Titre: Title:	University-Industry partnerships in the smart specialisation era
Auteurs: Authors:	Arman Yalvac Aksoy, Davide Pulizzotto, & Catherine Beaudry
Date:	2022
Type:	Article de revue / Article
Référence: Citation:	Aksoy, A. Y., Pulizzotto, D., & Beaudry, C. (2022). University-Industry partnerships in the smart specialisation era. Technological Forecasting and Social Change, 176, 121438 (12 pages). https://doi.org/10.1016/j.techfore.2021.121438

Document publié chez l'éditeur officiel
Document issued by the official publisher

Titre de la revue: Journal Title:	Technological Forecasting and Social Change (vol. 176)
Maison d'édition: Publisher:	Elsevier
URL officiel: Official URL:	https://doi.org/10.1016/j.techfore.2021.121438
Mention légale: Legal notice:	

Noname manuscript No.
(will be inserted by the editor)

University-Industry partnerships in the smart specialisation era.

Arman Y. Aksoy · Davide Pulizzotto · Catherine Beaudry

Received: October 22, 2021/ Accepted: date

Abstract The effect of diversification versus specialisation, as well as the technological proximity of R&D partners have been at the heart of innovation studies. Articles in this field either take a regional or company point of view. During the last few decades, studies on the relatedness of knowledge and its importance for innovation and commercialisation have pushed policy makers towards clustering strategies such as smart specialisation in the EU and the Innovation Supercluster Initiative in Canada. Interestingly, universities as the source of new knowledge and technologies have been absent from this literature as the focal point. This paper aims at filling one of the missing links between the literature on technological relatedness and university research commercialisation. We use patent and licence data from the USPTO and the AUTM survey to study the effect of patent portfolio composition on university research commercialisation. We use Shannon's entropy index to differentiate between the effects of related and unrelated diversification on the number of licences generating income. Our results show a positive association of related diversification with the number of licences, but none for unrelated diversification. Furthermore, technological proximity follows an inverted-U shaped association with the number of licences generating income. However, the effect is observed only for smaller universities. We conclude that the curvilinear association is the result of cognitive distance and the absence of boundary spanners. Our findings indicate that regional policy makers intending to use universities as an engine for innovation and regional economic growth should consider policies and initiatives aimed at bridging the cognitive gap between university and industry by either increasing technological proximity or reducing cognitive distances by financing boundary spanning organisations.

JEL Classification:

Keywords:

Arman Y. Aksoy
E-mail: arman.aksoy@polymtl.ca
· Davide Pulizzotto
E-mail: davide.pulizzotto@polymtl.ca
· Catherine Beaudry
E-mail: catherine.beaudry@polymtl.ca
Polytechnique Montreal, 2900 Edouard Montpetit Blvd, Montreal, QC H3T 1J4

1 Introduction

The literature on innovation management has identified the recombinant co-creative and path-dependent nature of the innovation process (Dosi, 1982; Cohen and Levinthal, 1990; Porter, 1998). These gave a solid footing for more complex theories and models explaining the triple helix of government-industry-university cooperation and the importance of innovation ecosystems for successful innovation and economic growth (Etzkowitz and Leydesdorff, 2000; Geels, 2002). Policy-then started introducing policies and programmes based on these studies such as smart specialisation in Europe and the Innovation Superclusters Initiative in Canada. However, researchers argue that these new policies are still lacking empirical evidence and are based on anecdotal evidence (Balland et al., 2019). The aim of this paper is to contribute to this discussion from a university standpoint. More specifically, we aim at understanding how the university patent portfolio composition affects its licensing activity.

Universities as a source of technological innovation play an important role in the commercialisation of new knowledge through licensing (Rothaermel et al., 2007a). There is a large and vibrant literature dealing with university research commercialisation going back to the 1980s (Geisler and Rubenstein, 1989; Rothaermel et al., 2007a; Nsanzumuhire and Groot, 2020). These studies have identified various internal and external factors that can enable or hinder university-industry knowledge transfer. However, they have long omitted the potential effect of patent portfolio composition and the synergy that can be created between the patent portfolio of the university and the local knowledge base (De Wit-de Vries et al., 2019).

The type of knowledge is known to influence the success rate of knowledge transfer. More specifically the diversity of the knowledge base and cognitive proximity between partners are seen as crucial to the endeavour (Boschma, 2005; Ceipek et al., 2019). Recent decades have seen the introduction of the relatedness concept pushing our understanding of diversification and proximity even further (Hidalgo et al., 2018). Researchers have started to study the effect of related diversification and found that the company's knowledge stock diversity in itself is not sufficient and requires relatedness to be more efficient be it for financial or R&D performance (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017; Ceipek et al., 2019).

We study knowledge relatedness in two aspects, university and state technological diversification, and the university technological proximity to its local state. The effects of both technological diversification and proximity are disputed in the literature, while some argue that they have linear positive association with innovation and financial performance, others have found curvilinear effects (Knoben and Oerlemans, 2006; Ceipek et al., 2019). Researchers have reasoned that this is the result of coordination cost, fear of product cannibalisation, and cognitive lock-ins related to the recombinant nature of innovation among others. Little is known on the effect of technological diversification and proximity on university research commercialisation. Unlike companies, universities cannot experience the direct benefits of innovation through improved sales or cost reduction. Nonetheless, both will absorb and transform new knowledge into commercial opportunities. This is best illustrated by technological diversification leading to more patenting in both cases (Acosta et al., 2018; Ceipek et al., 2019). Hence, while companies market new or improved offerings, the universities generate new licences.

In summary, the objective of this paper is to uncover the effects of university and state patent portfolio diversification and knowledge relatedness on university licensing activities. The remainder of this paper is organised as follows. Section 2 presents relevant studies and Section 3 our conceptual framework. Section 4 introduces the data and methodology used. The results are discussed in Section 5 and Section 6 concludes.

2 Literature review

2.1 University-Industry knowledge transfer

University-industry knowledge transfer is known to be a complex iterative process with multiple potential channels such as R&D partnerships, R&D contracts, personel exchange, publications, patents, and licensing among others (Nsanzumuhire and Groot, 2020). Recent literature reviews have identified some major enabling factors and barriers to university-industry knowledge transfer (Mascarenhas et al., 2018; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020). These can be broadly classified into governance-related and relational-related factors.

Governance-related factors are linked to the importance of R&D and knowledge transfer for the partners, their cultures, incentives, etc. Relational factors encompass absorptive capacities, boundary spanners and trust between the parties (Mascarenhas et al., 2018; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020). These factors influence the number of opportunities created and the rate of capitalising on them (George et al., 2016). Capitalisation could further be separated into the will to transfer and the ease in doing so (Cohen and Levinthal, 1990; George et al., 2016).

The main factor predicting successful knowledge transfer is related to governance. The size of the company and its R&D spending are known factors influencing its propensity to collaborate with universities (Foster et al., 2019). Size is also known to influence the outputs of the universities be it the number of publications or licences (Rothaermel et al., 2007b). The effect of governance goes beyond the allocation of R&D spending, the importance given to transfer by the management, the autonomy of researchers, royalties, rules and regulations are also determining factors for knowledge transfer efficiency which can help the transfer in some cases and hamper it in others (Mascarenhas et al., 2018; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020).

The second factor influencing knowledge transfer is considered to be absorptive capacity (Cohen and Levinthal, 1990). Absorptive capacity of the industrial partner and the knowledge exchange between parties can be increased by allocating resources for boundary spanners such as technology transfer offices (TTO), incubators, collaborative research centres, and university research parks (Nsanzumuhire and Groot, 2020). These boundary spanners are described as increasing similarities by setting frameworks for cooperation and thus increasing similarities in behaviours and goals. Furthermore, personel exchange and training are also cited as a viable option for boundary spanning and increasing absorptive capacity (Mascarenhas et al., 2018; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020). Besides absorptive capacity, another factor that can influence knowledge transfer is the trust between partners. Key elements necessary for trust include prior cooperation and similarities in terms of education, organisation, behaviours, and goals. Researchers also highlight the positive influence of university reputation and open science in that matter (Mascarenhas et al., 2018; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020).

2.2 Technological diversification and proximity

Technological diversification has been the subject of multiple studies since Penrose's (1959) seminal work. According to Ceipek et al. (2019) research on the subject has seen four phases since its inception in the 1980s: definition of the concept, exploration of the effects on financial outcomes, definition of the effects on innovation, and finally, study of moderating effects. The authors reported that the literature systematically separates technology and product diversification and indicates an inverted u-shape relationship between diversification, and company efficiency and innovation capabilities.

The literature on diversification can further be divided into two categories, those dealing with path dependency and those focusing on company performance (Kim et al., 2016). Recent articles have started to join the two approaches and shown that diversification in core fields is positively correlated with performance while diversification in unrelated non-core fields has no effect (Ceipek et al., 2019). The rationale behind this outcome is the difference between related and unrelated diversification. Companies can diversify for different purposes such as knowledge sourcing, technological risk reduction, and financial gains (Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). On the one hand, diversification into unrelated fields can help counter cognitive lock-ins and diminishing return effects while bringing resilience to the company. On the other hand, diversifying into multiple related fields can help companies take advantage of economies of scope (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017).

The diversification and relatedness of the knowledge base can be further extended to local actors. The effect of technological diversification versus specialisation at the regional level depends on both the level of industrial and geographical aggregation of the data (Beaudry and Schiffauerova, 2009). Previous studies have shown that regions with Marshal (specialisation) and Jacob (diversification) externalities differ in their innovation behaviour.

A specialised cluster encourages labour market pooling and spillover while also reducing the cost of R&D by spreading the cost over multiple companies. However, this comes at the cost of increased wages and employee turnover as companies will compete for talent. Furthermore such concentration might also create lock-in situation and negatively impact innovation industries (Beaudry and Schiffauerova, 2009).

In contrast, a more diverse industrial cluster can help counteract the negative sides of the Marshal externalities as companies will benefit from spillovers from other industries be it through imitation or recombination as innovations and ideas can be more easily sourced between similar yet different industries (Beaudry and Schiffauerova, 2009; Lee and Sohn, 2019).Beaudry and Schiffauerova (2009) noted the effect of data aggregation on the manifestation of the specialisation and diversification externalities. The authors expressed that more granular data leads to researchers observing specialisation effects while more aggregate data leads to diversification effects taking over.

Other aspects of the R&D partners can also play a role in the collaborations success. Proximities are dependent of the position of the actors in two types of space, Physical and Cognitive spaces (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015). Multiple different descriptions and classifications of cognitive proximities exist. For instance, social proximity has been described as relational proximity or personal proximity, while others have aggregated many forms by classifying them as non-spatial proximities (Knoben and Oerlemans, 2006). Hence, multiple types of proximities have been identified alongside geographic proximity, these include cognitive, organisational, social, institutional, technological, and cultural proximities (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015).

3 Conceptual framework

Our framework borrows from the business management literature. We believe that universities located in economically developed regions and those aligned with the needs of the local economy should be able to negotiate more licensing deals that generate income. We expect diversified and specialised universities to behave differently, and proximity to play a central role in determining the number of licenses generating income. Our framework is based on two (2) main arguments, the first is the necessity of a broad knowledge base for innovation and opportunity recognition (Ceipek et al., 2019; George et al., 2016). Thus, a more diversified university and local economy should be positively associated with the number of licenses generating income. The second argument is the necessity of a market pull component for the commercialisation of the innovation. Hence, the proximity of the university patent portfolio to the local region's patent portfolio should be an indicator of both a market for the knowledge since companies are active in the field, and sufficient absorptive capacities to commercialise the university research results (Cohen and Levinthal, 1990).

While we could not find studies on the effect of technological diversification on university research commercialisation, there is a large literature dealing with firm level technological diversification (Ceipek et al., 2019). Studies on diversification has argued for a long time on its effect on firm performance. While some defended that its effect is positive, others supported that it is negative, yet others found curvilinear relationships (Kim et al., 2016; Chen and Xie, 2018; Ceipek et al., 2019).

For instance, Miller (2006) showed the positive correlation between patent scope diversity and firm market value. Similar reports were given by Lee et al. (2017) and Chen et al. (2013) on the positive association of technological diversification and financial performance. However the authors also note the moderating effect of slack resources and report that more diversification with excess resources can lead to inefficiency.

Technological diversification is also described as being correlated with R&D spending and the number of patents for European firms of diverse sizes and active in various industries (Garcia-Vega, 2006). These findings were also supported by Quintana-García and Benavides-Velasco (2008) who showed that patent class diversification had a positive effect on the number of new patents. The relationship between the number of patents and diversification was also endorsed by Acosta et al. (2018) reporting that in the European context, a more diversified patent portfolio leads to more patenting for universities.

However, the relationship between diversification and research commercialisation might not be straightforward. For instance, Giuri et al. (2019) pointed out that in Europe, universities have different goals. Generalist low prestige universities focus on local development while specialised high prestige universities focus on income generation. Hence, we postulate that:

Hypothesis 1*: Technological diversification is positively associated with the number of licenses generating income granted by the university.*

Recent studies have pointed to the importance of relatedness (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). They argue that diversification on its own is not sufficient for success and that entities must strive to foster related diversification as this will have the greatest impact on innovation and commercialisation efficiency (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). The literature suggests that diversification positively influences financial performance. However, this relation is moderated by the diversification type as relatedness will positively affect the outcome (Ceipek et al., 2019).

For instance, Chen and Chang (2012) reported that for American pharmaceutical companies, related technological diversification has a positive effect on technological competence while unrelated diversification has an inverted U-shaped effect. The authors reached similar conclusions with the Taiwan's semiconductor industry (Chen et al., 2012). Diversification helps building new technological capacities which in turn can convert slack resources into company growth by enhancing their offering. They argued that growth through diversification is more efficient than growth in their core field due to the law of diminishing return. They further posited that related diversification is more desirable as it creates opportunities to share R&D resources and facilitate implementation of new knowledge. This is in contrast with unrelated diversification which can increase resource investment in disparate fields, and thus, increase coordination and integration costs through excessive complexity. Their results show that related diversification has a monotonic positive relationship to company growth while unrelated diversification has an inverted U-shaped relationship.

These results are also supported by the case of Korean manufacturing firms (Kim et al., 2016). Kim et al. (2016) reported that diversification exhibits an inverted U-shaped association with firm growth. They further showed that specialisation can facilitate unrelated knowledge exploitation due to the expertise the company develops in conducting R&D. They argued that the literature showed the positive effect of diversification on innovation through R&D expenditure and patent count. They also acknowledged that the positive correlation between technological diversification and firm growth and performance is offset by the decreasing returns on excessive diversification. This also holds true for the case of the Korean IT sector (Kook et al., 2017). Unrelated diversification is harder to exploit for smaller firms while related diversification has always a positive effect on financial performance and innovation capabilities. The authors argued that companies should first specialise intensively and then diversify into related fields accordingly as they grow to maximise the benefits.

Similar conclusions can be drawn for other studies. For instance, Pugliese et al. (2019) show that coherent diversification is conductive to higher labour productivity for European firms. Similarly, Choi and Lee (2019) report the inverted-U shaped effect of technological diversification on R&D productivity when accounting for knowledge spillovers and core-technology competences. Hence we argue that relatedness is an important factor influencing the effect of diversification on university licensing results and posit our second hypothesis:

Hypothesis 2*: Related Technological diversification has a stronger positive association with the number of licenses generating income granted by the university than unrelated technological diversification.*

Specialisation and technological proximity is at the heart of the debates on Europe smart specialisation policies and should be of great concern for Canadian policy makers dealing with the Innovation Superclusters Initiative. As noted by Bonaccorsi (2017), excellence although necessary, is not sufficient for proper innovation commercialisation. According to the author innovation commercialisation also needs critical mass of research, local absorptive capacities, co-specialisation and proper intermediaries to solve the search problem (Calcagnini et al., 2016; Bonaccorsi, 2017).

In fact, the importance of technological proximity for successful innovation and knowledge transfer was already reported by previous research (Boschma, 2005). For instance, Autant-Bernard (2001) showed the positive association of technological proximity for knowledge transfer between French departments. The positive association was only observed for close neighbours indicating the moderating effect of geographical proximity on knowledge spillovers between departments. The authors concluded that the positive externalities were linked to human capital movement rather than R&D expenditure. The positive externalities of technological proximity is further supported by micro-data on biotechnology firms in the Paris region (Boufaden et al., 2007). The authors reported on the positive effect of technological proximity on patenting and the positive moderating effect of collaboration with local universities.

The evidence of the positive effect of technological proximity on innovativeness is further extended to larger geographies in different contexts such as the Chinese regions. Chen and Xie (2018) reported an inverted U-shaped relationship between technological proximity and the number of university–industry joint patents. They further report a moderating effect of institutional distance, geographical distance, and the national ranking of the university on the relationship. In view of this evidence, we propose our last hypothesis:

Hypothesis 3*: Technological proximity between the university and the state in which it is located is positively associated with the number of licenses generating income granted by the university.*

4 Methodology

4.1 Data

Data on TTOs and their respective universities was obtained from "The Statistics Access for Technology Transfer" (STATT) database of "The Association of University Technology Managers" (AUTM). The database is the result of a voluntary yearly survey and contains 5280 observations for 254 North American universities that comprises yearly surveys between 1991 and 2018. We use a subset of the data due to missing observations for some of the variables of interest. Furthermore, participating universities either did not fill the survey completely every year or did not participate for some others. We further reduced the number of universities due to methodological concerns discussed in the limitation section. Hence, we obtain a highly unbalanced panel of 2789 observations over 212 universities for the years between 1997 to 2018. The mean number of observation is 20.79 and the standard deviation is 9.02 with a minimum of 1 observation and a maximum of 28.

We sourced our patent data from the USPTO website . The database contain all information for each patent granted up to 1978. There were a total of 2565197 patents granted to U.S. entities and 69853 patents granted to Canadian entities between 1991 and 2015 through the USPTO.

Patent matching was performed using the university names present in the STATT database. In the first step, the names were searched in the USPTO database and matched using the Levenshtein distance (Medvedev and Ulanov, 2011). Patent assignees known to be outside of the U.S. or in other states than the one the university is located in were ignored. Only the best match was reported by the algorithm. In the second step, the list was manually checked to remove false positives and to re-categorise mismatches. Finally, the results were added to the first list and used as the starting point for the next loop. The process was repeated until no new names appeared in the results. We then used regressions to verify the accuracy of our results by observing the yearly patent count for each university reported in the AUTM survey compared to the patent count obtained from the USPTO through our algorithm. We obtained an R value of 0.95 showing a high correspondence between AUTM and USPTO patent counts.

We converted all monetary values to Canadian dollars using purchasing power parity data obtained from the OECD. The conversion ensures that the monetary values between the Canadian and U.S universities are comparable. We further converted these values into 2015 dollars using the consumer price index (CPI) of each respective country provided from the same organisation. The data consist of a list of coefficients for the years 1991 to 2018.

4.2 Variables

4.2.1 Dependent

Our dependent variable is sourced from the STATT database:

nbLicGenInc represents the number of licenses generating income. Licensing is one of the later steps of the linear model (Mendoza and Sanchez, 2018). The average license per university has steadily grown through the survey period. We use this variable to measure successful technology transfer from university to its partners.

4.2.2 Independent

We source our independent variables from the USPTO database. We calculate three (3) variables based on the entropy index devised by Shannon (1948) and adapted to industry classifications by Jacquemin and Berry (1979). The indicator was recently used to study the effect of related diversification on company efficiency using patent data (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). These are the technological diversification (TD), the related technological diversification (TD_{REL}) and the unrelated technological diversification (TD_{UNREL}). We use the section and the subclass levels of the International Patent Classification (IPC)[1] of the World Intellectual Property Organisation (WIPO) to calculate these values [2].

TD, the Technological Diversification, represents the overall technological diversification of the university (TDU) and the state (TDS). Diversified universities are more likely to be situated in diversified states (cf. Fig. 1). It is the sum of related and unrelated diversification, and is calculated using the subclass of the patents with the following formula:

$$TD = \sum_{i=1}^{I} P_i ln(\frac{1}{P_i}) \quad (1)$$

Where I is the number of subclass and P_i is the number of patents in subclass i granted to the university (TDU) or a resident of the state (TDS) that year.

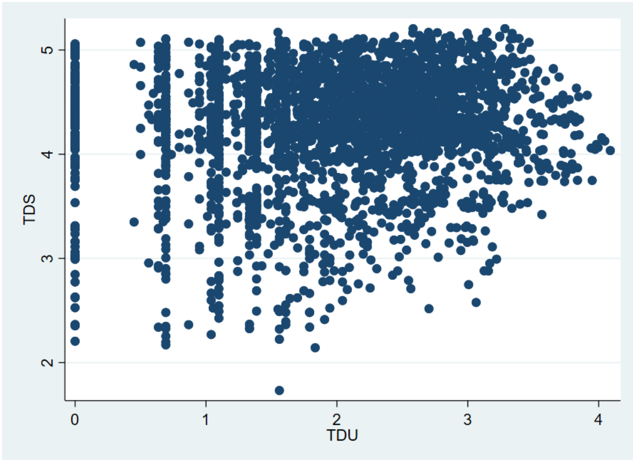

Fig. 1 University and state diversification

TD_{UNREL}, the Un-Related Technological Diversification, is calculated using the section of the patent classification. Universities and companies can have patents in the same section without having any patent in the same class or subclass. The assumpition of relatedness is based on Shannon (1948) entropy index and its adaptation by Jacquemin and Berry (1979) to industry classifications. More recent works have used similar approaches with patents (Chen et al., 2012; Kim et al., 2016). This indicator should help us study the effect of the patent portfolio coherence on our dependent variables. The formula used to calculate TD_{UNREL} is as follows:

$$TD_{UNREL} = \sum_{s=1}^{S} P_s ln(\frac{1}{P_s}) \quad (2)$$

[1] The IPC uses a five (5) level classification with the highest level being the Section, followed by the Class, the Subclass, the Group, and finally the Complete classification symbol

[2] This decision was based on two (2) reasons, first, this allows for comparison with previous studies, second, previous studies have shown that the best level to study the effect of diversification versus specialisation is at mid level of data aggregation (Beaudry and Schiffauerova, 2009).

Where S is the number of sections and P_s represent the number of patents in section s granted to the university (TDU) or a resident of the state (TDS) that year.

TD_{REL}, the Related Technological Diversification can be calculated as the difference between TD and TD_{UNREL}. It helps determine the relatedness of the patent portfolio by weighting the overall diversification using both the section and subclass of the patent. The assumption is that patents in different subclasses but the same section are more related than patents in different subclasses and sections Shannon (1948); Jacquemin and Berry (1979); Chen et al. (2012); Kim et al. (2016). We use the following formula to calculate it:

$$TD_{REL} = \sum_{i \in s} \frac{P_i}{P_s} ln(\frac{P_s}{P_i}) \tag{3}$$

Prox refers to the degree of technological proximity between the university's patent portfolio and that of its state's. We base our approach on the seminal work of Jaffe (1986). The author used the cosine similarity to calculate the correspondence between two (2) patent portfolios. This method is fairly common (Knoben and Oerlemans, 2006). We use the patent vector of the university and the patent vector of the state. The formula used is as follows:

$$Prox = \frac{\sum_{i=1}^{i} P_{i_{univ}} \sum_{i=1}^{i} P_{i_{state}}}{\sqrt{(\sum_{i=1}^{i} P_{i_{univ}})^2} \sqrt{(\sum_{i=1}^{i} P_{i_{state}})^2}} \tag{4}$$

MaxRTA is the highest revealed technological advantage of the university. It is calculated over the country as we are trying to capture the national advantage of the university. This indicator was used previously to determine company core technological competences and technological leadership (Chen and Chang, 2010a,b, 2012; Kim et al., 2016). This variable should increase the robustness of our finding as it is a more specialisation-oriented indicator compared to the entropy index that is more geared toward diversification. We use the following formula to calculate the value of revealed technological advantage for each subclass and choose the highest value:

$$MaxRTA = MAX(\frac{\frac{P_{i_{univ}}}{\sum_{i=1}^{i} P_{i_{univ}}}}{\frac{P_{i_{country}}}{\sum_{i=1}^{i} P_{i_{country}}}}) \tag{5}$$

4.2.3 Control

Our control variables are sourced from the STATT database. We use :

dCanada is a dummy variable for the university being located in Canada. As both countries have different education systems and economies, this variable will capture part of these nuances.

dMedSchl accounts for the presence of a medical school. It is a fairly common variable used in studies on university research commercialisation and is positively correlated with research and commercialisation (Rothaermel et al., 2007b; Cardozo et al., 2011; Cartaxo et al., 2013). Universities with medical schools represent 50.21% of the STATT database observations.

RDExp corresponds to the amount of R&D expenditure of the university. The amount of R%D expenditure is a popular indicator used in the literature to measure research activity and is correlated with disclosures, patents, and licences (Rothaermel et al., 2007b). Furthermore, large universities are more diversified than their smaller counterparts (cf. Fig. 2). Hence, the indicator should help us account for the size difference between them.

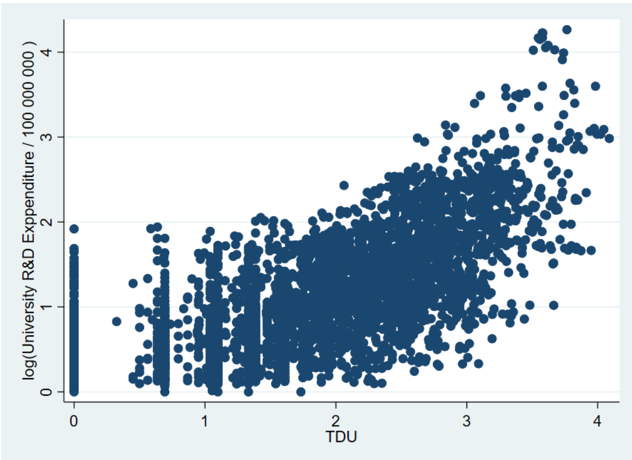

Fig. 2 University size and technological diversification

LegalL legal fees per licences are also used to measure university's investment in research commercialisation. Studies on legal expenditure indicate that higher legal expenditure is negatively correlated with the number of licenses but positively correlated with the amount of licensing income (Sine et al., 2003; Siegel et al., 2003, 2004; Prets and Slate, 2014). In order to account for growth in relation to the university size, we divide the amount of legal fees by the number of licenses.

PatentsD, the number of patents per disclosures, is used to measure the effort put into commercialisation. We divide the number of patents by the number of disclosures to better measure the effort put into commercialisation as both the number of patents and the number of disclosures are known through the literature to be correlated with the size of the university. Patenting can only take place for results close to being commercialised. It is deemed by some as a strategic choice and considered less effective at predicting licensing and income as it is not mandatory (Colyvas et al., 2002; Prets and Slate, 2014; Baglieri et al., 2018).

PropExclLic, the proportion of exclusive licences, is expected to be an indicator of the university's profile concerning the market readiness of the research results it tries to commercialise. Universities with a large portfolio of market ready technologies should grant less exclusive licences, generate more licences that generate income and greater licensing income (Thursby et al., 2001).

PatentState corresponds to the sum of all patents granted in the local state. This excludes any patent granted to the university itself. Similar to universities, states with more patents are more diversified (cf. Fig. 3). This variable will help us control for the effect of the local economy. From a market pull perspective, developed states should have more patent activity which could be an indicator of more demand for university-based knowledge and innovations.

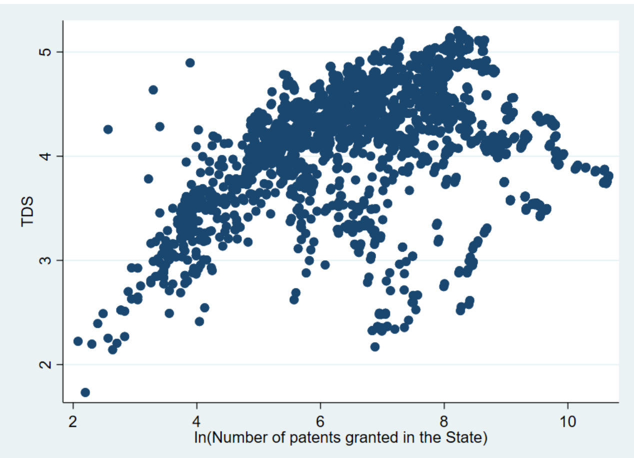

Fig. 3 Patents granted in the local state and technological diversification

IndRDT represents the share of the university's R&D expenditure coming from the industry over the total amount of R&D expenditure. A higher share of expenditure from the industry should indicate university-industry collaborations and is expected to positively affect the number of licenses generating income, as the research projects will be geared towards the direct needs of the partnering firm (Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020).

4.3 Model

We use a panel regression to estimate the association of our K independent variables X_{ik} and J control variables Z_{ij} with our dependent variables. Y_i [3][4]. The model to be estimated is as follows :

$$Y_i = \alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \sum_{j=1}^{J} \gamma_j Z_{ijt} + \epsilon_{it} \tag{6}$$

where i represents the university, the β_k's are the coefficients of the independent variables and the γ_j's are the coefficients of the control variables, t is the year, and ϵ_i is the error term.

5 Results and discussion

Our results show that diversification and proximity are associated with variations of the number of licenses generating income. We observe a positive association of diversification with licensing activity for both the university technological diversity (TDU)(cf. (4) in the table 1) and the university related technological diversity (TDU$_{REL}$) (6). The positive association between diversification and licensing is also supported by the university revealed technological advantage (MaxRTA)(2) that has a negative association to licensing. However, the positive association of diversification cannot be observed for unrelated diversification (TDU$_{UNREL}$)(8 & 9). These results are coherent with the wider literature on company technological diversification (Ceipek et al., 2019). They confirm that technological diversification is positively associated with value creation. Furthermore, they also support the previous findings on the importance of relatedness for successful diversification (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016;

[3] The results of our Hausman tests indicate that the most appropriate model is fixed effect.

[4] Normality being a pre-requisite for ordinary least square we transformed our variables, the transformations can be found in the annexes table A1, their descriptive statistics and the correlation table are in tables A2 and A4

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Year dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
dMedschl	-0.3911*	-0.3866*	-0.3913*	-0.3909*	-0.3972*	-0.3919*	-0.3921*	-0.3910*	-0.3953*	-0.3910*	-0.3964*	-0.3784*	-0.4096**	-0.3858*	-0.3989*	-0.3860*	-0.4192**	-0.3960*
RDExp	0.2621***	0.2652***	0.2692***	0.2477***	0.2562***	0.2501***	0.2514***	0.2608***	0.2612***	0.2513***	0.2556***	0.2480***	0.2523***	0.2522***	0.2656***	0.2579***	0.2500***	0.2478***
LegalL	-0.2772***	-0.2734***	-0.2718***	-0.2853***	-0.2743***	-0.2829***	-0.2815***	-0.2780***	-0.2759***	-0.2834***	-0.2804***	-0.2846***	-0.2825***	-0.2829***	-0.2782***	-0.2793***	-0.2840***	-0.2887***
PatentsD	0.1884***	0.1743***	0.1714***	0.1709***	0.1682***	0.1735***	0.1733***	0.1869***	0.1867***	0.1842***	0.1847***	0.1843***	0.1841***	0.1858***	0.1905***	0.1870***	0.1854***	0.1683***
propExLicL	-1.9062***	-1.8600***	-1.8633***	-1.8996***	-1.8879***	-1.9183***	-1.9181***	-1.9040***	-1.8937***	-1.8938***	-1.8867***	-1.8607***	-1.9583***	-1.8578***	-1.9698***	-1.8984***	-1.8531***	-1.9578***
PatentState	0.0231	0.0296	0.0231	0.0232	0.0236	0.0214	0.0214	0.0233	0.0245	0.0300	0.0297	0.0388	-0.0021	0.0267	-0.0051	0.0305	0.0228	-0.0011
IndRDT	0.0852	0.0886	0.0877	0.0893	0.0897	0.0839	0.0841	0.0860	0.0874	0.0901	0.0862	0.0702	0.0426	0.0641	0.0411	0.0844	0.0964	0.0392
dCanada x PatentsD	0.1606**	0.1767**	0.1780**	0.1690**	0.1766**	0.1749**	0.1757**	0.1606**	0.1621**	0.1660**	0.1629**	0.1495**	0.1535**	0.1448**	0.1530**	0.1601**	0.1425**	0.1700**
dCanada x IndRDT	0.1243**	0.1210**	0.1216**	0.1200**	0.1183**	0.1215**	0.1213**	0.1239**	0.1224**	0.1235**	0.1225**	0.1271**	0.1321**	0.1261**	0.1284**	0.1252**	0.1271**	0.1209**
dMedschl x LegalL	0.1622***	0.1635***	0.1639***	0.1592***	0.1608***	0.1605***	0.1607***	0.1619***	0.1625***	0.1619***	0.1616***	0.1585***	0.1643***	0.1592***	0.1630***	0.1612***	0.1655***	0.1611***
dMedschl x IndRDT	-0.0316	-0.0309	-0.0308	-0.0285	-0.0261	-0.0275	-0.0274	-0.0314	-0.0303	-0.0321	-0.0305	-0.0293	-0.0295	-0.0285	-0.0287	-0.0314	-0.0315	-0.0236
LegalL x propExLicL	0.2607***	0.2523***	0.2526***	0.2617***	0.2586***	0.2625***	0.2621***	0.2607***	0.2600***	0.2606***	0.2604***	0.2548***	0.2550***	0.2538***	0.2603***	0.2599***	0.2522***	0.2575***
propExLicL x IndRDT	0.0834	0.0815	0.0815	0.0809	0.0809	0.0842+	0.0845+	0.0829	0.0814	0.0809	0.0811	0.0800	0.1006*	0.0819	0.0978*	0.0821	0.0838+	0.0986*
PatentState x IndRDT	-0.0153+	-0.0157+	-0.0156+	-0.0159+	-0.0162+	-0.0154+	-0.0155+	-0.0154+	-0.0156+	-0.0157+	-0.0153+	-0.0130	-0.0104	-0.0123	-0.0101	-0.0152+	-0.0166*	-0.0103
PatentsD x propExLicL	-0.2981***	-0.2848***	-0.2846***	-0.2993***	-0.2912***	-0.3009***	-0.2998***	-0.2980***	-0.2966***	-0.2991***	-0.3033***	-0.2948***	-0.2920***	-0.2988***	-0.3037***	-0.2960***	-0.2959***	-0.3000***
RDExp x LegalL	-0.0231**	-0.0233**	-0.0237**	-0.0214*	-0.0236**	-0.0220**	-0.0223**	-0.0230**	-0.0234**	-0.0217**	-0.0224**	-0.0207*	-0.0221**	-0.0212*	-0.0232**	-0.0225**	-0.0217*	-0.0204*
dCanada x RDExp	-0.2464***	-0.2582***	-0.2567***	-0.2436***	-0.2389***	-0.2403***	-0.2398***	-0.2465***	-0.2451***	-0.2459***	-0.2479***	-0.2501***	-0.2408***	-0.2503***	-0.2540***	-0.2471***	-0.2426***	-0.2617***
dMedschl x PatentsD	-0.0948**	-0.1043**	-0.1038**	-0.0921**	-0.0988**	-0.1001**	-0.1008**	-0.0939**	-0.0969**	-0.0969**	-0.0955**	-0.0899**	-0.0823*	-0.0889**	-0.0849**	-0.0942**	-0.0900**	-0.0963**
MaxRTA		-0.0433***	0.0112															-0.0329**
MaxRTA^2			-0.0048															
TDU				0.0403**	-0.0271													
TDU^2					0.0212+													
TDU$_{REL}$						0.0708**	0.0586											0.1195**
TDU$_{REL}{}^2$							0.0080											
TDU$_{UNREL}$								0.0066	-0.0742									
TDU3$_{UNREL}{}^2$									0.0478									
Prox										0.1284*	0.3501*							0.6129**
Prox^2											-0.3505							-0.9428*
TDS												0.0952**	1.5458***					
TDS^2													-0.1909***					
TDS$_{REL}$														0.1471***	1.1521***			1.1283***
TDS$_{REL}{}^2$															-0.2300***			-0.2287***
TDS$_{UNREL}$																0.0527	2.8208***	
TDS3$_{UNREL}{}^2$																	-0.8833***	
TDU$_{REL}$ x Prox																		-0.6069*
TDU$_{REL}$ x Prox^2																		0.9180**
Const.	4.8499***	5.0334***	4.9216***	4.8511***	4.8399***	4.8747***	4.8696***	4.8477***	4.8603***	4.8123***	4.7785***	4.3621***	2.0334***	4.4598***	3.6573***	4.7196***	2.6874***	3.8640***
Nb of obs.	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789
Nb of groups	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212	212
p	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Log likelihood	-1294.45	-1288.43	-1287.84	-1292.33	-1291.02	-1291.03	-1291	-1294.42	-1293.69	-1292.52	-1291.54	-1291.57	-1275.84	-1290.42	-1280.12	-1294.30	-1287.51	-1269.51
Log likelihood$_0$	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03	-2223.03
BIC	2906.23	2902.13	2908.88	2909.92	2915.24	2907.33	2915.20	2914.10	2920.57	2910.30	2916.27	2908.40	2884.88	2906.10	2893.44	2913.86	2908.22	2919.82
AIC	2668.89	2658.85	2659.68	2666.65	2666.04	2664.05	2666.00	2670.83	2671.37	2667.03	2667.07	2665.13	2635.67	2662.83	2644.24	2670.59	2659.01	2635.02
R^2_{within}	0.4862	0.4884	0.4886	0.487	0.4874	0.4874	0.4875	0.4862	0.4865	0.4869	0.4873	0.4872	0.493	0.4877	0.4914	0.4862	0.4887	0.4953
$R^2_{between}$	0.2263	0.3086	0.3106	0.2704	0.2705	0.2709	0.2717	0.2295	0.2220	0.2454	0.2491	0.2678	0.2634	0.2714	0.2783	0.2339	0.2198	0.3770
$R^2_{overall}$	0.2689	0.324	0.3222	0.2971	0.3062	0.3018	0.3033	0.2705	0.2692	0.2828	0.2833	0.2940	0.2848	0.2975	0.2933	0.2731	0.2652	0.3610
$R^2_{adjusted}$	0.4356	0.4378	0.4378	0.4362	0.4365	0.4367	0.4365	0.4354	0.4354	0.4361	0.4363	0.4365	0.4426	0.4370	0.4409	0.4354	0.4379	0.4438
F	61.5769***	60.5477***	59.0986***	60.2017***	58.8232***	60.3168***	58.8250***	60.0164***	58.5927***	60.1849***	58.7786***	60.2689***	60.1443***	60.3710***	59.7701***	60.0271***	59.1275***	52.8250***

***$p \leq 0.001$, **$p \leq 0.05$, *$p \leq 0.1$ +$p \leq 0.15$

Table 1 Results of our panel regressions predicting the number of licenses generating income

Kook et al., 2017). Thus, together these results confirm our hypotheses H1 and H2.

The technological diversification of the state (TDS) was also found to be positively associated with the number of licenses generating income (12). Further investigations show that the association is quadratic and has an inverted-U shape (13). Similar to the university technological diversification, the state unrelated diversification is behaving differently than overall or related diversification (14, 15, 16, and 17). Unrelated diversification does not show a positive association to licensing like overall or related diversification and has a steeper slope when considering a quadratic fit [5]. These results point out that other factors, not accounted for, might be at play when it comes to state diversification. Nonetheless, these findings support our hypotheses H1 and H2.

Proximity is also exhibiting a positive association with the number of licenses generating income (10 and 11). We could not find a strong quadratic relationship between proximity and the number of licenses generating income as reported in some cases in the literature (Chen and Xie, 2018). Nonetheless, we managed to reproduce the curvilinear association when accounting for interactions between our independents (18). This shows that although proximity might be necessary for collaboration, it can hamper the universities licensing activities in some cases. Hence, we verify our hypothesis H3.

The interactions between our independent variables further nuance our findings (18). The first major difference that we observe is the loss of the quadratic effect of the state technological diversification (15) and the strengthening of the quadratic effect of proximity (11). Furthermore, we also identify the interaction between university technological diversification and proximity [6]. We believe this to be the result of larger universities having an advantages over smaller ones, such as having more boundary spanners and experience in licensing, that our variables could not capture. This is coherent with previous studies showing that larger universities were earlier in conducting knowledge transfer and commercialisation activities (Etzkowitz, 2003), establishing TTOs (Castillo et al., 2016), and that previous experience in knowledge transfer and commercialisation a positive association with outputs (Di Gregorio and Shane, 2003; De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020).

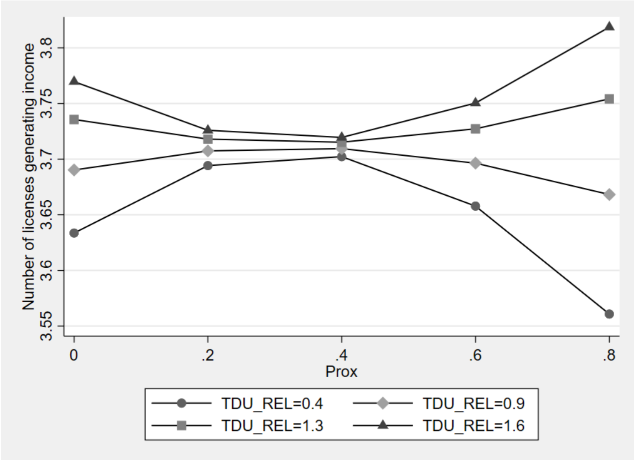

Fig. 4 Marginal effect of diversification and proximity at 25% 50% 75% and 90% percentiles of TDU_{REL}

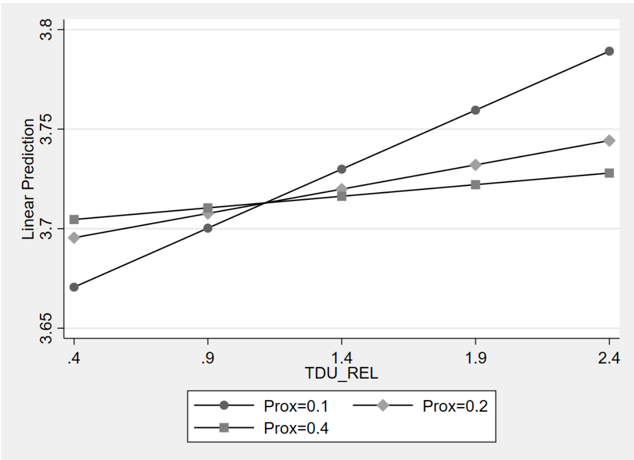

Fig. 5 Marginal effect of diversification and proximity at 25% 50% and 75% percentiles of proximity

A closer look at the interaction between the diversification and proximity shows that diversification can lessen the negative effect of too much or too little proximity (see Fig. 4 and 5). In fact, universities with higher related diversification seem to thrive when proximity is too high or too low. We impute these differences to two (2) factors that we could not measure: the relational capital and the presence of boundary spanners. First, larger universities have the advantage of having more employees and researchers, as their num-

[5] We could not normalise this variable and decided to use it as is with a skewness of -1.5 and a kurtosis of 5.72. Hence, the difference might be due to the variable not being normalised.

[6] Our pairwise correlation table shows that some of our independent variables are correlated beyond 0.3 and 0.5. The correlation between diversity and proximity are to be expected since both are positively associated with the size of the university and the number of patents granted in the state. We calculated the Variance inflation factor (VIF) to measure of the amount of multicollinearity but found no value above 3 (cf. annexe Table A3).

ber grows so does the number of potential connections. This confers relational capital that goes beyond the size of the university and participates to opportunity discovery leading to spillovers and knowledge transfer (De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020). Second, larger universities have started knowledge transfer and licensing earlier than their smaller counterparts (Etzkowitz, 2003; Castillo et al., 2016), as such they had the time to develop boundary spanning structures such as prototyping facilities and incubators that can bridge the gap between researchers and the industrial partners (De Wit-de Vries et al., 2019; Sjöö and Hellström, 2019; Nsanzumuhire and Groot, 2020). Once again, this advantage goes beyond the age of the TTO since these structures require funding that smaller universities might not have [7]. We distinguish four (4) extreme scenarios: low proximity-diversity, high proximity-diversity, low proximity high diversity, and high proximity low diversity. A summary of can be found in fig 6.

Low proximity-diversity universities might not have the same boundary spanners of their larger counterparts. This would explain why they are unable to generate licenses from their research as the increased distance between their knowledge base and the knowledge base of the surrounding companies might not overlap to allow knowledge transfer. In the absence of boundary spanners or other proximities these opportunities might never be discovered. Low proximity high diversity universities do not have the same problem concerning the lack of boundary spanners. These organisations and individuals might help bridge the knowledge gap between the university and its surroundings. For instance, a research park or an incubator might show the capabilities of the university and a prototyping facility might help translate the university knowledge into opportunities the industry can grasp. Furthermore, the increased technological distance between the university and the local industry reduces outgoing spillover while boundary spanning organisations can still translate the knowledge into useful technologies for local companies or help establish links with non-local companies.

Whether high or low proximity, universities tend to follow the same pattern regarding diversity: those with a higher diversity rate have the advantage over those with a low diversity rate. However, multiple reasons besides boundary spanners might be at the source of this difference when it comes to high proximity universities. The quality of the faculty, the size of the network, trust between partners and spillovers are the most likely candidates. In fact, neither companies nor researchers prefer knowledge transfer through licensing and startups (Jensen et al., 2003; De Wit-de Vries et al., 2019; Nsanzumuhire and Groot, 2020). Furthermore, faculty quality and field are known to positively influence licensing (Thursby et al., 2001; Jensen et al., 2003). Therefore, researchers in smaller universities and less developed states with high technological proximity to local companies might find it more convenient to share knowledge through other means than licensing and capture value through other mechanisms than royalties such as for instance R&D funding. These collaborations can further help smaller less diversified universities in deciding the direction in which to diversify and complement local industrial R&D capabilities.

Larger universities might have more time to transform the knowledge into licensable codified knowledge due to the size of their networks which can delay opportunity discovery and spillover towards industry. Besides, time to market is known to positively influence commercial success (Jensen et al., 2003). Hence, the presence of boundary spanners might hasten and facilitate the translation of research results into commercial opportunities. Furthermore, other factors might also be at play for highly diversified universities. Our examination of these universities showed that the universities in the upper 25 percentile of related technological diversification are all very large and highly prestigious universities which is coherent with previous reports on the skewed nature of university licensing and royalty income[8] (Thursby et al., 2001).

6 Conclusion

This study contributes to the literature on university research commercialisation. It is the first to look at the effect of the university's patent portfolio composition on licensing. Our results suggest that related diversification has a greater positive impact on research commercialisation compared to unrelated diversification. Furthermore, we also establish the positive role of the proximity to the local industry for knowledge transfer and confirm previous studies indicating the role of proximity between partners for successful knowledge transfer.

Our findings also suggest that small and large universities might be subjected to different challenges when it comes to knowledge transfer. Larger more diversified

[7] We present alternative models taking age into account to illustrate our point in the annexes table A5 (18a, 18b, and 18c). The alternative models do not change our conclusions. We decided not to include age in our final model due to its high pairwise collinearity (0.55) with the amount of R&D expenditure

[8] We used subsamples in the annexes table A5. 18d and 18e use observation in the lower 75 percentile of TDU_{REL} ($<=1.3$), and 18d and 18e use observations in the lower 75 percentile of proximity ($<=0.4$).

Technological Proximity	Technological Diversity −	Technological Diversity +
+	-Small university in low patent activity state -Less boundary spanners to translate and adapt university capabilities to partners needs -Does not have access to knowledge from diverse fields -Patenting aligned with local industry R&D activities -Average potential for opportunity discovery and high spillover -Take on the role of knowlege intensive business service to answer local needs	-Large university in high patent activity state -More boundary spanners to translate and adapt university capabilities to partners needs -Can recombine diverse internal knowledge to innovate -Patenting aligned with local industry R&D activities -High potential for opportunity discovery and high spillover -Lower number of licenses generating income due to technological proximity and knowledge spillover through other channels
−	-Small university in low patent activity state -Less boundary spanners to translate and adapt university capabilities to partners needs -Does not have access to knowledge from diverse fields -Patenting not aligned with local industry R&D activities -Low potential for opportunity discovery and low spillover -Lowest number of licenses generating income due to low possibility of opportunity discovery	-Large university in high patent activity state -More boundary spanners to translate and adapt university capabilities to partners needs -Can recombine diverse internal knowledge to innovate -Patenting not aligned with local industry R&D activities -Average potential for opportunity discovery and low spillover -Highest number of licenses generating income due to technological distance and low knowledge spillover through other channels

Fig. 6 Summary of the four (4) extreme scenarios

universities might have the upper hand when it comes to generating licenses and licensing income. We found a curvilinear inverted-U shaped association of proximity with the number of licenses generating income. We impute this to university idiosyncratic characteristics. More specifically we believe this difference to stem from the lack of boundary spanners which can help transform research findings into commercialisable codified knowledge in the case of smaller universities.

These findings have implication for regional policy-makers and university technology managers especially with the emergence of local specialisation initiatives such as smart specialisation and superclusters. They underline the importance of a vibrant innovation ecosystem for successful knowledge transfer and value extraction. Regional policy-makers should encourage and help finance boundary spanning structures such as science parks and prototyping facilities if they intend to make full use of the universities as tools for innovation and regional economic development. Failing to do so opens the way to knowledge spillovers through other mediums that might be less influenced by physical proximity and thus have less impact on local economic growth.

7 Limitations

Pairing the universities from the STATT database with the USPTO database was not always possible. A number of patent assignees corresponded to multiple universities in the AUTM database and couldn't be singled out. This was the result of the STATT datasets not always indicating the scope of the report. In some cases the reporting was indicated as being for the whole university system while in others, it was for only one campus or department. Furthermore, some state universities had to be removed from the database as they were only reporting partial results of the university in a single city while the patents were granted to an assignee representing every university in the state. Some ambiguity was also stemming from multiple universities having similar names. For instance, the patent holder "new york university" could correspond to "the university of new york", "the state university of new york", or "the city university of new york".

Other patents could not be classified due to a lack precision. For instance "state of oregon acting by and through the state board of higher education" could correspond to the assignee "state of oregon acting by and through the state board of higher education on behalf of oregon state university" or "state of oregon acting by and through the state board of higher education on behalf of the university of oregon" which are two different universities. This was even more difficult for assignees such as "board of trustees of the university" which is found in multiple states.

References

M. Acosta, D. Coronado, and M. Á. Martínez, "Does technological diversification spur university patenting?" *The Journal of Technology Transfer*, vol. 43, no. 1, pp. 96–119, 2018.

C. Autant-Bernard, "The geography of knowledge spillovers and technological proximity," *Economics of Innovation and New Technology*, vol. 10, no. 4, pp. 237–254, 2001.

D. Baglieri, F. Baldi, and C. L. Tucci, “University technology transfer office business models: One size does not fit all,” *Technovation*, vol. 76, pp. 51–63, 2018.

P.-A. Balland, R. Boschma, and K. Frenken, “Proximity and innovation: From statics to dynamics,” *Regional Studies*, vol. 49, no. 6, pp. 907–920, 2015. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/00343404.2014.883598

P.-A. Balland, R. Boschma, J. Crespo, and D. L. Rigby, “Smart specialization policy in the european union: relatedness, knowledge complexity and regional diversification,” *Regional Studies*, vol. 53, no. 9, pp. 1252–1268, 2019.

C. Beaudry and A. Schiffauerova, “Who’s right, marshall or jacobs? the localization versus urbanization debate,” *Research policy*, vol. 38, no. 2, pp. 318–337, 2009.

A. Bonaccorsi, “Addressing the disenchantment: universities and regional development in peripheral regions,” *Journal of Economic Policy Reform*, vol. 20, no. 4, pp. 293–320, 2017.

R. Boschma, “Proximity and innovation: a critical assessment,” *Regional studies*, vol. 39, no. 1, pp. 61–74, 2005. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/0034340052000320887

N. Boufaden, N. Boufaden, and A. Plunket, “Proximity and innovation: Do biotechnology firms located in the paris region benefit from localized technological externalities?” *Annales d’Economie et de Statistique*, pp. 197–220, 2007.

G. Calcagnini, G. Giombini, P. Liberati, and G. Travaglini, “A matching model of university–industry collaborations,” *Small Business Economics*, vol. 46, no. 1, pp. 31–43, 2016.

R. Cardozo, A. Ardichvili, and A. Strauss, “Effectiveness of university technology transfer: an organizational population ecology view of a maturing supplier industry,” *The Journal of Technology Transfer*, vol. 36, no. 2, pp. 173–202, 2011. [Online]. Available: http://link.springer.com/article/10.1007/s10961-010-9151-1

R. M. Cartaxo, M. M. Godinho, and G. J. Gama, “The University Transfer Technology performance of American Universities,” *Management Science*, vol. 48, no. 1, pp. 90–104, 2013. [Online]. Available: http://druid8.sit.aau.dk/acc_papers/k6orur56xqrhn3a8kq7r8ipai19v.pdf

F. Castillo, J. K. Gilless, A. Heiman, and D. Zilberman, “Time of adoption and intensity of technology transfer: an institutional analysis of offices of technology transfer in the United States,” *The Journal of Technology Transfer*, pp. 1–19, 2016.

R. Ceipek, J. Hautz, M. C. Mayer, and K. Matzler, “Technological diversification: A systematic review of antecedents, outcomes and moderating effects,” *International Journal of Management Reviews*, vol. 21, no. 4, pp. 466–497, 2019.

H. Chen and F. Xie, “How technological proximity affect collaborative innovation? an empirical study of china’s beijing–tianjin–hebei region,” *Journal of Management Analytics*, vol. 5, no. 4, pp. 287–308, 2018.

Y.-M. Chen, D.-H. Yang, and F.-J. Lin, “Does technological diversification matter to firm performance? the moderating role of organizational slack,” *Journal of Business Research*, vol. 66, no. 10, pp. 1970–1975, 2013.

Y.-S. Chen and K.-C. Chang, “Exploring the nonlinear effects of patent citations, patent share and relative patent position on market value in the us pharmaceutical industry,” *Technology Analysis & Strategic Management*, vol. 22, no. 2, pp. 153–169, 2010.

——, “The relationship between a firm’s patent quality and its market value—the case of us pharmaceutical industry,” *Technological Forecasting and Social Change*, vol. 77, no. 1, pp. 20–33, 2010.

——, “Using the entropy-based patent measure to explore the influences of related and unrelated technological diversification upon technological competences and firm performance,” *Scientometrics*, vol. 90, no. 3, pp. 825–841, 2012.

Y.-S. Chen, C.-Y. Shih, and C.-H. Chang, “The effects of related and unrelated technological diversification on innovation performance and corporate growth in the taiwan’s semiconductor industry,” *Scientometrics*, vol. 92, no. 1, pp. 117–134, 2012.

M. Choi and C.-Y. Lee, “Technological diversification and r&d productivity: The moderating effects of knowledge spillovers and core-technology competence,” *KAIST College of Business Working Paper Series*, no. 2019-014, 2019.

W. M. Cohen and D. A. Levinthal, “Absorptive capacity: A new perspective on learning and innovation,” *Administrative science quarterly*, pp. 128–152, 1990. [Online]. Available: http://www.jstor.org/stable/2393553

J. Colyvas, M. Crow, A. Gelijns, R. Mazzoleni, R. R. Nelson, N. Rosenberg, and B. N. Sampat, “How do university inventions get into practice?” *Management science*, vol. 48, no. 1, pp. 61–72, 2002.

E. De Wit-de Vries, W. A. Dolfsma, H. J. van der Windt, and M. P. Gerkema, “Knowledge transfer in university–industry research partnerships: a review,” *The Journal of Technology Transfer*, vol. 44, no. 4, pp. 1236–1255, 2019.

D. Di Gregorio and S. Shane, “Why do some universities generate more start-ups than others?” *Research policy*, vol. 32, no. 2, pp. 209–227, 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0048733302000975

G. Dosi, “Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change,” *Research policy*, vol. 11, no. 3, pp. 147–162, 1982. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0048733382900166

H. Etzkowitz, “Research groups as ‘quasi-firms’: the invention of the entrepreneurial university,” *Research policy*, vol. 32, no. 1, pp. 109–121, 2003.

H. Etzkowitz and L. Leydesdorff, “The dynamics of innovation: from National Systems and “Mode 2” to a Triple Helix of university–industry–government relations,” *Research policy*, vol. 29, no. 2, pp. 109–123, 2000. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0048733399000554

L. Foster, C. Grim, and N. Zolas, “A portrait of us firms that invest in r&d,” *Economics of Innovation and New Technology*, pp. 1–23, 2019.

M. Garcia-Vega, “Does technological diversification promote innovation?: An empirical analysis for european firms,” *Research policy*, vol. 35, no. 2, pp. 230–246, 2006.

F. W. Geels, “Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study,” *Research policy*, vol. 31, no. 8, pp. 1257–1274, 2002. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0048733302000628

E. Geisler and A. H. Rubenstein, “University—industry relations: A review of major issues,” *Cooperative research and development: The industry—university—government relationship*, pp. 43–62, 1989.

N. M. George, V. Parida, T. Lahti, and J. Wincent, “A systematic literature review of entrepreneurial opportunity recognition: insights on influencing factors,” *International Entrepreneurship and Management Journal*, vol. 12, no. 2, pp. 309–350, 2016.

P. Giuri, F. Munari, A. Scandura, and L. Toschi, “The strategic orientation of universities in knowledge transfer activities,” *Technological Forecasting and Social Change*, vol. 138, pp. 261–278, 2019.

C. A. Hidalgo, P.-A. Balland, R. Boschma, M. Delgado, M. Feldman, K. Frenken, E. Glaeser, C. He, D. F. Kogler, A. Morrison *et al.*, “The principle of relatedness,” in *International conference on complex systems.* Springer, 2018, pp. 451–457.

A. P. Jacquemin and C. H. Berry, “Entropy measure of diversification and corporate growth,” *The journal of industrial economics*, pp. 359–369, 1979.

A. B. Jaffe, “Technological opportunity and spillovers of r&d: evidence from firms’ patents, profits and market value,” 1986.

R. A. Jensen, J. G. Thursby, and M. C. Thursby, “Disclosure and licensing of university inventions:‘the best we can do with the s** t we get to work with’,” *International journal of industrial organization*, vol. 21, no. 9, pp. 1271–1300, 2003.

J. Kim, C.-Y. Lee, and Y. Cho, “Technological diversification, core-technology competence, and firm growth,” *Research Policy*, vol. 45, no. 1, pp. 113–124, 2016.

J. Knoben and L. A. Oerlemans, “Proximity and inter-organizational collaboration: A literature review,” *international Journal of management reviews*, vol. 8, no. 2, pp. 71–89, 2006.

S. H. Kook, K. H. Kim, and C. Lee, “Dynamic technological diversification and its impact on firms’ performance: An empirical analysis of korean it firms,” *Sustainability*, vol. 9, no. 7, p. 1239, 2017.

B. K. Lee and S. Y. Sohn, “Disparities in exploitative and exploratory patenting performance across regions: Focusing on the roles of agglomeration externalities,” *Papers in Regional Science*, vol. 98, no. 1, pp. 241–263, 2019.

C.-Y. Lee, Y.-C. Huang, and C.-C. Chang, “Factors influencing the alignment of technological diversification and firm performance,” *Management Research Review*, 2017.

C. Mascarenhas, J. J. Ferreira, and C. Marques, “University–industry cooperation: A systematic literature review and research agenda,” *Science and Public Policy*, 2018.

T. Medvedev and A. Ulanov, “Company names matching in the large patents dataset,” *Hewlett-Packard Development Company, LP*, 2011.

X. P. L. Mendoza and D. S. M. Sanchez, “A systematic literature review on technology transfer from university to industry,” *International Journal of Business and Systems Research*, vol. 12, no. 2, pp. 197–225, 2018.

D. J. Miller, “Technological diversity, related diversification, and firm performance,” *Strategic Management Journal*, vol. 27, no. 7, pp. 601–619, 2006.

S. U. Nsanzumuhire and W. Groot, “Context perspective on university-industry collaboration processes: A systematic review of literature,” *Journal of cleaner production*, vol. 258, p. 120861, 2020.

E. T. Penrose, *The Theory of the Growth of the Firm.* Oxford university press, 1959.

M. E. Porter, "Cluster and the new economics of competition," 1998.

R. A. Prets and J. R. Slate, "Predicting income generated from licensing universities'intellectual property," *International Journal of University Teaching and Faculty Development*, vol. 4, no. 1, p. 19, 2014.

E. Pugliese, L. Napolitano, A. Zaccaria, and L. Pietronero, "Coherent diversification in corporate technological portfolios," *PloS one*, vol. 14, no. 10, 2019.

C. Quintana-García and C. A. Benavides-Velasco, "Innovative competence, exploration and exploitation: The influence of technological diversification," *Research policy*, vol. 37, no. 3, pp. 492–507, 2008.

F. T. Rothaermel, S. D. Agung, and L. Jiang, "University entrepreneurship: a taxonomy of the literature," *Industrial and corporate change*, vol. 16, no. 4, pp. 691–791, 2007. [Online]. Available: http://icc.oxfordjournals.org/content/16/4/691.short

——, "University entrepreneurship: a taxonomy of the literature," *Industrial and corporate change*, vol. 16, no. 4, pp. 691–791, 2007.

C. E. Shannon, "A mathematical theory of communication," *The Bell system technical journal*, vol. 27, no. 3, pp. 379–423, 1948.

D. S. Siegel, D. Waldman, and A. Link, "Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study," *Research policy*, vol. 32, no. 1, pp. 27–48, 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0048733301001962

D. S. Siegel, D. A. Waldman, L. E. Atwater, and A. N. Link, "Toward a model of the effective transfer of scientific knowledge from academicians to practitioners: qualitative evidence from the commercialization of university technologies," *Journal of engineering and technology management*, vol. 21, no. 1, pp. 115–142, 2004. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0923474803000626

W. D. Sine, S. Shane, and D. D. Gregorio, "The halo effect and technology licensing: The influence of institutional prestige on the licensing of university inventions," *Management Science*, vol. 49, no. 4, pp. 478–496, 2003. [Online]. Available: http://pubsonline.informs.org/doi/abs/10.1287/mnsc.49.4.478.14416

K. Sjöö and T. Hellström, "University–industry collaboration: A literature review and synthesis," *Industry and higher education*, vol. 33, no. 4, pp. 275–285, 2019.

J. G. Thursby, R. Jensen, and M. C. Thursby, "Objectives, characteristics and outcomes of university licensing: A survey of major us universities," *The journal of Technology transfer*, vol. 26, no. 1, pp. 59–72, 2001.

Appendices

Variable name	Description	Transformation used in the regressions
nbLicGenInc	The number of licenses generating income logarithm.	ln(nbLicGenInc + 1)
RDExp	The total amount of R&D expenditure of the university.	ln(RDExp / 100 000 000 + 1)
LegalL	The amount of legal fee per licence granted.	ln(LegalL / 10 000 + 1)
PatentsD	The number of patents per disclosures.	ln(PatentsD * 10 + 1)
propExLicL	The proportion of exclusive licences over the total number of licences granted.	ln(propExLicL + 1)
PatentState	The number of patents granted in the state excluding those to the university.	ln(PatentState + 1)
IndRDT	The proportion of R&D expenditure sourced from the industry.	ln(IndRDT x 10 + 1)
MaxRTA	The highest revealed technological advantage index value.	ln(MaxRTA / 10 + 1)
TD	The technological diversity index adapted from the entropy index (Shannon, 1948).	N/A
TD_{REL}	The related technological diversity index adapted from the entropy index (Shannon, 1948).	N/A
TD_{UNREL}	The unrelated technological diversity index adapted from the entropy index (Shannon, 1948).	N/A
Prox	The proximity of the patent portfolio of the university and the state developed by Jaffe (1986).	N/A

Table A1 Description of our variables

stats	nbLicGenInc	RDExp	LegalL	PatentsD	propExLicL	PatentState	IndRDT	MaxRTA	TDU	TDU_{REL}	TDU_{UNREL}	Prox	TDS	TDS_{REL}	TDS_{UNREL}
min	0	0.055503	0	0	0	2.079442	0	1.056922	0	0	0	0	1.732868	0.5198603	0.8599673
max	7.574558	8.832404	11.02408	3.433987	0.7884574	10.66109	6.479766	9.598869	4.088879	2.382221	1.967115	0.8478552	5.205395	3.513834	1.957421
mean	3.698321	5.258892	6.074499	1.136055	0.3775214	7.001923	4.128352	5.653351	2.006938	0.8931205	1.113818	0.2635835	4.261236	2.565687	1.695549
skewness	-0.0410771	-0.1394316	-0.481121	0.2414617	-0.0038039	-0.3538517	-1.033084	-0.2484117	-0.34577	0.0604291	-1.079703	0.5541827	-1.045783	-1.06977	-1.536573
kurtosis	2.824003	3.131857	5.240506	3.612264	2.216379	2.936194	6.596467	2.996797	2.642254	2.316762	3.684921	2.519741	4.177562	4.211604	5.723038
N	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789

Table A2 Statistics of our transformed variables

Variable	VIF	1/VIF
TDU_{REL}	2.48	0.4035
RDExp	2.17	0.4599
PatentState	1.71	0.5861
TDS_{REL}	1.58	0.6309
Prox	1.46	0.6842
MaxRTA	1.35	0.7395
PatentsD	1.25	0.8018
propExLicL	1.17	0.8559
LegalL	1.12	0.8952
IndRDT	1.06	0.9430
Mean VIF	1.53	

Table A3 VIF values for regression 18

	nbLicGenInc	LegalL	PatentsD	propExLicL	PatentState	IndRDTmD	RDExp	MaxRTA	Prox	TDU
nbLicGenInc	1									
LegalL	-0.0837	1								
PatentsD	0.0504	0.1797	1							
propExLicL	-0.3688	0.0748	-0.0338	1						
PatentState	0.2797	0.2244	0.145	-0.1739	1					
IndRDT	0.0427	0.0443	-0.0661	0.1052	0.0451	1				
RDExp	0.7876	0.1396	0.0379	-0.2983	0.2903	0.0410	1			
MaxRTA	-0.3561	-0.0697	-0.0259	0.0324	-0.3473	-0.1782	-0.3513	1		
Prox	0.3095	0.1328	0.1722	-0.0802	0.3069	0.0555	0.3582	-0.3267	1	
TDU	0.6111	0.2214	0.3333	-0.1917	0.3741	0.0273	0.6775	-0.3164	0.4681	1
TDU_{REL}	0.6118	0.2002	0.3326	-0.1847	0.3899	0.0453	0.6663	-0.3369	0.4714	0.9112
TDU_{UNREL}	0.4496	0.1903	0.2466	-0.1503	0.2558	-0.0027	0.5138	-0.2072	0.3408	0.8506
TDS3	0.0171	0.0625	0.0258	0.0531	0.3693	0.1517	0.0128	-0.2485	0.3385	0.1151
TDS_{REL}	0.0863	0.0906	0.0454	0.0061	0.526	0.1238	0.0771	-0.3126	0.3591	0.1838
TDS_{UNREL}	-0.1768	-0.0382	-0.0374	0.1594	-0.2005	0.1674	-0.1661	0.0231	0.1495	-0.1161

Table A4 Pairwise correlation of our transformed variables

	TDU_{REL}	TDU_{UNREL}	TDS	TDS_{REL}	TDS_{UNREL}
TDU_{REL}	1				
TDU_{UNREL}	0.5584	1			
TDS3	0.1200	0.0786	1		
TDS_{REL}	0.1928	0.124	0.9647	1	
TDS_{UNREL}	-0.1241	-0.0753	0.7014	0.4889	1

	(18a)	(18b)	(18c)	(18d)	(18e)	(18f)	(18g)
Year dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.
dMedschl	-0.3330+	-0.3458*	-0.5956**	-0.4822**	-0.4967**	-0.5298**	-0.5327**
RDExp	0.1427*	0.1534*	-0.3834***	0.1907*	0.1870*	0.1315	0.1286
LegalL	-0.3456***	-0.3423***	-0.2439***	-0.3186***	-0.3249***	-0.3652***	-0.3655***
PatentsD	0.1550***	0.1592***	-0.0654	0.1508**	0.1529**	0.0895+	0.0892+
propExLicL	-1.6498***	-1.7603***	-1.1792***	-2.1799***	-2.1919***	-2.0873***	-2.0561***
PatentState	0.0220	-0.0103	-0.2845***	0.0171	0.0177	-0.0034	-0.003
IndRDT	0.0672	0.0449	0.0757	0.0043	-0.0001	0.043	0.0434
Age	0.6994***	0.7158***	1.9522***				
dCanada x PatentsD	0.1773**	0.1872***	0.2148***	0.1819**	0.1731**	0.2008***	0.1957**
dCanada x IndRDT	0.1224**	0.1248**	0.0902*	0.1019*	0.0992*	0.0867+	0.0872+
dMedschl x LegalL	0.1429***	0.1465***	0.1745***	0.1678***	0.1684***	0.1807***	0.1802***
dMedschl x IndRDT	-0.0232	-0.0234	-0.0142	0.015	0.0163	-0.0042	-0.0036
LegalL x propExLicL	0.2382***	0.2450***	0.2222***	0.2737***	0.2755***	0.2753***	0.2743***
propExLicL x IndRDT	0.0608	0.0763		0.1080+	0.1107*	0.0717	0.0668
PatentState x IndRDT	-0.0113	-0.0091	-0.0108	-0.0071	-0.0067	-0.0074	-0.0073
PatentsD x propExLicL	-0.3087***	-0.3147***	-0.3146***	-0.1957*	-0.2012*	-0.2029*	-0.2045*
RDExp x LegalL	-0.0043	-0.0061	-0.0450***	-0.0138	-0.0127	-0.0057	-0.0057
dCanada x RDExp	-0.2255***	-0.2276***	-0.2533***	-0.2080***	-0.2084***	-0.2351***	-0.2373***
dMedschl x PatentsD	-0.0869**	-0.0828*		-0.1659***	-0.1657***	-0.1284**	-0.1269**
RDExp x PatentState			0.0996***				
PatentsD x PatentState			0.0259*				
dMedschl x RDExp			0.1188*				
dMedschl x propExLicL			-0.2826**				
dMedschl x Age			-0.5274***				
PatentState x Age			-0.2189***				
LegalL x Age			0.0840***				
MaxRTA	-0.0338**	-0.0323**	-0.0273**	-0.0348**	-0.0316*	-0.0413**	-0.0383**
TDU_{REL}	0.1067**	0.1041**	-0.6337*	0.0967*	0.1530**	0.1371***	0.1399**
Prox	0.5176*	0.5079*	0.5130+	0.1500	0.8042**	0.4494**	1.0320*
$Prox^2$	-0.8482*	-0.8150+	-0.7555+		-1.1907*		-1.7135
TDS_{REL}	0.1064*	1.1357***	0.6870**	1.0259***	1.0075***	1.1460***	1.1176***
${TDS_{REL}}^2$		-0.2363***	-0.1510**	-0.2129***	-0.2109***	-0.2540***	-0.2497***
TDU_{REL} x Prox	-0.5190*	-0.4804+	-0.6142*	-0.0839	-0.8387*	-0.4246**	-0.6361
TDU_{REL} x $Prox^2$	0.7898*	0.7379+	0.8326*		1.3629*		0.8089
TDU_{REL} x TDS_{REL}			0.5561*				
TDU_{REL} x ${TDS_{REL}}^2$			-0.0988+				
Const.	4.1043***	3.2604***	5.2216***	3.9014***	3.8945***	4.5069***	4.5128***
Nb of obs.	2784	2784	2784	2073	2073	2117	2117
Nb of groups	209	209	209	205	205	205	205
p	0	0	0	0	0	0	0
Log likelihood	-1265.8587	-1254.8650	-1216.266	-1057.5705	-1055.4824	-1010.9207	-1010.0381
Log likelihood_0	-2220.9858	-2220.9858	-2220.9858	-1667.1515	-1667.1515	-1669.4476	-1669.4476
BIC	2912.43	2898.38	2876.70	2466.43	2477.52	2374.09	2387.6484
AIC	2627.71	2607.72	2544.53	2207.14	2206.96	2113.84	2116.07
R^2_{within}	0.4965	0.5005	0.5141	0.4446	0.4457	0.4632	0.4636
$R^2_{between}$	0.6195	0.6179	0.5987	0.3282	0.3287	0.3398	0.3338
$R^2_{overall}$	0.5469	0.5394	0.5413	0.3269	0.3255	0.3558	0.3503
$R^2_{adjusted}$	0.4457	0.4498	0.4634	0.3688	0.3693	0.3916	0.3915
F	53.0376***	52.7412***	48.4801***	32.4328***	31.1593***	35.8006***	34.3021***

***$p \leq 0.001$, **$p \leq 0.05$, *$p \leq 0.1$ +$p \leq 0.15$

Table A5 Alternative models