we have limited knowledge of how author sequence works. Finally, it is worth acknowledging that the number of publications resulting from academic engagement having lead authors from industry or dual-affiliated lead authors is relatively small (n = 114 and 97, respectively). This limited sample size poses challenges in detecting statistically significant differences when examining the various pathways of technological impact analyzed in Chapter 6 (i.e., individual, organizational, and knowledge spillover), and in identifying interaction effects.

This limited sample size makes it more challenging to obtain statistically significant differences, to examine the various types of technological impact analyzed in the Chapter 6 (i.e., individual technological impact, organizational technological impact, and knowledge spillover) and to identify interaction effects. Despite all these limitations, this study provides novel insights into the intricacies of academic engagement, particularly concerning scientific and technological outcomes.

Based on the aforementioned limitation regarding the assumption that all first authors occupy the same role in research collaborations, further investigation is warranted to gain a deeper understanding of author sequence dynamics in the context of academic engagement. Future research should aim to explore the nuances and variations in author contributions within research teams in academic engagement. This could, for instance, involve researchers conducting regular interviews or focus group interviews to gather insights into how authorship is determined, the significance of author order, and the impact of individual contributions on publication outcomes. Additionally, comparative studies between academia and industry could be conducted to examine potential differences in authorship practices and their influence on research outputs. By addressing these gaps in understanding, future research could provide a more comprehensive understanding of author sequence dynamics, contributing to improved collaboration outcomes as well as improving the accuracy and fairness of credit allocation in scientific publications.

7.6 Conclusion

The primary objective of this research was to quantitatively analyze the influence exerted by the lead author on both the scientific and technological impacts of academic publications, with a specific focus on how their type of affiliation, distinguishing between academia, industry, and dual affiliated, shapes the overall outcomes. The exact research question guiding this endeavor was formulated as follows (which is also RQ3 of this Ph.D. dissertation):

How does the scientific and technological impact of the papers resulting from academic engagement depend on the affiliation of the lead author?

Relating to the research question, five hypotheses were proposed. Table 7.5, below, summarizes the conclusions drawn in relation to these hypotheses. This is followed by concluding remarks, while implications are discussed in Chapter 8 of this dissertation.

Table 7.5. Hypotheses: empirical evidence for confirmation or refutation – Chapter 7.

Hypothesis	**Empirical findings**
7.1. Academic-led publications originating from academic engagement collaborations are associated with higher article impact.	Supported
7.2. Academic-led journal articles originating from academic engagement collaborations are associated with higher journal reputation.	Rejected
7.3. Firm-led publications originating from academic engagement collaborations are associated with higher technological impact.	Supported
7.4. Dual-affiliated-led publications originating from academic engagement collaborations are associated with higher article impact.	Rejected
7.5. Dual-led publications originating from academic engagement collaborations are associated with higher technological impact.	Rejected

The findings suggest that the type of lead-author affiliation has a significant impact. Specifically, the data indicate that publications resulting from lead authors affiliated solely with a university showed higher article impact and technological impact, with no statistically significant effect on journal reputation. Dual-affiliated lead authors *only* demonstrated a statistically significant impact on one of the outcome variables, and that was a negative effect on the probability of publishing in highly reputed journals. Similarly, lead authors affiliated solely with firms also *only* exhibited a statistically significant influence on one of the dependent variables, namely, the technological impact, and it was a positive influence of a notably high magnitude.

8 Conclusion

This chapter begins by revisiting the purpose of this Ph.D. dissertation and comparing the present findings with those of previously discussed research, thereby considering their collective implications rather than viewing them in isolation. The chapter then transitions to the main research questions and addresses them concisely. Subsequently, the chapter discusses the policy and practical implications of this undertaking. The chapter concludes by acknowledging the limitations of this research and suggesting potential directions for future studies.

8.1 Revisiting the purpose and highlighting main contributions

This Ph.D. dissertation has analyzed collaborative research between universities and firms in the field of electrical engineering in Sweden, conceptualizing it as one form of academic engagement that fosters knowledge networks among individuals and organizations. The purpose has been to analyze the impacts of collaborative research between universities and firms, as compared with similar research conducted without firms. In doing so, this dissertation has examined and selected among measures of impact, both scientific and technological, as well as variables that capture relevant dimensions of collaborative research.

By utilizing a dataset based on the employment records of faculty members from five leading Swedish engineering universities in the domains of biomedical, communication, control, and signal processing engineering, this dissertation covers 8455 scholarly publications authored by 184 professors affiliated with Chalmers University of Technology, the Faculty of Engineering at Lund University, KTH Royal Institute of Technology, Linköping University, and Uppsala University.

Of all publications published by the sampled professors, 17.3% were classified as resulting from academic engagement. The prevalence of this type of publication has been on the rise during the analyzed 2000–2018 period. This finding is interesting in itself for at least two reasons. First, this percentage is significantly higher than what has been reported in other studies conducted in different empirical settings (McKelvey & Rake, 2020; Tijssen et al., 2016). For instance, McKelvey and Rake (2020) found that only 6.4% of publications in the field of pharmaceutical cancer research, published between 2001 and 2008, were attributed to academic engagement. Second, this type of publication is becoming increasingly common, which contradicts previous studies, such as those by Arora et al. (2018) and Lariviére et al. (2018), that suggested a growing monopoly of universities in published research. Throughout this dissertation, it has been argued that there are likely two reasons for the observed positive trend: one reason can be attributed to the field of study, namely, engineering, and the institutional context, specifically Sweden; the other reason can be attributed to the utilization of a specific methodological strategy, namely, sampling professors exclusively.

The main findings of this Ph.D. dissertation are visually depicted in Figure 8.1, below. The figure underscores the potential advantages inherent in collaborative research projects involving academic researchers and firms within the engineering sciences: they are associated with increased article and technological impacts, while simultaneously being associated with a negative influence on journal reputation.

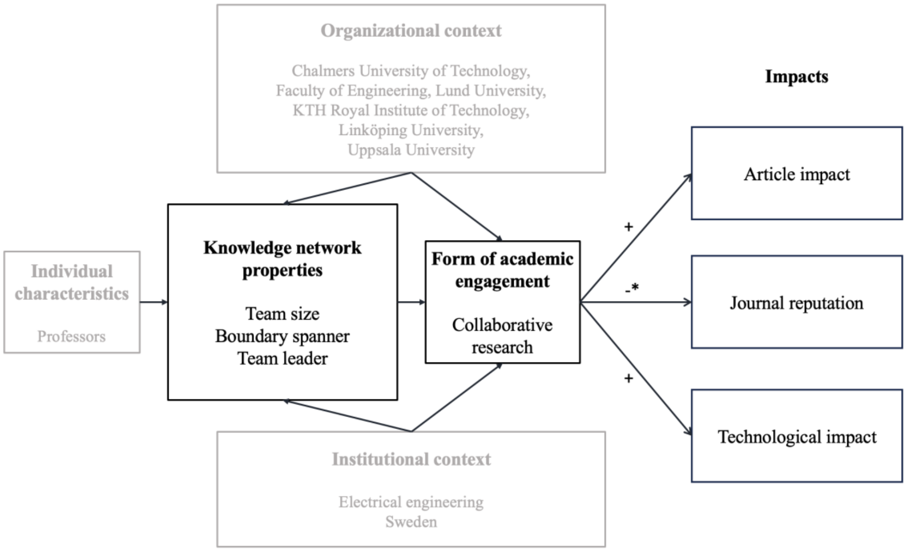

Figure 8.1. The observed relationships between academic engagement and the outcome variables (i.e., article impact, journal reputation, and technological impact).

* Reduced statistical power, i.e., the *p*-value is between 0.1 and 0.05.

These findings underscore the significance of combining different knowledge bases. The collaborators in these academic engagement projects likely have a more "optimal cognitive distance," using the terminology of Nooteboom et al. (2007), than those in academic projects. It is likely that the deep application knowledge essential for practical problem-solving, generally represented by the participating firms, when combined with the more abstract and distant search within the domain of engineering science, typically exemplified by the academic contributors, produces a positive synergy between the scientific and technological aspects of the resulting scholarly work.

Consequently, these publications appeal to a broader audience with an interest in the findings, as they offer a valuable combination of divergent knowledge sources. This insight holds significance for the ongoing debates surrounding the relative impacts of science and technology, as highlighted by Fleming and Sorensen (2004) and Kaplan and Vakili (2015). Furthermore, they position collaborative research between universities and firms in a favorable light. This is particularly noteworthy because previous studies, such as those by Bekkers and Freitas (2008), Frenken et al. (2010), and McKelvey and Rake (2016), have not consistently demonstrated a clear positive influence of firm involvement in research outcomes.

However, it should be reiterated that the benefits of "combining different knowledge bases" hinges on the cognitive proximity among collaborators, as an individual's capacity to assimilate information is largely a function of prior related knowledge (e.g., Cohen & Levinthal, 1990). In the specific empirical context of this Ph.D. dissertation—electrical engineering—where scientific pursuits are often use inspired (Stokes, 1997), this prerequisite appears to be satisfactorily met. This alignment between science and technology in electrical engineering is further corroborated by findings presented in Chapter 6, which demonstrated a preference for the individual technological pathway over the organizational pathway (i.e., organizations are more likely to involve the same employee in both activities—publishing scientific papers and patenting technological inventions based on that knowledge—than to divide these activities among different employees). As posited, in scenarios in which science and technology are intricately linked, the individual pathway tends to be more resource efficient, as it circumvents the need for knowledge transfer from researcher to inventor.

While these collaborative projects between academic scholars and firms are indeed linked to heightened article and technological impact, they do not exhibit an increased likelihood of publication in esteemed, high-reputation journals. In fact, the data suggest a diminished probability in this regard, under certain conditions. The question that persists pertains to the nature of this outcome—whether it is a deliberate choice on the part of these projects, implying a preference for lower-ranked, potentially more applied journals, or whether it is an outcome stemming from the inherent characteristics of the research itself, such as a potential deficiency in scientific rigor that precludes publication in top-tier journals. Discussions with several academic and dual-affiliated engineering professors following the "Collaboration forum" workshop presentation, conducted by the present author and Maureen McKelvey, and organized by the Department of Electrical Engineering at Chalmers University of Technology, clearly suggest the belief that this difference can be attributed to choice. A more rigorous analysis of this matter is, however, warranted, and could constitute one of the recommendations for future research outlined in Section 8.6, below.

In relation to the knowledge network, the strongest effect in terms of academic engagement occurs when the number of authors is larger than three. The logic behind the observed effect is quite straightforward: a larger authorship typically signifies a wider collective knowledge base, which in turn positively influences the research outcome, as supported by studies like those of Becker and Murphy (1992) and Katz and Martin (1997). Additionally, dual-affiliated professors who hold simultaneous positions in both academia and industry were found to positively affect the article impact of the resulting publications. Their deep understanding of both sectors likely allows them to resolve conflicts and act as intermediaries, fostering indirect knowledge transfer between various collaborators, as suggested by Gertner et al. (2011).

Furthermore, the lead author's affiliation is shown to influence knowledge outcomes: academics tend to lead to high-article-impact publications, firms to high technological impact, and dual-affiliated researchers to publications in journals of lower reputation. This aligns with Thelwall et al.'s (2023) finding that lead authors with significant article impact play a crucial role in shaping the collaboration outcome. In summary, while these variables reflecting key dimensions of collaborative research have been examined to varying degrees in the literature, their analysis here contributes to the literature on academic engagement, particularly through the lens of collaborative electrical engineering research in Sweden.

The subsequent three subsections transition to directly addressing the main research questions, deliberately maintaining a certain degree of repetition. These sections provide explicit answers that further clarify the impact of collaborative research between universities and firms in Sweden's electrical engineering field, as conceptualized within the academic engagement framework of Perkmann et al. (2013, 2021).

8.1.1 RQ1: scientific impact of academic engagement publications

How does the scientific impact of publications resulting from academic engagement projects differ from that of publications resulting from academic projects?

The concept of the scientific impact of publications can be assessed using two quantifiable constructs: article impact and journal reputation. Article impact concerns the number of forward citations received from other scientific papers, while journal reputation emphasizes the impact factor of the journal in which the work was published. Although there is some overlap between these constructs, they can be distinguished by considering that article impact measures the degree to which the scientific community perceives the publication as valuable, whereas journal reputation emphasizes scientific rigor and quality.

Of all publications, 64.3% resulted in article impact within three years of publication, meaning that more than half of all publications had obtained at least one citation within three years of publication, with similar rates throughout the observation period. Papers resulting from academic engagement were more likely to have any article impact than were those resulting from academic projects, i.e., 71.0% versus

62.9%. Regarding journal reputation, 17.4% of all journal articles secured publication in top-reputed journals, as determined by evaluating whether the article appeared in a journal within the top 15% of the 2018 Journal Impact Factor distribution relevant to my sample. Scientific papers resulting from academic engagement were relatively less likely to be published in top-reputed journals than those resulting from academic projects, i.e., 16.0% versus 17.7%. How this compares with prior empirical research is ambiguous as these numbers are not commonly reported.

Scientific papers resulting from academic engagement exhibited a notable premium in terms of article impact compared with those resulting from academic projects. This discovery sheds new light on the scientific outcomes of academic engagement, challenging previous empirical findings that indicated a neutral or a somewhat negative effect on article impact of publishing with industrial researchers (e.g., Frenken et al., 2010).

Furthermore, this article premium can be attributed to collaborations with at least three co-authors, and especially to those with four or five co-authors—the "sweet spot." This implies that collaborations with a moderate number of co-authors seem to strike a balance between collective human capital and efficient knowledge transfer (or communication), resulting in research outputs with a higher scientific impact. The findings also suggested that dual-affiliated professors have a positive effect on article impact. This suggests that dual-affiliated professors, who bring together diverse perspectives and understanding from the two types of organizations, further enhance the potential for impactful collaborations.

Publications resulting from academic engagement had a comparatively lower journal reputation than those resulting from academic projects. This indicates a lower likelihood of being published in top-reputed journals. However, it is important to note that when employing alternative operationalizations that more narrowly define what constitutes a top-reputed journal, the statistical difference in journal reputation between academic engagement and academic projects weakens. This finding is more in line with prior research (Abramo et al., 2009; McKelvey & Rake, 2020). Moreover, the number of authors involved in a study and the presence of dual-affiliated professors did not display a statistically significant influence on journal reputation.

8.1.2 RQ2: technological impact of academic engagement publications

How does the technological impact of publications resulting from academic engagement projects differ from the impact of those resulting from academic projects?

The concept of technological impact concerns whether the technological community perceives a publication as valuable. Its construct concerns the quantification of citations received from the technological domain (i.e., patents). This measure can be divided into three constructs: individual technological impact, organizational technological impact, and knowledge spillover. The first construct, individual technological impact, emphasizes author–inventor pairs and highlights the personal aspect of knowledge. It recognizes that knowledge developed in one setting or project can be applied in another. The second construct, organizational technological impact, focuses on affiliation–assignee pairs. It underscores the transfer of knowledge within organizational boundaries, showcasing knowledge transfer within specific organizations. The third and final construct, knowledge spillover, emphasizes the knowledge that “spills over” to external actors. It considers the impact of publications on individuals and/or organizations outside the immediate scope of the research.

Of all scientific publications, 15.5% had any technological impact within five years of publication, and this trend decreased throughout the studied period. Interestingly, this percentage is higher than those reported in previous studies. For instance, Ke (2020) found that only 11.2% of papers in the biomedical field had any technological impact. Scientific papers resulting from academic engagement were more likely to have technological impact than those resulting from academic projects, with percentages of 20.3% and 14.3%, respectively.

Additionally, when the technological impact window was not limited to five years but instead extended to the entire 2000–2018 period, it was discovered that most of these technologically impactful papers received their first citation within one year of publication and that the mean lead time was two years. This timeframe is shorter than in many other fields, as noted by previous research. For example, Ahmadpoor and Jones's comprehensive study published in 2017, which analyzed 32 million research papers and close to five million patents, found an average time lag of approximately six to seven years.

Publications resulting from academic engagement projects had a higher technological impact than did those resulting from academic projects. This observation remained consistent across all three impact pathways, signifying that both the participating parties and external actors perceived the research as possessing heightened technological value. Although, to the best of my knowledge, no studies have quantitatively examined the technological impact of collaborative research between universities and firms in as much detail, these findings are in line with those of, for example, Poege et al. (2019), who found a correlation between high article impact and high technological impact. The results further show a higher prevalence of the individual technological pathway than the organizational pathway, giving support for the close proximity between science and technology in electrical engineering.

8.1.3 RQ3: role of the lead author's affiliation in academic engagement publications

How does the scientific and technological impact of resulting papers depend on the affiliation of the lead author?

The concept of a lead author emphasizes the notion that team members have distinct roles and that their contributions are not of equal weight (e.g., Bhandari et al., 2014). Simultaneously, it is commonly understood that in a multi-authored research paper, the author who contributes the most is typically listed as the first author (Wren et al., 2007). Overall, 10.0% of the publications resulting from academic engagement projects had first authors affiliated with industry. The results further indicate that this proportion has been decreasing over the observed 2000–2018 period. Interestingly, this contradicts the overall trend regarding the prevalence of academic engagement, which has become more common with time.

The regression results indicate that publications resulting from academic engagement, having a lead author affiliated only with industry, are associated with a high technological impact. Similar projects led by an academic had higher article impact and technological impact, while those led by a dual-affiliated researcher were associated with a lower probability of being published in a top-ranked journal. In other words, the regression models suggest that the impact of the resulting publication is significantly influenced by the type of organization with which the lead author is affiliated. For instance, if he or she is employed solely in industry, the impact is most likely to be primarily technological.

8.2 Implications for policy and practitioners

The results of this dissertation highlight the evolving landscape of academic engagement in the field of the engineering sciences. These findings are of significant value for policymakers, academic institutions, and industry partners, enabling them to design and implement effective strategies that maximize the potential impacts of collaborative research, thereby driving scientific and technological excellence while solving real-world problems. Although recommendations are required by practitioners as well as policy- and decision-makers, further research is needed before implementing any drastic decisions with far-reaching consequences.

Policymakers play a crucial role in developing policies and financial mechanisms that promote and incentivize impactful collaborative research projects between academia and industry, facilitating the bridging of the gap between the two types of organizations. A policy worth considering is easing employee mobility between the public and private sectors. This could manifest itself as specialized research grants that sponsor short- to medium-term exchanges between entities of both sectors to cultivate knowledge transfer, mutual understanding, and subsequent joint efforts. Such targeted policy recommendations are instrumental in establishing a conducive environment for academic engagement, nurturing knowledge dissemination, and enhancing collaboration between academic and industrial entities. It is noteworthy that prior industrial experience is an indicator of prospective academic engagement (e.g., Abreu & Grinevich, 2017; Gulbrandsen & Thune, 2017), suggesting that initial policy interventions may catalyze a self-sustaining increase in engagement levels. Execution of these policies can enable academic bodies, industry players, and policymakers to fully exploit the benefits of academic engagement, culminating in research breakthroughs, inventive solutions, and economic progress.

Academic institutions should leverage these insights to foster environments conducive to inter-organizational collaboration, equipping scholars with the means and motivation to partner with industrial counterparts. A practical measure is the thorough assessment of the employment of dual-affiliated researchers at varying stages of academic careers and in diverse companies, and assessment of the unique expertise they contribute. Focusing on quality over quantity by identifying the ideal candidates is essential for enhancing knowledge exchange and collaborative efforts between academia and industry. Additionally, the observation that publications resulting from academic engagement are less likely to be featured in top-reputed journals, despite their significant article and technological impacts, underscores the need to revisit the metrics of academic success. This reinforces an argument that has been made for some time, exemplified by scholars such as Abramo et al. (2023), who advocate for a reduced emphasis on journal reputation in academic evaluations. Instead, the practical applications and technological contributions of research should warrant greater recognition in the scholarly community, which may lead to changes in the way research is conducted, evaluated, and acknowledged.

From the industrial perspective, and recognizing the shared value of knowledge exchange and collaborative problem-solving, industry should proactively forge partnerships with academic researchers. The obvious link between higher technological impact and academic engagement highlights the gains firms can make through such collaborations. Engaging dual-affiliated researchers and endorsing sustained collaborative projects can prove to be strategic initiatives. Prior research indicates that consistent collaborations allow academic scientists to immerse themselves in industry-specific challenges (Rivera-Huerta et al., 2011), build trust among participants, and facilitate an understanding of each other's incentives and goals (Bruneel et al., 2010; Kunttu & Neuvo, 2019). Another complementary approach for firms is to employ academic researchers full time, enhancing their ability to collaborate with university scholars and, over time, leverage their work to the firm's advantage.

8.3 Limitations and recommendations for future research endeavors

The empirical studies in this dissertation have several limitations that should be acknowledged. These limitations are discussed in greater depth in the chapters presenting the individual empirical studies, i.e., Chapters 5–7. In this section, some overall remarks regarding these limitations are made, which naturally lead to a few recommendations for future research.

The limitations of this empirical study can be categorized into three broad themes: methodological, data, and contextual limitations.

One major methodological limitation of this empirical study is its failure to account for certain factors related to the industrial researchers who are the sampled university scientists' co-authors. Instead, it treats them as "black boxes," disregarding aspects such as their prior article impact and prior employment that could influence or explain the findings. The analysis in this study relies heavily on bibliometric data, which restricts the focus to successful outcomes rather than overall activity. While this approach limits the scope of the study, the use of bibliometric data is considered a reliable means of measuring successful scientific knowledge creation. Another methodological limitation stems from the assumption that all first authors in research collaborations have the same role, which may not hold true in reality. This assumption is particularly questionable considering that these publications are outcomes of academic engagement, an area where our understanding of how author sequence works is limited.

There are also data limitations related to the relatively small number of articles resulting from academic engagement projects. This limitation becomes especially evident when analyzing academic engagement projects in which dual-affiliated professors are involved, as the number of researchers in this category is limited to only 11 in my research.

In terms of contextual limitations, the empirical context of this study is narrow, focusing on four subfields of electrical engineering in Sweden. This limited context reduces the generalizability of the findings and necessitates caution when extending the implications to other disciplines and nations.

The limitations of this empirical study highlight the need for several recommendations to guide future research endeavors.

In terms of methodology, it is crucial to conduct a more comprehensive analysis of the researchers from the industrial sector who collaborate as co-authors with university scientists. Furthermore, it is essential to explore the roles and contributions of authors, particularly first authors, in research collaborations. Given our limited understanding of author sequence in academic engagement, future studies should delve deeper into this aspect to shed light on its impact on research outcomes.

Regarding data, efforts should be made to increase the sample size and broaden the scope beyond the narrow focus on four subfields of electrical engineering in Sweden. Expanding the research to encompass a wider range of fields and nations would enhance the generalizability of the findings. Specific attention should be paid to academic engagement projects involving dual-affiliated researchers, as this subgroup may offer unique insights and dynamics that warrant further exploration.

Both qualitative and quantitative studies could be fruitful in this regard. For instance, conducting in-depth interviews with dual-affiliated researchers and their collaborators could provide rich qualitative data about their experiences, challenges, and perceptions related to academic engagement. These interviews could explore their unique insights, dynamics, and the role they play in bridging the gap between academia and industry. The qualitative data obtained from these interviews could help identify key factors that contribute to successful collaborations and could provide recommendations for improving such engagements. Additionally, analyzing bibliometric data from a larger number of dual-affiliated researchers, not limited to dual-affiliated professors, could offer more robust quantitative insights into the impact of dual-affiliated researchers in academic engagement.

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APPENDIX A: ADDITIONAL DESCRIPTIVE STATISTICS

This appendix consists of additional descriptive statistics focusing on the similarities and differences between the sampled universities (CTH, KTH, LiU, LTH, and UU) and the most common sub-fields (automation and control systems, computer science, and telecommunications).

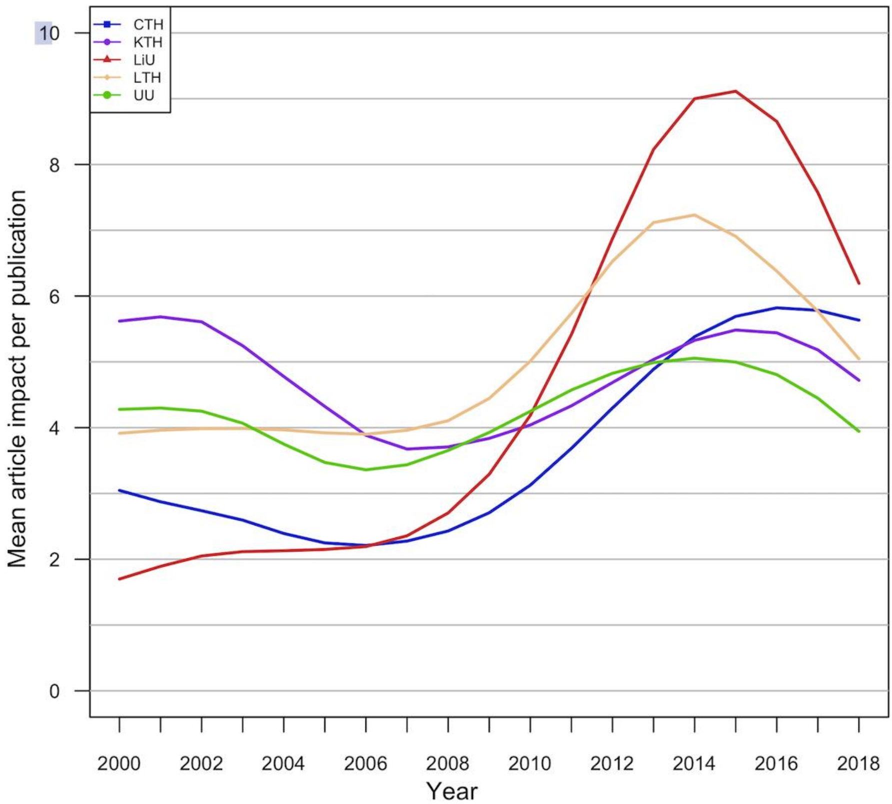

Figure A.1. The mean article impact of publications, per university. (Chapter 5)

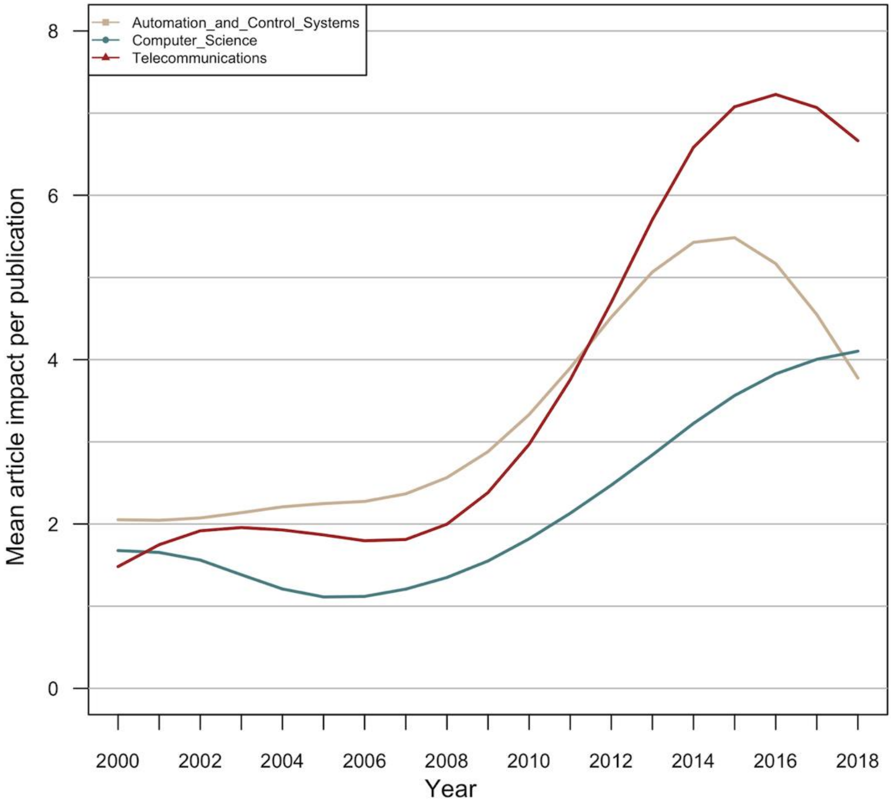

Figure A.2. The mean article impact of publications, per sub-field. (Chapter 5)

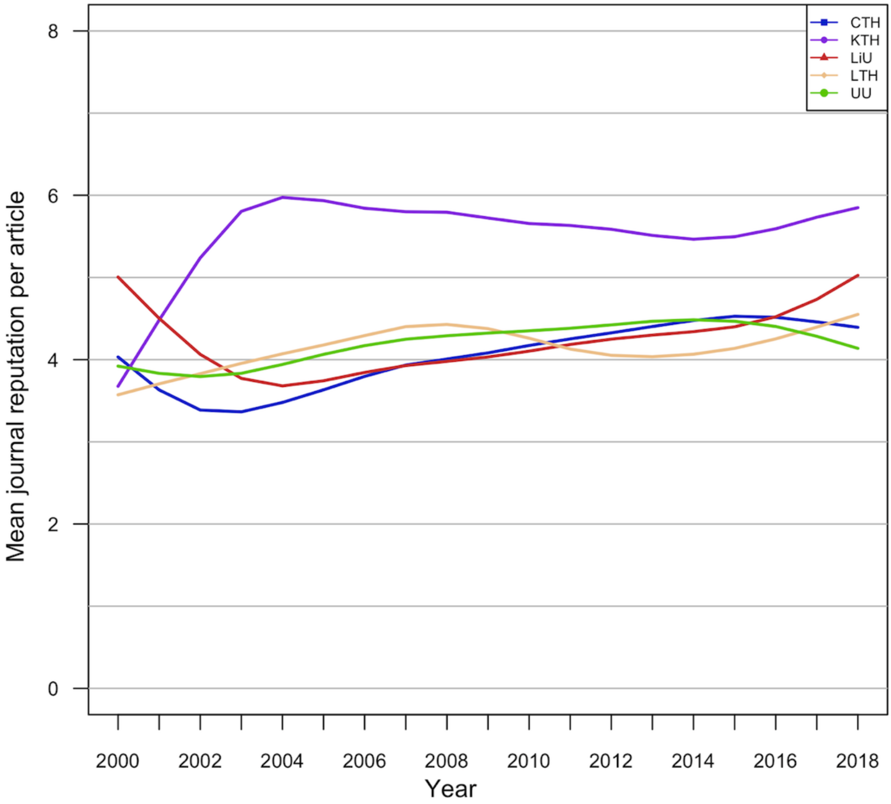

Figure A.3. The mean journal reputation of articles, per university. (Chapter 5)

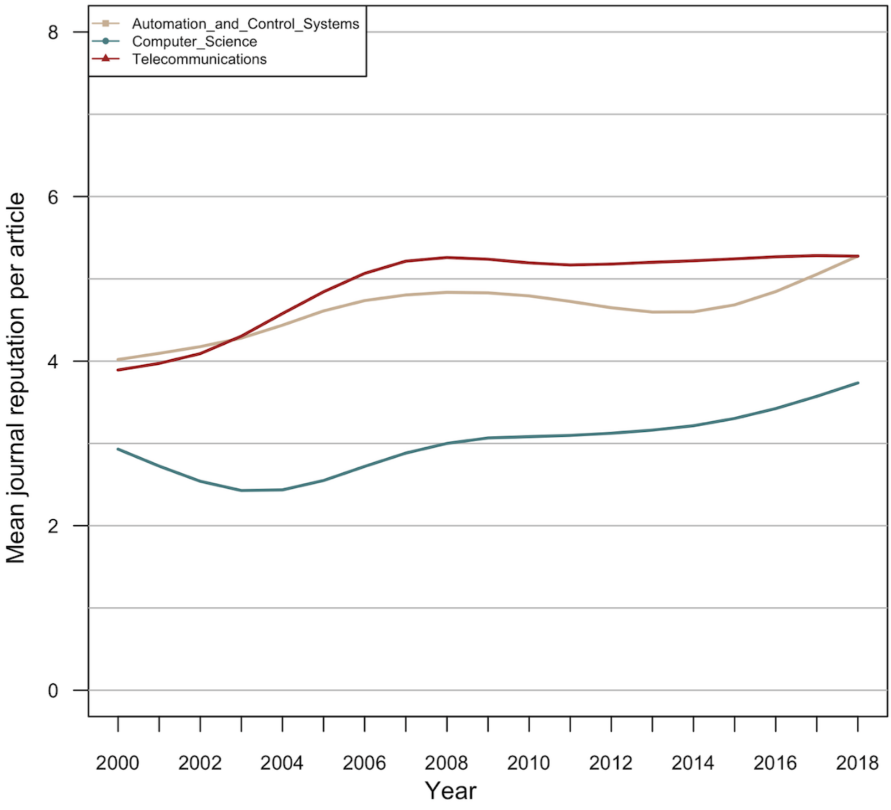

Figure A.4. The mean journal reputation of articles, per sub-field. (Chapter 5)

Table A.1. Descriptive statistics technological impact, per university. (Chapter 6)

Variable	**CTH**	**KTH**	**LiU**	**LTH**	**UU**
Publications with any technological impact (%)	16.1	12.5	15.2	18.8	15.7
Publications resulting from academic engagement with any technological impact (%)	20.1	17.6	17.7	22.3	32.4
Publications resulting from academic collaboration with any technological impact (%)	14.7	11.7	14.7	17.2	13.8
Total_technological_impact					
Minimum	1	1	1	1	1
1st Quartile	1	1	1	1	1
Median	2	2	2	3	2
Mean	4.2	4.7	6.4	7.3	5.9
3rd Quartile	4	4	5	5	6
Maximum	46	63	181	181	54
Time_lag_first_tech_impact (in years)					
Minimum	0	0	0	0	0
1st Quartile	0	0	0	0	0
Median	1	1	1	0	1
Mean	2.1	2.0	2.3	1.5	2.7
3rd Quartile	3	3	3	2	4
Maximum	12	12	14	14	13

Table A.2. Descriptive statistics technological impact, per sub-field. (Chapter 6)

Variable	**Automation and control systems**	**Computer science**	**Telecommunications**
Publications with any technological impact (%)	5.0	10.9	20.7
Publications resulting from academic engagement with any technological impact (%)	6.9	15.5	27.7
Publications resulting from academic collaboration with any technological impact (%)	4.7	10.2	19.0
Total_technological_impact			
Minimum	2	1	1
1st Quartile	3	2	3
Median	7	3	7
Mean	13.9	9.1	11.6
3rd Quartile	13	8	13
Maximum	181	181	181
Time_lag_first_tech_impact (in years)			
Minimum	0	0	0
1st Quartile	0	0	0
Median	0	0	1
Mean	1.0	1.1	1.6
3rd Quartile	2	2	2
Maximum	4	8	14

APPENDIX B: CORRELATION TABLES

This appendix contains two correlational matrices, one associated with Chapter 5 and the other with Chapter 6.

Table B.1. Correlational matrix. (Chapter 5)

	Article_impact	Journal_reputation	Academic_engagement	Number_authors	Dual_affiliated_professor	Prior_article_impact	Prior_patenting	Prior_coauthors	Top_university	Number_universities	Number_nations	Number_fields	Article	Female
Article_impact	1.0	0.24308877	0.08953185	0.17525598	NA	0.18229086	0.02568813	0.14346106	0.12499078	0.22354688	0.14275623	-0.09527828	0.54208224	NA
Journal_reputation	0.24308877	1.0	NA	0.05135140	NA	0.07799869	NA	0.03852627	0.07444028	0.09387472	0.09323065	0.04792032	0.21909036	NA
Academic_engagement	0.08953185	NA	1.0	0.23819454	0.20768854	NA	0.06394468	0.02417071	0.06851439	0.07047011	0.10401337	-0.02811349	0.10006328	NA
Number_authors	0.17525598	0.05135140	0.23819454	1.0	0.04537524	0.14453126	0.03920060	0.21787897	0.21375732	0.43753904	0.32114654	-0.02858788	0.13113058	0.06275000
Dual_affiliated_professor	NA	NA	0.20768854	0.04537524	1.0	-0.13550059	0.09404317	-0.09214988	-0.02672003	NA	-0.04241434	-0.03688259	0.06682105	0.02266547
Prior_article_impact	0.18229086	0.07799869	NA	0.14453126	-0.13550059	1.0	0.16306476	0.67789795	0.12024897	0.09261065	0.21495814	-0.02495634	0.08484134	-0.11008438
Prior_patenting	0.02568813	NA	0.06394468	0.03920060	0.09404317	0.16306476	1.0	0.15916773	-0.04675266	-0.03045472	-0.03273712	NA	NA	-0.12069812
Prior_coauthors	0.14346106	0.03852627	0.02417071	0.21787897	-0.09214988	0.67789795	0.15916773	1.0	0.11221408	0.11093661	0.18759847	-0.02383117	0.07761565	-0.04985099
Top_university	0.12499078	0.07444028	0.06851439	0.21375732	-0.02672003	0.12024897	-0.04675266	0.11221408	1.0	0.23343281	0.29009549	NA	0.05624943	NA
Number_universities	0.22354688	0.09387472	0.07047011	0.43753904	NA	0.09261065	-0.03045472	0.11093661	0.23343281	1.0	0.46662590	-0.09654120	0.22424489	0.11000777
Number_nations	0.14275623	0.09323065	0.10401337	0.32114654	-0.04241434	0.21495814	-0.03273712	0.18759847	0.29009549	0.46662590	1.0	NA	0.07855902	NA
Number_fields	-0.09527828	0.04792032	-0.02811349	-0.02858788	-0.03688259	-0.02495634	NA	-0.02383117	NA	-0.09654120	NA	1.0	-0.13242410	NA
Article	0.54208224	0.21909036	0.10006328	0.13113058	0.06682105	0.08484134	NA	0.07761565	0.05624943	0.22424489	0.07855902	-0.13242410	1.0	NA
Female	NA	NA	NA	0.06275000	0.02266547	-0.11008438	-0.12069812	-0.04985099	NA	0.11000777	NA	NA	NA	1.0

Note: Non-significant values are set to NA (p-values > 0.05). The correlation matrix excludes the control variables related to university, sub-field, and year.

Table B.2. Correlational matrix. (Chapter 6)

	Total_tech_impact	**Individual_tech_impact**	**Organizational_tech_impact**	**Knowledge_spillover**	**Academic_engagement**	**Number_authors**	**Dual_affiliated_professor**	**Journal_reputation**	**Prior_article_impact**	**Prior_patenting**	**Prior_coauthors**	**Top_university**	**Number_universities**	**Number_fields**	**Number_nations**	**Female**
Total_tech_impact	1.0	0.42419005	0.20332244	0.94462031	0.06777420	0.05851879	-0.03349688	0.07967386	0.04477523	0.10598852	0.03499963	0.04811477	NA	NA	-0.03027840	-0.03273669
Individual_tech_impact	0.42419005	1.0	0.25143155	0.20364342	0.07956743	0.04140207	NA	0.04279285	0.04228694	0.05472777	0.04368552	0.05678565	0.02921683	NA	NA	NA
Organizational_tech_impact	0.20332244	0.25143155	1.0	0.13515364	0.09345974	NA	0.04619809	NA	NA	NA	NA	NA	NA	NA	NA	NA
Knowledge_spillover	0.94462031	0.20364342	0.13515364	1.0	0.04218252	0.04941171	-0.04822297	0.08095703	0.03981913	0.10082240	NA	0.03046724	NA	NA	-0.04095439	-0.03182614
Academic_engagement	0.06777420	0.07956743	0.09345974	0.04218252	1.0	0.20734870	0.21709264	NA	NA	0.07511199	NA	0.06645424	0.05948069	NA	0.10294910	-0.04795454
Number_authors	0.05851879	0.04140207	NA	0.04941171	0.20734870	1.0	0.05693915	NA	0.14707978	NA	0.23851019	0.22440757	0.38017175	NA	0.24579619	0.02903479
Dual_affiliated_professor	-0.03349688	NA	0.04619809	-0.04822297	0.21709264	0.05693915	1.0	NA	-0.12980978	0.08818185	-0.10277744	-0.02814517	NA	NA	-0.04551434	NA
Journal_reputation	0.07967386	0.04279285	NA	0.08095703	NA	NA	NA	1.0	0.10965624	0.03608951	0.05525419	0.07761977	0.04848376	0.11756766	0.10180439	-0.03961565
Prior_article_impact	0.04477523	0.04228694	NA	0.03981913	NA	0.14707978	-0.12980978	0.10965624	1.0	0.13922901	0.69019308	0.14228178	0.14505492	-0.04707087	0.23373666	-0.12320066
Prior_patenting	0.10598852	0.05472777	NA	0.10082240	0.07511199	NA	0.08818185	0.03608951	0.13922901	1.0	0.15042733	-0.03274267	NA	NA	-0.03283768	-0.12106811
Prior_coauthors	0.03499963	0.04368552	NA	NA	NA	0.23851019	-0.10277744	0.05525419	0.69019308	0.15042733	1.0	0.12491229	0.16967031	-0.03188081	0.20935288	-0.05147030
Top_university	0.04811477	0.05678565	NA	0.03046724	0.06645424	0.22440757	-0.02814517	0.07761977	0.14228178	-0.03274267	0.12491229	1.0	0.26680432	-0.03537822	0.28371301	NA
Number_universities	NA	0.02921683	NA	NA	0.05948069	0.38017175	NA	0.04848376	0.14505492	NA	0.16967031	0.26680432	1.0	-0.08116698	0.45100864	0.11468648
Number_fields	NA	NA	NA	NA	NA	NA	NA	0.11756766	-0.04707087	NA	-0.03188081	-0.03537822	-0.08116698	1.0	NA	0.03205348
Number_nations	-0.03027840	NA	NA	-0.04095439	0.10294910	0.24579619	-0.04551434	0.10180439	0.23373666	-0.03283768	0.20935288	0.28371301	0.45100864	NA	1.0	NA
Female	-0.03273669	NA	NA	-0.03182614	-0.04795454	0.02903479	NA	-0.03961565	-0.12320066	-0.12106811	-0.05147030	NA	0.11468648	0.03205348	NA	1.0

Note: Non-significant values are set to NA (p-values > 0.05). The correlation matrix excludes the control variables related to university, sub-field, and year.

APPENDIX C: ADDITIONAL REGRESSION ANALYSES (ROBUSTNESS TESTS)

This appendix includes additional regression analyses conducted as robustness checks. Unless specified otherwise, the following applies:

- The variables "*University_dummies*," "*Field_dummies*," and "*Year_dummies*" are included, indicated by "*Dummies*" being set to "Yes"
- Robust standard errors in parentheses
- Significant codes: *p<0.1; **p<0.05; ***p<0.01

Table C.1. Regression results with modified "Number_authors" variable (three bins). (Chapter 5)

Results

	Dependent variable: Article_impact			
	(1)	(2)	(3)	(4)
Academic_engagement		0.145***	-0.021	0.128**
		(0.053)	(0.094)	(0.058)
Academic_engagement: 3-4_Number_authors			0.271**	
			(0.126)	
Academic_engagement: 5+_Number_authors			0.193	
			(0.137)	
Academic_engagement:Dual_affiliated_professor				0.390**
				(0.171)
3-4_Number_authors	0.070	0.048	0.013	0.049
	(0.067)	(0.068)	(0.074)	(0.067)
5+_Number_authors	0.051	0.007	-0.021	0.013
	(0.107)	(0.108)	(0.115)	(0.107)
Dual_affiliated_professor	-0.123			-0.380***
	(0.092)			(0.133)
Journal_reputation	0.955***	0.949***	0.949***	0.956***
	(0.099)	(0.097)	(0.096)	(0.097)
Prior_article_impact	0.0003***	0.0003***	0.0003***	0.0003***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Prior_patenting	-0.0001	-0.001	-0.001	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.284***	0.277***	0.274***	0.275***
	(0.084)	(0.084)	(0.083)	(0.083)
log(Number_universities)	0.288***	0.303***	0.301***	0.305***
	(0.096)	(0.097)	(0.096)	(0.096)
log(Number_nations)	0.204***	0.187***	0.187***	0.180***
	(0.061)	(0.060)	(0.060)	(0.060)
Number_fields	-0.060**	-0.059**	-0.059**	-0.060**
	(0.029)	(0.029)	(0.029)	(0.029)

Article	1.342***	1.334***	1.335***	1.338***
	(0.050)	(0.050)	(0.050)	(0.051)
Female	-0.253**	-0.242**	-0.234**	-0.234**
	(0.099)	(0.100)	(0.100)	(0.099)
Dummies	Yes	Yes	Yes	Yes
Constant	-0.051	-0.056	-0.042	-0.036
	(0.220)	(0.215)	(0.208)	(0.216)
Observations	8455	8455	8455	8455

Table C.2. Regression results with modified “Article_impact” variable (5-year long time-window). (Chapter 5)

Results

	Dependent variable: Article_impact			
	(1)	(2)	(3)	(4)
Academic_engagement		0.248***	0.077	0.218***
		(0.061)	(0.150)	(0.067)
Academic_engagement:Number_authors			0.033	
			(0.028)	
Academic_engagement:Dual_affiliated_professor				0.281*
				(0.171)
Number_authors	0.009	0.001	-0.005	0.001
	(0.014)	(0.015)	(0.016)	(0.015)
Dual_affiliated_professor	-0.098	-0.177*	-0.169*	-0.302**
	(0.092)	(0.091)	(0.090)	(0.121)
Journal_reputation	1.007***	0.996***	0.987***	1.004***
	(0.115)	(0.111)	(0.109)	(0.112)
Prior_article_impact	0.0004***	0.0004***	0.0004***	0.0004***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Prior_patenting	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	-0.0004*	-0.0004*	-0.0004*	-0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.255***	0.246***	0.248***	0.244**
	(0.095)	(0.095)	(0.095)	(0.095)
log(Number_universities)	0.275***	0.287***	0.287***	0.289***
	(0.085)	(0.086)	(0.086)	(0.086)
log(Number_nations)	0.172**	0.146**	0.142**	0.141**
	(0.068)	(0.067)	(0.067)	(0.067)
Number_fields	-0.099***	-0.095***	-0.094***	-0.097***
	(0.032)	(0.032)	(0.032)	(0.032)
Article	1.265***	1.259***	1.259***	1.259***
	(0.055)	(0.056)	(0.056)	(0.055)
Female	-0.459***	-0.454***	-0.448***	-0.442***
	(0.101)	(0.099)	(0.100)	(0.099)
Dummies	Yes	Yes	Yes	Yes
Constant	0.830***	0.865***	0.901***	0.863***
	(0.244)	(0.228)	(0.213)	(0.231)
Observations	8455	8455	8455	8455

Table C.3. Regression results with author-clustered standard errors. (Chapter 5)

Results

	Dependent variable: Article_impact			
	(1)	(2)	(3)	(4)
Academic_engagement		0.143**	-0.048	0.124*
		(0.068)	(0.159)	(0.066)
Academic_engagement:Number_authors			0.037	
			(0.027)	
Academic_engagement:Dual_affiliated_professor				0.400
				(0.283)
Journal_reputation	0.954***	0.948***	0.941***	0.955***
	(0.113)	(0.112)	(0.110)	(0.112)
Number_authors	0.013	0.006	-0.001	0.008
	(0.016)	(0.016)	(0.018)	(0.016)
Dual_affiliated_professor	-0.124			-0.385***
	(0.211)			(0.140)
Prior_article_impact	0.0003***	0.0003***	0.0003***	0.0003***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Prior_patenting	-0.0002	-0.001	-0.001	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.282**	0.275**	0.277**	0.274**
	(0.115)	(0.112)	(0.113)	(0.112)
log(Number_universities)	0.283***	0.297***	0.296***	0.298***
	(0.091)	(0.092)	(0.092)	(0.091)
log(Number_nations)	0.206***	0.189***	0.184**	0.180**
	(0.079)	(0.073)	(0.073)	(0.073)
Number_fields	-0.060*	-0.060*	-0.058*	-0.061*
	(0.033)	(0.032)	(0.032)	(0.032)
Article	1.342***	1.334***	1.335***	1.339***
	(0.074)	(0.074)	(0.074)	(0.074)
Female	-0.248**	-0.239**	-0.232**	-0.231**
	(0.099)	(0.098)	(0.098)	(0.092)
Dummies	Yes	Yes	Yes	Yes
Constant	-0.051	-0.052	-0.012	-0.032
	(0.241)	(0.235)	(0.223)	(0.235)
Observations	8455	8455	8455	8455

Table C.4. Regression results with quasi-Poisson estimation. (Chapter 5)

Results

	Dependent variable: Article_impact			
	(1)	(2)	(3)	(4)
Academic_engagement		0.248***	0.077	0.218***
		(0.061)	(0.150)	(0.067)
Academic_engagement:Number_authors			0.033	
			(0.028)	
Academic_engagement:Dual_affiliated_professor				0.281*
				(0.171)
Number_authors	0.009	0.001	-0.005	0.001
	(0.014)	(0.015)	(0.016)	(0.015)
Dual_affiliated_professor	-0.098	-0.177*	-0.169*	-0.302**
	(0.092)	(0.091)	(0.090)	(0.121)
Journal_reputation	1.007***	0.996***	0.987***	1.004***
	(0.115)	(0.111)	(0.109)	(0.112)
Prior_article_impact	0.0004***	0.0004***	0.0004***	0.0004***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Prior_patenting	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	-0.0004*	-0.0004*	-0.0004*	-0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.255***	0.246***	0.248***	0.244**
	(0.095)	(0.095)	(0.095)	(0.095)
log(Number_universities)	0.275***	0.287***	0.287***	0.289***
	(0.085)	(0.086)	(0.086)	(0.086)
log(Number_nations)	0.172**	0.146**	0.142**	0.141**
	(0.068)	(0.067)	(0.067)	(0.067)
Number_fields	-0.099***	-0.095***	-0.094***	-0.097***
	(0.032)	(0.032)	(0.032)	(0.032)
Article	1.265***	1.259***	1.259***	1.259***
	(0.055)	(0.056)	(0.056)	(0.055)
Female	-0.459***	-0.454***	-0.448***	-0.442***
	(0.101)	(0.099)	(0.100)	(0.099)
Dummies	Yes	Yes	Yes	Yes
Constant	0.830***	0.865***	0.901***	0.863***
	(0.244)	(0.228)	(0.213)	(0.231)
Observations	8455	8455	8455	8455

Table C.5. Regression results with modified “Journal_reputation” variable (cut-off point at 75%). (Chapter 5)

Results

	Dependent variable: Journal_reputation			
	(1)	(2)	(3)	(4)
Academic_engagement	-0.119^{*}	-0.119^{*}	-0.265	-0.094
	(0.066)	(0.066)	(0.171)	(0.070)
Academic_engagement:Number_authors			0.026	
			(0.028)	
Academic_engagement:Dual_affiliated_professor				-0.232
				(0.229)
Number_authors	0.045^{***}	0.045^{***}	0.039^{***}	0.045^{***}
	(0.014)	(0.014)	(0.015)	(0.014)
Dual_affiliated_professor				0.047
				(0.155)
Prior_article_impact	0.0003^{***}	0.0003^{***}	0.0003^{***}	0.0003^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior_patenting	0.002^{**}	0.002^{**}	0.002^{**}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	0.0005^{**}	0.0005^{**}	0.0005^{**}	0.0005^{**}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Top_university	0.100	0.100	0.099	0.100
	(0.086)	(0.086)	(0.086)	(0.086)
log(Number_universities)	0.263^{***}	0.263^{***}	0.261^{***}	0.260^{***}
	(0.059)	(0.059)	(0.059)	(0.059)
log(Number_nations)	0.051	0.051	0.048	0.050
	(0.068)	(0.068)	(0.068)	(0.068)
Number_fields	0.170^{***}	0.170^{***}	0.172^{***}	0.171^{***}
	(0.037)	(0.037)	(0.037)	(0.037)
Female	-0.008	-0.008	-0.006	-0.016
	(0.151)	(0.151)	(0.151)	(0.150)
Dummies	Yes	Yes	Yes	Yes
Constant	20.165*	20.165*	20.136*	19.125*
	(11.344)	(11.344)	(11.344)	(11.387)
Observations	3,414	3,414	3,414	3,414

Table C.6. Regression results with modified “Journal_reputation” variable (cut-off point at 95%). (Chapter 5)

Results

	Dependent variable: Journal_reputation			
	(1)	(2)	(3)	(4)
Academic_engagement	-0.046	-0.046	-0.577	-0.053
	(0.097)	(0.097)	(0.353)	(0.102)
Academic_engagement:Number_authors			0.084^{*}	
			(0.050)	
Academic_engagement:Dual_affiliated_professor				-0.213
				(0.316)
Number_authors	0.053^{**}	0.053^{**}	0.036	0.050^{**}
	(0.024)	(0.024)	(0.026)	(0.023)
Dual_affiliated_professor				0.409^{**}
				(0.205)
Prior_article_impact	0.00001	0.00001	0.00001	0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior_patenting	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Prior_coauthors	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Top_university	0.063	0.063	0.063	0.067
	(0.117)	(0.117)	(0.121)	(0.118)
log(Number_universities)	0.233^{**}	0.233^{**}	0.225^{**}	0.237^{**}
	(0.093)	(0.093)	(0.093)	(0.093)
log(Number_nations)	0.372^{***}	0.372^{***}	0.367^{***}	0.380^{***}
	(0.098)	(0.098)	(0.097)	(0.098)
Number_fields	0.202^{***}	0.202^{***}	0.208^{***}	0.204^{***}
	(0.056)	(0.056)	(0.056)	(0.056)
Female	0.090	0.090	0.094	0.016
	(0.230)	(0.230)	(0.231)	(0.232)
Dummies	Yes	Yes	Yes	Yes
Constant	24.796	24.796	24.902	25.499
	(20.706)	(20.706)	(20.690)	(21.051)
Observations	3,414	3,414	3,414	3,414

Table C.7. Regression results with binary dependent variables. (Chapter 6)

Results

	Dependent variable: Model 1-2: Any_tech_impact Model 3-4: Any_individual_tech_impact Model 5-6: Any_organizational_tech_impact					
	(1)	(2)	(3)	(4)	(5)	(6)
Academic_engagement		0.059***		0.028***		0.019***
		(0.014)		(0.008)		(0.005)
Number_authors	0.009***	0.007***	0.002	0.001	0.0004	-0.0002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Dual_affiliated_professor	-0.053***	-0.071***	0.014	0.005	0.015*	0.009
	(0.019)	(0.019)	(0.013)	(0.013)	(0.008)	(0.008)
Prior_article_impact	0.00005***	0.00005***	0.00001	0.00001	0.00000	0.00000
	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Prior_patenting	0.0003*	0.0003	-0.0001	-0.0001	0.00000	-0.00000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Prior_coauthors	-0.0001	-0.0001	0.00000	-0.00000	0.00000	0.00000
	(0.00004)	(0.00004)	(0.00002)	(0.00002)	(0.00001)	(0.00001)
Journal reputation	0.098***	0.098***	0.026***	0.027***	0.005	0.005
	(0.018)	(0.018)	(0.010)	(0.010)	(0.005)	(0.005)
Top_university	0.053***	0.052***	0.028**	0.028**	0.004	0.004
	(0.020)	(0.020)	(0.011)	(0.011)	(0.005)	(0.005)
log(Number_universities)	-0.007	-0.004	0.0004	0.002	-0.001	0.0002
	(0.012)	(0.012)	(0.006)	(0.006)	(0.003)	(0.003)
log(Number_nations)	-0.002	-0.009	-0.004	-0.007	0.001	-0.001
	(0.014)	(0.014)	(0.007)	(0.007)	(0.003)	(0.003)
Number_fields	-0.001	-0.001	0.002	0.002	0.0002	0.0002
	(0.007)	(0.007)	(0.004)	(0.004)	(0.001)	(0.001)
Female	-0.022	-0.016	-0.016*	-0.013	-0.003	-0.001
	(0.021)	(0.021)	(0.009)	(0.009)	(0.004)	(0.004)
Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	29.305***	29.566***	3.011***	3.136***	1.664***	1.746***
	(2.331)	(2.326)	(1.113)	(1.111)	(0.641)	(0.643)
Observations	5143	5143	5143	5143	5143	5143

Table C.8. Regression results with "Knowledge_spillover" as the dependent variable. (Chapter 6)

Results

	Dependent variable: Knowledge_spillover	
	(1)	(2)
Academic_engagement		0.397**
		(0.170)
Number_authors	0.359**	0.281*
	(0.168)	(0.157)
Dual_affiliated_professor	-0.880***	-0.966***
	(0.334)	(0.364)
Prior_article_impact	0.001***	0.001***
	(0.0001)	(0.0001)
Prior_patenting	0.007***	0.007***
	(0.002)	(0.002)
Prior_coauthors	-0.0004	-0.0003
	(0.0004)	(0.0004)
Journal reputation	0.941***	0.938***
	(0.240)	(0.238)
Top_university	0.033	0.036
	(0.235)	(0.232)
log(Number_universities)	-0.069	-0.044
	(0.144)	(0.145)
log(Number_nations)	-0.157	-0.217
	(0.196)	(0.199)
Number_fields	-0.048	-0.034
	(0.080)	(0.080)
Female	-0.181	-0.084
	(0.363)	(0.363)
Dummies	Yes	Yes
Constant	435.619***	442.004***
	(23.878)	(24.485)
Observations	5143	5143

Table C.9. Regression results with modified dependent variables (using application-citations only). (Chapter 6)

Results

	Dependent variable: Model 1-2: Total_tech_impact Model 3-4: Individual_tech_impact Model 5-6: Organizational_tech_impact					
	(1)	(2)	(3)	(4)	(5)	(6)
Academic_engagement		0.696***		0.932***		1.315***
		(0.182)		(0.266)		(0.297)
Number_authors	-0.016	-0.057	0.129**	0.103*	0.123	0.064
	(0.042)	(0.041)	(0.055)	(0.060)	(0.089)	(0.099)
Dual_affiliated_professor	-0.465	-0.700*	-0.090	-0.567*	1.454***	0.800**
	(0.359)	(0.399)	(0.311)	(0.306)	(0.392)	(0.389)
Prior_article_impact	0.001***	0.001***	-0.0002	-0.00004	-0.00003	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Prior_patenting	0.007***	0.006***	-0.008*	-0.008	-0.001	-0.001
	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)
Prior_coauthors	-0.006***	-0.005***	0.001*	0.001	0.0003	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Journal reputation	0.942**	0.979***	0.880**	0.741*	1.576***	1.606***
	(0.419)	(0.371)	(0.425)	(0.416)	(0.386)	(0.383)
Top_university	0.120	0.028	0.809**	0.730**	1.208***	1.233**
	(0.261)	(0.278)	(0.315)	(0.316)	(0.422)	(0.482)
log(Number_universities)	-0.407**	-0.318*	-0.020	0.0002	0.022	0.132
	(0.183)	(0.171)	(0.206)	(0.209)	(0.331)	(0.354)
log(Number_nations)	-0.031	-0.087	-0.333	-0.354	0.131	-0.033
	(0.255)	(0.263)	(0.291)	(0.295)	(0.301)	(0.324)
Number_fields	0.020	0.025	-0.029	-0.054	0.197	0.238
	(0.104)	(0.106)	(0.142)	(0.145)	(0.149)	(0.156)
Female	-0.278	-0.211	-1.767*	-1.823*	-0.918	-1.111
	(0.630)	(0.664)	(0.990)	(1.021)	(0.894)	(0.953)
Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	417.929***	419.423***	162.855***	179.579***	318.821***	364.361***
	(31.674)	(31.127)	(39.346)	(39.862)	(60.831)	(59.149)
Observations	5143	5143	5143	5143	5143	5143

Table C.10. Regression results with author-clustered standard errors. (Chapter 6)

Results

	Dependent variable: Model 1-2: Total_tech_impact Model 3-4: Individual_tech_impact Model 5-6: Organizational_tech_impact					
	(1)	(2)	(3)	(4)	(5)	(6)
Academic_engagement		0.540***		0.981***		2.659***
		(0.194)		(0.218)		(0.717)
Number_authors	0.090*	0.058	0.119**	0.081	0.224*	0.095
	(0.047)	(0.043)	(0.059)	(0.062)	(0.124)	(0.188)
Dual_affiliated_professor	-0.610*	-0.778**	-0.393	-0.904**	2.101***	0.761
	(0.347)	(0.361)	(0.506)	(0.423)	(0.698)	(0.915)
Prior_article_impact	0.0005***	0.0005***	-0.0001	0.00002	-0.0002	0.0003
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.001)	(0.0004)
Prior_patenting	0.006***	0.006***	-0.004	-0.004	0.002	0.0005
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
Prior_coauthors	0.0001	0.0001	0.002***	0.002***	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Journal reputation	0.889***	0.879***	0.943***	0.962***	1.390	1.583
	(0.243)	(0.237)	(0.289)	(0.270)	(1.172)	(1.073)
Top_university	0.279	0.259	0.561**	0.533**	1.309*	2.373***
	(0.183)	(0.187)	(0.268)	(0.260)	(0.710)	(0.690)
log(Number_universities)	-0.125	-0.069	-0.045	-0.008	-0.495	-0.533
	(0.122)	(0.122)	(0.188)	(0.181)	(0.630)	(0.795)
log(Number_nations)	-0.163	-0.224	-0.211	-0.240	0.100	-0.442
	(0.194)	(0.192)	(0.319)	(0.334)	(0.615)	(0.662)
Number_fields	-0.022	-0.009	-0.018	-0.054	-0.225	-0.242
	(0.085)	(0.084)	(0.120)	(0.120)	(0.377)	(0.592)
Female	-0.264	-0.150	-1.036**	-0.970**	0.536	-0.510
	(0.279)	(0.276)	(0.487)	(0.464)	(1.292)	(2.054)
Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	409.922***	420.306***	164.731***	178.131***	317.952***	380.288***
	(25.488)	(25.677)	(40.761)	(40.782)	(89.892)	(98.271)
Observations	5143	5143	5143	5143	5143	5143

APPENDIX D: ALLOCATING CREDIT IN SCIENCE

The objective of this section is to give the reader a better understanding of how the scientific enterprise credit allocation system has evolved and how it sought to operate.

The section begins with an exploration of the concept of authorship, highlighting the guidelines established by the International Committee of Medical Journal Editors, commonly referred to as the Vancouver criteria for authorship (Figure D.1), as well as The Institute of Electrical and Electronics Engineers (Figure D.2). Following this, the discussion transitions to a chronological presentation of seven prevalent credit allocation models (Equations D.1-D.7). The practical application of these models is then exemplified through the distribution of credit in a research paper with four authors (Table D.1). The section concludes with a brief discussion on the evolution of these credit allocation models.

In the scientific enterprise, authorship provides a basis for peer recognition, and it is via forward citations research scholars are acknowledged for their work (Merton, 1973; Moed, 2005). Consequently, it is essential to accurately give symbolic profit where it is due, especially when it is considered the main currency (Bourdieu, 1975; see also Desrochers et al., 2018). The continuous shift towards multiauthored papers (Wuchty et al., 2007a) has made this fundamental task more difficult because authors can have different responsibilities in the partnership, and their contributions are not equally valued (e.g., Bhandari et al., 2014; Corrêa Jr. et al., 2017; Nylenna et al., 2014; Wren et al., 2007). To solve this problem, journals have both made the criteria for authorship clearer and research scholars have proposed a plethora of different co-authorship credit allocation models.

Criteria for authorship

The Vancouver criteria for authorship, developed by the International Committee of Medical Journal Editors, is arguably the most famous criteria used for clarifying what authorship constitute. The criteria recommend all those designated as authors should meet the following four criteria presented in Figure D.1 below. The Vancouver criteria for authorship assumes, for example, that all authors either draft the paper or critically revise it (criterion #2), which is a questionable assumption giving the increasing trend of hyperauthorship, that is, papers with 100+ authors (see Cronin, 2001). Hyperauthorship is no longer a phenomenon only found in physics and biomedicine but is also a phenomenon in other scientific fields, such as engineering, as mentioned in Chapter 5. [37] Nevertheless, even though it was developed for the medical sciences, it is used all around the world in many subject areas, as illustrated by this quote "Lund University Ethics Council supports the Vancouver rules for authorship and recommend that all researchers affiliated to Lund University, regardless of the field of research, follow these rules" (LTH, 2019, p. 4).

The ICMJE recommends that authorship be based on the following 4 criteria:

- Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND
- Drafting the work or reviewing it critically for important intellectual content; AND
- Final approval of the version to be published; AND
- Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Figure D.1. The Vancouver criteria for authorship (ICMJE, 2023).

[37] In my sample of 8455 publication, 10 publications had 100 or more co-authors.

The Institute of Electrical and Electronics Engineers, commonly known as IEEE, has a very similar definition of what constitute authorship (Figure D.2 below). The notable difference between the two is the explicit consideration of contributions made to "prototype development" (criterion #1).

The Institute of Electrical and Electronics Engineers considers individuals who meet **all** of the following criteria to be authors:

1. made a significant intellectual contribution to the theoretical development, system or experimental design, prototype development, and/or the analysis and interpretation of data associated with the work contained in the article;
2. contributed to drafting the article or reviewing and/or revising it for intellectual content;
3. approved the final version of the article as accepted for publication, including references.

Figure D.2. The Institute of Electrical and Electronics Engineers criteria for authorship (IEEE, 2023).

Credit allocation models

(One of) The first approaches for allocating credit to authors is the first author counting model (Cole & Cole, 1973). Here, only the first of the N authors (position = P = 1) receive the total number of credit C that the scientific publication created.

Equation D.1. The first author counting model.

$$Author_{P=1} = C$$
$$Author_{P>1} = 0$$

The second approach is the normal or standard counting model, also known as the total author counting model (Lindsey, 1980). Here, each of the N authors receives the total number of credit C that the scientific publication created.

Equation D.2. The total author counting model.

$$Author_{P=1,2\ldots N} = C$$

The third approach is the fractional counting model, also known as adjusted counting (Price, 1981). Here, each of the N authors receives the total credit C that the scientific publication has created divided equally between the number of authors N.

Equation D.3. The fractional counting model.

$$Author_{P=1,2\ldots N} = \frac{C}{N}$$

The fourth approach is the proportional counting model (van Hooydonk, 1997). Here, if an author has position P in a paper with N authors, that researcher receives a share of the total credit C that the scientific publication created according to the following mathematical equation:

Equation D.4. The proportional counting model.

$$Author_{P=1,2\ldots N} = \frac{2C\left(\frac{1-P}{N+1}\right)}{P}$$

The fifth approach is the pure geometric counting model (Egghe et al., 2000). Here, if an author has position P in a paper with N authors, that researcher receives a share of the total credit C that the scientific publication created according to the following mathematical equation:

Equation D.5. The proportional counting model.

$$Author_{P=1,2\ldots N} = \frac{C * 2^{N-P}}{2^{N-1}}$$

The sixth approach is the first-last-author-emphasis model (Tscharntke et al., 2007). Here, the first of the N authors receive the total number of credit C that the article resulted in, the last author receive half of the total credit C, and the remaining middle author receive the total credit C divided equally between the number of authors N.

Equation D.6. The first-last-author-emphasis model.

$$Author_{P=1} = C$$

$$Author_{P=N} = \frac{C}{2}$$

$$Author_{P>1\ \&\ P<N} = \frac{C}{N}$$

The seventh approach is the harmonic counting model (Hagen, 2008). Here, if an author has position P in a paper with N authors, that researcher receives a share of the total credit C that the scientific publication created according to the following mathematical equation:

Equation D.7. The harmonic counting model.

$$Author_{P=1,2\ldots N} = \frac{\left(\frac{C}{P}\right)}{\left[1 + \left(\frac{1}{2}\right) + \cdots + \left(\frac{1}{N}\right)\right]}$$

Table D.1 below demonstrates how these models distribute credit to a four authored research paper—the comparison aims to enhance the models' concreteness and interpretability through an example.

Table D.1. Credit allocation models.

Counting model (reference)	Four authors, where C = 1; Position: 1	2	3	4
First author (Cole & Cole, 1973)	1	0	0	0
Normal counting (Lindsey, 1980)	1	1	1	1
Fractional counting (Price, 1981)	0.25	0.25	0.25	0.25
Proportional counting (Van Hooydonk, 1997)	2	0.75	0.333	0.125
Pure geometric (Egghe et al., 2000)	1	0.5	0.25	0.125
First-last-author-emphasis (Tscharntke et al., 2007)	1	0.25	0.25	0.5
Harmonic counting (Hagen, 2008)	0.48	0.24	0.16	0.12

To sum up, the credit allocation models have principally evolved from only counting the first author, to equally counting everyone, to emphasize the importance of the byline, that is, the position an author has in the paper.

In greater detail, it has been argued (e.g., Lindsey, 1980) that the first model—the first author counting model—had two key benefits, namely that it "solved" the issue of distributing credit for multiauthored work by ignoring everyone but the first author, and it significantly lessened the amount of work necessary to gather data on any sample of scientists, which was a quite tedious task during that time.

The second and the third model—the normal counting model, and the fractional counting model—acknowledged the shift towards multiauthored papers but neglected the importance of author sequence. In other words, they gave the same amount of credit to all authors regardless of their position on the byline.

The remaining models—the proportional counting model, the pure geometric counting model, the first-last-author-emphasis model, and the harmonic counting model—acknowledged both the shift towards multiauthored papers and the importance of author position. Only one of these four models emphasized the importance of both the first and the last author (the first-last-author-emphasis model), whereas the other distributed more credits to authors the earlier they were on the byline.

This examination of the evolution of allocating credits to authors has clearly showcased the theoretical importance that the first author has in a multiauthored work, which validates the choice of positioning this study around the first author.