Company-University Collaboration Types As A Determinant For Knowledge Transfer

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Abstract

This paper develops a framework for a novel measurement of outcomes of different types of company-university collaboration. We test whether the level of formalization and the type of interaction influences the outcomes, in particular knowledge transfer. We extend the existing research by applying novel statistical computational methods form the field of natural language processing to identify the knowledge transfer. We investigate how the level of formalization of collaboration affects the knowledge transfer between universities and companies. Preliminary results indicate that we are able to identify additional forms of knowledge transfer and give companies insights into their potential benefits from different types of relationships. We propose a new perspective that enables companies to shape and adapt their external knowledge search as effective as possible.

Introduction

Universities have traditionally key roles in national R & D infrastructures and are today key players for research driven inventions (Cohen et al. 2002). Government and/or EU financing incentives, like the EU Research Framework Programs[1] increased the interest and value of university-industry joint research projects. Companies use them to increase their expertise using external knowledge sources (Fabrizi et al. 2016, Azagra-Caro et al. 2009). Hence, interaction between firms and universities is a key aspect for research driven innovation todays industries.

Changes in the last decades in regulations and policies increased collaborative activities of universities and companies (Geuna & Rossi 2011). Most fostering aspects are the intensified public funding, available tax reduction schemes, changes in the intellectual property rights (IPR) and access to vast interdisciplinary research facilities at the universities (Lissoni et al. 2009, Geuna & Rossi 2011, Munari et al. 2016). Relationships and collaboration between companies and universities differ greatly in their structures, intensity and quality, leading to varying outcomes and benefits for the companies (D'Este & Patel 2007). Knowledge transfer (KT) includes the acquisition and utilization of novel technologies or innovations. Among scholars most discussed are benefits from university collaboration when they generate either inventions that are commercialized, including licenses, royalties and patents or create any other outcome that is IPR protected (Arundel & Bordoy 2008, Crespi et al. 2011, Rothaermel et al. 2007) .

[1] (European Commission 2016)

Since only a small proportion of KT is actually directly commercialized (Agrawal & Henderson 2002) an expansion of the measurement is indispensable. Thus, we propose an additional perspective to identify and verify outcomes of differently structured relationships between companies and universities. As companies often invest highly into university collaboration and by far not all investments lead to potentially commercializable innovations(Jensen et al. 2003, Cohen et al. 2002) we aim to assess whether the level of interaction transforms the level of KT for the companies.

To identify the levels of KT we use new computational metrics: *text mining*. We trace patterns from texts related to university research, university publications, and texts from companies, company homepages, to identify commonalities. Novel statistical methods allow us to identify common content and therefore detect KT. We aim to show that companies in qualitatively different relationships to universities can very well harvest commercially relevant outcomes, which are displayed on the companies online presences.

Theoretical framework

In order to be fruitful the collaboration between universities and companies various determining factors have been identified. This study, however, aims to investigate two main factors directly related to the company perspective of the matter. First we aim to investigate the influence of the type of the relationship between company and university (Ankrah et al. 2013). Second we investigate whether company features like absorptive capacity of the company, influences the potential outcome of the collaborations (Fontana et al. 2006).

First, the absorptive capacity of a company, as originally defined by (Cohen & Levinthal 1990) is depending on a firms ability "to recognize value of new, external information, assimilate it and apply it". This basic understanding shows that the absorption of university research by a company might not depend only on their interaction, but also on the company‘s features. In the literature on university-industry relations different levels of formalization can be distinguished, including: i) longstanding formalized research collaboration (Bruneel et al. 2010, Perkmann & Walsh 2007) [2],ii) medium and short-term formalized research collaboration (Hagedoorn et al. 2000) [3], iii) direct formal relationship not based on research related activities (Link et al. 2007), iv) having a common partner with a university resulting in an indirect relationship, v) confirmed geographical proximity to the university (Arundel & Geuna 2004).

To capture the benefits of university-industry collaboration outcome it is common to measure the transfer of knowledge, described as technology transfer or knowledge transfer (KT)(Agrawal 2001) [4]). KT is used to assess the implications of formalized and also informal collaboration (Nomaler & Verspagen 2008, Freitas et al. 2013). Two main distinctions between for KT can be made: formal and informal (Grimpe & Hussinger 2013).

Formal knowledge transfer is clearly defined by the outcomes of interac-

[2]We set the time frame for more than 3 years and/or recurrent contracting.

[3]We set a maximum of 3 years without subsequent contracting

[4]The term Knowledge transfer will in the following be used interchangeably for Technology transfer

tions, which are the result of direct formal ties (contracts) between the partners. Formal KT comprises all "transfer mechanisms that embody or directly result in a legal instrumentality such as, for example, a patent, license or royalty agreement" (Link et al. 2007) [p. 642]. Current quantitative research focuses mainly on formal KT measurements, looking at the outcomes including profits generated by patents, spin-outs, royalty and/or licenses agreements(Grimpe & Hussinger 2013). Hereby the actual KT is not fully captured (Agrawal & Henderson 2002), because many joint activities do not results in an IP protected innovation, but the knowledge might still be transferred.

Informal knowledge transfer "is facilitating the flow of technological knowledge through informal communication processes, such as technical assistance, consulting, and collaborative research" (Link et al. 2007) [p. 642]. It comprises any form of KT that does not imply a IPR regulated outcome and might not be the result of a formalized relation ship. Informal KT is not easily measured and is mainly identified via in-depth case studies (Broström 2012), but the actual outcomes are no quantitative measures.

Types of collaboration

We aim to identify the characteristics of companies that would suggest most higher observable KT taking into account the type of relationship. First we aim to assess whether the observable KT is related to the type of commitment in the company-university relationship.

> ***H 1a:*** *Longstanding collaboration, including large research projects or recurring collaboration, (potentially with formal KT) result in* ***high*** *observable KT for the collaborating company.*

However, given the varying absorptive capacity of companies, we suggest to diversify the picture by focusing on more lose relationships. Further differentiation between contract based connections is necessary to identify further potential benefits.

> ***H 1b:*** *Short-term research collaboration with no subsequent contracting result in* ***high*** *observable KT for the collaborating companies.*

> ***H 1c:*** *Short-term non research related contracts result in* ***high*** *observable KT for the collaborating companies.*

Consequently this model has to be extended to companies with no direct collaboration with the university. The notion of knowledge spillovers in proximity of universities (Drucker & Goldstein 2007, Arundel & Geuna 2004) lead to the following assumptions:

> ***H 2a:*** *Collaboration with companies that are collaborating with universities results in* ***medium*** *or* ***high*** *observable KT.*

> ***H 2b:*** *Companies, which are located in the geographical proximity of the university, receive* ***low*** *or* ***medium*** *observable KT.*

Sample and Method

As our dependent variable we propose **observable knowledge transfer**.Due to the limitations of the KT concepts we seek to include a new metric that allows us to capture any type utilized knowledge coming from a university independent from the transfer channel or formalization of the relationship. For the purpose of this study we define observable KT as KT that can be identified via text mining algorithms, which allow comparing university research outcomes (publications) with company online presences (websites, social media sites and annual reports). Commonalities in the content indicate a commercial use of research. The level of observable KT is ranked within the four quartiles of the given identification level of KT, which is defined by intensity of the expressed overlap between the contents. A company ranked in the first quartile (identified KT lower than 25%) has low KT, companies ranked in the 2nd and 3rd quartiles (from 25% to 75%) will be seen as intermediate and every company ranked in the 4th quartile (above 75%) will be considered having a high KT. All remaining companies are considered as having no observable KT.

Text Samples

We collected relevant text data representing a) company profiles and b) university research knowledge. We use publication data from the Technical University of Denmark (DTU), representing the research output and a collection of online texts from company websites.

Between 2006-2017 DTU had a total of 78,627 publications and provides 43,745 academic abstracts and 23,402 full-text publications. Relevant publications have to be co-authored by at least one member of the university and need to have English text. We divided the texts into 21 separate research fields including mathematics, biochemistry, chemistry, civil engineering, electrical engineering, energy conversion, environmental engineering, management, mechanics, nanotechnology, photonics, physics, biology, transport, wind energy, nutrition science, aquatics, space research, veterinary, nuclear technologies and one with diverse entries.

Companies with any type of contract between 2006 and 2016 were considered to be relevant, as well as partners of these companies (second degree partners). We identified 1256 companies and 768 second degree partners [5].Relevant websites have to display a Danish registry number of the firm (CVR number) and partly English content. The content was stored as HTML files.

Control Variables

As control variables for an even comparison of the companies we propose: a) the firm size (defined as number of employees), b) the company's type of industry (using NACE codes [6]), to account for low and high tech industries and c) company employees educational level; information that can be retrieved from the national Danish statistics bureau (Statistics Denmark).

[5] To identify indirect partner firms, we created a network based on hyperlinks between websites.

[6] `http://ec.europa.eu/competition/mergers/cases/index/nace_all.html`

Text mining Methods

We use statistical tools from the field of natural language processing (NLP) to identify text correlation and similarities (Indurkhya & Damerau 2010, Collobert et al. 2011).We apply common text pre-processing steps, which convert unstructured raw text into statistical useful units (Paukkeri & Honkela 2010).

For pattern recognition we use term-frequency, inverse document frequency (TFIDF) a simple numerical indexing method, which has proven to give promising results. It allows identifying the most relevant words by extracting the words most unique to a given text(Zhang et al. 2016).

For content identification we use latent dirichlet allocation (LDA), a fully automated method based on statistical learning. It identifies latent (unobservable) content structures (Blei et al. 2003, Griffiths & Steyvers 2004) and translates them into topics. These topics enable classification of text content.

We use word2vec (w2v) to further identify communalities between the texts and ensure computational optimal outcomes. It describes methods that are used to reconstruct the contexts of words by taking texts and producing a vector space. Word vectors are assigned by contexts and so related words are located in close proximity to one another(Rong 2014). We use this to identity strongly related words and texts. The combination of our methods ensures minimal manual work.

Conclusion

The study aims to achieve a more coherent understanding about the benefits and innovative potential of university-company interactions. Our approach allows to gather a more coherent picture about the benefits of university collaboration for companies. The assessments of company-university collaboration outcomes have been predominantly focused on the measures of formal knowledge transfers (Salter & Martin 2001, Teixeira & Silva 2013, Jensen et al. 2003). This study has the potential to add a new perspective to current metrics and thus opens insights into the variation in outcomes of different types of relationships. This can be used by the industry to re-asses their engagements and activities. The results are also likely to influence the common view on university- company collaboration, as it can provide an additional measure for acquired and used knowledge obtained from a university.

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