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Using Organizational Learning to assess micro-incentives of the Triple Helix

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Abstract

The Triple Helix model claims that actors from academia, industry and governments increasingly collaborate with each other. As such, universities become increasingly involved in patenting, while firms increasingly develop knowledge that is codified in scientific publications. However, these macro-level developments are at odds with micro-incentives of the actors in the Triple Helix. Researchers at universities are mostly expected to write publications instead of filling patents, while for private firms this works the other way around. Consequently, we ask if these micro-incentives can lead to stable macro Triple Helix patterns, and if government funding can contribute to stabilizing the Triple Helix. Therefore the aim of this paper is to study the influence of knowledge bases that combine different types of knowledge and prior collaborations on the publication and patent output of organizations in the Triple Helix.

We use insights from Organizational Learning to formulate hypotheses about how the micro-incentives for knowledge development in the Triple Helix. We make an important distinction between how combinations of declarative and procedural knowledge bases influence the publication and patent output.

We test our hypotheses on data about publications, patents and funding in the domain of carbon capture technology

Our main result is that the incentives to engage in Triple Helix knowledge development come from the organization?s

own prior declarative and procedural knowledge bases, but not much from collaboration with other parties.

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Keywords: Triple Helix, Organizational Learning, University-Industry Interaction, Innovation, Carbon Capture

1. Introduction

To this date, the Triple Helix model (Leydesdorff and Etzkowitz, 1998; Etzkowitz and Leydesdorff, 2000) is the most recent major co-evolutionary view on innovation. It describes how knowledge institutes, firms and governments, as important actor types in the innovation process, increasingly collaborate with each other. Thereby more knowledge from academia can be utilized by industry, while industry inspires academia with relevant questions. For these reasons governments foster Triple Helix collaborations.

A result of these collaborations, the distinction between the traditional roles of these actors is not clear-cut anymore. This is especially true for academia and industry (Etzkowitz and Leydesdorff, 2000). Traditionally, researchers at universities wrote publications to gain scientific credibility (Latour and Woolgar, 1979; Hessels and van Lente, 2008), while firms in industry applied for patents that allowed them to commercially benefit from the R&D process (Brouwer and Kleinknecht, 1999). The traditional knowledge base of a university thus consists of scientific knowledge, while the knowledge base of firms is usually of a more applied nature. However, universities have become increasingly involved in patenting (Henderson et al., 1998), while firms codify more knowledge into scientific publications (Tijssen, 2004). This leads to knowledge bases in which scientific and applied elements are combined.

However, the macro-level Triple Helix claims are at odds with the micro-incentives that both actor types receive from their own institutional context (Etzkowitz and Leydesdorff, 2000; Van Looy et al., 2006). Researchers at universities are usually not much rewarded for their work on patents (Packer and Webster, 1996). Firms that (co-)publish results in scientific journals might gain scientific credibility, but they also take a large risk, since their knowledge becomes widely available without intellectual property protection (Blumenthal et al., 1997; Louis et al., 2001). The contradiction between the Triple Helix model and it's micro-incentives has led to a number of studies that assess if long-term Triple Helix knowledge development is possible, or if the misaligned incentives will eventually cause the actor types to work only on their own mission (Etzkowitz and Leydesdorff, 2000). This research can be categorized around three questions.

The first question is if organizations with a prior knowledge base consisting of both scientific and applied elements create more publication and patent output than organizations that do not have such a combined knowledge base? Empirical evidence mostly indicates that this is indeed the case both for universities (Owen-Smith, 2003; Geuna and Nesta, 2006; Meyer, 2006; Van Looy et al., 2006; Larsen, 2011) and firms (Gittelman and Kogut, 2003; Fabrizio, 2009). However, for the latter the output is also dependent on whether the publications represent basic or applied research (Lim, 2004).

The second question is if R&D collaborations positively influence the output of publications and patents? There are studies that claim that collaboration between researchers leads to more publications (Landry et al., 1996; Melin, 2000), but these claims are empirically disputed (Lee and Bozeman, 2005; Abramo et al., 2009). There is also evidence for a positive effect of university-industry collaboration on publication output (Landry et al., 1996), but non-significant results have also been reported (Carayol and Matt, 2004). The effect of collaboration on publication output thus remains unclear. In contrast, studies show consistently that collaboration between firms leads to a larger patent output (see Ahuja, 2000; Schilling and Phelps, 2007), as does collaboration between universities and firms (Ruef, 2002).

A third related question is if government funding of collaborative R&D projects has a positive effect on the output of publications and patents? Past studies predominantly found that externally acquired (semi-)public funds are positively related to the output of publications and patents of academics (Dundar and Lewis, 1998; Payne and Siow, 2003; Gulbrandsen and Smeby, 2005; Defazio et al., 2009) and firms (Czarnitzki and Licht, 2006; Hussinger, 2008; Fornahl et al., 2011). However, for the latter the output also depends on the project consortium (Schwartz et al., 2012) and individual differences (Goldfarb, 2008).

Until now these questions have been addressed mostly separate from each other, with the focus on only one type of actor. However, since the collaboration between academia and industry has as consequence that actors partly take over each other's roles in the innovation process, these questions need to be addressed within one research design for all actor types. Only then can we assess if the combined micro-incentives lead to a stable Triple Helix.

Therefore the aim of this paper is to study *the influence of knowledge bases that combine different types of knowledge and prior collaborations on the publication and patent output of organizations in the Triple Helix.*

To achieve our aim we present in the next section a short background of the Triple Helix and use insights from Organizational Learning (Levitt and March, 1988; Cohen and Sproul, 1996) to formulate hypotheses about the micro-incentives for Triple Helix knowledge development. In section 3 we describe how these hypotheses are tested using data sets about publications, patents and the (semi-)public R&D-funding experience of organizations in the field carbon capture technology. The results of these analyses are presented in section 4. In section 5 we present our conclusions, limitations and avenues for further research. Moreover, we discuss how the study informs policy makers how to promote the Triple Helix.

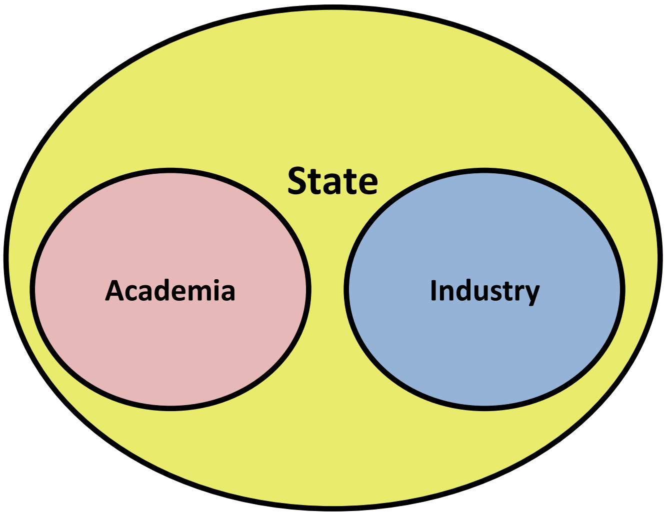
2. Theory

2.1. Triple Helix models

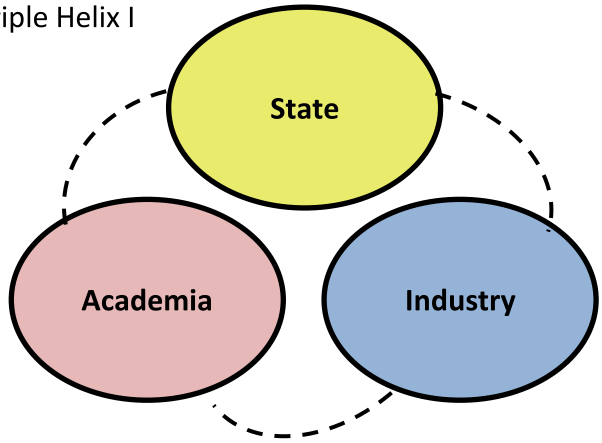
The Triple Helix model distinguishes three historical situations of how academia-industry-government relations are arranged (see figure 1). First, there is the Triple Helix I model, in which 'the state encompasses academia and industry and directs the relationships between them' (Etzkowitz and Leydesdorff, 2000, p.111). This form of the triple helix was mostly found in socialist states. The Triple Helix II model is more laissez faire. It claims that academia, industry and state operate in separate institutional spheres, with only limited relations between them. This model is most in line with the aforementioned micro-level incentives that inhibit collaboration between actor types. Finally, the Triple Helix III describes overlapping institutional spheres that can ensure that organizations have incentives to collaborate. This means networks emerge in which knowledge institutes, firm in industry and governments jointly produce and commercialize knowledge. Consequently, the distinction between the publication and patenting function of the different actor types fades away. The Triple Helix III is a state that many governments try to achieve in their policy, for example by subsidizing collaborative innovation projects. However, since all organizations are also pressed to conform to the norms of their own institutional spheres, Etzkowitz and Leydesdorff (2000) explicitly hypothesize that the Triple Helix III is not stable, but in a continuous state of transition. Only if the Triple Helix III state strengthens the competitive position of all its participating actor types can it become stable. This means that the micro-incentives should be aligned with the desired macro-outcome.

We consider all three actor types in the Triple Helix, but we make three amendments. First, academia does not only include universities, but also other knowledge institutes that have knowledge development as primary aim. Second, firms in industry are heterogeneous (see Hannan and Freeman, 1989; Tidd et al., 2001). Larger firms have more resources to invest in R&D, but smaller firms are usually credited as being more innovative (Chandy and Tellis, 2000). For this reason we make a distinction between small and large firms. Third, we include intermediary organizations like NGO's, consultants or semi-public institutes (Howells, 2006; Boon et al., 2011). Conceptually we treat these intermediary organizations the same as governments. This is in line with the trend in the Triple Helix literature to expand the concept of government to governance (Leydesdorff and Meyer, 2006, 2007). Our motivation for this choice is theoretically motivated. In contrast to academia and industry, neither governments nor intermediaries have the task to create publications and patents, rather they act as regulator, facilitator (Etzkowitz, 2003; Howells, 2006) and funder (Van Rijnsoever et al., n.d.; Nooteboom and Stam, 2008). This makes it difficult to distinguish between the work conducted by governments from that of intermediaries. Moreover, the number of governments and intermediaries in our data is too small to be considered separately. Our choice to treat governments and intermediaries as one category has as consequence that we do not include funding organizations.

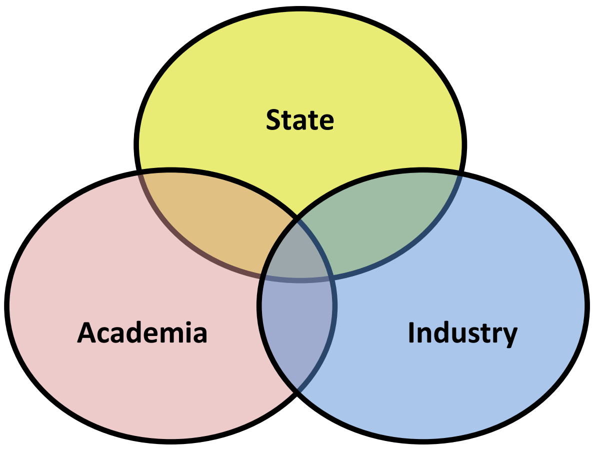
Figure 1: graphical representations of the Triple Helix I, II and III. Adapted from Etzkowitz and Leydesdorff (2000).



Triple Helix I



Triple Helix II



Triple Helix III

2.2. Publication and patent output

In this study the publication and patent output of an organization are the dependent variables. Both are used to measure knowledge (see Narin et al., 1987; Dietz and Bozeman, 2005; Sharma and Thomas, 2008), but there is a difference in the type of knowledge they capture (Fabrizio, 2009). Scientific journal publications are primarily research reports. They store novel knowledge that is the result of scientific enquiry, but there is no need for commercial applicability or commercialization. Patents are, first and foremost, legal documents. They usually contain new knowledge that has at least some potential for commercial application, but patents do not need to be based on scientific research per se.

Next to being output variables, prior publications and patents indicate the organizational knowledge base, which is the accumulated knowledge and experience that the organization has gathered in the past (Cohen and Levinthal, 1990). As such, they facilitate learning and thus the creation of more publications (Merton, 1968) and patents (Owen-Smith, 2003). According to Organizational Learning the knowledge base can be expanded via two processes (Huber, 1991). The first is experiential learning, which is trial and error learning using the internal organizational knowledge base. The second is learning from others, which is primarily achieved through collaboration. Experiential learning is less efficient and much more risky than learning from others, but it allows the organization to develop a unique knowledge base that can used to gain a first mover advantage (Lieberman and Montgomery, 1988). These learning processes form the basis for our independent variables.

2.3. Knowledge base combinations

Learning from past experience entails that organizations expand their knowledge base by accumulating information and experience over time (Levitt and March, 1988; Huber, 1991). Not only is the knowledge base expanded with knowledge about the topic, routines are also developed (Nelson and Winter, 1982; Becker, 2004). Therefore, Organizational Learning makes a distinction between the acquisition of declarative and procedural knowledge (Kogut and Zander, 1992; Cohen and Bacdayan, 1994; Wilcox King and Zeithaml, 2003). Declarative knowledge (e.g. know what) is the scientific or technical knowledge about a topic. It is knowledge about the content, which is in our study is the knowledge about carbon capture that is codified in publications and patents. Procedural knowledge (e.g. know how) accumulates over a longer period of time. It is stored in routines (Cohen and Bacdayan, 1994) and is usually of a tacit nature. In our case procedural knowledge consists of the routines for acquiring declarative knowledge and codifying it into publications or patents. We argue that both knowledge types are required for successful repetitive publishing and patenting.

2.3.1. Declarative publication and patent knowledge

Declarative knowledge gives the organization the absorptive capacity to search, discover and interpret novel elements of knowledge (see Cohen and Levinthal, 1990). A sufficient declarative knowledge base thus form the basis for new scientific discoveries and technological innovations. Publications and patents largely originate from the same declarative knowledge base (Agrawal and Henderson, 2002), but as argued above, the knowledge stored in publications is different from that of patents. For this reason we treat declarative publication knowledge conceptually different from patent knowledge. Following the argument that a declarative knowledge base enables the organization to learn, we hypothesize a positive influence of both types of declarative knowledge on their respective outputs.

- *Hypothesis 1a: Declarative publication knowledge has a positive influence on publication output.*
- *Hypothesis 1b: Declarative patent knowledge has a positive influence on patent output.*

2.3.2. Combining declarative publication and patent knowledge

It has also been suggested that combination publication and patenting activities can strengthen each other (Gittelman and Kogut, 2003; Owen-Smith, 2003; Van Looy et al., 2006). Fabrizio and Di Minin (2008), provide an extensive set of arguments for why this is the case. First, as mentioned above, patents and publications have, to a large extent, the same underlying knowledge base (Agrawal and Henderson, 2002). The knowledge base that consists of publications can also be a rich resource to base patents on (Fabrizio, 2009). Second, working on both patents and publications might prompt additional research questions that are relevant to both academia and industry (Mansfield, 1998; Siegel et al., 2003). Combining activities can thus serve as a source of inspiration and ideas, that can lead to additional publications and patents. Third, publications can lend credibility to knowledge codified in a patent, which can be an incentive to publish more publications about the knowledge codified in a patent (Fabrizio and Di Minin, 2008). Finally, the commercial value of patents can lead to extra revenues. Organizations can license out the patent to gain access to funds that can be invested in additional research facilities (Siegel et al., 2003; Fabrizio and Di Minin, 2008). For these reasons we hypothesize:

- *Hypothesis 1c: A combination of declarative publication and patent knowledge has a positive influence on publication output*
- *Hypothesis 1d: A combination of declarative publication and patent knowledge has a positive influence on patent output*

2.3.3. Declarative publication or patent knowledge and external funding

In this paper, external funds are defined as funds that the organization has acquired from public or semi-public sources to conduct R&D. Externally acquired funds allow the organization to expand its R&D effort, by investing in facilities and human resources. However, organizations can only benefit from these investments if they already have a strong knowledge base (Penner-Hahn and Shaver, 2005). Otherwise, the organization will be unable to utilize the money in an appropriate manner. This means that we only expect a positive effect of funding if it is combined with declarative publication or patent knowledge.

- *Hypothesis 1e: A combination of declarative publication knowledge and external funds has a positive influence on publication output.*
- *Hypothesis 1f: A combination of declarative patent knowledge and external funds has a positive influence on patent output.*

2.3.4. Procedural publication and patent knowledge

The different purposes of publications and patents (research reports vs. legal documents) imply that the routines required for writing a publication differ from the routines required for filing a patent, even if both share the same declarative knowledge base. Most academics with publication experience are aware that publishing a scientific article is almost an art by itself. First, the research has to adhere to minimum academic standards. Moreover, authors have to write the article in such a manner that it complies to journal standards, argue that it is of sufficient quality and that it is of interest to their respective field. A patent on the other hand, has to be written in such a manner that it provides the largest amount of juridical protection for an invention. Further, applicants have to adhere to specific writing formats and need to know how the filing process itself works. These routines develop through experience (Epple et al., 1991). The more developed these routines become, the higher the output will be (Becker, 2004).

- *Hypothesis 2a: Procedural publication knowledge has a positive influence on publication output.*
- *Hypothesis 2b: Procedural patent knowledge has a positive influence on patent output.*

2.3.5. Combining procedural publication and patent knowledge

The next question is if both types of procedural knowledge are complementary?

Even after fully mastering the routines, creating knowledge for publications and patents remains a time- and therefore resource-intensive process. Whether at a knowledge institute or a firm, publications are mostly written by the investigators that conducted a scientific study. However, these researchers are also often involved in the patenting process, which means that they have less time to spent on publishing papers (Fabrizio and Di Minin, 2008). Universities often have separate entities like technology transfer offices to facilitate this patenting process (Friedman and Silberman, 2003; Markman et al., 2005). Firms also have in-house specialists or hire an external agencies to assist them in the patenting process (Machin, 2013). These activities enable individual researchers to focus more on publications, but they draw on the resources of the organization as a whole. This means that on an organizational level patenting activities do compete with publication activities. Therefore, we hypothesize:

- *Hypothesis 2c: A combination of prior procedural publication and patent knowledge has a negative influence on publication output*
- *Hypothesis 2d: A combination of prior procedural publication and patent knowledge has a negative influence on patent output*

2.3.6. Procedural publication or patent knowledge and funding knowledge

Next to having access, organizations can also develop routines for gaining access to external funds. Part of this procedural knowledge is developed in the writing process of publications. However, many larger funding programs, such as the European Framework programs or Horizon 2020, specifically demand the building of consortia with various actor types. This requires routines to build and manage partnerships (Schilke and Goerzen, 2010). These routines are mostly acquired through experience (Rothaermel and Deeds, 2006) and often stored in dedicated units to manage alliances (Kale et al., 2002). Acquiring and maintaining such routines competes in terms of time and resources with mastering publication or patenting routines. Therefore, we hypothesize a negative interaction effect:

- *Hypothesis 2e: A combination of procedural publication knowledge and procedural knowledge about external funding has a negative influence on publication output.*
- *Hypothesis 2f: A combination of procedural patent knowledge and procedural knowledge about external funding has a negative influence on patent output.*

2.4. Collaboration

Next to experiential learning, organizations can build on the discoveries of others (Hoppe, 2000) and make novel combinations that lead to new innovations (Nelson and Winter, 1982). This is often done through collaboration between organizations (Powell et al., 2005; Van Rijnsoever et al., 2008). We look at what actor type an organization needs to collaborate with in order to enhance its innovative output. For all arguments in this section we argue that organizations collaborate with each other to gain access to resources, knowledge or capabilities that they do not possess themselves. This can be to enhance their publication or patent output, but other motives can also play a role. This approach is in line with view about collaboration from a knowledge institute (Melin, 2000) and industry perspective (Santoro and Chakrabarti, 2002).

2.4.1. Collaboration with knowledge institutes

One of the core activities of knowledge institutes is to translate findings from research into scientific journal publications. Knowledge institutes thereby possess the declarative and procedural knowledge required to write publications, which makes them attractive collaboration partners for organizations that wish to conduct research for breakthrough technologies or that simply wish to gain scientific credibility through publications.

Further, as argued above, especially universities have started to invest in procedural knowledge to obtain for patents. The number of patent applications by US universities has increased strongly since the 1980's (Mowery et al., 2001; Thursby and Thursby, 2003). Also in Europe there is an upward trend in university patenting (Geuna and Nesta, 2006; Geuna and Rossi, 2011). Combined with the fact the knowledge institutes have a strong declarative knowledge base, the procedural knowledge about patenting means that knowledge institutes can also be an attractive collaboration partner for obtaining a patent. Therefore we hypothesize:

- *Hypothesis 3a: Collaboration with a knowledge institute is positively related to publication output.*
- *Hypothesis 3b Collaboration with a knowledge institute is positively related to patent output.*

2.4.2. Collaboration with industry

Not all firms are equally likely to produce patents. Smaller firms generally have less resources than large firms (Chandy and Tellis, 2000) and therefore produce a lower volume of patents (Scherer, 1965; Brouwer and Kleinknecht, 1999; Hall and Ziedonis, 2001)[1]. The fact that larger firms produce more patents means that they are better able to develop procedural knowledge about patenting than their smaller counterparts. Next to the fact that they possess the right routines, larger firms are also more attractive collaboration partners to develop publications and patents with than smaller firms. First, collaboration between organizations does involve transaction costs (Geyskens et al., 2006). Larger firms are more likely to have the resources for this. Second, larger firms usually have a broader than knowledge base than smaller firms. This facilitates learning (Cohen and Levinthal, 1990), and increases the chances of making novel combinations that is publishable and patentable. Finally, larger firms give more legitimacy to the outcomes of the project (Chandy and Tellis, 2000) and have more market power to make an innovation successful (Howells, 2002). Therefore we hypothesize:

- *Hypothesis 4a: Collaboration with a large firm is positively related to publication output.*
- *Hypothesis 4b: Collaboration with a large firm is positively related to patent output.*

3. Methods

We test our hypotheses using data sets coming from the field of carbon capture for underground storage. This is a set of technologies used to separate CO_2 gas from other emissions at large point sources, such as power plants or steel factories. The technology is part of the Carbon Capture and Storage (CCS) process, which aims to reduce greenhouse gas emissions by storing the captured CO_2 underground (Metz et al., 2005; Haszeldine, 2009). Over the past decade, governments and private parties all over the world have invested billions of dollars in R&D and demonstration of this promising set of climate change mitigation technologies. Due to data availability, we limit ourselves to organizations from North-America and Europe. These two regions are which are financially responsible for 85% of all CCS R&D in the world. Most of the investments were aimed at creating more cost effective CO_2 capture technologies, which has contributed to a large number of scientific publications and patents. These characteristics make carbon capture an ideal case to test our hypotheses on.

3.1. Data collection

We collected data about the publications, patents and external funding of organizations active in the field of carbon capture between 2002 and 2010. We started at 2002, because that is when funding data became available. The final year was 2010 because the patent data is incomplete afterwards[2]. For each organization in each year we collected information about (1) the number of publications, patents or funded projects, (2) the collaboration between organizations.

Publication data was collected from the Thompson ISI Web of Science database. We identified all publications about carbon capture for the given time period. Publications were

[1] This claim refers to the absolute number of patents, not to a relative measure, such as patent output per FTE.
[2] The time between application and publication of a patent can be up to 18 months, since data was collected in 2013, the data is reliable until 2010.

identified using a series of queries that was iteratively established using CCS reports and publications as input. The final list of queries was checked and validated by a number of field experts from the Global CCS Institute. The resulting publications were checked by their title, and if in doubt their abstract to determine whether the publication focused on CO_2 in relation to carbon capture. A total of 976 publications were identified in this manner. These were (co-)authored by 454 organizations.

Patent data was collected from the European Patent Office PATSTAT database, which contains all worldwide patents. This database contains separate CCS categories, which enabled us to identify individual patents that related to carbon capture only. This resulted in 1379 patents, filed by 446 organizations.

Funding data was collected for publicly (co-)funded R&D projects. Information was gathered from the National Energy Technology Laboratory (NETL), Natural Resources Canada, CORDIS and European grant databases of national research programs. NETL is part of the U.S. Department of Energy national laboratory system and implements research and development programs in the energy field. Natural Resources Canada is the ministry of the government of Canada which is, amongst others, responsible for energy related matters and CCS funding. CORDIS is the funding database of the European Union. Finally, examples of sources used to retrieve R&D project data (co-)funded by European member states include the IEA Greenhouse Gas R&D program and the UK EPSRC databases. In all, we identified 253 government funded research projects executed by 430 organizations.

After all databases were combined, a list of 1069 unique organizations remained. For 1025 of these the data was complete.

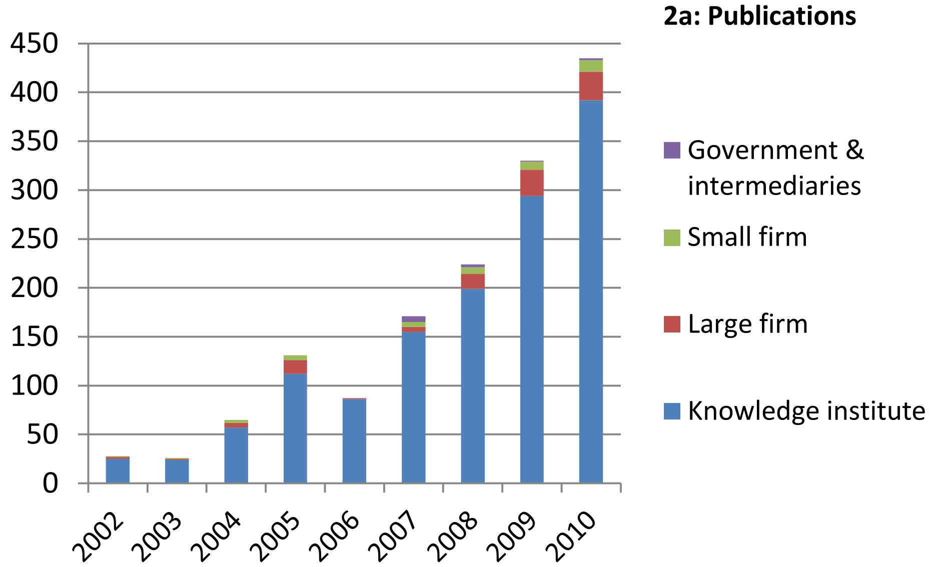
We are interested in testing the effect of independent variables measured at *time t-1* on dependent variables measured at time *t*. An issue to be dealt with while compiling the data is how long can we expect past actions to have an influence on future performance (Ancona et al., 2001; Mitchell and James, 2001). For example, it is often unknown how long connections between collaboration partners are maintained (Ahuja, 2000) and how the age of network connections influences organizational output (Soda et al., 2004). Also in our study it is unknown what the exact time scales are on which the relationships from our hypotheses operate. For this reason we use three different time intervals for *t-1*: 1 year before t, 1-2 years before t and 1-3 years before *t*. The larger the time interval the longer the model assumes that the past experience has an influence on publication and patent output.

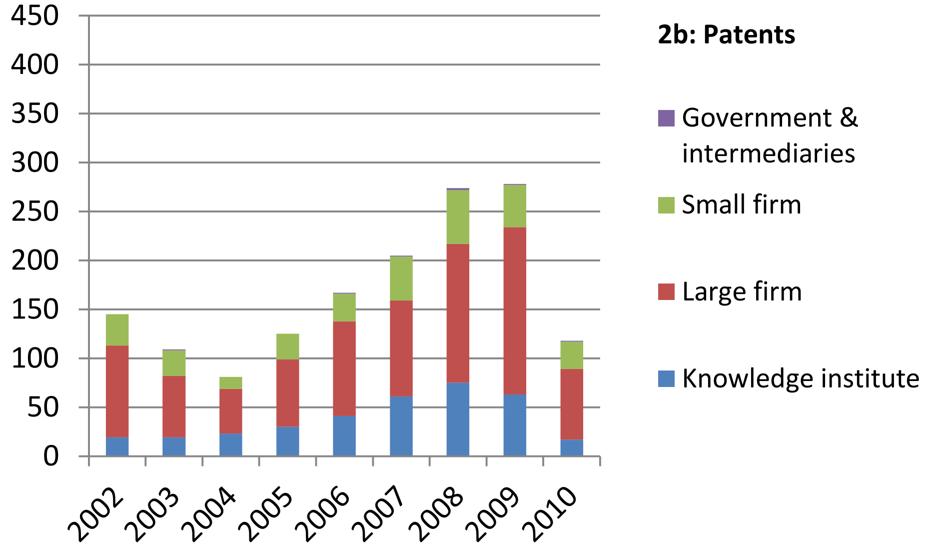
3.2. Measurement

Prior to measuring the variables from our theory we first classified all organizations according to the *types of actors* that we described in section 2.1: (1) knowledge institutes, (2) large firms, (3) small firms and (4) government & intermediaries. An organization was classified as knowledge institute if had the development of knowledge and technology as primary mission. Among these are universities, but also government laboratories or applied research institutes. Organizations that do not have knowledge development as core mission, but that have commercial objectives were classified as either a large or small firm. Since we do not have data about the exact size of each organization, we used the criterion of whether a firm is a multinational as a proxy for size. If a firm had offices in multiple countries it was classified as a large firm, otherwise it was a small firm. All remaining organizations were part of government & intermediaries. There were 559 knowledge institutes, 208 large enterprises, 267 small enterprises and 35 government & intermediaries.

Publication output was measured as the number of scientific articles an organization published in a given year *t*. *Patent output* was similarly measured as the number of patent applications by an organization in a given year *t.* Over the entire time period, each organization had on average of 1.40 publications and 1.40 patents. Figure 2 presents how the publications and patents are distributed over time and actor type.

Figure 2: Publications (2a) and patents(2b) by year per actor type. Some publications and patents are double counted in this graph, since both publications and patents can have multiple actor types as author or applicant.





First, Figure 2 gives some insights into how much information is lost by setting 2002 as cutoff point. For publications the cut-off is reasonable. The bulk of the scientific output in the field is generated from 2009 and onwards (van Egmond et al., 2012) and only 1% comes from 2002. Prior to 2002 there were hardly any scientific articles in the field. For patents the year 2002 accounts for around 10% of the observations. This is a substantial amount and the chance exists that are relevant patents prior to 2002. It would be possible to include patents and publications prior to 2002 in our measure. However, given that there is no funding data available and that the number of publications is very low before 2002, this will introduce a bias in our results. Therefore we choose to use 2002 as cut-off point, and statistically correct for these differences by creating three binary control variables that indicate if an organization had publications, patents or funding in 2002. Second, the Figure 2 clearly shows that over the years knowledge institutes are dominant in publication output, while large firms are most prominent in patent output. For neither type of output is there a discernable change in proportion of actor types.

Declarative publication knowledge was measured as a binary variable that indicated if the organization published a scientific article in the period *t-1*. *Declarative patent knowledge* was measured as a binary variable that indicated if the organization applied for a patent in the period *t-1*. Measuring only at *t-1* implies that we ignore parts of the declarative knowledge base that was codified prior to *t-1*. Our argument for this is that learning new knowledge is a path-dependent and cumulative process (Nelson and Winter, 1982; Cohen and Levinthal, 1990). This means that declarative knowledge base at *t-1* is the result of the knowledge acquired over time prior to that moment. However, since both require state-of-art knowledge, recent output is more important for new publications and patents than older output. Second, an alternative to using a binary variable would have been to use the total output at t-1. However, it is unknown how the different publications or patents add up to a single knowledge base. It is well possible that publications or patents have overlap, or that some make a larger contribution than others. To avoid this issue, we choose for a binary variable that only indicates if the organization possesses the state-of-the-art declarative knowledge required to come to more publications or patents.

External funding was measured as a binary variable that indicated if the organization received external (semi-)public funding in the period *t-1*. Unfortunately, the amount of funding was not always available, nor is it known how the money was exactly distributed over multiple partners in a consortium. Therefore we measured if the organization received any funds at all. Over the entire time period each organization was involved on average in 1.19 funded projects.

Procedural publication knowledge was measured as the number of publications that the organization had written at *t-1* since 2002. *Procedural patent knowledge* was measured as the number of patent applications between 2002 and *t-1*. *Procedural funding knowledge* was measured as the number of times external funds were granted at *t-1* since 2002. Research on organizations has shown that acquiring routines have a learning curve that follows a power law relationship (Argote and Epple, 1990; Arthur and Huntley, 2005); the growth in efficiency declines with each extra unit of output. To approximate this learning curve we took the natural logarithm of each of the procedural knowledge variables. Since we have binary variables for output generated in 2002, we can control for the missing data prior to our period of observation.

Collaboration was measured using dummy variables for each actor type. If an organization collaborated with a specific organization type at *t-1* in any of the three data sources the variable is 1, otherwise it is 0.

3.3. Analysis

Since our dependent variables are count data over time over time, we fitted a series of mixed-Poisson models to test our hypotheses. This was done using the R-program (R Development Core Team, 2013) and the lme4 package (Bates and Sarkar, 2006). The models contained a random intercept dependent on the organization to account for unobserved differences between organizations. Further, we corrected for over-dispersion of the dependent variable by adding a second random intercept dependent on each individual observation. This transforms the model to a lognormal Poisson model that deals with over-dispersion and allows for estimating both fixed and random effects (Elston et al., 2001; Bolker, 2010).

To prevent a bias in our results we only included observations in the model of organizations that were active in the field of carbon capture at time *t*. An organization was considered active if it had either a publication or patent output larger than 0 at time *t or* if it had publications, patents or external funding at *t-1*.

We specified separate models with as dependent variables either the number of publications or the number of patents at year t for each time interval for *t-1*. Since we have two dependent variables and three time intervals we estimated six models in total.

As independent variables we added the *t-1* dummies for declarative publication knowledge, patent knowledge and external funding. Moreover, we added 2 and 3-way interaction terms between these dummies to the model to test the interaction effects. In this manner we tested hypotheses 1a-1f. To test hypotheses 2a-2f we added the three indicators for procedural knowledge and the 2 and 3-way interaction effects between these variables to the models. Hypotheses 3a-b and 4a-b were tested by adding collaboration dummies with each actor type to the models. We also added a series of control variables to the models. First, we added a nominal variable that indicated the actor type to control for expected differences in output[3]. Second, we added dummy variables that indicated if an organization had a first publication, patent or external funding at *t*, which indicated if it was active for the first time. This is because each organization that is observed in the data for the first time has by definition no prior knowledge, funding or collaborations, but it does have an output. Omitting this variable would give a negative bias in estimators. Third, we added the three dummy variables that indicate if the organization had publications, patents or external funding in 2002. Fourth, a nominal variable that indicated the year was added.

4. Results

Table 1 presents the estimators of the mixed-lognormal Poisson models. The columns '1 year', '2 year' and '3 year' denote the time interval of *t-1*.

The control variables show that knowledge institutes produce more publications than other actor types, while large companies file more patents than other actor types,

[3] We extensively tested for interactions between organization type and collaboration, but this did not give any significant results.

which was expected. Moreover, as expected that the control variables for output in 2002 are significant for patents, but not for publications or external funds. This is because there were a lot of patents in 2002, but hardly any publications or external funds. Through this control variable the model has corrected for these differences.

			Publications						Patents					
			1 year		2 year		3 year		1 year		2 year		3 year	
Random effects	Intercept	Observations (variance)	0.14		0.13		0.11		0.31		0.31		0.31	
		Organization (variance)	0.00		0.00		0.00		0.02		0.02		0.03	
Intercept			-3.35	***	-4.04	***	-4.74	***	-3.34	***	-3.98	***	-4.44	***
Control variables	Actor type	Knowledge institute	ref.		ref.		ref.		ref.		ref.		ref.	
		Large firm	-0.70	***	-0.66	***	-0.66	***	0.25	*	0.25	*	0.23	*
		Small firm	-0.86	***	-0.78	***	-0.70	***	-0.02		-0.03		-0.05	
		Government & intermediaries	-0.47		-0.39		-0.30		-0.33		-0.30		-0.26	
	First output	Publications	3.24	***	3.94	***	4.69	***	-0.26		-0.09		0.02	
		Patents	-0.03		0.11		0.22		3.37	***	4.03	***	4.50	***
		Funding	0.24		0.30	.	0.26		0.64	***	0.65	***	0.68	***
	Output in 2002	Publications	0.02		-0.11		-0.20		0.00		-0.29		-0.29	
		Patents	0.09		0.13		0.28		0.88	***	0.94	***	1.02	***
		Funding	0.11		0.22		0.34		0.71	a	0.68	a	0.64	
	Year	2003	ref.		ref.		ref.		ref.		ref.		ref.	
		2004	0.61	*	0.55	a	0.55	a	-0.07		-0.09		-0.06	
		2005	0.47	a	0.43		0.42		0.06		-0.01		0.00	
		2006	-0.05		-0.05		-0.08		0.26		0.22		0.16	
		2007	0.20		0.15		0.13		0.05		0.02		0.01	
		2008	0.19		0.12		0.09		0.08		0.06		0.05	
		2009	0.28		0.25		0.19		-0.11		-0.14		-0.13	
		2010	0.29		0.25		0.21		-0.95	***	-1.02	***	-1.01	***
Knowledge base	Declarative knowledge	None	ref.		ref.		ref.		ref.		ref.		ref.	
		Publications	0.61	**	1.43	***	2.22	***	-1.13	**	-0.85	a	-1.20	**
		Patents	-0.95	***	-0.57	*	-0.39		0.07		0.69	**	1.06	***
		Publications * Patents	0.84	*	0.59	a	0.39		1.01	*	1.25	**	1.58	***
		Funding	-0.77	***	-0.58	**	-0.63	***	-1.69	***	-1.37	***	-1.12	***
		Publications * Funding	0.87	***	0.68	***	0.78	***	1.53	***	0.88	.	0.81	
		Patents * Funding	1.06	**	0.79	*	0.68	*	1.63	***	1.35	***	1.24	***
		Publications * Patents * Funding	-0.97	*	-0.71	a	-0.67	a.	-1.90	***	-1.45	**	-1.13	*
	Procedural knowledge	Publications	1.54	***	1.44	***	1.38	***	0.36		0.36		0.65	*
		Patents	0.28	*	0.22		0.20		1.49	***	1.46	***	1.47	***
		Publications * Patents	-0.15		-0.13		-0.10		-0.15		-0.29	a	-0.49	**
		Funding	0.72	***	0.64	***	0.64	***	0.85	***	0.80	***	0.70	***
		Publications * Funding	-0.32	***	-0.26	***	-0.26	***	-0.21		-0.18		-0.28	a
		Patents * Funding	-0.11		-0.10		-0.11		-0.24	***	-0.20	***	-0.19	**
		Publications * Patents * Funding	0.07	*	0.06	a	0.06	a	0.12	*	0.14	*	0.20	**
Collaboration		Knowledge institute	-0.17		-0.20	a	-0.14		-0.13		-0.14		-0.15	
		Large firm	0.19		0.19		0.23	*	-0.04		-0.12		-0.11	
		Small firm	0.01		0.03		0.05		0.04		0.03		0.01	
		Government & intermediaries	-0.09		-0.09		-0.12		-0.48	**	-0.59	***	-0.57	**
Number of observations			3784		4080		4270		3784		4080		4270	
Number or organizations			1025		1025		1025		1025		1025		1025	
LogLikelihood			-825.5		-825.3		-803.4		-812.9		-830.8		-838.4	

Table 1: Results of the mixed lognormal Poisson model. a: $p<0.1$, *:$p<0.05$, **:$p<0.01$, ***:$p<0.001$.

4.1. Knowledge base combinations

For all three time intervals there are positive effects of declarative publication knowledge on publication output, which supports Hypothesis 1a. There are also positive effects of declarative patent knowledge on patent output for the 2 and 3 year intervals, but not for the 1 year interval. This lends support to hypothesis 1b, but it shows that this effect takes place after some delay. Moreover, having only declarative patent knowledge, but no declarative publication knowledge has a negative effect on publications. The same is true for having only declarative publication knowledge on patents. This is evidence for that the knowledge bases underlying publications and patents are not entirely the same.

It should be noted that the 2-way interaction term for declarative knowledge indicates how the estimated effect differs from the sum of the two main effects the interaction is comprised of. In other words, it indicates how much the sum of the main effects is larger or smaller than its individual parts. Similarly, the 3-way interaction estimates the difference from the sum of the main effects and 2-way interactions. Adding estimators together gives the total impact of the combined declarative knowledge base. These are presented in Table 2.

Declarative knowledge input			**Publications**			**Patents**		
Publications	**Patents**	**Funding**	**1 year**	**2 year**	**3 year**	**1 year**	**2 year**	**3 year**
0	0	0	0	0	0	0	0	0
1	0	0	0.61	1.43	2.22	-1.13	-0.85	-1.20
0	1	0	-0.95	-0.57	-0.39	**<u>0.07</u>**	0.69	1.06
1	1	0	0.51	1.45	2.22	-0.05	**<u>1.10</u>**	**<u>1.44</u>**
0	0	1	-0.77	-0.58	-0.63	-1.69	-1.37	-1.12
1	0	1	**<u>0.72</u>**	1.53	2.38	-1.29	-1.34	-1.50
0	1	1	-0.65	-0.36	-0.33	0.00	0.67	1.18
1	1	1	0.71	**<u>1.63</u>**	**<u>2.40</u>**	-0.48	0.50	1.25

Table 2: Total interaction effects for declarative knowledge. The underlined bold values are the highest estimates.

A combination of declarative publication and patent knowledge significantly improves both publication and patent output. Thereby, the data supports hypotheses 1c and 1d. The effect becomes weaker for publications and stronger for patents as the time interval increases. Table 2 reveals that the difference between having only prior knowledge in publications and having a combination of knowledge in patents and publications is quite small for publication output. The interaction effect compensates mostly for the negative effect of having only patents. However, there is a substantial effect of having both types of declarative knowledge on patent output for the 3 year time interval. Patent output thus benefits more from having a combination of declarative publication and patent knowledge than publication output. This is in line with the claim that publications are a rich resource to base patents on (Fabrizio, 2009).

As anticipated, having only external funding without any declarative publication or patent knowledge negatively influences publication and patent output. In contrast, having a combination of funding and either declarative publication or patent knowledge is positively related to both types of output. This lends to support to hypotheses 1e and 1f. Table 2 confirms that a combination of external funding and publications leads to more publication output, but this effect is not found for patents. Possible explanations for this difference are that public funding programs are often aimed at developing scientific knowledge or that it is not always allowed to patent findings from publicly funded programs. Finally, the 3-way interaction effect demonstrates that having both types of declarative knowledge and external funding reduces both publication and patent output. However, Table 2 reveals that for publication output this negative interaction merely implies that having all three factors present does not contribute as much as would be expected from the sum of the main effect estimators. For patents, a combination of all three factors leads is negatively related to output. An explanation for this effect could be that extra funding leads to 'over searching' (Laursen and Salter, 2006), which happens when organizations dedicate too much slack resources to exploration.

Consistent with hypotheses 2a and 2b, there is a positive effect of procedural publication knowledge on publication output and of procedural patent knowledge on patent output. There are also some significant effects of procedural publication knowledge on patent output and vice versa, but these are really small and can only be observed for one time interval.

Interaction effects between continuous variables are more difficult to interpret than interactions between dummy variables. To allow interpretation we simulated all possible combinations of the discrete values of all three procedural knowledge variables. We used these combinations as input for the regression equation from Table 1, limiting ourselves to the coefficients for procedural knowledge[4]. Thus we determined which combinations of procedural publication, patent and funding knowledge lead to the highest publication and patent output. In Table 3 we present the results of these analysis by giving the results for all combinations of highest and lowest input values. This includes all optimal points.

Procedural knowledge input			**Publication output**			**Patent output**		
Publications	**Patents**	**Funding**	**1 year**	**2 year**	**3 year**	**1 year**	**2 year**	**3 year**
0	0	0	0.00	0.00	0.00	0.00	0.00	0.00
69	0	0	**<u>6.55</u>**	**<u>6.12</u>**	**<u>5.88</u>**	1.55	1.55	2.76
0	89	0	1.25	0.99	0.91	6.72	6.55	6.60
69	89	0	4.97	4.63	4.80	5.44	2.56	0.03
0	0	33	2.54	2.24	2.25	2.98	2.83	2.48
69	0	33	4.33	4.47	4.29	1.41	1.66	1.11
0	89	33	2.06	1.63	1.36	5.91	6.21	6.12
69	89	33	5.71	5.33	5.66	**<u>9.74</u>**	**<u>9.13</u>**	**<u>8.80</u>**

Table 3: Simulated interaction effects for the maximum values of procedural knowledge. The underlined bold values are the highest estimates.

Table 1 shows that there are no significant negative interactions between procedural publication and patent knowledge on publication output, which leads us to reject Hypothesis 2c. However, Table 3 shows for all time intervals that the highest publication output is achieved by having only procedural publication knowledge, which is evidence for the claim that routines compete. Table 1 shows evidence for that a combination of procedural publication and patent knowledge is harmful to patent output. This effect

[4] This is basically the same calculation as for table 2, only the number of combinations is much larger. Publications ranged between 0 and 70, patents between 0 and 89, and funds between 0 and 33 funds. In total we tested the outcome of 70*90 *34 = 214200 combinations.

becomes really significant for the 3 year interval. Also Table 3 confirms that having a maximum of both procedural publication and patent knowledge leads to a lower patent output. This lends some support to Hypothesis 2d.

Procedural funding knowledge is beneficial to both publication and patent output for all time intervals. This means that at least some parts of the routines that are required for funding are also applicable to publishing and patenting. However, the combinations of procedural funding knowledge and either procedural publication or patent knowledge are negatively significant for all time intervals. Table 3 also shows that the combination of both types leads to a lower output than having only publication or patent routines. These findings support hypotheses 2e and 2f. Finally, the 3-way interaction effects reveal small but significant positive effects on publication output. The same effect is found for patent output, but stronger. Table 3 demonstrates that the difference in 3-way interactions ensures that the maximum number of publications is achieved by only investing in the procedural publication knowledge, while the maximum number of patents is achieved by investing in all three types of procedural knowledge.

4.2. Collaboration

There are hardly any significant results for collaboration. Collaborating with knowledge institutes does not increase publication output, which is in line with claims by Lee and Bozeman (2005), but contradicts hypothesis 3a. Nor does it contribute to patent output, which rejects hypothesis 3b. Collaboration with a large firm can increase publication output, but this result is only significant for the 3-year interval and quite small. It does lend some support to hypothesis 4a. Collaboration with large firms has no effect on patent output, which rejects hypothesis 4b. This results seems to contradict findings from earlier studies (see Powell et al., 1996; Ahuja, 2000; Schilling and Phelps, 2007). However, we note that this is not the case since these studies are all based on a social network perspective that quantifies different network characteristics. We have not done so in this study[5]. Notable is that collaboration with governance & intermediaries has a very strong negative effect on patent output. This can be due to the fact that these type of organizations do not have knowledge development or commercialization as their core mission.

A possible explanation for lack of results for collaboration can be that the effect is already explained by declarative and procedural knowledge. For this reason we also estimated models with only the control variables and the collaboration dummies. These models confirmed the effect that collaboration with multinationals enhances publications for all time intervals, but yielded no further insights.

5. Conclusions

In this paper we studied *the influence of knowledge bases that combine different types of knowledge and prior collaborations on the publication and patent output of organizations in the Triple Helix.* Thereby we investigated the micro-incentives for Triple Helix knowledge production.

[5] We tested for effects of several network characteristics, but this yielded little consistent results.

Our main result is that the incentives to engage in Triple Helix knowledge development come from the organization's own prior declarative and procedural knowledge bases, and not from collaboration with other parties. Overall, this suggests that it is possible to have a long lasting Triple Helix in which actor types collaborate and where the traditional distinction between roles partly fades away. However, our analysis adds some important nuances. Knowledge institutes that wish to maximize their publication output need have a combination of both declarative knowledge bases, external funding, and procedural publication knowledge. They do not need to focus on developing patenting or funding routines, since these compete with publication routines. Collaborating with large firms is beneficial for knowledge institutes. Not only does it lead to more publications, it also allows knowledge institutes to leave the development of patent and funding routines to firms. For firms these routines increase patent output. Our results show that collaboration with knowledge institutes is not directly attractive to firms, but it also has no negative effect on patent output. However, large firms can benefit from a collaboration with knowledge institutes in other ways, for example by gaining access to other resources like human capital (e.g. future employees) and scientific credibility. Collaboration with knowledge institutes allows firms to be more actively engaged in the publication process, which enables them to develop publication routines as well. This division of labor optimizes for both actor types the output desired by their institutional environment and maximizes the innovative output from the Triple Helix. A stable Triple Helix thus has collaboration between knowledge intensive actors from academia and industry as it's nexus. Our analysis shows no advantages for collaborating with small firms. Finally, since collaborating with governments & intermediaries leads to less patents, it is not attractive for firms to collaborate with this actor type to develop new knowledge. However, given that their regulatory tasks, this type of actor might be beneficial when the new innovations are being demonstrated or implemented.

6. Discussion

There are a number of limitations in our study that warrant further discussion. First, in our theory and analyses we used an Organizational Learning perspective. This resulted in the important distinction between declarative and procedural knowledge. However, it also placed the focus primarily on patent and publication output as organizational aspirations. Although this idea is prominent in Triple Helix literature, it ignores other benefits that can come from the Triple Helix, such as access to human, or social capital or legitimacy. Future research should include these other benefits as well. Second, we limited ourselves only to the domain of carbon capture. The major advantages of this choice was that data was available, and that we were able to rule out influence from other domains. As argued above, carbon capture is a critical case where Triple Helix knowledge development was expected. The incentives for the Triple Helix are probably even more misaligned in domains where there is a larger distance between fundamental knowledge development and application. However, focusing only on one domain also limits the external validity of our results. Future studies should focus on other domains to validate these findings. A third limitation is that we did not look at the content of the publications and patents. This might have allowed us to assess how much knowledge was developed and could have helped us to improve our measure of declarative knowledge. We now used dummies to measure declarative knowledge, which means that we assessed if the organization had sufficient knowledge to publish or patent, we do not know how much declarative knowledge the organization exactly had. Analyzing content could have alleviated this problem, but would have required an extensive qualitative analysis of all publications, patents and funding applications. Next to the sheer amount of work involved in analyzing thousands of documents in this manner, is it also next to impossible to quantify the contribution of each. Therefore we chose not to do this.

Most of the policy implications follow directly from the conclusions described above and shall not be repeated here. However, the most important policy implication follows from the question if government funding can support the Triple Helix. Our results imply that the initiative to obtain such external public funds is best placed at firms in industry, who benefit most from developing these routines. To promote triple Helix knowledge development, a condition for obtaining these funds should be collaboration between the firm and knowledge institutes. In this manner policy makers can facilitate optimizing both types of knowledge development in the Triple Helix.

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