POLYTECHNIQUE MONTRÉAL
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UNIVERSITY LICENSING STRATEGY DETERMINANTS AND OUTCOMES

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RÉSUMÉ

La commercialisation de la recherche universitaire fait l'objet d'une attention croissante depuis l'adoption de la loi Bayh Dole en 1980. L'attention croissante accordée à l'innovation et au changement technique au cours de ces dernières décennies a poussé les gouvernements à mettre en œuvre de nouvelles politiques pour s'assurer que les recherches qu'ils subventionnent sont utilisées pour améliorer leurs économies. La pléthore de travaux sur les partenariats université-industrie publiés au cours du siècle dernier indique que le partenariat université-industrie était mené par de grandes entreprises cherchant à améliorer des produits ou des processus existants. Toutefois, ces dernières décennies ont vu le ralliement de nombreux chercheurs autour de la création d'entreprises dérivées, qui ont étudié leur création, leur survie et leur succès. Malheureusement, la plupart, sinon la totalité, de ces études adoptent le point de vue de l'entreprise et on sait peu de choses sur les déterminants et les résultats de la collaboration avec des entreprises en place ou des startups pour les universités. Cette thèse utilise des données sur les brevets et les licences pour aider les parties prenantes à comprendre les différentes stratégies que les universités peuvent déployer pour concéder des licences sur leurs technologies.

La première contribution de cette thèse consiste à identifier les différents systèmes de paiement utilisés par les entreprises de différentes tailles pour payer les licences universitaires et leurs résultats. Nous distinguons les grandes entreprises, les PME et les start-ups et identifions trois stratégies : le paiement de redevances, le paiement d'étapes et l'octroi de fonds propres. Nos données montrent que la part des licences universitaires accordées à chaque taille d'entreprise est associée à différents schémas de paiement et horizons temporels. La part des licences accordées aux grandes entreprises est corrélée à des paiements d'étape plus élevés pendant les deux premières années, tandis que la part des licences accordées aux PME est corrélée à des paiements de redevances plus importants sur plusieurs années. La part des licences accordées aux startups n'est associée à aucun de ces deux éléments et est plutôt corrélée à davantage d'octrois d'actions mais n'influence pas les revenus générés par les ventes d'actions.

La deuxième contribution de cette thèse est liée à la composition de la base de connaissances des universités. Nous montrons que les licences accordées aux entreprises en place et aux startups sont associées à une base de connaissances différente. Plus précisément, tant les licences générant des revenus que le nombre de startups sont associés à des portefeuilles de brevets universitaires plus diversifiés. Cependant, alors que le nombre de start-ups est positivement associé à la diversification liée et non liée, seule la diversification liée présente une association positive avec le nombre de licences générant des revenus. En outre, la source de connaissances est également un déterminant important de la stratégie déployée pour commercialiser la technologie. La proximité technologique est positivement associée au nombre de licences générant des revenus pour les universités non diversifiées et au nombre de startups pour les universités diversifiées. Nous soutenons que cette différence s'explique par la présence d'un phénomène de " boundary spanners " et de " knowledge spillover ". Ces résultats ont des implications importantes pour les décideurs politiques et les universités, qui doivent adapter leur stratégie à l'objectif qu'elles poursuivent.

ABSTRACT

Universities research commercialisation has been the focal point of increasing scrutiny since the passage of the Bayh Dole Act in 1980. The increasing attention given to innovation and technical change during these last decades has pushed governments to implement new policies to ensure the research they subsidize are used to improve their economies. The plethora of work on university-industry partnerships published in the last century indicates that the university-industry partnership was conducted by large companies looking at improving existing products or processes. However, these last decades have seen the rally of many researchers around spinoff creation as they studied their creation, survival, and success. Unfortunately, most, if not all, of these studies take a company point of view and little is known about the determinants and outcomes of working with incumbent companies or startups for universities. This thesis uses patent and licensing data to help stakeholders understand the different strategies universities can deploy to license their technologies.

The first contribution of this thesis is in identifying the different payment schemes used by companies of different sizes to pay for university licenses and their outcome. We distinguish between large companies, SMEs, and startups and identify three strategies, royalty payment, milestone payment, and equity grants. Our data shows that the share of university licenses granted to each company size is associated with different payment schemes and time horizons. The share of licenses granted to large companies is correlated with higher milestone payments for the first couple of years while the share of licenses granted to SMEs is correlated with more royalty payment over multiple years. The share of licenses to startups is associated with neither and instead is correlated with more equity grants but does not influence the income generated by equity sales.

The second contribution of this thesis is related to university knowledge base composition. We show that licenses to incumbent companies and startups are associated with a different knowledge base. More specifically, both licenses generating income and the number of startups are associated with more diverse university patent portfolios. However, while the number of startups is positively associated with both related and unrelated diversification, it is only related diversification that exhibits a positive association with the number of licenses generating income. Moreover, the source of knowledge is also an important determinant of the strategy deployed to commercialise the technology. Technological proximity is positively associated with the number of licenses generating income for undiversified universities and with the number of startups for diversified universities. We argue that the reason behind this difference is the presence of boundary spanners and knowledge spillover. These findings have important implications for policy-makers and universities as they need to adapt their strategy to the goal they pursue.

CONDENSÉ

Cette thèse a été inspirée par des études antérieures sur les stratégies de commercialisation de la recherche universitaire et les relations entre la base de connaissances et les performances. De nombreuses recherches traitent des licences et des retombées de la recherche universitaire. Cependant, ces études adoptent soit le point de vue de l'université et ignorent les caractéristiques de leurs partenaires, soit le point de vue de l'entreprise et ne tiennent pas compte des caractéristiques propres à l'université. L'objectif de ce travail est d'établir quel type d'entreprise est le plus lucratif pour les universités afin qu'elles concentrent leurs efforts d'octroi de licences. Plus précisément, ce travail vise à identifier l'effet de la taille de l'entreprise à qui l'université a octroyé la licence sur les revenus de licence de l'université et à établir comment la combinaison des sujets de recherche influence le choix de ces entreprises.

Notre cadre est basé sur l'importance de la diversification des connaissances pour la découverte d'opportunités. Un portefeuille technologique universitaire diversifié indique un plus grand potentiel de fertilisation croisée des idées. Cependant, la reconnaissance des opportunités ne dépend pas uniquement des connaissances techniques et nécessite également une connaissance du marché. Des études sur l'entrepreneuriat universitaire ont montré que l'octroi de licences technologiques peut être très lucratif pour les universités. Pourtant, la nature asymétrique de la répartition des revenus de licence parmi les universités nord-américaines indique qu'une activité de R-D plus importante en soi n'est pas nécessairement synonyme de revenus plus élevés. Certains travaux antérieurs ont suggéré l'importance du domaine scientifique comme facteur influençant l'activité de concession de licences. D'autres ont souligné l'importance de la vitesse d'innovation et de l'état de préparation de la technologie au marché. À notre connaissance, aucune étude ne s'est penchée sur l'importance du partenaire de commercialisation de l'université avec pour point focal l'université elle-même. On peut soutenir que les technologies prêtes à être commercialisées trouvent des partenaires en place pour les commercialiser, tandis que leurs homologues moins développées sont concédées sous licence à des jeunes pousses.

Des études antérieures sur l'octroi de licences universitaires ont montré que les responsables des bureaux de transfer technologique considéraient les jeunes pousses comme le dernier recours pour commercialiser une technologie. Cette approche semble s'être lentement éloignée, et aujourd'hui le nombre de jeunes pousses et leur survie sont considérés comme un indicateur primordial du succès de la commercialisation des technologies universitaires. À cela s'ajoutent des études indiquant les revenus potentiels plus élevés qui peuvent être générés par les jeunes pousses et des études qualitatives montrant le succès de certaines universités renommées. L'intérêt pour les jeunes pousses

est également alimenté par le climat politique et économique actuel qui encourage les comportements entrepreneuriaux, que ce soit par le biais d'incitations et de programmes gouvernementaux ou par les réussites de jeunes pousses et d'entrepreneurs dans le monde. Il est indéniable que ces entreprises sont nécessaires au changement technique progressif comme le soulignait Schumpeter. Cela est illustré par les innombrables jeunes pousses qui ont changé l'économie mondiale au cours des dernières décennies et les activités entrepreneuriales ultérieures de leurs anciens employés. Cependant, pour les universités, le résultat de la concession de licences à ces entreprises est au mieux mal défini et ces réussites ne sont pas à l'abri du biais de survie. Dans ce contexte, le premier et le second article contribuent à identifier les déterminants et les résultats des retombées pour les universités, et laissent entrevoir des possibilités d'amélioration pour réduire les inefficacités de l'innovation liées à la recherche exploratoire.

Certaines lacunes subsistent dans la littérature sur les licences accordées par les universités aux entreprises. Les travaux antérieurs sur les partenariats université-industrie ont surtout adopté le point de vue des entreprises et montré que les partenariats sont plus courants pour les grandes entreprises. Cela pourrait être lié à leur propension à mener des activités de R-D en premier lieu, un avantage qui s'estompe, car on a observé que les petites entreprises, considérées par beaucoup comme l'épine dorsale de l'économie, ont augmenté leurs dépenses de R-D au cours des dernières décennies. En outre, l'activité de concession de licences n'est pas nécessairement synonyme de revenus de licences. Premièrement, les grandes entreprises peuvent simplement avoir un plus grand pouvoir de négociation en raison de leurs ressources plus importantes. Deuxièmement, une préoccupation importante partagée par toutes les entreprises qui s'associent pour la R-D est la diffusion des connaissances sortantes. Il a été constaté que les PME et les grandes entreprises ont des stratégies et des objectifs différents lorsqu'elles travaillent avec des universités. Par exemple, les grandes entreprises utilisent les universités pour développer leurs propres compétences non essentielles, tandis que les PME utilisent ces partenariats pour améliorer leurs propres compétences essentielles. Cela souligne encore l'importance de la taille et des ressources disponibles pour la R-D et son effet sur les partenariats université-industrie, car les entreprises partenaires perçoivent différemment les avantages et les inconvénients, ce qui entraîne inévitablement des différences dans leur accord de licence. En fait, la littérature sur les systèmes de paiement des licences fournit des arguments théoriques importants sur les raisons de ces divergences de comportement. Ceux-ci sont examinés en détail dans le premier article, et complétés dans le troisième article en montrant l'importance de l'optimisation de la variété de la de recherche pour maximiser les revenus des licences.

Nos résultats sont cohérents avec la littérature antérieure sur le changement technique. Le premier article montre que les jeunes pousses sont associées à moins de revenus de licence par rapport à leurs homologues plus établis. L'association négative de la proportion de licences accordées aux jeunes pousses est persistante au cours des cinq (5) premières années, ce qui indique que l'octroi de licences aux jeunes pousses a un coût d'opportunité pour les universités. Les entreprises en place se comportent différemment, la proportion de licences accordées aux grandes entreprises est associée à des revenus de licence plus élevés au cours des deux (2) premières années, mais au prix de paiements de redevances plus faibles au cours des années suivantes. En fait, l'étude montre que le revenu des redevances est associé à la proportion de licences accordées aux PME et qu'il est persistant dans le temps.

Les deuxième et troisième articles se concentrent sur la nature recombinante de l'innovation. Ils montrent tous deux l'importance de la diversification de la base de connaissances pour la reconnaissance des opportunités, car la diversification technologique est associée à la fois à plus de retombées et à plus de licences générant des revenus. Cependant, nous établissons certaines différences importantes entre les deux stratégies. La création de spinoffs est positivement associée à la diversification indépendamment de la parenté, tandis que les licences qui génèrent des revenus sont associées à la diversification liée.

Ces articles montrent également que les universités peuvent rencontrer des difficultés à trouver des partenaires en place pour concéder des licences sur leur technologie, même si elles ont une grande proximité technologique. La proximité technologique avec l'industrie locale est associée à un plus grand nombre de licences générant des revenus pour les universités non diversifiées. Cela indique que ces universités assument le rôle de services aux entreprises à forte intensité de connaissances dans les régions moins diversifiées. En revanche, la proximité technologique est associée à davantage de créations d'entreprises pour les universités diversifiées. Bien que cela semble contre-intuitif, c'est le résultat de l'université qui capitalise sur la connaissance du marché de ses partenaires et tente de combler les lacunes structurelles de la chaîne d'approvisionnement par des retombées.

Enfin, nos résultats sur la spécialisation indiquent une association négative de l'avantage technologique révélé (RTA) avec le nombre d'entreprises dérivées et de licences générant des revenus. Nous pensons que cela est lié aux caractéristiques idiosyncratiques de l'indicateur RTA. Ces résultats montrent que les universités ayant une expertise dans des domaines de niche ont plus de difficultés à concéder des licences sur leurs technologies, que ce soit à des jeunes pousses ou à des entreprises en place.

Les résultats montrent l'importance d'établir le bon mélange de R-D pour répondre aux besoins de la stratégie d'octroi de licences des universités. Les universités doivent élaborer leur programme de R-D en fonction des besoins locaux et de leurs capacités existantes. Cela leur permet de générer des revenus de licence, mais aussi d'encourager la collaboration entre les universitaires et les industriels, ce qui peut conduire à la découverte d'opportunités débouchant sur de nouvelles technologies et des retombées.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

TTO	Technology Transfer Office
IP	Intellectual Property
AUTM	Association of University Technology Managers
USPTO	The United States Patent and Trademark Office
FTE	Full Time Equivalent
PhD	A Doctor of Philosophy
U.S	United States of America
R&D	Research and Development
GDP	Gross domestic product
PRO	Public Research Organisation
VC	Venture Capital
SBIR	Small Business Innovation Research
ESA	European Space Agency
CPI	Consumer Price Index
OECD	The Organisation for Economic Co-operation and Development
RTA	Revealed Technological Advantage

LISTE DES ANNEXES

CHAPITRE 1 INTRODUCTION

The importance of innovation has grown in the last century and today technological innovation is touted as the engine of economic growth and social change ("OECD", 2010). Innovations are more often than not the pinnacle of the collaboration and arduous work of legions of contributors (Takeuchi and Nonaka, 1986). However, the exploitation of newly acquired knowledge comes with its challenges. On the one hand, technological innovation equates to new products and services whose successful deployment can generate great wealth and benefit humanity. This is perhaps the most important argument put forward by governments and researchers to invest in basic and applied sciences ("OECD", 2010). On the other hand, the allocation of this new-found wealth is not always proportional to the resources invested. In fact, innovation can be described as a relay race where only the last runner wins (Takeuchi and Nonaka, 1986; Agarwal and Gort, 2002). In that sense, early investors in the R&D leading to a new technology might never see any direct monetary return on their investments (Thursby and Thursby, 2007). It is in this context that universities, seen as the linchpin of technological and scientific evolution, must invest in R&D and demonstrate the efficient use of the resources they have been entrusted with (Thursby and Thursby, 2002).

Today universities are expected to teach, research, and transfer their results to society, the so-called three missions (Etzkowitz, 2004). At the micro-level, the reasons for knowledge transfer and commercialisation are highly dependent on the researchers' motivations (Landry et al., 2006; Perkmann et al., 2013). However, at the meso level, knowledge and technology transfer are influenced by the actions and interactions of the triple helix actors: university, industry, and government (Etzkowitz, 2004). The recent smart specialisation policy framework developed in Europe has led many countries, including Canada, to adopt similar policies. The policy emphasizes the development of local competitive advantages by coordinating local actors and leveraging capabilities (Gómez Prieto et al., 2019). Universities, specifically in Europe and Canada, are depending on government funding to a large extent to conduct their activities (Daraio et al., 2011). Therefore, these policies will directly influence their research and commercialisation activities. However, the effect of specialisation on university research commercialisation is not established.

Previous studies have shown the importance of the knowledge base diversification for opportunity discovery (George et al., 2016) and the central role technological proximity is playing in technology transfer (Boschma, 2005; Balland et al., 2015). Unfortunately, these studies have taken a researcher (Perkmann et al., 2013), company, (Werker, 2015) or geographic (Agrawal, 2001) point of view when studying these effects and have overlooked the university side of the equation. Therefore, this thesis seeks to contribute to the literature by providing evidence from a university standpoint.

The consensus is that diversification has an inverted U-shape association, where too much or too little diversification hinders innovation (George et al., 2016). Researchers have suggested that this was the result of diminishing return from R&D activities and that diversification was related to difficulties in absorbing the radically new knowledge (Cohen and Levinthal, 1990; George et al., 2016). More recent works have suggested that the reason behind the diminishing return might be the unrelatedness of the R&D being conducted by these firms (Hidalgo et al., 2018). A similar story is reported for technological proximity (Boschma, 2005; Balland et al., 2015). The phenomenon is known as the proximity paradox where not enough proximity is hindering absorption and too much proximity is conducive to myopic behaviour (Cassi and Plunket, 2014).

Measuring the impact of R&D is not an easy task as universities can transfer knowledge to society through multiple channels, these include publications, conferences, consulting, R&D collaborations and contracts, patents, technology transfer, and licenses among others (Agrawal, 2001). The type of transfer methods is determined by many factors such as the tacit versus explicit nature of the knowledge (Agrawal, 2001), the market readiness of the technology (Jensen and Thursby, 2001), the type of innovation (e.g. product or process) (OECD, 2005), and the scope (radical or incremental) (Forés and Camisón, 2016). The abundance of transfer methods also creates the need for different measurement strategies to fully grasp the impact of university knowledge transfer. These include simple publication and patent counts but also encompass more complex indicators like local GDP growth (OECD, 2005; Rossi and Rosli, 2015). This thesis concentrates on the last leg of the journey from the laboratory to the market. More specifically, we examine university research commercialisation through technology licensing and study the determinants and outcomes of university licensing strategies.

Since the passage of the Bayh-Dole Act in 1980, universities have shown increased interest in commercialising their research through licensing to firms. When licensing their technologies, researchers can either license them to incumbent or new companies (Di Gregorio and Shane, 2003). The debate on the most lucrative strategy for the licensor is still ongoing (Bray and Lee, 2000; Savva and Taneri, 2014). Furthermore, universities are known to have different objectives when transferring knowledge, while some are motivated by the additional income the activity might generate, others give more importance to simply transferring the knowledge to society (Baglieri et al., 2018). Perhaps the most important factor for the choice of licensing partner, independent of university control, is the existence of incumbent companies with interest and adequate absorptive capacities to successfully commercialise the technology, in other words, the market pull forces (Cohen and Levinthal, 1990; Dixon, 2001). However, the importance given to commercialisation through spinoffs[1] indicate that there might be other forces at play too.

Historically, spinoffs have long been considered by technology transfer officers as the last resort to push a technology out of the door (Swamidass, 2013). This is not surprising since these companies are usually created to commercialise innovations that are not quite market-ready (Jensen and Thursby, 2001), and commercial knowledge transfer is rated as the least preferred method of transfer by academics and industrials alike (Nsanzumuhire and Groot, 2020). However, these past few decades have seen an increase in university knowledge transfer activities through licensing (Castillo et al., 2016). This steady growth was also accompanied by an increase in the share of licences being granted to spinoffs (Di Gregorio and Shane, 2003). Several factors could be at play in this change of attitude towards startups and might be tied to both university governance and the technology licensing market.

On the one hand, there might be genuine interest and rewards in launching startups. This might be the result of the investor communities' and universities' interest in spinoffs due to the eye-catching, mouth-watering, return on investment of some unicorn startups in Silicon Valley. Universities seeing the results of some of their pairs like Standford's massive gain from its shares in Google might be more inclined to invest in startup support (PRESS, 2005). Furthermore, this new strategy is also accompanied by more recent studies which put forward the notion that spinoffs are more lucrative for universities (Bray and Lee, 2000; Savva and Taneri, 2014). Besides, launching startups has a positive effect on university prestige through the halo effect and can be used as positive signals by the TTO and university to impress government and industrial partners through showcasing capabilities and hinting at job creation (Siegel and Phan, 2005; Pitsakis et al., 2015). Moreover, launching startups might be less costly to find potential applications and customers for the technology than spending resources such as the TTO employees' or the researcher's time. Finally, based on Schumpeterian principles, startups are considered a necessity to establish new industries stemming from the research on the scientific frontier (Schumpeter, 1942).

On the other hand, the increase in the number of startups might stem from the inability of the market to absorb the knowledge (Cohen and Levinthal, 1990) or a lack of interest in the technology by incumbent companies (Dixon, 2001). This would make sense since startups are a way for society to develop new skills and industries that might not fit their current infrastructures, technologies, or socio-economic paradigms (Schumpeter, 1942; Geels, 2002). Furthermore, the gradual entry of new universities into the technology licensing market (Castillo et al., 2016) and the increased emphasis put on the importance of commercialisation (Mowery et al., 2001) might create a race to

[1] Spinoffs are startups created for the main purpose of commercialising technology stemming from research. Although not all startups are spinoffs the two terms will be used interchangeably in this thesis.

be the first to the market and push researchers to disclose technologies that would have previously never left the laboratory bench due to having no commercial value in their current state or context (Dixon, 2001; Geels, 2002; Godfrey et al., 2020). Startups have garnered a lot of traction in the literature and the mind of the public. In a bid to obtain the favours of stakeholders and secure more funding universities might simply be using the startups as a signalling tool devoid of any tangible benefit.

The coordination of the university internally and with local actors in its research and development efforts should improve the opportunity discovery process (George et al., 2016) and facilitate local absorption by incumbents (Cohen and Levinthal, 1990). In fact, university commercialisation strategies and outcomes are path-dependent. This means that the choice of incumbent versus startup partner will be determined well before the commercialisation process begins. The commercialisation strategy and outcome will therefore depend on the initial research scope and field. Universities that serve their local incumbent companies will subject their researchers to industry sourced problems and diversify their source of knowledge. Furthermore, being active in similar fields and being internally coordinated will facilitate knowledge absorption by incumbents. Therefore, universities serving local companies will fare better than universities that are trying to commercialise technologies by creating new local industries. This, in turn, should demonstrate the positive effect that smart specialisation type policies could have on university research commercialisation.

The three articles presented in this thesis seek to contribute to the literature on university research licensing. The first article presents evidence of the different time scales for return on investment when licensing to differently sized companies. It establishes the positive association of licensing income with licences to incumbent companies and refutes claims that licensing to startups is more lucrative for universities, at least in the short term.

The second and third articles attest to the positive association of opportunity discovery with the knowledge base diversity and the technological proximity to the local industry. The second article concentrates on startups while the third focuses on licenses generating income. Together they illustrate how startup creation is positively affected by the lack of incumbents to commercialise the technology, and how diversification and proximity can help universities find incumbent partners to carry their technologies to the market while enhancing opportunity discovery.

The rest of the thesis is structured as follows: it reviews the literature in Chapter 2; it presents a summary of our objectives, hypotheses in Chapter 3, and the articles in Chapters 4, 5, and 6; Chapter 7 discusses the findings and implications of this research and it concludes in Chapter 8.

CHAPITRE 2 LITERATURE REVIEW

2.1 Introduction

Innovation is a collaborative activity. From a university standpoint research commercialisation is the result of the triple helix actors's interaction Etzkowitz and Leydesdorff (2000). Government, university, and industry, each have their own idiosyncratic agenda. The following chapter presents why these actors are engaging in knowledge transfer and research commercialisation activities, the tools they are using and the factors affecting commercialisation.

2.2 Why is knowledge transferred

2.2.1 Why do governments push for innovation and knowledge transfer

Economic growth and the efficient use of resources have been at the heart of economic studies ever since the classical economists (Smith, 1776; Malthus, 1888; Ricardo, 1891; Marx, 2012). Researchers have started being interested in innovation and its impact on society and the economy in the wake of the past century (De Tarde, 1903; Schumpeter, 1942; Kinnunen, 1996). However, it is only after the end of the second world war that governments and researchers truly paid attention to innovation (Bush, 1945; Godin, 2006; Patanakul and Pinto, 2014). After the second world war, three main models were used to explain the technology transfer process: the appropriability model (1945 to the late 1950s); the dissemination model (late 1950s to late 1970s); and the knowledge utilization model (late 1970s to the present) (Devine et al., 1987).

The appropriability model stipulates that the role of the government is to procure high-level research. Industries under competitive pressure will find ways to integrate the results by themselves. In the dissemination model the government goes one step further, and through various centralized technology transfer programs connected to governmental agencies, disseminates the knowledge to the public. To do so the agencies determine which results would be useful, package and publicise research products, and make them available to public and private organisations. In the dissemination model, a more market-oriented approach is adopted. Instead of stimulating research and disseminating the results, the government encouraged the collaboration of industry and research institutes via collaborative arrangements, thus letting the industry set the research agenda according to its needs (Devine et al., 1987).

This last approach led the National Science Foundation in the US to launch two initiatives seen as models to follow by other agencies: the Industry-University Cooperative Research Centers (IU-CRC) program (1973) and the Engineering Research Centers (ERC) program (1984). Support for the centres came from government, local and regional administrations and industry. As noted earlier, the cooperation of industry and research institutes is seen as beneficial by all parties as it procures means to reach complementary resources such as funding and expertise. Furthermore, it also contributes to other broader social benefits such as enhancing industrial competitiveness of the region (Devine et al., 1987).

A similar division was made by Bozeman (2000). Before the 1980s, technology transfer was mostly studied between nations. During the 1980s and 1990s, this focus shifted toward intranational technology transfer in the US and was followed by other countries. Bozeman (2000) divided this new literature into three competing paradigms: the market failure paradigm, the mission paradigm, and the cooperative technology paradigm. The descriptions of these paradigms are very close to the previously described models of Devine et al. (1987).

Under the market failure paradigm, the government's role is minimal and is there to remove barriers to the free market. The role of the university in this paradigm is to educate and produce basic science. In the mission paradigm, the government conducts R&D in specific fields where the private industry is not optimal, these can include defence, national security, but also includes health, space and agriculture. This vision has risen post-world war II and is common to many countries. The cooperative technology policy paradigm promulgates cooperation between government, universities and industry; as well as inter-firm and cross-sector collaborations. The university and government research institutes are seen as a source of technology and applied science. Technology development and basic science are seen as major missions by universities and government labs alike, and both these organisations are fairly active in technology transfer. This approach existed prior to 1980 in other nations but the literature on the subject was greatly increased after the 1980s due to the many policy changes adopted by the US (Bozeman, 2000).

2.2.2 Why do companies innovate

Companies need the reasons, resources and opportunity to innovate (Ashford, 2000). Multiple factors are considered by the firms when deciding whether or not to invest in R&D and innovate, chief amongst which is the need for innovation.

Researchers have long studied the effect of market concentration and competition on the firms' willingness to innovate (Nicholson, 2009). While some argued that competition is good for innovation, others defend the opposite. The truth seems to be in between as some studies suggested the inverted-U shape relationship between market competition and innovation (Tingvall and Poldahl, 2006).

The industry in which the company operates is a key factor in the decision to invest in R&D and the return on investment. Schumpeter distinguishes two innovation patterns. Mark I entrepreneurial and Mark II routinised industries differ in their types of innovators, the first pattern evolves by innovating through startups and small companies while the second pattern produces innovation through large incumbent companies (Schumpeter, 1942). Hence, the maturity of the industry plays an important role in R&D and innovation activities, the type of partnerships, and the knowledge sourcing strategy of the company. Companies undertake R&D and knowledge sourcing with different partners for various reasons (Pavitt, 1984; Freitas et al., 2013; Du et al., 2014). The deployed strategy for technology and knowledge sourcing is idiosyncratic to the company and different in newly industrialised countries, emerging industries and mature industries (Pavitt, 1984; Freitas et al., 2013). Further distinctions can be made through sectoral patterns (Pavitt, 1984). Pavitt (1984) distinguishes four (4) types of firms each with their strategy to source technology: science-based, specialised supplier, scale intensive, and supplier-dominated firms. Other classifications were also proposed since these two (2) seminal work (Schumpeter, 1942; Pavitt, 1984) to identify other aspects of companies and the innovation process (De Jong and Marsili, 2006).

The size of the market also influences R&D and innovation decision (Nicholson, 2009). Studies in both Northern Ireland and the U.S. on companies willingness to conduct R&D have found that firms with local markets were less likely to invest in R&D activities compared to firms with national and international markets (Harris and Trainor, 2009; Foster et al., 2020). These studies were supported by others from around the world, showing that companies behave differently according to their industry and national paradigm (Motohashi et al., 2004; Tsai, 2005; Munos, 2009; Badillo et al., 2014).

Management support plays a key role in R&D investment decisions and the innovation process (Bach et al., 2002; Bozeman, 2000; Freitas et al., 2013). The decision to conduct R&D in-house or through partnerships is highly persistent. Companies which are undertaking R&D are more likely to continue investing in innovation while those without R&D activities are more likely to refrain from R&D in the future (Harris and Trainor, 2009; Foster et al., 2020). This is not surprising since past experiences with universities lead firms and universities to develop common routines and practices. These companies also have greater experience in negotiating IP and can thus reduce the conflicts that may arise (Bruneel et al., 2010). Interacting with universities via various channels brings additional benefits to firms as different types of interactions are complementary. However, in doing so the firm has to interact with a panoply of actors and this can raise conflicts and transaction-related barriers (Bruneel et al., 2010). While the universities have institutionalised the transfer process, the industry did not do so in a widespread manner. Only a small portion of big companies actively scout for external IP and only interaction with highly qualified upper management seems to yield results (Klein et al., 2010).

2.2.3 Why do universities transfer knowledge

At a macro-economic level, the entrepreneurial university is seen as a motor of economic growth as it constitutes the backbone of the knowledge economy (Cassia et al., 2014; Etzkowitz, 2003; Guerrero et al., 2014; Todorovic et al., 2011). At a meso-level however, universities' motivations for engaging in entrepreneurial activities can differ. Commercialising their research is one way for universities to finance themselves aside from government subsidies and student fees (Daraio et al., 2011).

Universities have various goals and can use different business models to reach a mix of these goals (Baglieri et al., 2018). These goals can be contradictory as is the case for publications and patenting. A success for the business might not be one for the community, and a success for the community might not be a success for the business. Baglieri et al. (2018) divide TTOs along two axes, faculty engagement and local or global community engagement. Four quadrant results from this approach. The first quadrant is the Traditional Shop: TTO engage local communities with a broad set of faculties and focus on patents; Licensing is not very important and technology transfer is seen as a cost centre; The TTO might be very efficient in the transfer process with a lot of disclosure, patents, and licenses, but do not bring much revenue. An example of this model is the University of South Florida. The second quadrant is the Orchestrator of Local Buzz: TTOs in this quadrant focus on income and start-up and are very selective of faculty engagement and work at a local scale; TTOs are seen as revenue centres and work with incubators and science parks; They also try to orchestrate the technology transfer process by any means possible by leveraging consulting, research partnerships and students. An example of this model is the New York University. The third quadrant is the Catalyst: TTOs in this quadrant relied on disruptive innovations to generate revenue. TTOs were thus seen as profit centres, they rely on selective engagement of the global community and international markets to maximise profit for the university and the community. An example of this model is MIT. The fourth quadrant is the Smart Bazaar, it is less selective and call on the global community; TTOs in this quadrant use nonexclusive licenses and search for increased community support by implementing open databases to make use of crowd fueled science and crowdfunding platform to generate revenue for research; TTOs are considered as value centres for society. An example is Johns Hopkins.

A similar approach was devised by Graham (2014) who divided the university approach to entrepreneurship into two models of bottom-up led by the community and top-down led by management. According to the author, the first model aims at developing an entrepreneurship ecosystem outside and within the local community, the second model sees entrepreneurship as a new source of revenue for the university and seeks international and national partnerships.

2.3 How is knowledge transferred

2.3.1 Government tools

As can be understood from these previously cited models, the government plays an important role in the university research commercialisation process (Graham, 2014; Fitzgerald and Cunningham, 2015). Government actions are aimed at increasing opportunities and the rate of capitalisation on these opportunities, but this is not guaranteed. Public regulations can encourage technology transfer between actors when successfully planned and implemented (Bozeman, 2000) or hinder it when not corresponding to the market needs (Grimm and Jaenicke, 2012). For instance, in Ireland and Germany, TTOs complain about wasting too much time on IP protection, and contract drafting versus commercialisation (Boehm and Hogan, 2013). Government support can have a major impact in shaping demand through several mechanisms: influencing the retention of multinational companies via tax incentives; funding research and collaboration (Boehm and Hogan, 2013; Bozeman, 2000; Freitas et al., 2013); or enacting other policies such as local development objectives for the university (Belenzon and Schankerman, 2009). Furthermore, they can help determine the revenue sharing between parties (Boehm and Hogan, 2013; Guerrero et al., 2014), or as in the Spanish case, permit the temporary pausing of teaching activities to help academics launch companies and guaranty a part of the benefits generated (Guerrero et al., 2014). Moreover, start-ups still suffer from the difficulties of attracting investors, public-sector support, such as winning competitions or university endowment have been shown to contribute to positive signalling and attracting venture capital attention (Gubitta et al., 2016).

A good framework to understand the effects of government activities on firm innovation and university research commercialisation is to distinguishes the three (3) levers governments can use to enhance innovation: 1) increasing the number of opportunities; 2) enhancing the companies' capacities; and 3) stimulating their willingness to innovate (Ashford, 2000; Patanakul and Pinto, 2014). In reality, of course, policies are not concerned with improving only one aspect and can aim at enhancing a combination of all three (3) at the same time.

A highly cited and emulated policy in the US, the Bayh-Dole, was devised as a solution to the US competitiveness decline in the 60s and 70s and the identification of a lack of university research transferability (Etzkowitz and Leydesdorff, 2000). This piece of legislation gave the ownership of patents to universities to encourage commercialisation, and is seen as the most influential policy regarding technology transfer (Audretsch, 2014; Etzkowitz, 2003). This was only the beginning of a long list of other legislation passed by the US to stimulate technology transfer (Bozeman, 2000). These were in turn followed by many universities creating technology transfer offices to take advantage of these regulatory changes (Castillo et al., 2016; Rogers et al., 2001). Other countries also adopted similar approaches to stimulate university-industry collaboration (Boehm and Hogan, 2013; Etzkowitz and Leydesdorff, 2000).

For instance, The Irish national policy of Strategy for Science, Technology and Innovation (SSTI) aimed at increasing commercialisable knowledge output and strengthening the commercialisation process. This policy led to a great increase in start-up and licensing activity and to a shift from Industrial Liaison Offices to TTOs, the latter having a narrower mission and greater resources (Fitzgerald and Cunningham, 2015). Similarly, in response to growing budgetary constraints, the UK government has changed its policy toward university entrepreneurship to encourage more local interaction and self-financing of entrepreneurial ventures. To develop the innovation ecosystem, it launched several initiatives and implemented various policies to help the collaboration of university and industry (McAdam et al., 2012).

More recently, governments around the globe started emulating the European Smart Specialisation Initiative. The initiative aims at improving the competitiveness of regions by helping them identify their strength and concentrate their science technology and innovation efforts into these industries and activities (Gómez Prieto et al., 2019).

2.3.2 University Tools

Knowledge and technology can be transferred in a large number of ways (Murray, 2002; Arvanitis et al., 2008). Arvanitis et al. (2008) identified 19 single forms of KTT activities such as exchanging scientific and technical information; educational activities; research activities; activities related to technical infrastructure; consulting and cooperation in research. Furthermore, academics also transfer knowledge to industry via start-ups. In her case study, Murray (2002) mentioned the complex ties developed by scientists who oscillate between university laboratories and industry. This type of transfer also has other advantages as the revenue generated via equity is relatively greater than licensing for cash to incumbent firms in the long run, and studies show that this way of commercialisation is more efficient in bringing revenue when considering the person-year research invested. This is argued as being the result of the limited life of licensing deal versus the prospects of growth for the newly formed firm (Owen-Smith and Powell, 2004). Spinoffs and licences are also a great source of economic growth for the society at large (Rogers et al., 2001). These knowledge transfers are also derived from mergers, acquisitions, scientist collaboration and student placement which are not always observable via co-publishing and co-patenting networks (Murray, 2002). As can be understood spillovers can occur via the mobility of the labour force but other means can also influence the process such as colocation and strategic alliances (Owen-Smith and Powell, 2004).

These transfer activities can be broadly classified into formal and informal interactions, both having their advantage and disadvantage. According to Howells et al. (2012) the influence of formal versus informal links on firms' innovative performance is negligible. The results showed that both formal and informal interactions enhance the innovativeness of firms. They argued that the two mechanisms might work together with informal ties taking the role of a conduit for formal transfers to occur.

This was confirmed by Bruneel et al. (2010), who identified two types of barriers to university-industry collaboration: orientation-related barriers related to different orientations; and transaction-related barriers related to conflicts over IP and dealing with university administration. They showed that interacting with universities via various channels might bring additional benefits to firms as different types of interactions might be complementary thus lowering orientation-related barriers. However, in doing so the firm has to interact with a panoply of actors and thus raised conflicts and transaction-related barriers (Bruneel et al., 2010). These conflicts related to the distribution of revenue also occur when the transfer mechanism is through spillovers and informal channels, as these transfers don't generate revenue and are hard to quantify, they cannot contribute to the necessity to show the value created by the research and bring justification to the governmental spending.

The transfer media can also create tensions between the university and the firm. University researchers are motivated by peer recognition while the industry is motivated by financial gain. Thus, they both value different types of knowledge, scientists want to work on problems recognised by their peers, while industry wants to work on new products and services (Bruneel et al., 2010). From an industry point of view collaborative research, contract research and consulting are more valuable than IP transfer through patents and licenses (Perkmann and Walsh, 2009). Industry rates the academic patents as an ineffective way of technology transfer compared to publications and interaction with academic scientists (Breschi and Catalini, 2010). However, patent fillings can help by increasing the perceived value of the technology as it can create a monopoly if granted, furthermore, patent as codified knowledge is easier to transfer than tacit knowledge and thus accelerate the transfer process (Du et al., 2014). Yet, publication versus patenting is still a concern as knowledge diffusion and protection culture are different (Bruneel et al., 2010). This view is also shared by other scientists on the ground of university-industry collaboration leading to secrecy, delays in publications, and bias in results (Cassia et al., 2014; Perkmann and Walsh, 2009). Thus, the industry is eager to collaborate with academics but don't want them to share the knowledge created, be it through patents or publications.

Perkmann and Walsh (2009) reported that knowledge-generating projects were the most in-phase type for publication, while the three other types -problem-solving, technology development, and ideas testing- lacked complementarity as data collection would be impossible due to time pressure, or the data collected would not yield publishable results. Furthermore, idea testing projects were also encountering problems, in most cases, secrecy was deemed necessary by the company or the academics to patent or keep the knowledge away from competitors. Thus the authors derived that the further from the market the project is, the better complementarity is, this also leads to less need for secrecy, hence more publications. While application-oriented collaborations yielded fewer publications, the authors reported that close collaboration of these types benefited tacit knowledge exchange and the creation of communities of practice. Moreover, close interaction with industry also gave access to knowledge bases otherwise out of the reach of researchers, and these application-oriented collaborations were followed by other research projects ideas for the academics. The authors noted that most researchers engaged in different levels of projects with the same industrial and created trust and benefited from knowing their partners in more basic research-oriented projects as well as receiving their support via access to resource, participation and funding (Perkmann and Walsh, 2009). This complementarity between both worlds was also observed by many others, the literature shows that researchers prolific in patenting also contribute greatly to publications. (Abramo et al., 2009; Bruneel et al., 2010; Cassia et al., 2014; Baglieri and Lorenzoni, 2014).

Baglieri and Lorenzoni (2014) showed that entrepreneurship and research don't need to be traded off since interested researchers can successfully perform both tasks. This entrepreneurial activity is also seen as a source of new information by the researchers and contributes to the research and commercialisation of the IP. Moreover, Cassia et al. (2014) validated that collaboration with the industry increase the amount and quality of publications. Their results verified that in the case of entrepreneurship research centres axed toward research and transfer activities, the transfer process influences positively the research activities. This positive effect was also validated by Abramo et al. (2009). Their studies on scientists determined that while collaboration did not affect the resulting paper, scientists collaborating with industry achieved better qualitative and quantitative results on overall publications than their colleagues in the same sector. Furthermore, collaboration with industry was also characterised by a higher multidisciplinary compared to other publications.

Hence, the involvement of academics in industry R&D is a great source of innovation. From a research point of view, consulting generates new ideas and research projects as problems present in the industry are an important source for follow-on scientific research. Researchers report contradictory results present in the literature, on the one hand, interaction with the industry and patenting activity has a positive impact on publishing, on the other, excessive interaction leads to less publication (Perkmann and Walsh, 2009).

Several best practices have been observed and reported by different authors for university research commercialisation. The most successful universities not only take advantage of their cluster strength, but they also create the necessary structures to incubate the cluster and grow it, the most notable example of such attitude have been reports as MIT and Stanford (Etzkowitz and Leydesdorff, 2000; Etzkowitz, 2003; Etzkowitz et al., 2007; Swamidass, 2013). Nowadays, one widely used tool to achieve commercialisation are the TTOs. As boundary-spanning organisations, their activities spread from helping to create the right environment for innovation to occur, to transfer of results to industry, and even beyond in the case of start-ups.

The most commonly used tools to commercially transfer university research to the industry are patenting, licensing, and startup creation (Boehm and Hogan, 2013; Etzkowitz, 2003; Todorovic et al., 2011). Consequently, several tools have been created to measure the effectiveness of the transfer process. Usually, these transfer activities are gauged via various tools derived from the different models used to describe the process and encompass publications, research funds, counts of disclosures, number of licenses, licensing revenue, equity, and start-up creation (Graham, 2014; Guerrero et al., 2014; Rogers et al., 2001; Thursby and Kemp, 2002). These indicators are nonetheless criticised as they only measure specific output of TTO activity and are deemed incoherent and inadequate in measuring entrepreneurship culture and activity. Instead, experts promoted the use of agendas, participation levels and interaction with local communities as indicators (Graham, 2014). For instance, Coccia (2008) reported multiple ways to transfer: learning by doing, by using, and by interacting. Moreover, Murray (2002) identified other mechanisms through which knowledge transfer is realised, these can be: human capital movement from academia to industry, unformal interaction during conferences, patenting by research institutes, consulting by the researcher for the industry, licensing, sponsored research, and membership to scientific advisory boards. Furthermore, academics also transfer knowledge to industry via start-ups. In the case study, the author mentioned the complex ties of scientists who oscillate between university laboratories and industry. These knowledge transfer mechanisms are also derived from mergers, acquisitions, scientist collaborations and student placements which are not always observable via co-publishing and co-patenting networks (Murray, 2002).

Aside TTOs, other structures are also used by the university to stimulate entrepreneurship and technology transfer, these include entrepreneurship research centres, science parks, incubators, and proof of concept centres (Audretsch, 2014; Cassia et al., 2014; Etzkowitz and Leydesdorff, 2000; Guerrero et al., 2014; Todorovic et al., 2011). These boundary spanning structures aim at reducing the risk associated with technology transfer for companies and thus reduce the cost of the process by leveraging the university's relational, financial and human capital (Etzkowitz, 2003; Etzkowitz and Leydesdorff, 2000; Guerrero et al., 2014). However, technology and knowledge transfer can also be achieved by other means such as: publishing (Rogers et al., 2001); consulting (Boehm and Hogan, 2013; Martinelli et al., 2008; Todorovic et al., 2011); education and training (Boehm and Hogan, 2013; Guerrero et al., 2014; Todorovic et al., 2011); PhDs students (Guerrero et al., 2014; Martinelli et al., 2008); cooperative R&D agreements (Boehm and Hogan, 2013; Martinelli et al., 2008; Rogers et al., 2001); and networking (Rogers et al., 2001).

Another important mechanism used by universities to enhance entrepreneurship is networking (Etzkowitz and Leydesdorff, 2000). Interdisciplinary and inter-organisational collaborations are the drivers of knowledge transfer (Boehm and Hogan, 2013; Guerrero et al., 2014; Rogers et al., 2001). The collaboration with multiple actors, therefore, ensures that the university develops an adequate strategy and contributes to creating a competitive region in a global economy, this can also lead it to create new networks and orchestrate local actors to develop an entrepreneurial culture as noted by some (Baglieri et al., 2018; Etzkowitz, 2003; Guerrero et al., 2014). Studies show that collaboration with industry increases the amount and quality of outputs (Cassia et al., 2014; Guerrero et al., 2014). Another important factor in the rise of entrepreneurship is the growing strength and impact of the student entrepreneurial movement around the globe with students creating networks with industry partners and other student associations. The mobilisation of the student community via extracurricular entrepreneurial activities and events also plays a role in the change toward the entrepreneurial university, and is fueled by past entrepreneurial experience and networks; communication with supportive management; and dedicated funding (Baglieri et al., 2018; Graham, 2014).

2.3.3 Company tools

Companies can leverage their R&D capabilities through partnerships to enhance opportunity discovery. Each R&D partnership; vertical, horizontal and institutional, have their own goal: customers and competitors for new products; suppliers for cost reduction; and institutions for new products and generic technologies (Belderbos et al., 2004).

Du et al. (2014) identified two types of partnerships to accelerate research and transfer activities, the first is science-based partnerships (universities, research institutions, etc.), the second is market-based partnerships (customers, supplier, competitors). The first strategy procures knowledge about scientific advances, while the second procures knowledge about market needs and possibilities. The authors argued that market-based partnerships help in defining a research agenda, expedite the research and transfer processes by procuring insight on development, and increase the attractiveness of results for business units as they are endorsed by market need. As for the science-based partnerships, they identified three advantages: access to complementary and advanced scientific knowledge; access to research infrastructure and equipment; and access to research personnel. Furthermore, Du et al. (2014) proposed that science-based partnerships are more effective in complex product development as complementary scientific and technical knowledge could accelerate the research by helping determine the technological space, and avoid time-consuming mistakes and rework of problematic parts. Results showed that science-based partnerships accelerate the transfer speed only on very complex projects (Du et al., 2014).

Similar reports are given by others who argued that the most cited incentive to enter into cooperation with universities is access to funding, and cost-risk mitigation (Link and Rees, 1990; Mohnen and Hoareau, 2003; Arranz and de Arroyabe, 2008; Segarra-Blasco and Arauzo-Carod, 2008; Chun and Mun, 2012; Badillo and Moreno, 2016). For instance, in the Spanish automotive sector, companies are attracted toward cooperations with public institutions by the possibility of accessing public funding (Arranz and de Arroyabe, 2008). Access to talent and equipment are also among the aims of the collaborations. Link and Rees (1990) report that major reasons to collaborate with universities research are to recruit potential employees and product development. They also note the importance of problem-solving in production processes and add that using universities computational resources and facilities are also important factors for small [1] and very large [2] companies. Chun and Mun (2012) argued that since internal R&D is costly and risky for SMEs, these firms prefer to mitigate the risk by cooperating in R&D projects.

[1] less than 499 employees.
[2] over 10000 employees.

According to Freitas et al. (2013), the sourcing of knowledge is dependant on the maturity of the industry, in the early emerging phase of an industry, tacit and disembodied knowledge is more important for innovative activities. Emerging industries rely on universities and suppliers, while in mature industries, the preference is for customers and competitors. They added that mature industries are also more technologically diverse than emerging industries as they already cycled through many developments and recombination phases. Furthermore, collaboration with universities also differs as emerging industries use informal tools and tacit knowledge transfer mechanisms, while mature industries used formal contracts and codified knowledge to improve products and processes.

Collaboration with universities can arise from various needs of the firm. Perkmann and Walsh (2009) identified two modes of contributions of university R&D to firm R&D: initiation of projects and completion of projects. The authors argued that most collaboration is aimed at completing the projects. They identified four types of collaborative projects: Problem-solving, Technology development, Ideas testing, and Knowledge generation.

In the case of problem-solving projects, the firm approaches academics for specific requests concerning particular problems in products or processes. The solutions deployed in these instances are either already existing or close to commercialisation. Examples given by the authors included prototype fixing and pipeline modelling. These types of projects are not subject to uncertainty as the requirements are dictated in advance.

The second type of project, Technology development, is one step further from market readiness. In this case, they collaborate on projects where only general requirements are known. The authors gave examples of equipping an existing oven model with automation technology and developing flexible printed circuit boards to replace wire harnesses in cars. In both cases, the government and multiple companies were invested in the project.

The Idea testing type refers to projects usually initiated by the client who wants to test ideas with commercial potential and lack the in-house R&D or sees the project as high risk. The authors gave the example of an automotive components supplier approaching academics to test the feasibility of laser-based measurement techniques on the combustion process.

Knowledge generating projects are usually initiated by academics to further science. These projects are removed from commercialisation and long term oriented, thus industrial partners collaborate only marginally, in most cases the funding source is governmental (Perkmann and Walsh, 2009). This makes sense since the main sources for new project initiation in emerging sectors are students and companies. This might be due to the lack of market knowledge necessary to propose a project which is more available in mature industries. Although diverse, the financing of these projects is more governmental based than in the case of mature industries. Emerging industries also have a higher output yield and usually produce papers and post-graduate theses, followed by new products, patents and new processes (Freitas et al., 2013).

2.4 Factors affecting commercialisation

2.4.1 University side factors

Several factors will play a role in the commercialisation process. Previous studies have documented these TTO and university-related factors (Rothaermel et al., 2007a) which can be related to university idiosyncratic characteristics and goals (Baglieri et al., 2018) as well as external factors such as the characteristics of the local ecosystem (Porter, 1998). Furthermore, the strategy adopted by the university will be dependent on the market readiness of the research results (Thursby et al., 2001a). For instance, Thursby et al. (2001a) noted that early-stage technologies are more inclined to generate research funds and exclusivity clauses.

Studies have shown that TTO characteristics influence their efficiency (Rogers et al., 2000; Thursby and Kemp, 2002; Anderson et al., 2007). Studies were conducted on university and TTO idiosynchastic characteristics (Powers, 2003; Markman et al., 2004; Xu et al., 2011), contextual factors (Sine et al., 2003; Belenzon and Schankerman, 2009), TTO and university strategies (Baglieri et al., 2018) and the impact on the economy (Roessner et al., 2013). The autonomy level of the TTO is known to influence its behaviour (Brescia et al., 2016), which in turn impact their way of managing the commercialisation process (Markman et al., 2009). University research can be commercialised through three (3) avenues (Markman et al., 2005, 2009): licensing for cash (Lach and Schankerman, 2004; Powers, 2003), for equity (Link and Siegel, 2005; Markman et al., 2004) or for research partnership (Thursby et al., 2001a; Thursby and Kemp, 2002). Two (2) main factors influencing the choice of strategy are the market readiness of the technology (Thursby et al., 2001a), and the financial and behavioral autonomy level of the TTO (Di Gregorio and Shane, 2003; Markman et al., 2005; Belenzon and Schankerman, 2009).

The most important factor affecting technology transfer is the size of the university and the TTO (Siegel et al., 2008). The positive association can be observed throughout the commercialisation funnel for the number of disclosure, patents, licenses, and licensing income (Sine et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014). Various dimensions of the TTO and the university have been used to verify this relationship such as the amount of research expenditure, the number of disclosure, the amount of legal expenditure and the number of TTO employees (Sine et al., 2003; Friedman and Silberman, 2003; Turk-Bicakci and Brint, 2005; Link and Siegel, 2005; Xu et al., 2011; Prets and Slate, 2014). However, others have argued that the relative size of the TTO compared to the university is also important (Lach and Schankerman, 2008). For instance, the number of disclosure is known to be highly correlated with the number of TTO employees (Sine et al., 2003). The authors showed that a smaller staff to disclosure ratio was negatively associated with licensing activities. The hindrance of TTO personnel shortage on the licensing process was also noted by others (Swamidass and Vulasa, 2009). One way TTOs reduce the effect of these shortages is the use of outsiders. However, this comes with its own drawbacks. The amount of legal expenditure was reported as being positively associated with the amount of licensing income but negatively associated with the number of licenses granted. These results were imputed to the aggressive tactics used by outside lawyers during negotiations (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014).

2.4.2 Company side factors

A lot has been written about the relationship between the decision to conduct R&D and the company size. The effect of size is different for startups compared to incumbents. University startups are known to invest heavily into R&D. In fact, ties to university were found to be an important factor for startups' success (Rothaermel and Thursby, 2005). However, for incumbents the size of the company is reported as a key determinant of companies propensity to invest in R&D, the relationship between firm size and R&D expenditure was shown by multiple researchers, and constraints on cash flow negatively impact the level of R&D investment (Cohen et al., 1987; Cohen and Klepper, 1996; Kumar and Saqib, 1996; Hall et al., 2016; Foster et al., 2019). Startup's or incumbent, investments in R&D are important, as they will create the absorptive and transformative capacities necessary to create marketable products and processes (Guellec and Van Pottelsberghe de la Potterie, 2004; Baglieri and Lorenzoni, 2014).

However, more expenditure does not necessarily result in more efficiency. Cohen and Klepper (1996) remark that larger firms are less efficient at generating patents and innovations per R&D dollar. They argue that this is due to cost spreading where large companies engage in more R&D projects than their smaller counterparts. This is also supported by others (Zenger, 1994; Tsai, 2005; Munos, 2009; Li, 2011; Almeida et al., 2013; Shackelford, 2013; Spiganti, 2017; Merz, 2019). Incumbent firms do not have the flexibility to deal with radical innovations and new start-ups might encounter difficulties in finding financial capital (Klein et al., 2010). However, companies achieving commercialisation are reported as smaller and younger (Bozeman, 2000). For instance, Almeida et al. (2013) argued that financial slack leads to inefficient investments in marginal R&D

projects while financial constraints lead to efficient use of resources. The difference in R&D activities and outcomes between small and large companies goes beyond patents and financials. Small companies higher scrutiny of R&D investment and the subsequent patent valuation is not lost on others (Shackelford, 2013; Merz, 2019). Patents are considered as quality signals by stakeholders and beneficial to small firms and startups when seeking external funding but do not necessarily influence the stakeholders' perception of larger firms (Hottenrott et al., 2016). This success can also be observed through the stock price as financial constraints for R&D intensive firms increase stock return (Li, 2011).

The lack of resources is also conducive to behavioural changes as it leads to more risk-taking and more success for innovative projects (Spiganti, 2017). Of course, these results need to be nuanced as R&D efficiency can easily be influenced by the local context and the industry. For instance, Munos (2009) reported that small companies in the pharmaceutical industry in the U.S. contribute more to innovation with fewer resources than their larger counterparts. These findings are nuanced by Tsai (2005) who showed that small and large companies are more efficient than medium-sized firms in Taiwan's electronics industry. Furthermore, although the propensity to invest in R&D is persistent, the constant evolution of the paradigm influences the profile of R&D spenders over long periods. This is best illustrated by the growing share of small U.S. firms engaging in R&D since the 1980s (Foster et al., 2019).

Similar to R&D expenditure and efficiency, the propensity to enter into university-industry partnerships and the efficiency of these collaborative arrangements is size-dependent. The size of the company was found to influence the choice of the partner, larger companies being more likely to engage in partnerships with universities (Mohnen and Hoareau, 2003; Belderbos et al., 2004; Badillo et al., 2014). For instance, in the Spanish automotive industry, companies of different sizes engage in collaborations for different reasons and with different partners. Results indicate that small firms are less active in cooperation than large companies. The most common partners are vertical while institutional partnerships are not frequent and are mostly conducted by larger firms (Badillo et al., 2014).

This preference is reciprocal as universities also prefer to work with larger firms that can more easily absorb the knowledge created and participate financially in its creation. Of course, this might be due to public initiatives being more oriented toward larger companies in the past (Shapira et al., 1995). Once again, startups stand out from incumbents as those with ties to the university enjoy a higher survival rate (Rothaermel and Thursby, 2005).

Previous research also supports the fact that the preference for collaboration partners might be tied to contextual factors. For instance, Carraquico and Matos (2019) reports that collaborating with universities is very important for SMEs too. This seems reasonable since smaller firms can benefit from these relationships through access to otherwise too costly resources (Link and Rees, 1990).

The efficiency of the cooperation with universities is also related to company size and might very well be influenced by the industry and the government. For example, Yu and Lee (2017) argued that older and larger firms in the Korean manufacturing sector benefit more from collaboration with universities and research institutions. They also added that firms that are exploring rather than exploiting are benefiting more from these collaborations. Therefore, it makes sense that firms that are more exploratory in their R&D activities collaborate more with universities (Bercovitz and Feldman, 2007). Santoro and Chakrabarti (2002) reported that in the U.S. larger companies are using university partnerships to strengthen non-core competencies while smaller firms use these relationships to build up core competencies. However, Chun and Mun (2012) found that in Korea smaller firms engage in R&D cooperation for knowledge spillover and benefit more from said spillover.

This might also be related to differences in cooperative activities as exploration creates more spillover measured through patent citations than exploitation (Akcigit and Kerr, 2018), and spillovers are more important for small firms than large firms (Acs et al., 1994). Furthermore, exploration does not scale as strongly with firm size as exploitation. Hence, small firms and startups have an advantage in taking exploratory R&D as they do not have as many product lines that would divert resources toward exploitation R&D (Akcigit and Kerr, 2018). Thus, it is not surprising that small companies achieve better results through cooperation with universities than their larger counterparts as illustrated by the Japanese and Italian case for which firm R&D is important for every company, but knowledge spillover from universities to firms is more important for small companies (Audretsch and Vivarelli, 1996; Motohashi, 2005). However, the incoming spillover effectiveness is determined by the firm absorptive capacities (Belderbos et al., 2004), and is enhanced when companies also search for knowledge through other types of partnerships (Dezi et al., 2018).

2.4.3 Environment side factors

Other factors outside of the university or the company can also play a role in the amount of knowledge transferred between the actors. For instance, the co-location of actors is a known research subject. The argument is based on the effects of clustering for knowledge spillovers. Porter (1998) defined a cluster as *"a geographic concentration of interconnected firms and institutions in a particular field"*. He further elaborated that in past eras competition was driven by input costs. The proximity to cheap labour or ports was the main factor affecting it. In the modern era, this comparative advantage can be mitigated by the use of outsourcing. Instead, the competitive advantage comes from the efficient use of inputs. Clusters can harbour: clients, suppliers, and competitors as well as governmental institutions and service industries such as universities, and think tanks; and can form around similar products, skills, technologies or other forms of inputs. Clusters can stay hidden if only industrial classifications are used as they will span over national and state boundaries and will encompass multiple aspects of the value chain from raw material production to marketing.

Proximity to suppliers enhances the cooperation and coordination capabilities. Experimenting becomes cheaper and faster as vertical players can cooperate more easily (Porter, 1998; Balland et al., 2015). This proximity is also beneficial to new firm formation as clients will be co-located, and as clusters form around similar input types, the client base can be expanded to other industries. The complementarity of different businesses will affect the efficiency of the whole, Porter (1998) gave the example of a tourism cluster where the overall tourist experience is influenced by a panoply of attractions and businesses.

Furthermore, by staying close to competition firms can more easily pool necessary inputs, such as employees, information, and suppliers, into one geographical area and increase flexibility and efficiency (Porter, 1998; Boschma, 2005; Balland et al., 2015). This pooling effect is also affecting other aspects of the business; customers are more likely to shop for a specific product in an area of high seller concentration. Trade shows and fairs will be located in the vicinity and contribute to the overall reputation. Governments will invest in specific infrastructures to help the cluster thrive. Monitoring the market will be easier as competition will be closer and information fallouts will be captured effortlessly (Porter, 1998; Boschma, 2005; Balland et al., 2015). Clusters can form due to the historical presence of industries, specific local demands or characteristics, or by the arrival of an anchor governmental institution or company (Porter, 1998; Etzkowitz, 2003). Once it begins to form, a cluster will benefit from self-reinforcing loops that will help its development (Porter, 1998; Balland et al., 2015). A cluster can shift its focal industry over time due to external factors such as a change in institutions, new technology or a shift in buyers' needs. If a cluster fails to see the change in the environment and doesn't pivot swiftly and accordingly, it encounters the risk of missing opportunities and declining (Porter, 1998; Boschma, 2005; Balland et al., 2015).

Physical proximity is only part of the equation of knowledge transfer. The proximity between different knowledge branches and groups of individuals will play an important role in the transfer of technology. Proximities are depending on the position of the actors in two types of space, Physical and Cognitive spaces leading to spatial and non-spatial proximities. Spatial proximity refers to geography while the categorisation of non-spatial proximities is subject to debate as multiple definitions and labels exist. For instance, social proximity has been described as relational proximity or personal proximity, while others have aggregated many forms by simply classifying them as non-spatial proximities (Knoben and Oerlemans, 2006). However, some researchers have proposed frameworks to classify them (Balland et al., 2015; Boschma, 2005; Knoben and Oerlemans, 2006). Boschma (2005) classified proximities into five categories, cognitive, organisational, social, institutional and geographic. Knoben and Oerlemans (2006) added technological and cultural proximities and argued that these seven forms of proximity could be aggregated into three specific forms of proximity affecting inter-organisational collaborations: geographical proximity; organisational proximity with organisational, social, institutional and cultural proximities; and technological proximity including cognitive and technological proximities.

Proximities can be measured at the dyadic level or an aggregate level between all actors. Researchers agree that the absence of one type of proximity is not a deal-breaker and can be replaced by other types of proximities (Boschma, 2005; Knoben and Oerlemans, 2006; Mattes, 2012; Balland et al., 2015). Thus, clustering and geographical proximity are neither a necessary nor a sufficient factor to knowledge transfer and innovation as they can be replaced by other types of proximities and alleviated by communication technologies and temporary proximity (Boschma, 2005; Knoben and Oerlemans, 2006; Mattes, 2012; Balland et al., 2015; Werker, 2015). Furthermore, Mattes (2012) suggested that radical and incremental innovation are drawing on different types of knowledge, tacit versus explicit, and as such are influenced by different types of proximities.

In his seminal paper Boschma (2005) argued that too much proximity hinders learning by creating lock-ins while too little proximity is detrimental to coordination and control. Partnerships are reported as being mainly consumed between partners who share common space, however, this homogeneity hurts their innovative output (Cassi and Plunket, 2014; Werker, 2015). This effect is known as the proximity paradox (Cassi and Plunket, 2014). An illustration of this can be found in a study of the German nanotechnology clusters where the collaborations started between high proximity partners but were more efficient if the collaborations were between distant partners (Werker, 2015). Balland et al. (2015) reported that the literature on proximity adopted mostly a static point of view and argued that this approach was lacking explanatory power as proximity increases over time. Thus they proposed a dynamic approach to study the interdependence and co-evolution of knowledge creation and proximity. Each proximity evolves at its own pace and while cognitive proximity can be achieved without consent from both parties, cooperation and coordination are necessary to increase proximity in other areas. As relationships evolve, the actors are subjected to social influence and develop similarities and proximity increases (Mattes, 2012; Balland et al., 2015). Thus, networking can be sparked by proximities, however, over time the networking of actors might lead them to increase proximity and inefficiency if they don't entertain multiple partnerships with distant partners (Balland et al., 2015).

For Knoben and Oerlemans (2006), cognitive proximity refers to the sharing of common frames of reference. The interpretation made by the author is that it is the similarities between the customs, norms, and routines of the actors. An interpretation very close to cultural proximity. The author also acknowledged that several authors use the term to refer to a community of practice. Boschma (2005) however described cognitive proximity as the sharing of similar knowledge base and expertise which is closer to the way Nooteboom et al. (2007) defined the concept in the first place (Nooteboom, 1999). This definition corresponds to that used by Knoben and Oerlemans (2006) for technological proximity as it refers to the overlapping of process or product knowledge related to technology. The distance is generally measured by product and patent similarities (Knoben and Oerlemans, 2006; Nooteboom et al., 2007). This form of proximity facilitates communication and learning between actors as well as absorptive capacities for companies (Cohen and Levinthal, 1990; Knoben and Oerlemans, 2006).

Boschma (2005) also pointed to the negative effects of cognitive proximity. Novelty is the source of creativity and new ideas. Cognitive proximity must be balanced in order to bring enough novelty to spark innovation (Boschma, 2005; Knoben and Oerlemans, 2006; Nooteboom et al., 2007; Balland et al., 2015). This was also shown by Beaudry and Schiffauerova (2011) who reported that repeated collaboration was hurting patent quality. Thus, too much cognitive proximity is detrimental to learning and innovation as no new information is presented to the actors. However, this distance should not be too important as not to hinder communication and new knowledge absorption. In a study on the effect of cognitive distance on explorative and exploitative patent production, Nooteboom et al. (2007) results showed that the optimal proximity between partners was depending on the type of partnership. Explorative collaboration needed more cognitive distance to create radical innovation while exploitative collaborations needed less cognitive distance to build upon common ground. Some authors pointed at the geographical cluster as a solution to the balancing problem. Collaboration between vertical actors and competitions between horizontal actors create an optimal environment for a balanced cognitive proximity of actors and leads to innovation by avoiding communication problems brought by too much distance or lack of novelty brought by too much proximity (Balland et al., 2015; Boschma, 2005; Porter, 1998).

Cultural proximity is defined as the shared patterns of thought and symbols used to interpret the world. It is shared by every member of the group and defines its identity. Culture at the individual level is related to a geographical space such as nation, continent or region. At the organisational level, company culture refers to a way of doing business, thus the concept becomes entwined with organisational proximity as defined in the literature (Knoben and Oerlemans, 2006).

According to Knoben and Oerlemans (2006), organisational proximity refers to actors belonging to the same system, their interactions are facilitated by rules and routines of behaviour and they share similar values or beliefs. Boschma (2005) on the other hand, defined it as the organisation's autonomy in the relationship. Various forms of governance such as market, firm and networks exist. Actors in these spaces have to organise their interactions to share information in an optimal way to create innovation and protect themselves from opportunism. Similar to the previously cited proximity type, organisational proximity also needs balancing. On the one hand, organisational proximity can lead to lock-ins by bureaucracy and rigidity in the network and hinder new knowledge sourcing. On the other hand, too loose coupling and innovation can lead to opportunism. The author argued that loosely coupled organisations are more innovative as actors can coordinate their actions, access new information and reorganise if the need arises (Boschma, 2005; Balland et al., 2015). A solution to counter lock-ins by rigidity for companies is to launch spin-outs (Maine, 2008).

Social proximity defines the relationships between actors at the micro-level. For instance, kinships and friendships are considered high proximity relationships (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015). It is also seen as a facilitator of tacit knowledge exchange but is not indispensable (Mattes, 2012), and although it reduces the risk of opportunistic behaviour, high social proximity and embeddedness in a group might lead to underestimate these risks and give rise to cronyism and lock-ins. Thus, Social proximity and organisational proximity can be complementary or hinder each other. Different types of proximities are also related in other ways, for instance, geographic proximity can give rise to social proximity which over time can increase cognitive proximity. Agglomeration is seen as one way to counter the negative effects of social proximity as more opportunities for partnerships will be presented, thus cognitive distance will be conserved (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015). In the right circumstances and over time social proximity and embeddedness rise and the network becomes a "small world" (Milgram, 1967; Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015).

Finally, institutional proximity refers to the sharing of similar political, economic and social constructs. At the national level, they refer to legislations, business practices, accounting rules, etc., and can be formal as in contracts or informal as in etiquette. At the organisational level, this refers to the use of norms and routines to conduct business and thus the concept of institutional proximity becomes entangled with cultural and organisational proximity as described by Knoben and Oerlemans (2006). These common institutions regulate interactions and relations between individuals and organisations. By their presence, these norms decrease uncertainty and lower transaction costs. Information transfer is assisted by institutional proximity via common language and values (Liker and Choi, 2004; Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015). However, too much proximity can give rise to lock-in. The change will be localised to a specific institution. Institutions being interdependent restructuration or readjustments become impossible and innovation is blocked (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015).

Proximity is an important aspect of collaboration, be it between two organisations or at the network level. The optimal distance between the participants is hard to pinpoint and is dependent on multiple factors as well as the objectives defined by the collaborators. These indicators must be tracked over time to ensure that no lock-in or myopic behaviours are developed by the partners.

2.5 Conclusion

The literature review shows that the three (3) main actors: university, government, and industry have different and complementary roles in the university research commercialisation process and collaborate to achieve their idiosyncratic goals. The government is setting the framework and agenda, for universities to create and disseminate knowledge, and firms to absorb and transform that knowledge into new products and processes, to ultimately generate economic and social benefits.

The literature review on university-industry partnerships shows that smaller and larger companies have different needs and capabilities. Research on university research commercialisation have ignored these nuances and presents gaps regarding the antecedents and outcome of licensing partner choice for universities. No research has been conducted on the relationship between licensing schemes, income, and partner choice. The literature on licensing payment scheme choice by licensor and licensee presented in the first article is in dire need of empirical evidence.

Furthermore, most research on patent portfolio composition approaches the subject from a researcher, firm or geographic focal point. Therefore, little is known about the relationship between the university patent portfolio composition and knowledge transfer. Similar to the aforementioned research, the literature on technological diversification and proximity is also mainly taking a company or regional point of view. Therefore, the literature is missing evidence from a university standpoint. The following chapter presents the framework and hypothesis, as well as, the methodology used to partly fill these gaps.

CHAPITRE 3 METHODOLOGY

3.1 Framework

The framework for this thesis is based on two (2) main arguments: the necessity of a wide knowledge base for opportunity discovery (George et al., 2016), and the need for sufficient absorptive capacities to grasp these opportunities (Cohen and Levinthal, 1990).

Innovation requires a vast and diverse set of people due to its recombinant nature and the asymmetric distribution of knowledge over the population (Mokyr, 2002; George et al., 2016). The existing knowledge and practices, defined as the scientific and technologic paradigm, will define what can be discovered (Kuhn, 1962). The technological trajectory (Dosi, 1982) and the context (Geels, 2002), through the aggregation of talent and knowledge, also play a role in defining how people and knowledge is blended together through human interactions and increase or decrease the probability of innovation in certain technologic and scientific directions. However, not every innovation is necessarily adopted. The context (Geels, 2002) will play an important role in how innovation diffuses through society (Rogers, 1962). The technological trajectory, combined with previous investments will define how capable (Cohen and Levinthal, 1990) and willing (Geels, 2002) society and industry is to adopt the innovation. Therefore, universities that coordinate their activities with local incumbent companies should have better commercialisation results compared to those working with distant technologies and startups since they will be more in tune with the existing needs and capabilities. Their cognitive proximity (Boschma, 2005; Balland et al., 2015) should allow them to benefit from more opportunity discovery through local incumbent companies experiences when conducting R&D activities and develop market-ready licensable technologies, while at the same time having the necessary incumbents to commercialise these innovations (Abramo et al., 2009; Bruneel et al., 2016; Baglieri and Lorenzoni, 2014).

The literature shows that universities research commercialisation is subjected to the same market forces of supply-push and demand-pull. Universities are competing with one another for students, researchers, and financing, and have to demonstrate the efficient use of their resources to their stakeholders. In this context, they have to not only choose the right research orientation to be relevant on the international scientific scene (Dosi, 1982) but they also need to prove that their research can be transferred to society (Cohen and Levinthal, 1990; Geels, 2002) and is creating positive externalities. Previous research on university research commercialisation has identified two licensing strategies for universities: licensing to an incumbent or a startup. However, the choice of licensing partner is not necessarily made by the university or the researcher and can very well be the result of prior choices made by stakeholders concerning the research orientation of the uinversity and be influenced by external forces such as existing infrastructures, supply-chains and incumbent interest (Dosi, 1982; Cohen and Levinthal, 1990; Geels, 2002).

The literature on university-industry partnerships have taken a researcher or firm point of view and the literature on university research commercialisation have outright ignored the importance of the demand for university research. Hence, this thesis addresses the gap in the literature regarding the antecedents and outcomes of university research orientation and commercialisation strategies. More specifically the research question of this thesis is: what are the antecedents and outcomes of university research licensing partner choice?

3.2 Objectives

The first objective of this thesis is to contribute to the literature on research licensing. More specifically it is aimed at identifying the relationship between the university licensing partner and the licensing income type and amount. Ample research has been conducted on university-industry partnerships (Geuna et al., 2003; Perkmann and Walsh, 2009; Ponomariov, 2013). These studies have shown that companies enter into licensing agreements for different reasons. Large companies are reported as being more interested in improving non-core competencies than to develop their core strengths. By contrast, SMEs and startups are more interested in developing their core competencies (Santoro and Chakrabarti, 2002). Ties and collaboration with their parent universities is a matter of life or death for startups (Rothaermel and Thursby, 2005). However, SMEs ad startups do not have the same resources that are at the disposal of large companies. This has two (2) implications, first, they cannot outright buy the licensing right and take what would be considered an important financial risk by investing in new technologies that might not be adapted to their need. Second, they might not have the necessary absorptive and transformative capacities to implement the technology (Cohen and Levinthal, 1990). Therefore, the choice of the licensee will influence the type and amount of income that the university will receive for its license grants. Licenses to startups should be associated with more equity, licenses to SMEs should be associated with long term high income, and licenses to large companies should be associated with short term low income.

This first objective is addressed in the first article. The reason to begin with the outcomes instead of the antecedents is to establish the relationship between licensing income type, amount, and partner. This approach helps to establish the broad strategies used by universities to commercialise their research and guide the subsequent choice of output indicators that will represent these strategies when studying antecedents. The choice was made to study all three categories of companies, startups, SMEs, and large companies, in the same article to facilitate comparison between the outcome of licensing to each company type.

The second objective of this thesis is to study the effect of university knowledge base diversification and research commercialisation. Previous research shows that opportunity discovery and innovation commercialisation is positively associated with knowledge base diversification (George et al., 2016). However, diversification is not enough for technological adoption by the partnering firms (Cohen and Levinthal, 1990). Being too different from prior technologies can downright be a hindrance to the diffusion of innovation in the industry (Hidalgo et al., 2018). This is based on two (2) arguments, first incumbents might fight the diffusion of the new technology if they have a vested interest in the status-quo such as sunk costs. Second, the incumbent might not be able to reorganise and absorb the new knowledge and adopt the new technology due to its stark difference from their prior investments (Cohen and Levinthal, 1990; Hidalgo et al., 2018). This thesis concentrates on the second argument and aims to demonstrate how proximity and relatedness are affecting research commercialisation and licensing from a university standpoint by increasing the absorbability of the newly created knowledge and technologies.

The second objective is divided between the second and third articles. The division was made along the strategy line instead of determinant factors: technological diversity, relatedness, and proximity. The second article deals with the association between knowledge base characteristics and startup creation, while the third article studies the relationship with licenses generating income. This choice of dependent variables was following the lessons learned from the first article which showed that the number of startups and the number of licenses generating income were the most appropriate indicators to identify the different university commercialisation strategies.

3.3 Hypotheses

Hypotheses are divided into three (3) sets. The first set is dealing with the relationship between licensee type and the licensing income type and amount. These hypotheses are confined to the first article. The second set is about technological diversification. It is composed of three (3) hypotheses divided between the second and third articles. The last set of hypotheses is similarly divided among the second and third articles and deals with the association of absorptive capacities and outcome. The reasoning behind each general hypothesis is given down below. A graphical conceptual framework and summary of the hypotheses can be found in Fig. 3.1).

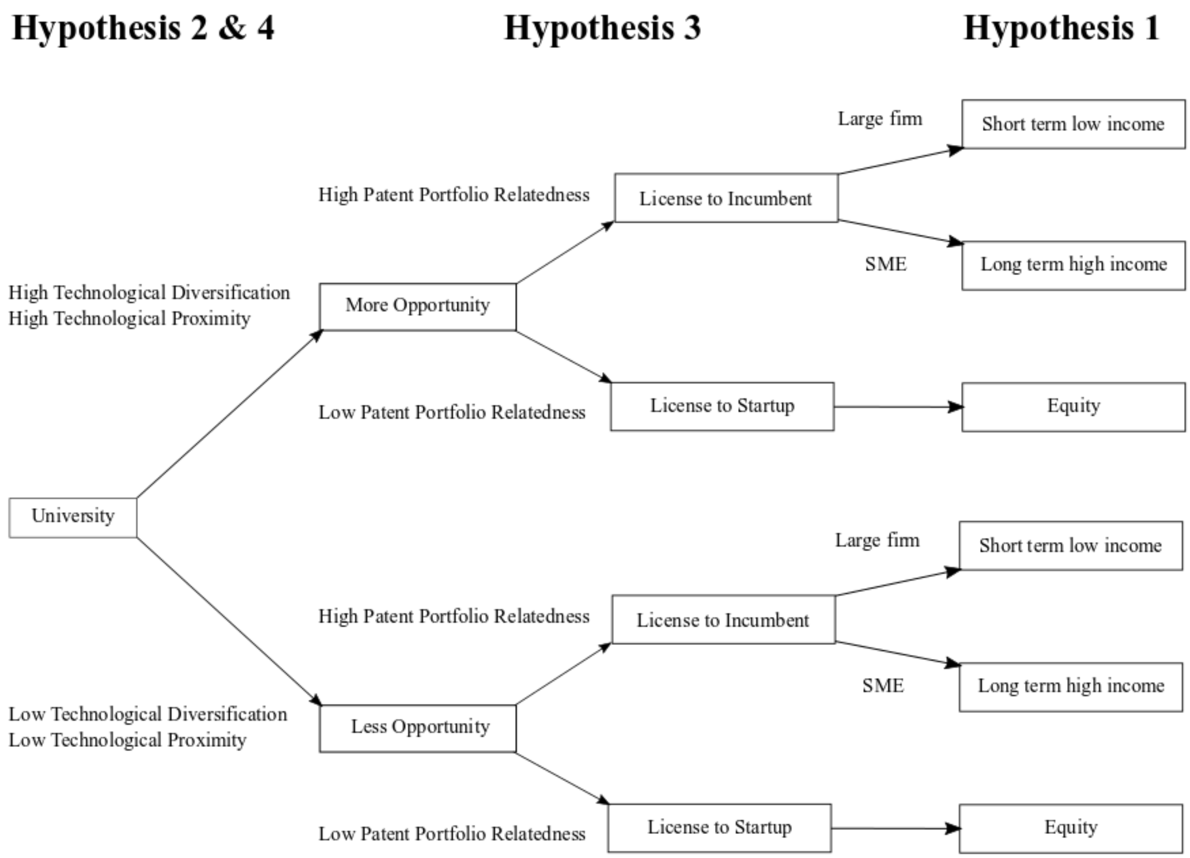

Figure 3.1 Conceptual framework and summary of hypotheses.

Companies can pay for licenses in three (3) broad manner: royalty, milestone payments, and equity in the company (Vishwasrao, 2007; Cebrián, 2009; Savva and Taneri, 2011). Each strategy has its strengths and drawbacks. Royalty has the advantage of generating costs for the company only to the extent that the license is used. This means that if the company does not use the license it will not have to pay. Furthermore, the performance-based pay has the advantage of increasing the licenser's interest in the success of the company leading them to collaborate more to implement the technology. Of course, this implies that any income generated will be divided amongst the partners (Vishwasrao, 2007; Cebrián, 2009). As noted by Vishwasrao (2007) in the case of licenses between companies, royalty is used in the case of proven sales records. This hints at royalty being more common in the case of market-ready technologies. Furthermore, as noted in the previous chapter, the size of the company is an important determinant of R&D spending and efficiency. Considering the limited resources of SMEs (Foster et al., 2019) it can be argued that these companies will need more cooperation from the licensor to implement the new knowledge (Cohen and Levinthal, 1990). Therefore, these companies are more likely to negotiate royalty to insure that cooperation. However, this also entails that any benefit over the long term will be divided amongst the parties, which in turn should yield higher incomes for the university. Milestone payments are as the name implies only made when specific milestones are reached such as contract signature, anniversary date, successful deployment and so on. Depending on the structure of the contract, this creates less pressure on the university researcher to collaborate and any additional income generated by the license will be fully captured by the licensee. This can be advantageous since outgoing spillover is known to be a friction point for companies. Hence outright buying the license can be a viable strategy if resources such as absorptive capacities and finances are not a problem. (Vishwasrao, 2007; Cebrián, 2009). This of course is only possible if the company has sufficient slack resources. Larger companies have more R&D spending and slack resources leading to more absorptive capacities (Hottenrott et al., 2016). This allows them to outright buy the patent or negotiate fixed fees to avoid closer collaborations and scrutiny of the licensor and potential outgoing spillovers. However, although this might generate higher fixed fees up front, over the long term, any benefits derived from the license will be fully captured by the licensee thus lowering the overall licensing income of the university. Equity is different from the previous two since it is mostly used by startups. It has the advantage of not requiring any financial resources and does not create cost over the use of the license. Furthermore, it has the same persuasive power as royalty to draw the licensor to collaborate for implementation. The drawback being the dilution of the company's ownership and no direct licensing income for the university until the sale of the equity (Savva and Taneri, 2011). Therefore, I posit the following hypothesis:

Hypothesis 1*: The size of the university licensing partner influences the license payment scheme and outcome:*

> *a)The share of licenses to startups is associated with more equities and lower licensing income.*
>
> *b)The share of licenses to large companies is associated with lower licensing income over a shorter period.*
>
> *c)The share of licenses to SMEs is associated with higher licensing income over a longer period.*

Innovation is known to be a recombinant co-creative process. Innovation needs a vast array of knowledge on various subjects, defined as knowledge diversity, to emerge. This is perhaps best illustrated by the entrepreneurship literature reporting the importance of knowledge base diversification for opportunity discovery through the use of patent classes as an indicator of knowledge diversity (Shane, 2000a; Hindle and Yencken, 2004; George et al., 2016). Similar positive associations of knowledge base diversification with innovativeness were observed for incumbent companies (Ceipek et al., 2019). The positive association was also noted in the case of universities patenting (Acosta et al., 2018) and regional technological diversification was found to be beneficial to startup growth (Innocenti and Zampi, 2019) which shows that the effect is ubiquitous. Hence, I postulate:

Hypothesis 2*: Technological diversification is positively associated with opportunity discovery.*

Although technological diversification is overall positively associated with innovativeness, the literature indicates that it is not benefiting from economies of scale but instead suffering from diminishing marginal return (Ceipek et al., 2019). This was demonstrated by studies on diversification relatedness in various sectoral and geographical settings (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). The degree of relatedness is defined as the similarity of knowledge or inputs necessary for an activity. In the case of R&D this entails the use of similar resources and knowledge (Hidalgo et al., 2018). Recent studies have looked at the relatedness of patent classes and defined it as technological relatedness. The argument is that patents in different sub-categories but in the same category are more related than those in different categories (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). The authors of these studies argued that the diminishing return of technological diversification on innovativeness and more importantly on firm financial performances were connected to unrelated diversification. More specifically, they argued that unrelated diversification was creating difficulties in absorbing and transforming knowledge. In contrast, related diversification would more easily synergise and create value that the companies could capture. Thus, I propose my third hypothesis:

Hypothesis 3*: Technological diversification relatedness is positively associated with licensing income.*

The importance of synergy between knowledge bases also extends beyond the boundaries of the university. Technological proximity is known to influence the outcome of R&D partnerships (Boschma, 2005; Balland et al., 2015). Like diversity and relatedness, technological proximity is calculated using patent classes. A common technique used is the cosine similarity of the patent portfolio vectors of the two entities being studied (Jaffe, 1986). Multiple studies have shown the positive association of technological proximity and knowledge transfer in various industries and geographies (Harhoff, 2000; Boufaden et al., 2007; Aldieri, 2011; Broekel and Boschma, 2012; Chen and Xie, 2018). This is not surprising since partners would need a common ground to communicate, absorb, and transform the knowledge into useful products and processes (Cohen and Levinthal, 1990). Of course, even good things can become bad if they are excessive and proximity is no exception. The proximity paradox is well known by scholars and shows the diminishing return of too much proximity on innovativeness (Harhoff, 2000; Cassi and Plunket, 2014). However, the diminishing return observed for R&D partners does not necessarily mean that the partnership did not generate knowledge and opportunities. For instance, using OECD data it was shown that the knowledge stock of regions and the inefficiency of incumbents to exploit that knowledge was conducive to more startups (Acs et al., 2009). Consequently, I submit my last hypothesis:

Hypothesis 4*: The technological proximity between the university and its local state is positively associated with opportunity discovery.*

3.4 Data

I gathered data on university R&D commercialisation from the Association of university technology managers' (AUTM) Statistics Access for Technology Transfer Database (STATT). The database is the result of a voluntary yearly survey and contains 5280 observations for 254 North American universities in Canada and the U.S between 1991 and 2018. It contains information about university TTO age, staff, R&D expenditure, disclosures, patents, licenses, and startups. Some variables have also complementary details. For instance, R&D expenditure is divided between Government and industry sourced and TTO staff is divided between licensing staff and others. However, some important details such as the information concerning patents' classes are missing. The survey has gone through multiple modifications since its inception and was not necessarily filled systematically by all participants. Therefore, the resulting panel data is highly unbalanced. The mean number of observations is 20.79 and the standard deviation is 9.02 with a minimum of 1 observation and a maximum of 28.

I converted all monetary values into Canadian dollars using the International Monetary Fund and the Organisation for Economic Co-operation and Development (OECD) purchasing power parity indexes. These values were then further transformed using the consumer price index (CPI). These steps ensured that the universities' financials were comparable across countries and time.

I further added data on university patents from the USPTO. The choice of USPTO over their Canadian counterpart was made due to the larger number of U.S based universities and the propensity of Canadian inventors to patent in the U.S versus the lower rate of U.S inventors patenting in Canada. We identified university patents by comparing the university name with the name of the patent assignees. We used the Levenshtein distance to compare the names and identify any misspellings or alternative names under which the universities might have patented. The patent count obtained through the USPTO was then compared to the self-reported patent count in the STATT using a linear regression which showed an R-value of 0,95 and indicating a high correspondence.

3.5 Variables

The variables used in this study are anchored into previous studies on university research commercialisation and knowledge transfer as well as indicators stemming from the university-industry collaboration and regional innovation literatures.

The dependent variables for the first article are the number of licenses generating royalty and licenses with equity stakes. These are completed by the amount of income from licensing income, equity sales, and other licensing income which represents the three (3) strategies used to pay for licenses. These variables were chosen to study the first set of hypotheses. The number and amounts of income were used in tandem to verify the validity of the hypotheses since licensing income is known to be highly skewed (Thursby and Thursby, 2007).

The dependent variables for the second and third articles are the number of licenses generating income and the number of startups launched. These variables were chosen following the results of the first article and are representative of the two (2) strategies of licensing to incumbent versus launching startups.

The independent variables for the first article are the proportion of licenses to each category of company startups, small, and large companies. The size of the company was chosen due to its importance in determining its resources and R&D expenditure. The choice of the number and composition of categories was limited by the availability of the data.

The independent variables for the second and third articles are the diversity of the patent portfolio calculated using both the Herfindahl-Hirschman Index (Ceipek et al., 2019) and the Entropy Index (Shannon, 1948; Jacquemin and Berry, 1979). The Herfindahl-Hirschman Index was chosen due to its popularity in the literature while the Entropy Index was chosen for its ability to be divided into related and unrelated diversity which are used to study the effect of knowledge relatedness. These variables were complemented by the maximum revealed technological advantage ratio which is an adaptation of the location quotient to patent portfolios (Chen and Chang, 2010a,b, 2012; Kim et al., 2016). The choice to use the maximum value instead of the average value was motivated by the will to be comparable to previous studies using the same technic (Chen and Chang, 2010a,b, 2012; Kim et al., 2016). The last independent variable used is the technological proximity which is calculated as the cosine similarity of the two patent vectors of the university and its local province for Canada or state in the case of the U.S. (Jaffe, 1986).

The control variables are based on previous studies on university research commercialisation (Rothaermel et al., 2007b; Cunningham et al., 2020). Commercialisation activities can be described as a simplified funnel following the path of research expenditure, disclosure to TTO, patent, license, and finally licensing income. Two important factors to consider are therefore the size of the input which is R&D expenditure and the capacity of the funnel accounted for through the number of TTO employees. These variables were also used in previous studies (Rothaermel et al., 2007b; Cunningham et al., 2020). I further consider qualitative factors related to the technology being commercialised, the effort being put into commercialisation, and the context of the activities.

The technology being commercialised will depend on R&D field (Rothaermel et al., 2007b; Cunningham et al., 2020), the presence of a medical school can hint at the composition of research being conducted at the university and a dummy variable is added to control for their presence following other studies (Cardozo et al., 2011; Cartaxo et al., 2013). Another important difference between R&D field and universities is their propensity to patent (Baglieri et al., 2018)). Patents being optional the number of patents per disclosure is used to account for patenting propensity. The source of R&D funding is known to influence commercialisation (Di Gregorio and Shane, 2003; Chukumba and Jensen, 2005; Siegel et al., 2008). The ratio of government versus industry sourced funding is added to account for the university-industry ties similar to previous studies (Di Gregorio and Shane, 2003; Chukumba and Jensen, 2005; Siegel et al., 2008). Finally, market readiness is an important factor in licensing income and is tied to exclusivity (Markman et al., 2005; Thursby and Thursby, 2007), the proportion of exclusive licenses was added to control for the proportion of early-stage inventions. TTOs use external lawyers to supplement their existing staff (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014). The effort put into commercialisation was measured using legal expenditure per license. Finally, the context was accounted for through country and economic activity. Canada and the U.S. have different economies, cultures and various other aspects which can affect the outcome of commercialisation efforts. These differences were controlled for via a dummy variable for the country. Finally, the number of patents granted to other entities in the state was added to control for economic activity.

3.6 Methodology

We conducted our ordinary least square (OLS) regressions using a clustered approach in the first article and a panel approach in the second and third. The choice to use a clustered method in the first article was related to the dependent variables having small variations and the method being less demanding in terms of requirements. Furthermore, clustered method allowed to correct for the repetition of measurments of the same university over time. A more adapted fixed effect OLS was used for subsequent articles. The choice of fixed versus random effect was stemming from the presence of the country as a fixed effect dummy variable. This decision was also support by Hausman tests.

The OLS approach was chosen over other methods to have comparable results across variables and articles. The OLS method requires a linear function, variables with normal distribution, no multicollinearity, no or low correlation between independent variables, and homoscedasticity.

The normality of the variables used was controlled for and results are presented in the annexes. Variables exhibiting too high or too low skewness and kurtosis were transformed to attain a skewness of $|1.5|$ and a kurtosis in the 1.5 to 4.5 range. The transformations and distribution of the variables of the first article are reported in the table A2. The transformations of the variables of the second article are reported in table A1 and their distribution can be found in table A2. The transformations of the variables of the third article are reported in table A1 and their distribution can be found in table A2.

Correlation and multicollinearity was tested for. Some independent variables were found to be correlated and were tested for interactions. Appropriate corrections were made to the models when interactions were detected. Pairwise correlation results are presented in the annexes. The results for the first article are in table A8, the second article are in table A3, and the third article are in table A4. Multicollinearity was tested using the variance inflation factor (VIF). No multicollinearity was found. The results are presented in table A10 for the first article, table A5 for the second, and table A3 for the third.

Homoscedasticity was tested using Breusch-Pagan Cook-Weisberg tests. Each year was tested separately. Only two (2) years were found to be heteroskedastic for the first article. The value for 2003 was 0.0483 and the value for 2013 was 0.0384. The smallest value beside these two (2) was 0.1665 for 2014. Results can be found in annexe table A1. Similar heteroskedastic years were observed for the second and third article.

CHAPITRE 4 ARTICLE 1: HOW ARE COMPANIES PAYING FOR UNIVERSITY RESEARCH LICENSES? EMPIRICAL EVIDENCE FROM UNIVERSITY-FIRM TECHNOLOGY TRANSFER

Arman Yalvac Aksoy & Catherine Beaudry. Published in the Journal of Technology Transfer, pages 1-71 on February 11th 2021 (Aksoy and Beaudry, 2021). The article demonstrates the different payment schemes companies are using to pay for university licenses. Determining the right indicator to use is an important step prior to analysing the effect of patent portfolio composition. The results show that licenses to incumbent companies generate income right away or in a short period of time after the license is granted compared to licenses granted to startups which do not generate income during the studied time frame.

4.1 Abstract

The knowledge economy has put the triple helix cooperation at the heart of economic growth. In this current paradigm, innovation is vital to firm survival, and universities are seen as an undeniable source of new ideas, talents and ventures. The optimal payment scheme for technology licensing be it from a licensee or licensor point of view is an ongoing debate. Researchers have disputed the advantage of fixed fees versus royalty for both parties involved and the benefits of entering the market for an outsider. A recurrent concern in the literature is the lack of empirical evidence to support these claims. Furthermore, while a plethora of studies defend the superiority of fixed fees over royalty, royalty payments still constitute a major part of licensing income for universities and licensor companies alike. Hence, there is a disconnect between the theoretical optimal payment scheme and the payment scheme adopted by companies and universities. We develop a framework to explain the source of this discrepancy. Using the AUTM STATT database, we analyse the effect of company size on the payment type. Our empirical results show that fixed fees are associated with licenses to large companies while royalty is associated with licenses to small companies. Startups pay neither and give equity instead of payment. Our results point to the importance of government intervention to level the field for different company types, and achieve successful university-industry cooperation and knowledge transfer.

JEL Classification: O20, O32, O51

Keywords: Royalty, Equity, Fixed fees, University, Research, Commercialisation.

4.2 Introduction

University research commercialisation has seen a steady growth of popularity since the passage of the Bayh-Dole act in 1980 (Castillo et al., 2016). This trend was also followed by an increase in patenting activity by universities (Mowery et al., 2001). However, the resulting gradual entry of newcomers into the market was not accompanied by a growth of university licensing income. Studies show that commercialisation income is highly skewed with a small number of universities generating most of the revenue (Thursby and Thursby, 2007). Furthermore, this concentration can also be seen with the licences generating income as only a small fraction of the licences will generate income and most of the income generated will be through royalty (Jensen and Thursby, 2001). The story is similar regarding the number of startups[1] and patents (Di Gregorio and Shane, 2003).

Previous studies indicate that the winners of this technological gold rush are large technical universities in well-developed regions who invest heavily in university-industry cooperation (Thursby and Kemp, 2002; Sine et al., 2003; Markman et al., 2004; Anderson et al., 2007; Siegel et al., 2008). This is not surprising since industrialised regions will more likely host companies with important R&D budgets, a characteristic which was shown to affect the likelihood of entering into R&D agreements with a university (Geuna et al., 2003). However, university-industry collaboration is not necessarily conductive to wealth creation for both parties.

On the one hand, university-industry collaboration creates a non-zero-sum game as innovation is brought to the market and benefits society. On the other hand, licensor and licensee find themselves in a zero-sum game during negotiations to capture value from the deal. A successful collaboration can lead to two-way knowledge transfers as both parties gather new knowledge from one another. This can lead to new research projects for researchers and commercialisation projects for the industrial partner (Boehm and Hogan, 2013). One way universities and their partner can influence the success of the knowledge transfer is to set the right incentive structures through the payment scheme. Universities negotiate different payment schemes to license their products such as equity, royalty and fixed fees (Thursby et al., 2001a).

The debate on the best strategy to benefit from licences for both licensor and licensee has been going on since Arrow's (1962) seminal paper. An important drawback of these studies is their theoretical nature and the lack empirical data to support more generally their theoretical propositions

[1] We acknowledge the fact that not all startups are spinoffs. However, we decided to use the term startup through the paper to stay consistent with previous studies using the AUTM STATT database (Prets and Slate, 2014; Hayter and Link, 2015). The AUTM survey defines startups as companies that were dependent upon the licensing of the institution's technology for initiation.

(Vishwasrao, 2007; Leone and Oriani, 2008; Lee et al., 2010). Furthermore, these studies do not account for licensees' size and capacities. From a resource based view, companies have different financial constraints (Hall et al., 2016) that can affect their level of R&D investment and lead to variations in absorptive capacities (Cohen and Levinthal, 1990). Differences in financial constraints and absorptive capacities can lead companies to diverge from one another in their needs of cooperation for implementation of the license and the timeframe for the payments to the licensor and their nature. This relative scarcity of resources will in turn influence the perceived risk and reward stemming from the collaboration with a university. Hence, we argue that the payment scheme is related to the licensee's resources and that the size of the company will determine the strategy adopted. We backup our claim by presenting findings from a detailed analysis of the Association of University Technology Manager's (AUTM) Statistics Access for Technology Transfer (STATT) database.

The goal of this paper is to contribute to the discussion on licence payment schemes by presenting empirical data and shed light on the different payment schemes companies and universities adopt when transfering university sourced technologies. The remainder of this paper is arranged as follows. Section 2 describes the various factors affecting university technology transfer and income generation, and justifies our conceptual framework. Section 3 presents the data and methodology used. Section 4 discusses the research results and finally, Section 5 concludes.

4.3 Literature Review

4.3.1 University research commercialisation

The path to the market

The path from the laboratory to the market is described as: research, disclosure, licence, and licensing income (Thursby and Thursby, 2002; Carlsson and Fridh, 2002; Godin, 2006; Cartaxo et al., 2013). This general approach can be described in a more or less detailed fashion (Bradley et al., 2013) and adapted to the idiosyncratic needs of an industry such as aerospace or biomedical (Mankins, 2009; FDA, 2004). Patenting is also used as an indicator of commercialisation activity in some studies but is considered less effective. This is due to patent-related shortcomings (Verbeek et al., 2002), patents being intermediary outputs (Jensen and Thursby, 2001), not all knowledge being patentable, and the use of various other strategies by universities to protect their interest such as keeping knowledge a trade secret, copyright, trademark, industrial designs, etc. (Colyvas et al., 2002; Prets and Slate, 2014; Baglieri et al., 2018). Nonetheless patents are a widely used protection tool and commonly used indicator of innovation (Hottenrott et al., 2016; Merz, 2019).

Universities can use three main strategies to transfer their knowledge, they can either licence for: cash (Lach and Schankerman, 2004; Powers, 2003), equity (Link and Siegel, 2005; Markman et al., 2004) or research partnership (Thursby et al., 2001a; Thursby and Kemp, 2002). Other methods can also be adopted (Arvanitis et al., 2008; Martinelli et al., 2008) and will be related to the type of technology, market readiness (Thursby et al., 2001a) and the needs of the stakeholders to which the university and TTO are answering such as financial or governmental constraints (Belenzon and Schankerman, 2009; Di Gregorio and Shane, 2003; Markman et al., 2005). Hence, the way universities will partner with companies is three folds: they will either be the technology intermediary between the principal investigator and the client company to negotiate the licensing or patent transfer deal (Howells, 2006), they will take an entrepreneurial stance and take equity in the startup (Etzkowitz, 2004), or they will behave as knowledge-intensive business services and offer R&D services to the company (Muller and Zenker, 2001).

The time it takes for the research to be commercialised is unclear and the average length of contracts is unknown. The literature on the subject gives different estimates. Bray and Lee (2000) reports that licenses can take up to eight (8) years to generate income, twelve (12) if clinical trials are involved. Similarly, Kim and Daim (2014) report that the time between research expenditure and licensing income can take anywhere from two (2) to twenty-seven (27) years. The time taken to generate income will depend on the path taken. For instance, the authors argue that the time is shortened when licences are granted in exchange of equity as universities can sell the shares during initial public offerings after three (3) or four (4) years. Other intermediary steps might also prolong the time necessary. McCarthy and Ruckman (2017) reports that it takes on average six (6) years from patenting to licensing. This is interesting since an earlier report by Markman et al. (2005) indicates that it takes four (4) to five (5) years after disclosure to grant a licence. Furthermore, granted licences also take time to generate income. This was demonstrated by Kim and Daim (2014) which reports a lag of three (3) years between the grant of the licence and the licence generating income. We did not find any information concerning the average time length of a licence, this might be due to the private nature of these contracts.

University and TTO characteristics

Previous research on university research commercialisation has focused on characteristics related to the university (Powers, 2003; Markman et al., 2004; Xu et al., 2011), the technology transfer office (TTO) (Anderson et al., 2007; Rogers et al., 2000; Thursby and Kemp, 2002) and the local ecosystem (Belenzon and Schankerman, 2009; Sine et al., 2003). Their findings show the importance of the size of the university (Siegel et al., 2008) through the positive effect of the amount of

R&D expenditure, and number of disclosures, on the number of patents, licences, and the amount of licensing income (Sine et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014).

The effort put into commercialisation and expertise of the TTO was also reported as important determinants of the number of licences granted and licensing income. Hence, the size and the age of the TTO were shown to play a positive role in the commercialisation process (Cartaxo et al., 2013) and some authors reported the negative effect of the shortage of personnel experienced by the TTOs on the licensing activities (Swamidass and Vulasa, 2009). The lack of personnel is often palliated by the use of outsiders to the TTO staff, but this can backfire if the objective is not clearly defined. Legal expenditure was shown to increase the amount of licensing revenue but decrease the number of licences, researchers impute this to the aggressive stance of outside lawyers during negotiations (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014).

However, these results come with a caveat since technical universities are known to be better financed than non-technical universities. Hence, the composition of the university's faculties was found to have a significant impact on the commercialisation process as technical universities were shown to have more research expenditure leading to more licensing and licensing income (Thursby and Kemp, 2002; Lach and Schankerman, 2004; Chukumba and Jensen, 2005). Furthermore, the size of the TTO is correlated with both its age and the amount of research expenditure of the university it belongs to (Xu et al., 2011; Castillo et al., 2016). Similar biases can be observed with quality indicators that are related to the size of the university (Thursby et al., 2001a; Thursby and Kemp, 2002; Xu et al., 2011).

Others pointed out that the end goal of every university might not be the same and that this will impact how they tackle technology transfer (Thursby et al., 2001a; Baglieri et al., 2018). It is unclear how these differences in objectives influence the TTOs size, internal organisation or relationship to the university they serve since TTOs can differ in these regards (Bercovitz et al., 2001; Markman et al., 2009; Brescia et al., 2016). For instance, the age of the TTO seems to influence the commercialisation process since TTOs grow in size and change their behaviour as they mature and gain experience (Xu et al., 2011; Castillo et al., 2016).

4.3.2 Industrial organisation

Firm size and R&D

The size of the industrial partner is another factor that impacts the commercialisation process. Previous research in the industrial organisation field establish the positive relationship between size and R&D expenditure which leads to higher absorptive capacities (Cohen and Levinthal, 1990; Kumar and Saqib, 1996; Hall et al., 2016; Dezi et al., 2018; Foster et al., 2019) and R&D collaborations (Segarra-Blasco and Arauzo-Carod, 2008; Chun and Mun, 2012). They also show the importance of financial slack and its negative relationship to R&D efficiency (Zenger, 1994; Cohen and Klepper, 1996; Tsai, 2005; Munos, 2009; Li, 2011; Almeida et al., 2013; Shackelford, 2013; Spiganti, 2017; Merz, 2019). They report that small firms are more efficient with their resources (Zenger, 1994; Cohen and Klepper, 1996; Munos, 2009; Shackelford, 2013; Merz, 2019) and that moderate financial constraints positively affect innovation efficiency (Li, 2011; Almeida et al., 2013; Spiganti, 2017)

Small and large companies diverge from one another in their R&D needs and approach to collaboration with R&D partners (Santoro and Chakrabarti, 2002; Akcigit and Kerr, 2018). Historically, university-industry collaboration has been dominated by large companies (Geuna et al., 2003; Mohnen and Hoareau, 2003; Motohashi et al., 2004; Chun and Mun, 2012). However, small companies are more efficient at absorbing the spillovers from collaborations with universities (Motohashi, 2005; Chun and Mun, 2012) and give more importance to these collaborations (Acs et al., 1994; Audretsch and Vivarelli, 1996). In the case of startups, these collaborations can even make the difference between success and failure as university startups are more likely to succeed when they entertain a strong link to the parent university (Rothaermel and Thursby, 2005).

Licence payment schemes

Once a company decide to collaborate with a university and to license a technology, it can pay for the licence in three main ways: fixed fees, royalty, or equity. They can also use a mix of two (2) or three (3) of these methods. Fixed fees are payment schemes where the licensee pays a fixed fee to the licensor when certain milestones are reached such as for instance a recurring date or steps of the transfer of the technology such as the drafting of the contract, proof of concept, first prototype, etc. Royalty schemes involve the payment of a variable sum of money that is dependent of usage. Finally, equity is a payment scheme where the partner firm gives shares of the company to the licensor. Each of these payment schemes can further be declined into subcategories. For instance, royalty can be paid either ad valorem or per unit (Bousquet et al., 1998; Heywood et al., 2014). Fixed fees can be paid as the result of an auction (Kamien and Tauman, 2002; Bagchi and Mukherjee, 2014); and shares in a company can be of different types and have different rights (Gornall and Strebulaev, 2020). Each of these types of payments has its own advantages and disadvantages for both parties involved depending on the situation. The main advantages of fixed fees are the reduction of uncertainty for the licensor and the reduction of transactional costs. Studies show that fixed fees are preferred by licensors in the case of low trust in the licensee or market uncertainty (Aulakh et al., 1998; Vishwasrao, 2007; Leone and Oriani, 2008). Using empirical data, Lihua Kuo et al. (2012) deduced that the patent holder prefers a fee-based scheme to reduce transactional costs. While fixed fee contracts take more effort to negotiate, they reduce communication, monitoring, and enforcement cost and ward against unexpected costs over the long term. This is also supported by Cebrián (2009) which reasons that if the moral hazard lays in the licensee's capacity for opportunistic behaviour than fixed fees are preferred by the licensor. This payment scheme can also be advantageous for the firm as fixed fees do not increase with the usage of the licence (Kamien and Tauman, 1986; Savva and Taneri, 2011). These results can be summarised as follows: on the one hand, this payment scheme guarantees an income for the licensor whether the licence is used or not. On the other hand, in the case of commercial success, the surplus will be captured entirely by the licensee.

The usage of royalty is based on two main arguments: moral hazard and information asymmetry. Advocates of royalty schemes argue that it increases the inventor's interest in the transfer success (Aulakh et al., 1998; Cebrián, 2009; Lee et al., 2010; Lihua Kuo et al., 2012). Royalty schemes are preferred by the licensee when the knowledge is tacit as it increases interactions between parties and transfer efficiency (Aulakh et al., 1998; Macho-Stadler et al., 1996; Lee et al., 2010). Hence, royalty is a way for the licensee to minimise risks by only paying for a successful transfer. The second argument in favour of royalty is that royalty schemes are preferred by the licensor when information is asymmetric (Beggs, 1992; Lihua Kuo et al., 2012; Savva and Taneri, 2014). It is used as a screening tool by the patent holder to extract information from the potential licensees and better capture value through the deal by identifying the potential market the innovation can serve and revenue that the licence can generate (Savva and Taneri, 2011, 2014). This also explained why proven sale records lead to more royalty-based payment schemes (Vishwasrao, 2007). In summary royalty payment schemes can improve the odds of a successful transfer by increasing the licensor's interest in a successful transfer but can also increase the cost for the licensee as it will be a function of the licence's usage.

As reported by Markman et al. (2005) sometimes the only way to get the technology out of the door is to launch a startup. Launching startups seems to be on the rise as an increasing number of universities are favouring this approach (Bray and Lee, 2000; Feldman et al., 2002). In the past few decades universities indeed changed their approach to equity stakes and started to take equity in startups in lieu of other payments. While these were previously seen as an alternative payment scheme for cash-starved startups, today, equity stakes are seen as a desirable strategy. However, these results are dependent of the market as lower equity sales number may push universities back into incumbent company deals (Feldman et al., 2002). The argument for taking equity instead of payments is that equity is more lucrative than other payment methods on the long run. Bray and Lee (2000) Reported that the ten (10) TTOs they studied showed interest in taking equity in startups. They argued that taking equity is more lucrative than traditional licences and compared equity sales results to a one (1) year royalty income. They calculated that average equity sales were worth two (2) to ten (10) years worth of average licence income from royalty and fixed fees depending on whether they take into account outlier equity sales or not. This argument was also voiced by Savva and Taneri (2014) who argued that taking equity is more lucrative for the TTO than royalty based payment schemes in the case of startups. Hence, equity increases the interest of the licensor in the technology transfer success without increasing the cost for the firm. However, this approach only yields fruits in the long run when the firm starts paying dividends or the licensor decides to sell the shares.

4.3.3 Conceptual framework

We argue that the choice of payment type will be influenced by the difference in perceived risks and rewards by the partners. Our framework takes a resource-based approach and considers that companies collaborate with universities and license university technologies to increase their competitive advantage through the acquisition of new knowledge (Barney, 1991). However, this collaboration will entail investment of resources which can create risks. The two main risks that companies experience with R&D cooperation are financial risks related to expended resources and the likelihood of outgoing spillover (Belderbos et al., 2004; Almeida et al., 2013). According to Barney (1991), the competitive advantage is derived from the qualitative aspects of the firms resources listed as their value, rareness, imitability, and substitutability. Hence, it is understandable that a small company might value financial resources more than a larger companies due to their scarcity, while larger companies might be more concerned by outgoing spillover that might erode their competitive advantage by increasing the imitability or substitutability of their products and services. The rewards for the companies depend on the value of the cooperation which is derived from the value of the incoming spillover (Van den Berghe and Guild, 2008). For the purpose of our study, we consider that the main risk for universities is the loss of the resources invested in the partnership and that the reward is the amount of financial income for the university. The parties will enter the agreement only if both sides are satisfied with the terms of the contract. We presume that no coercion is taking place between the parties. Hence, the resulting contract will be the fruit of negotiations between the licensor and the licensee and will not necessarily be preferred by neither nor optimal. However, we can expect the university's preferences to be relatively fix. Hence, any statistically significant variation in the terms of the contracts in a set of heterogeneous contracts between the university and different companies will be the manifestations of the preferences of the licensee companies.

Our model posit that large companies will be associated with fixed fee payment schemes, small companies will be associated with royalty based payment schemes, and startups will be associated with equity based payment schemes due to the differences in risk and rewards these contract terms bring to the collaboration and the idiosyncratic characteristics of the licensee company.

Fixed fee leads to high-risk and high-reward for the licensee as the company pay even in case of failure to implement and capture all the value in case of success (Cebrián, 2009). This is different than the effect for the licensor which incurs low-risks and low-reward that is dissociated from results (Aulakh et al., 1998; Cebrián, 2009). Royalty is conductive to an inverted scenario. The risk and rewards are high for the licensor which has to invest into the relationship to increase the chance of a successful transfer and can extract more value in the case of a successful deployment of the licence (Macho-Stadler et al., 1996; Aulakh et al., 1998; Cebrián, 2009). This in turn leads to a low-risk and low-reward situation for the company as it only pays for a successful implementation but has to share the value created (Macho-Stadler et al., 1996; Aulakh et al., 1998; Cebrián, 2009). Startups can further deploy a third approach and grant equity for payment instead of the two (2) previous methods. This is a high-risk high-reward scenario for the university which is invested in the success of the company and is a low-risk high-reward scenario for the company as it does not suffer financial consequences and has the vested interest of the university in its success (Bray and Lee, 2000; Savva and Taneri, 2014). All players avoid high-risk low-reward situations as they try to minimise risk and maximise reward by using a combination of these three (3) payment schemes.

In the case of university research commercialisation, it is unheard of that incumbent firms give equity in exchange of licensing rights for a technology. Hence, this strategy is solely adopted by startups. The main concern for a startup is to stay in operations since most startups fail in their first five (5) years (Gonzalez, 2017). Most university startups will negotiate equity stakes for a licence with exclusivity instead of paying licensing fees (Markman et al., 2005; Thursby and Thursby, 2007). Equity stakes in the startup will ensure the licensor cooperation similar to royalty (Savva and Taneri, 2011, 2014). This is crucial since the benefits of this interaction can be seen in the increase survival rate of startups that keep relationships with their parent universities (Rothaermel and Thursby, 2005). Hence, by creating vested interest of the researcher in the venture, they increase their chance of a successful commercialisation and survival. Furthermore, by accepting to take equity instead of pushing for royalty the licensor is increasing the survival chances of the venture by not adding more pressure to their finances (Lee et al., 2010). This can be very lucrative in case of a successful venture (Bray and Lee, 2000). The draw back of this strategy is that income from equity can take a long time to be generated as it requires the university to sell its share or the company to start paying dividends. In some cases, this can take many years (Kim and Daim, 2014). Furthermore, this payment scheme is risky for universities since they might get nothing if the venture closes prematurely. Hence, the university will try to determine the value of the startup. If the university believes that the company cannot go public or be sold to an incumbent, it will try to extract value from the deal by means of fixed fees or royalty (Savva and Taneri, 2014).

Although a good screening tool for TTOs in case of information asymmetry, royalties causes production distortions (Savva and Taneri, 2011). However, innovation in startups is constrained by a lack of funding (Hottenrott et al., 2016). Milestone payment and equity are better at mitigating inventor moral hazard than royalty as they do not hamper the production but an initial single payment might be too difficult for ventures (Lee et al., 2010). Furthermore, in the case of equity deals, including royalty is superior to fixed fee for screening (Savva and Taneri, 2014). Hence, if the university believes the startup to be of low value, they will increase the royalty shares that needs to be paid by the startup instead of subjecting it to higher fixed fees (Savva and Taneri, 2011). In summary, licensing to startups should generate more licences with equity. However, this will not necessarily generate equity income in the short term. Furthermore, while licences to startups should have a negative association with the amount of royalty, this should only be short term as the university will screen for low value startups and increase their share of royalty payment. Since these firms are cash constrained, licenses to startups should be negatively associated with the amount of fixed fees. Hence, we formulate our first set of hypotheses:

Hypothesis 1: The number of licences that a TTO grants to startup companies is:

a) negatively associated with the number of licences generating royalty;

b) negatively associated with the amount of royalty;

c) negatively associated with the amount of fixed fees;

d) positively associated with the number of licences with equity;

and, e) positively associated with the amount of licence income from equity sales.

Large companies have more absorptive capacities (Cohen and Levinthal, 1990), financial slack (Hottenrott et al., 2016) and are less risk averse (Cebrián, 2009) than small ones. The combination of these elements pushes them to prefer explorative R&D collaborations versus exploitative ones (Bruneel et al., 2016). The main perceived risk from collaboration for these companies is not financial but the risk of outgoing spillover that might end up in the competitors' hands (Belderbos et al., 2004). Protecting their proprietary knowledge is an important concern for these companies. Which is one of the reasons why the patent stock of the licensee is negatively influencing the preference for royalty-based payment schemes (Trombini, 2012). They must find a balance between the risk of the knowledge not being integrated and the risk of having outgoing spillover. These companies collaborate with universities to explore new research avenues and develop their knowledge in non-core technologies (Santoro and Chakrabarti, 2002). This minimises the value of the incoming spillover and the risk of outgoing spillover. In case of failure to integrate the new knowledge the cost to the company is the resources invested, which in their case is less vital than for their smaller counterparts (Hottenrott et al., 2016). This has two implications, first, fixed fee payments is possible and the cost is relatively less important for larger firms, second, the absorptive capacities of large firms can reduce the need for the licensor's collaboration for a successful implementation. Furthermore, in the case of a successful implementation of the new knowledge a fixed fee payment scheme can increase the value the company can extract from the licence without increasing the cost since the utilisation and the cost are independent from one another (Savva and Taneri, 2011). Hence, large companies will try to negotiate fixed fees over royalty to minimise usage cost. This is coherent with Cebriáns (2009) findings which showed that larger licensees prefer fixed fee payment schemes.

Similarly, fixed fees schemes can also be more desirable for universities when negotiating with larger firms. As ongoing contracts take resources to govern (Lihua Kuo et al., 2012) cheating might occur due to asymmetric information or to the patent holder's resource shortage to enforce the contract. Gilbert and Kristiansen (2018) showed that in the case of imperfect contract enforcement, the licensor reduces the royalty rate to avoid cheating. This also decreases income for the patent holder, price for the consumer, and increase innovation by the licensee. This is also supported by Cebrián (2009) who reasons that if the moral hazard lays in the licensee's capacity for opportunistic behaviour than fixed fees are preferred by the licensor. Thus, an upfront fixed fee can guarantee an income for the patent holder while reducing the need for subsequent work that can arise from monitoring and enforcing Lihua Kuo et al. (2012). Consequently, we deduce our second set of hypotheses:

Hypothesis 2: The number of licences that a TTO grants to large companies is:

a) negatively associated with the number of licences generating royalty;

b) negatively associated with the amount of royalty;

and, c) positively associated with the amount of upfront fixed fees.

Small companies are subjected to similar risk and reward concerns as their larger counterparts. However, they have less financial slack and absorptive capacities than larger companies (Cohen and Levinthal, 1990; Kumar and Saqib, 1996; Hall et al., 2016; Dezi et al., 2018; Foster et al., 2019). This leads them to require more collaboration from the licensor side and to pay more attention to cost centres in their budget. Since they have financial constraints, these companies prefer to use university research collaboration for exploitative purposes and to develop their core competencies instead of investing into riskier explorative R&D projects that would enhance non-core competencies (Santoro and Chakrabarti, 2002). This incite them to have less partnership but also explains why they give more importance to their partnerships and resulting incoming spillovers than large companies (Acs et al., 1994; Audretsch and Vivarelli, 1996; Lopez, 2008; Chun and Mun, 2012). Their lower absorptive capacities should lead them to require enhanced collaboration to implement the new knowledge and try to minimise the risk in case of a failure. This in turn should naturally push them towards a royalty payment scheme which ensures that the licensor has incentive to help the transfer succeed and can minimise the cost to the company in case of a failure to implement as the company will not pay a recurring fixed fee.

Licensing to a small company for royalty instead of fixed fees can also be more desirable for the university. Since these companies license for exploitative purposes (Santoro and Chakrabarti, 2002), an interest by small company can be an indication that the licence has potential market value. As was shown by Sen (2005), for an outside innovator in a Cournot oligopoly, royalty can be superior to fixed fees if the market is large enough. This is also a point made by Vishwasrao (2007) which argues that royalty is included in case of proven sales record. Hence, the university can increase their income by reducing the amount of fixed fees and increasing the share of royalty to be paid. Hence, we postulate our last set of hypotheses:

Hypothesis 3: The number of licences that a TTO grants to small companies is:

a) positively associated with the number of licences generating royalty.

b) positively associated with the amount of royalty.

and, c) negatively associated with the amount of fixed fees.

4.4 Methodology

4.4.1 Data

Data about universities and their TTOs was sourced from the STATT database that comprises yearly surveys of "The Association of University Technology Managers" (AUTM) between 1991 and 2015 for both the U.S. and Canada. Multiple missing entries yield a highly unbalanced panel. The sample we use spans from 2001 to 2014 due to missing entries. In order to have comparative results, we only used observations that included all our variables. The sample comprises 179 universities with 1562 observations. The minimum number of complete observation for a university is 1 and the maximum is 14 years.

We multiply all U.S. monetary variables with the Canadian yearly purchasing power parity (PPP) as to have all our results in Canadian dollars. PPP data was acquired from the International Monetary Fund. The set is a list of USD to CAD parity values for the years 2000 to 2015.

4.4.2 Variables

Dependent variables

Inspired by our review of the literature and in line with our defined framework, we extracted two (2) discrete variables to characterise the payment scheme adopted by the TTO and its partnering companies:

nbLicRoy, the number of licences generating royalty payments, is used to study the link between royalties and company size. The number of licences generating royalty is steadily growing over the years (see Figure 4.1) but the proportion over the total number of active licences is relatively steady and fluctuates around 45% (see Figure 4.2). This shows that universities still use royalty schemes in a large portion of their licensing deals despite the shortcomings mentioned in the literature. This attitude towards royalty schemes might be related to the large number of embryonic technologies being licensed by universities as was noted by Thursby et al. (2001a) which leads to more royalty-based schemes (Trombini, 2012) thus ensuring the cooperation of the licensor for a successful transfer. This variable will allow us to validate to hypothesis H1a, H2a, and H3a.

nbLicEqu, the number of licences with equity, shows little or no change between 1992 and 2015. During this period an average of 350 licences with equity were granted per year which only represents 1,5% of total active licences. While the absolute number of deals is increasing, the proportion over the total number of deals is relatively stable (see Figure 4.1 and Figure 4.2). The evidence is in sharp contrast to the literature which mentions a growing positive attitude towards taking equity in ventures (Bray and Lee, 2000; Feldman et al., 2002; Markman et al., 2005). However, a positive attitude does not necessarily mean taking action and the mentality and startup strategies might well have evolved since these studies. We hypothesised in H1d that the number of licences with equity should be positively associated with the proportion of licences to startups.

We also select three (3) continuous variables related to the amount of dollar generated by the

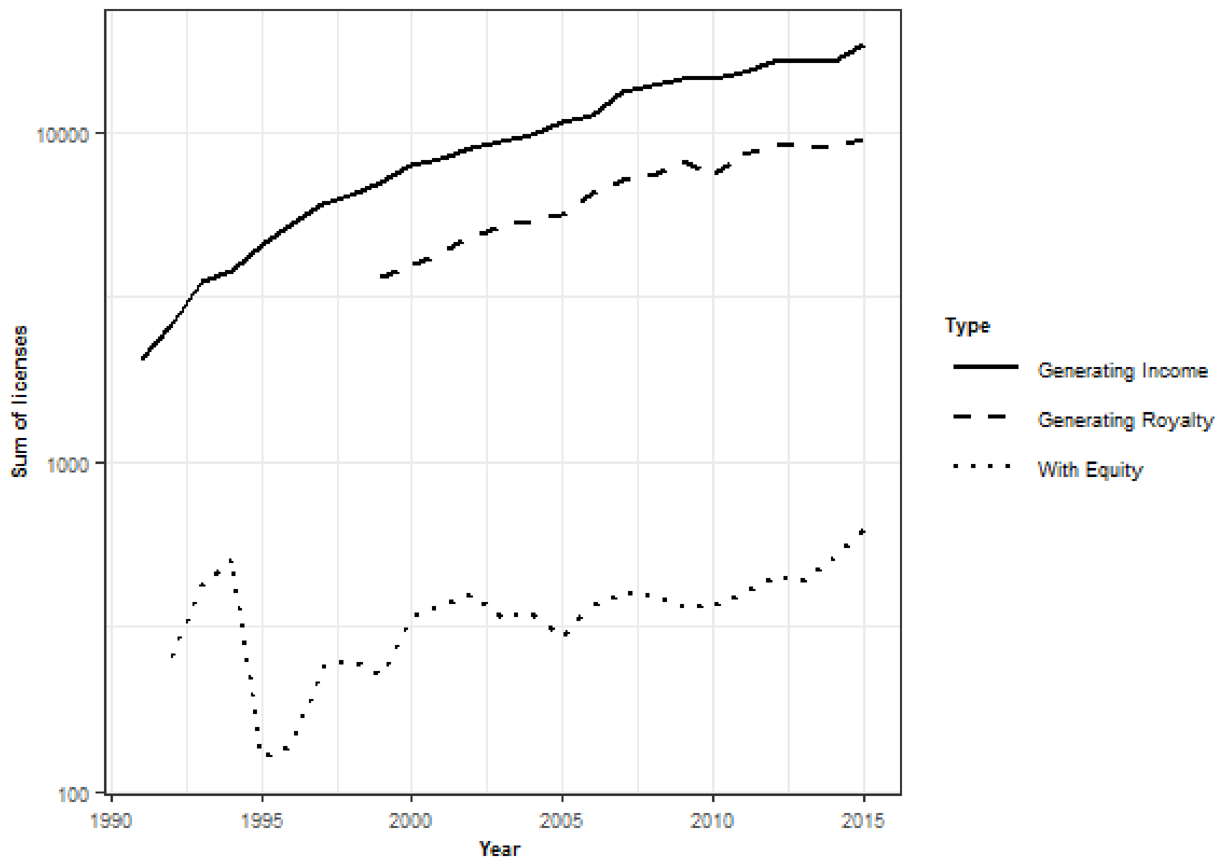

Figure 4.1 Log scale sum of active licences by year for all North American universities, source: AUTM Licensing STATT database.

different payment schemes.

Royalties, the amount of royalty received by the TTO is growing at a rapid pace compared to other types of payments (see Figure 4.3). It represents the overwhelming majority of licensing income universities generate (see Figure 4.4). We observe peaks of income in 2007 and 2008 which are related to two universities generating important amounts of royalty incomes. Furthermore the four (4) last years of our data show a slowing trend (see Figure 4.3), time will tell whether this is a temporary or permanent change of behaviour. The growth of average royalty income is disconnected from the stable proportion of licences generating royalty (see Figure 4.4). We deduce that TTOs are improving by either finding better disclosures to license or by refining their negotiation skills both of which might well be related to TTO age and employee experience. This variable is related to hypothesis H1b, H2b, and H3b.

IncEqu, the amount of income from equity sales, exhibits a small growth over the period with

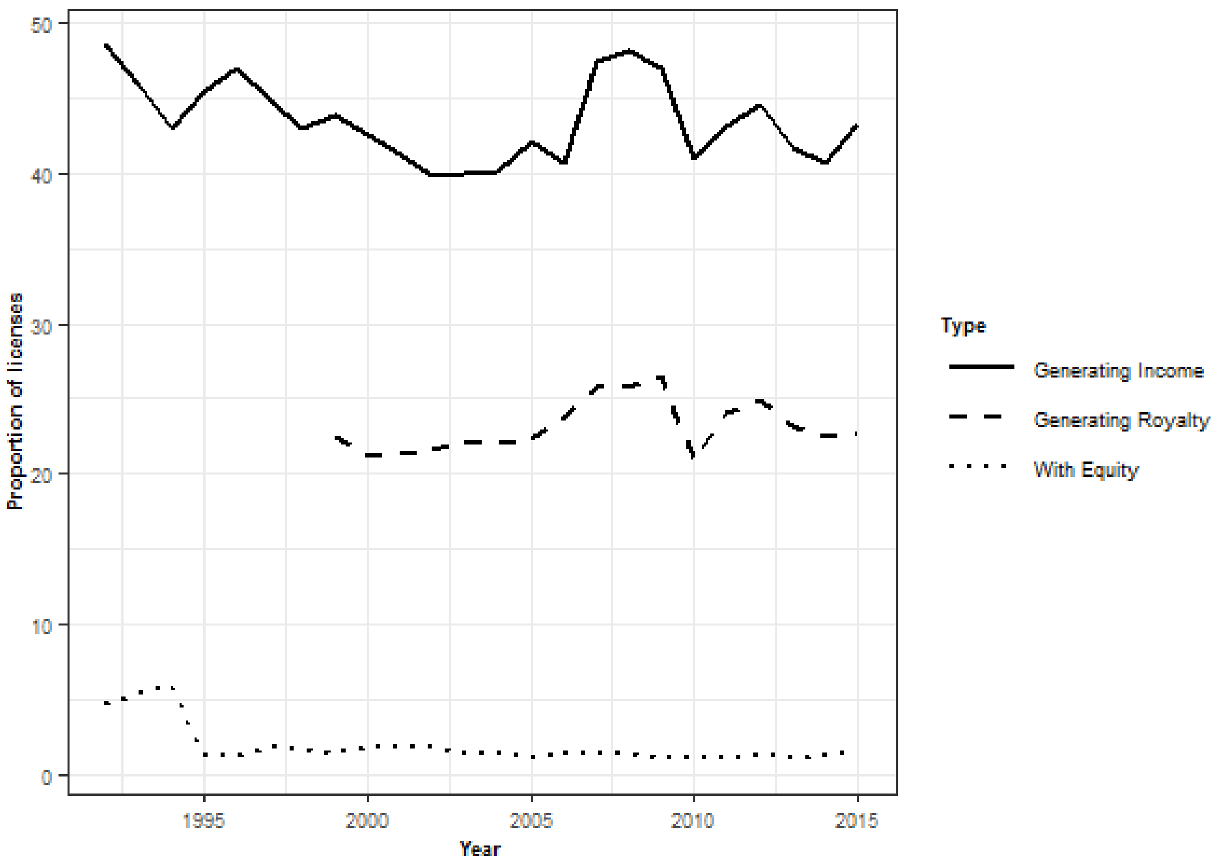

Figure 4.2 Proportion of active licences by year for all North American universities, source: AUTM Licensing STATT database.

a surge in 2000 and 2001 which we believe stems from the dotcom bubble (see Figure 4.3). This growth is clearly apparent despite the relative stability of the proportion of licences with equity (see Figure 4.4). Similarly to royalties, this growth might be related to the TTOs age and experience in making equity deals, which is coherent with previous literature reporting the positive effect of TTO age on the attitude towards taking equity in startups (Bray and Lee, 2000; Feldman et al., 2002; Markman et al., 2005). This type of income still represents the smallest portion of licensing income for universities (see Figure 4.3). Again, this provides support towards hypothesis H1e, i.e. the amount of income from equity sales should be positively associated with the proportion of licences to startups.

IncOther, the amount of other licensing income, is slowly growing between 1996 and 2015. We observe two (2) surges of income, one in 2000 and the other in 2005 (see Figure 4.3 and Figure 4.4). We believe the surge in 2000 is related to the dotcom bubble while that of 2005 is related to a university making a big royalty sale that year. This behaviour is observed for both the average value

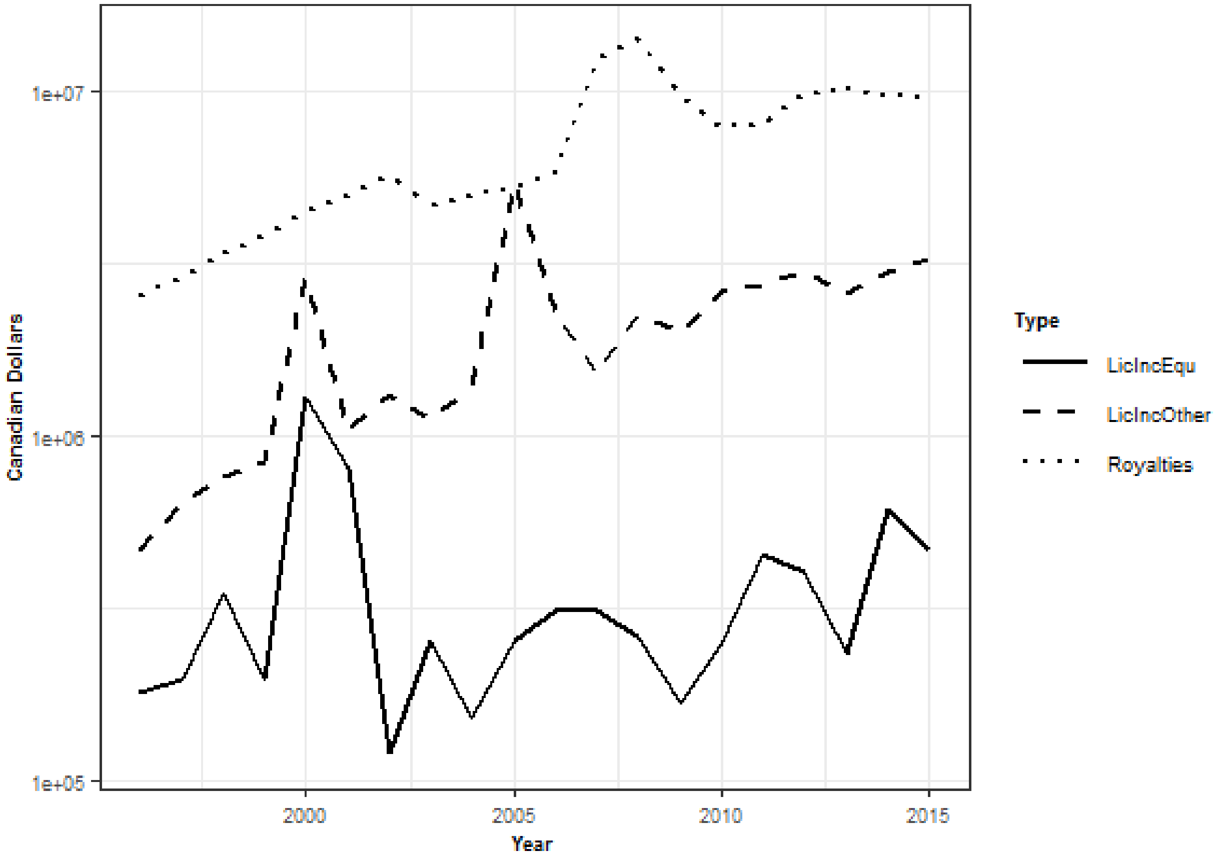

Figure 4.3 Log scale average licensing income in Canadian dollars by year for all North American universities, source: AUTM Licensing STATT database.

and total value of the variable for both cohorts (Canadian and American TTOs). Unfortunately, the data does not provide any details about the types of fees that constitute this category, as all income types that cannot be classified as royalty or equity sales are computed into this variable. This can include initial fees, milestone fees, and termination fees, as well as others. Furthermore, the survey does not record the number of licences generating other types of income; hence, this is the only variable that can be used to determine these types of payment. Both the amount of other licensing income and the number of licences to large companies are growing over the studied period (see Figure 4.3 and Figure 4.5). We expect the amount of other licensing income to be negatively associated with the proportion of licences to small companies and startups; and positively associated with the proportion of licences to large companies as stated in hypothesis H1c, H2c ,and H3c.

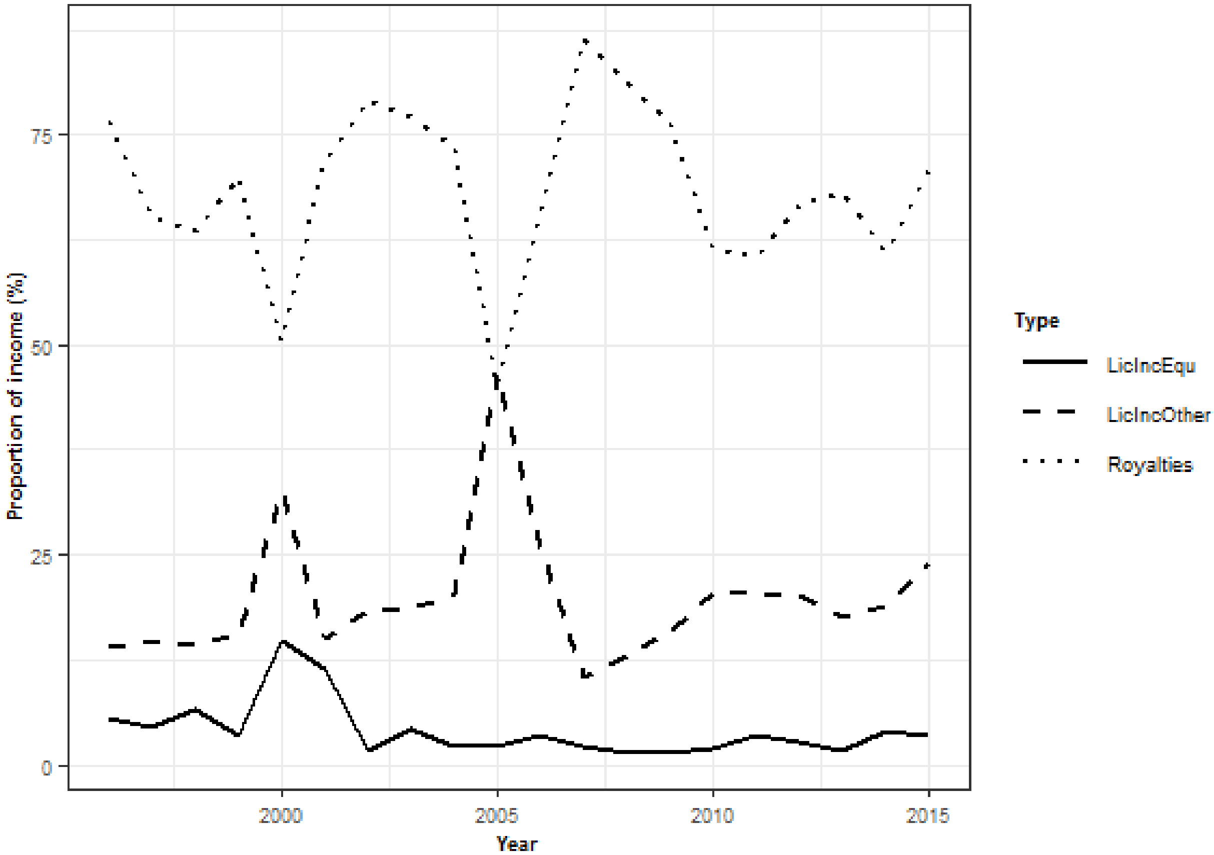

Figure 4.4 Proportion of licensing income by year for all North American universities, source: AUTM Licensing STATT database.

Independent variables

Inspired by the ratios developed by Baglieri et al. (2018), we decided to use similar proportions for our independent variables. Each variable is calculated by dividing the number of licences granted for that category by the total number of licences granted [2] [3]. This yields three (3) independent variables:

PropLicSmall refers to the proportion of licences granted to small companies with fewer than 50 employees. The number of licences in this category is growing at the same pace as the industry. While the number of licences is increasing over time (see Figure 4.5), the proportion of licences

[2]The AUTM survey defines three types of companies, large companies, small companies and startups. The sum of all licences granted to all three types is equal to the total number of licences granted by the university. Hence, these three variables are highly correlated.

[3]We study the lag structure of our independent variables up to five (5) years to account for any time-related effect that can stem from the size of the company

to this type of licensee is slightly decreasing over the years since the early 2000s (see Figure 4.6). This type of licence represents half of the licences granted by universities over the years and is the largest body of licensees between the three company sizes. The relationship with royalties is not directly observable as the number of licences generating royalty is much higher (see Figure 4.1) but represents only 30% of total licences granted (see Figure 4.2). While royalty is the largest type of income (see Figure 4.3) and constitutes most of the income generated (see Figure 4.4). Nonetheless, the proportion of licences granted to small companies should be positively associated with both the number of licences generating royalty and the amount of royalty and will be used to support our set of hypotheses H2.

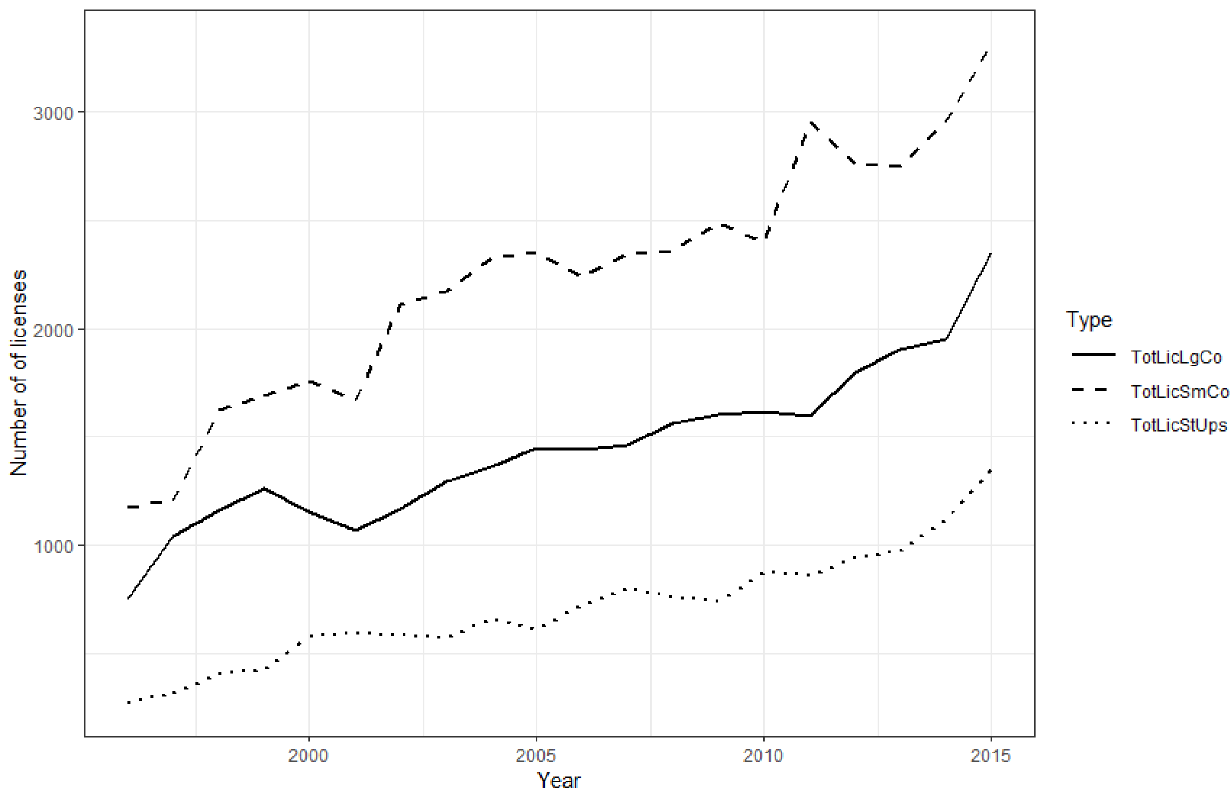

Figure 4.5 Sum of licences by licensee type by year for all North American universities, source: AUTM Licensing STATT database.

PropLicStartup describes the proportion of licences to startups. The number of this type of licensee is increasing over time (see Figure 4.5). Moreover, the increase is slightly faster than to other types of companies. We observe a slight growth of the share of this type of licensee over the total number of licences granted (see Figure 4.6). This is coherent with previous studies reporting the growing interest of TTOs to launch startups (Bray and Lee, 2000; Feldman et al., 2002). This growth of interest can also be observed through the number of licences with equity (see Figure 4.1) and the

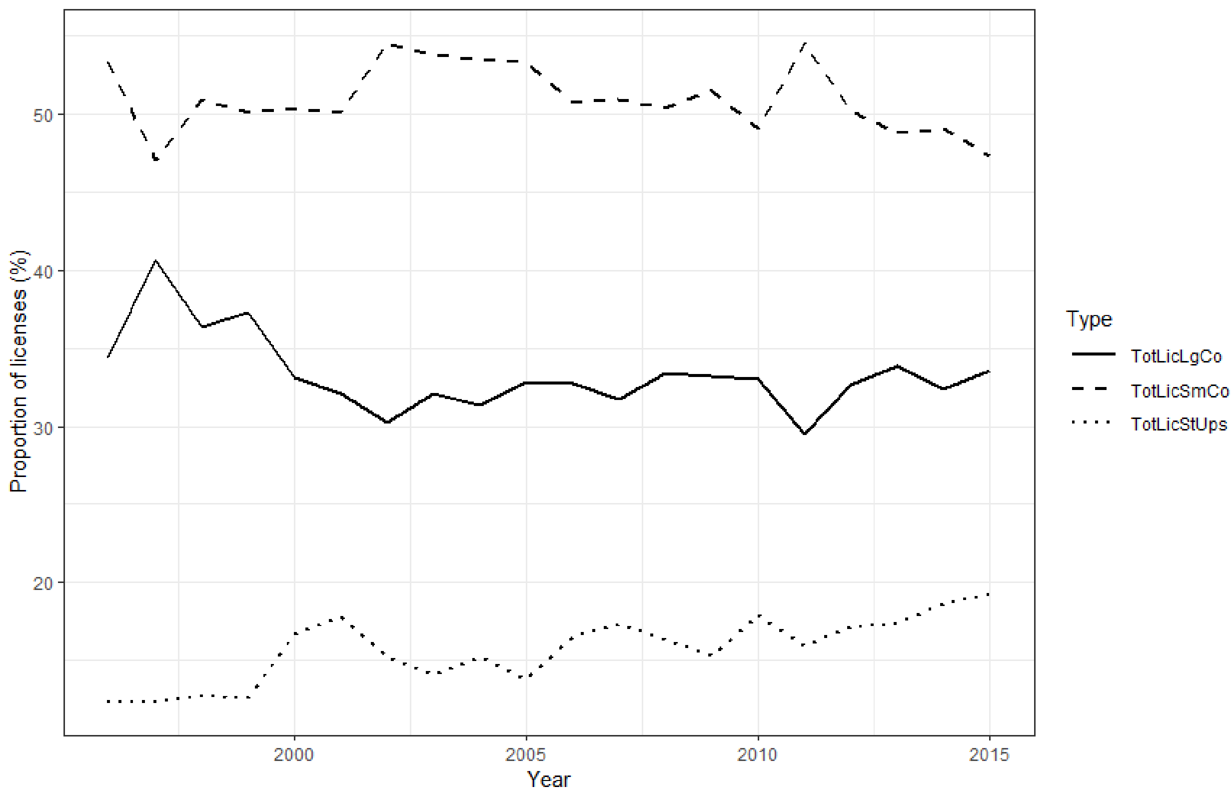

Figure 4.6 Proportion of licences granted by licensee type by year for all North American universities, source: AUTM Licensing STATT database.

amount of income from equity sales (see Figure 4.3). The proportion of licences granted to startups should be positively associated with both the number of licences with equity and the amount of income from equity sales and will be used to confirm the set of hypotheses H1.

PropLicLarge is the proportion of licences granted to large companies, i.e. companies which have more than 50 employees. Similar to small companies, the number of licences granted to large companies is growing over the years (see Figure 4.5 and Figure 4.6). The number of licences granted to large companies represents one third (1/3) of licences granted each year by all North American universities and is the second-largest licensee category. The proportion of licences granted to large companies should be positively associated with the amount of other licensing income which represents the second-largest type of income source (see Figure 4.3 and Figure 4.4). The proportion of licences granted to large companies will be used to determine the validity of our hypotheses set H3.

Control variables

Our control variables are derived from the information present in the STATT database, to which we add year dummy variables. Furthermore, we interact two (2) dummy variables representing the country and the presence of medical school to obtain four (4) dummy variables. This is due to differences between the four (4) types of universities leading to nuances that cannot be captured by simply considering the country or the medical school alone. Our control variables are described in the paragraphs below.

dCaMed is a dummy variable for Canadian universities with medical schools (CaMed). Interestingly, CaMeds are more closely related to U.S. universities without medical school (UsNoMed) than to other types of universities. They are more active than these concerning the number of TTO employees and similar in number of disclosures. They even show greater success when considering the average number of licences granted. However, they seem to fail at capturing the value of these licences as the average amount of gross licensing income they generate is lower (Table 4.1).

dCaNoMed is a dummy variable for Canadian universities without medical schools (CaNoMed). These universities have small TTOs similar to their U.S. counterparts. They also fall behind when looking at their commercialisation activity. They generate fewer disclosures, grant fewer licences and receive a smaller fraction of the gross licensing income created by the industry (Table 4.1).

dUsMed is a dummy variable for U.S. universities with medical schools (UsMed). These universities are the most active in terms of commercialisation. They have similar numbers of TTO employees to CaMeds but generate double the number of disclosures. They also grant 50% more licences than both CaMeds and UsNoMeds. However, they are much more apt at extracting rent from these licences as they generate five (5) to seven (7) times more gross licensing income than their counterparts (Table 4.1).

dUsNoMed is a dummy variable for UsNoMeds. These universities are comparable to CaMeds in terms of commercialisation activity. They have smaller TTOs than CaMeds on average and are closer to CaNoMeds for this indicator. They show similar number of disclosures with CaMeds on average but have higher maximum's leading to higher standard deviation. Although granting comparable number of licences with CaMeds, they generate nearly 50% more gross licensing income (Table 4.1)

Employees is the number of full-time equivalent (FTE) TTO employees and is a commonly used variable to measure the size of the TTO (Cartaxo et al., 2013; Prets and Slate, 2014). This variable is highly correlated with the size of the university which determines the age of the TTO (Cartaxo

Table 4.1 Sample values for major commercialisation indicators

	CaMed	CaNoMed	UsMed	UsNoMed	Total
			Federal R&D expenditure (CA$)		
N	313	215	1,970	1,414	3,912
Average	95,955,997.27	24,845,060.88	267,812,178.40	102,662,522.70	491,275,759.25
Std. Dev.	70,089,736.13	27,529,724.72	345,934,126.56	188,351,345.05	631,904,932.46
Min	100,000.00	0.00	0.00	0.00	100,000.00
Max	310,454,464.00	146,596,320.00	3,701,972,224.00	1,691,742,720.00	5,850,765,728.00
			Number of FTE TTO employee		
N	315	215	1,975	1,387	3,892
Average	12.45	3.88	12.12	4.43	32.88
Std. Dev.	8.70	3.35	18.67	5.17	35.89
Min	0.25	0.00	0.00	0.00	0.25
Max	48.00	16.00	223.90	44.00	331.9
			Number of disclosures per year		
N	324	216	2,025	1,447	4,012
Average	63.16	25.53	120.77	62.66	272.12
Std. Dev.	44.69	49.54	156.24	94.12	344.59
Min	0	0	0	0	0
Max	224	386	1,648	795	3,053
			Licenses granted per year		
N	309	214	1,925	1,365	3,813
Average	22.16	5.62	31.38	18.85	78.01
Std. Dev.	26.27	9.03	40.10	30.59	105.99
Min	0	0	0	0	0
Max	220	41	313	287	861
			Yearly licensing income (CA$)		
N	323	218	2,025	1,434	4,000
Average	2,641,650.05	392,945.93	14,822,475.63	3,529,491.33	21,386,562.94
Std. Dev.	3,937,767.86	870,934.14	48,147,113.17	13,863,943.57	66,819,758.74
Min	0.00	0.00	0.00	0.00	0.00
Max	34,663,672.00	9,914,199.00	1,027,235,072.00	176,294,336.00	1,248,107,279.00

et al., 2013) and the number of intermediary outputs in the process such as disclosures, patents, and licences (Table 4.1) [4].

PatentD, the number of patents per disclosures, is used to measure the patenting activity of the TTO. Patents are an important signalling tool for SMEs and startups (Hottenrott et al., 2016; Merz, 2019). By using the ratio of patents per disclosures, we aim at measuring the efficiency of the TTO in converting the disclosures they receive into marketable patents that represent a more applied and ready to use form of the knowledge compared to disclosures that can include embryonic technologies [5].

LegalL, the amount of legal fees per licences, is used to measure university's investment in research commercialisation. We expect outside lawyers to influence the payment schemes the university will prefer. We could not find any information in the literature regarding the impact of lawyers on payment schemes. We expect their effect to be positive for the amounts of income and negative for the number of licences as was reported by previous authors (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014).

PropExclLicL represents the proportion of exclusive licences. Thursby et al. (2001a) noted the important proportion of research contracts including an exclusivity close. Furthermore exclusivity is cited as important for embryonic inventions (Colyvas et al., 2002), and embryonic stage is mentioned as leading to more royalty-based payments schemes (Trombini, 2012). While it can be expected that early phase research will generate less income, firms will seek exclusivity if they believe they license is valuable (van Den Berghe and Guild, 2007).

4.4.3 Model

Considering that our independent variables are relatively stable through the period we study, we decided to fit the previously described dependent variables, represented by Y_i, by using an ordinary

[4] We replace this variable with FedRD the amount of federal research expenditures which represents the size of the university instead in our alternative model provided in the annexe tables A3, A4, A5, A6, A7, and A8.

[5] We replace this variable with nbDisclosureE the number of disclosures per FTE TTO employees which represents the workload of the TTO in our alternative model provided in the annexe tables A3, A4, A5, A6, A7, and A8. The choice of this ratio was based on reports of shortage in TTO employees which negatively affects the commercialisation process (Cartaxo et al., 2013; Swamidass and Vulasa, 2009).

least square (OLS) methodology accounting for repeated observations for the same universities [6][7]. We enter our variables in a hierarchical manner, only the relevant equations are presented in this paper. The equation includes four (4) main elements which are: a constant α_i with i representing the institution, the sum of K independent variables represented by X_{ik}, the sum of J control variables represented by Z_{ij}, and an error term ε_i. Our model is as follows:

$$Y_i = \alpha_i + \sum_{k=1}^{K} \beta_i X_{ik} + \sum_{j=1}^{J} \gamma_j Z_{ij} + \varepsilon_i \tag{4.1}$$

4.5 Results and Discussion

4.5.1 Royalty

Regression results are presented in tables 4.2 (number of licences generating royalty) and 4.3 (amount of royalty income) for royalties. We observe a significant negative association of the number of licences generating royalty with the proportion of licences to startups (cf. reg. NbRoy11) [8] the effect carries over multiple years when we lag the variable (cf. reg. NbRoy15). Furthermore, the proportion of licences to startup is also negatively associated with the amount of royalty income that the TTO is receiving (cf. reg. $Roy11) and although weak, the effect is carried over multiple years (cf. reg. $Roy13). This is coherent with the TTOs overall strategies for startups which seek growth instead of income. By not taking royalty, they increase the survival chances of the startups they invested in (Lee et al., 2010). However, royalty is a way for TTOs to extract information from the licensee, high value startups have lower royalty while low value startups have higher royalty payments (Savva and Taneri, 2014) and as reported by Bray and Lee (2000), most startups have low value. Thus, it is interesting to see that the negative association of the proportion of licences to startups with the amount of royalty (cf. reg. $Roy11), or the number of licences with royalty (cf. reg. NbRoy11), is not dissipating over time (cf. reg. $Roy13 and NbRoy15). These results confirm hypotheses H1a and H1b that the number of licences to startups is negatively associated with the number of licences with royalty and the amount of royalty on the short term.

[6] The use of OLS regressions necessitates the normal distribution of our variables and their independence from one another. Some of our variables exhibit large skewness values exceeding the |1.5| threshold or are outside of the 1.5 to 4.5 kurtosis range. We normalise these variables by multiplying them by factors of ten (10) and then applying the natural logarithm lnX=ln(X+1) represented by the prefixes : “ln”. The descriptive statistics of our variables can be found in the table A2 in the appendices. The pairwise correlation of our variables can be found in the table. A8

[7] We also conducted panel regressions not presented in this paper. However, the stability of our variables across the studied period permits the use of OLS instead of panels.

[8] The proportions of licences to different company sizes are relative to each other which leads to correlation. Thus, we study each company size proportion in separate regressions.

Table 4.2 Results for regressions of the number of licences generating royalty.

lnnbLicRoy	NbRoy1	NbRoy2	NbRoy3	NbRoy4	NbRoy5	NbRoy6	NbRoy7	NbRoy8	NbRoy9	NbRoy10	NbRoy11	NbRoy12	NbRoy13	NbRoy14	NbRoy15
dCaMed	1.4803	1.5493	1.5810	1.6163	1.6322	1.4695	1.5590	1.6322	1.6798	1.7218	1.2095	1.1947	1.1788	1.1595	1.1261
dCaNoMed	-0.6143	-0.5159	-0.4400	-0.3904	-0.3853	-0.7653	-0.8271	-0.6592	-0.6577	-0.6930	-0.7809	-0.9424	-0.9096	-0.9798	-1.0397*
dUsNoMed	0.2098	0.1905	0.1836	0.1878	0.1916	0.1919	0.1921	0.2043	0.2113	0.2227	0.1493	0.1513	0.1711	0.1617	0.1477
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnEmployees	1.2672***	1.2917***	1.2960***	1.3009***	1.3024***	1.2209***	1.2202***	1.2234***	1.2216***	1.2170***	1.1983***	1.1772***	1.1722***	1.1660***	1.1547***
lnPatentsDmD	0.1937	0.1825	0.1775	0.1745	0.1757	0.1789	0.1834	0.1787	0.1811	0.1811	0.1924	0.2076*	0.2157*	0.2225*	0.2169*
lnLegalLdDM	-0.1137	-0.1126	-0.1079	-0.1044	-0.1046	-0.0678	-0.0350	-0.0208	-0.0193	-0.0189	-0.1082	-0.0841	-0.0809	-0.0822	-0.0801
lnpropExLicL	0.7592	0.7991	0.8160	0.8363	0.8357	0.8635	1.0177	1.0994	1.0938	1.0549	0.8371	0.9069	0.9218	0.8926	0.8416
lnLegalLdDM#lnpropExLicL	-0.1218	-0.1063	-0.1105	-0.1172	-0.1165	-0.1192	-0.1543	-0.1567	-0.1497	-0.1462	-0.0939	-0.1388	-0.1335	-0.1225	-0.1244
dCaMed#lnLegalLdDM	-0.1870	-0.2040	-0.2246	-0.2328	-0.2381	-0.2171	-0.2590	-0.3148	-0.3227	-0.3452	-0.1818	-0.1965	-0.2041	-0.1999	-0.2044
dCaNoMed#lnLegalLdDM	-0.2061	-0.2323	-0.2401	-0.2411	-0.2401	-0.2231	-0.2659	-0.2566	-0.2576	-0.2505	-0.1942	-0.2058	-0.1698	-0.1620	-0.1546
dUsNoMed#lnLegalLdDM	-0.4314***	-0.4274***	-0.4251***	-0.4237***	-0.4225***	-0.4262***	-0.4219***	-0.4151***	-0.4092***	-0.4021***	-0.4317***	-0.4287***	-0.4211***	-0.4160***	-0.4116***
lnpropExLicL#lnEmployees	-0.4907	-0.5339	-0.5400*	-0.5487*	-0.5500*	-0.4436	-0.4691	-0.4889	-0.4878	-0.4747	-0.3834	-0.3524	-0.3470	-0.3335	-0.3067
dCaMed#c.lnEmployees	-0.6069	-0.6232	-0.6282	-0.6383	-0.6416*	-0.5905	-0.5947	-0.6013	-0.6141*	-0.6194*	-0.5416	-0.5303	-0.5214	-0.5157	-0.5024
dCaNoMed#lnEmployees	0.0014	-0.0410	-0.0769	-0.1007	-0.1022	0.0847	0.1480	0.0905	0.0964	0.1133	0.0738	0.1678	0.1627	0.1986	0.2185
dUsNoMed#lnEmployees	0.3781**	0.3815**	0.3777**	0.3749**	0.3739**	0.3709**	0.3796**	0.3742**	0.3723**	0.3663**	0.3872**	0.3941**	0.3994**	0.4052**	0.4054**
dCaMed#lnPatentsDmD	-0.0741	-0.0760	-0.0639	-0.0618	-0.0617	-0.0474	-0.0520	0.0010	0.0129	0.0289	0.0033	0.0172	0.0372	0.0482	0.0635
dCaNoMed#lnPatentsDmD	-0.3955	-0.3815	-0.3842	-0.3897	-0.3953	-0.2897	-0.2666	-0.3179	-0.3165	-0.3150	-0.3306	-0.3163	-0.3688	-0.3635	-0.3365
dUsNoMed#lnPatentsDmD	-0.1795	-0.1775	-0.1680	-0.1694	-0.1730	-0.1421	-0.1661	-0.1737	-0.1840	-0.1931	-0.1207	-0.1388	-0.1756	-0.1846	-0.1781
lnpropLicLargeL	-0.7171***	-0.5088***	-0.4497***	-0.4376**	-0.4299**										
lnpropLicLargeL(t-1)		-0.5643***	-0.4847***	-0.4492***	-0.4480***										
lnpropLicLargeL(t-2)			-0.2820*	-0.2248*	-0.2189*										
lnpropLicLargeL(t-3)				-0.2177	-0.2036										
lnpropLicLargeL(t-4)					-0.0602										
lnpropLicSmallL						1.1192***	0.7892***	0.6486***	0.6122***	0.5888***					
lnpropLicSmallL(t-1)							0.9015***	0.6969***	0.6440***	0.6263***					
lnpropLicSmallL(t-2)								0.6990***	0.6074***	0.5793***					
lnpropLicSmallL(t-3)									0.3371**	0.2758**					
lnpropLicSmallL(t-4)										0.2423*					
lnpropLicStartupL											-0.8594***	-0.6754***	-0.5453***	-0.5081***	-0.4914***
lnpropLicStartupL(t-1)												-0.5302***	-0.4011**	-0.3440**	-0.3258**
lnpropLicStartupL(t-2)													-0.5560***	-0.4935***	-0.4295***
lnpropLicStartupL(t-3)														-0.3082**	-0.2389*
lnpropLicStartupL(t-4)															-0.2827*
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	0.7837*	0.8602*	0.8971*	0.9312*	0.9378*	0.0965	-0.2001	-0.3756	-0.4323	-0.4639	0.7088	0.7159	0.7309	0.7442*	0.7817*
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.5700	0.5741	0.5752	0.5759	0.5759	0.5832	0.5947	0.6015	0.6032	0.6041	0.5710	0.5739	0.5772	0.5781	0.5790
Adj. R-Square	0.5610	0.5649	0.5657	0.5661	0.5659	0.5745	0.5860	0.5926	0.5941	0.5948	0.5621	0.5647	0.5677	0.5685	0.5691
F	34.1318***	31.7165***	30.3241***	30.3137***	29.6876***	36.0018***	34.9913***	37.2152***	35.1035***	34.8243***	34.2555***	32.6936***	32.0089***	30.6203***	31.5961***
Log likelihood	-1916.5108	-1908.9533	-1907.0204	-1905.7591	-1905.6585	-1892.1460	-1870.1887	-1856.9985	-1853.7222	-1851.8829	-1914.5604	-1909.2535	-1903.3353	-1901.5295	-1899.8973
BIC	4075.6944	4067.9331	4071.4210	4076.2523	4083.4048	4026.9648	3990.4039	3971.3773	3972.1785	3975.8535	4071.7937	4068.5335	4064.0509	4067.7930	4071.8823
AIC	3899.0215	3885.9065	3884.0408	3883.5183	3885.3171	3850.2920	3808.3773	3783.9970	3779.4445	3777.7658	3895.1209	3886.5069	3876.6706	3875.0590	3873.7946

***p≤0.001, **p≤0.01, *p≤0.05

Table 4.3 Results for regressions of the amount of royalty.

lnRoyalties	$Roy1	$Roy2	$Roy3	$Roy4	$Roy5	$Roy6	$Roy7	$Roy8	$Roy9	$Roy10	$Roy11	$Roy12	$Roy13	$Roy14	$Roy15
dCaMed	1.2299	1.3411	1.4043	1.4061	1.4003	1.2938	1.4539	1.5945	1.6326	1.7107	0.9194	0.9006	0.8951	0.8458	0.7480
dCaNoMed	0.9097	1.1346	1.3234	1.3259	1.3224	0.7797	0.7263	1.0892	1.0442	1.0192	0.5633	0.2446	0.3082	0.0908	-0.0458
dUsNoMed	0.5597	0.5371	0.5015	0.5007	0.4997	0.5007	0.5427	0.5885	0.5686	0.5899	0.4311	0.4520	0.5191	0.5096	0.4763
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnEmployees	2.5767***	2.6088***	2.6126***	2.6126***	2.6122***	2.5233***	2.5264***	2.5390***	2.5310***	2.5237***	2.4827***	2.4513***	2.4551***	2.4436***	2.4143***
lnPatentsDmD	0.8006**	0.7855**	0.7756**	0.7754**	0.7750**	0.7809**	0.7862**	0.7778**	0.7813**	0.7813**	0.7953**	0.8188**	0.8292***	0.8458***	0.8286***
lnLegalLdDM	0.6761**	0.6809**	0.6907**	0.6908**	0.6908**	0.7466**	0.7986**	0.8255**	0.8241**	0.8255**	0.7038**	0.7426**	0.7493**	0.7457**	0.7526**
lnpropExLicL	5.6183**	5.6986**	5.6930**	5.6916**	5.6923**	5.6913**	5.9994**	6.2166**	6.1360**	6.0801**	5.6676**	5.7993**	5.9154**	5.8658**	5.7482**
lnLegalLdDM#lnpropExLicL	-1.1016	-1.0913	-1.0998	-1.1000	-1.1001	-1.1180*	-1.1846*	-1.1981*	-1.1799*	-1.1761*	-1.0792	-1.1517*	-1.1509*	-1.1214*	-1.1288*
dCaMed#lnLegalLdDM	-0.5774	-0.5876	-0.6228	-0.6231	-0.6217	-0.6283*	-0.6660*	-0.7673**	-0.7772**	-0.8186**	-0.6091	-0.6283	-0.6524*	-0.6510*	-0.6784*
dCaNoMed#lnLegalLdDM	-0.5338	-0.5406	-0.5455	-0.5457	-0.5466	-0.5518	-0.6085	-0.5685	-0.5812	-0.5563	-0.5720	-0.6135	-0.5617	-0.5569	-0.5194
dUsNoMed#lnLegalLdDM	-0.6879*	-0.6837*	-0.6812*	-0.6812*	-0.6815*	-0.6834*	-0.6752*	-0.6623*	-0.6570*	-0.6446*	-0.6867*	-0.6799*	-0.6658*	-0.6512*	-0.6370*
dCaMed#lnpropExLicL	-1.1957	-1.3126	-1.3641	-1.3651	-1.3619	-1.1566	-1.3610	-1.3320	-1.2989	-1.2930	-0.9883	-1.0260	-0.9568	-0.8909	-0.7993
dCaNoMed#lnpropExLicL	-4.2551*	-4.4848**	-4.5565**	-4.5544**	-4.5504**	-4.4171**	-4.4904**	-4.7072**	-4.5887**	-4.6864**	-4.0660**	-3.9048**	-3.9551**	-3.8522*	-3.9758**
dUsNoMed#lnpropExLicL	-1.3002	-1.3047	-1.2585	-1.2561	-1.2569	-1.2050	-1.2908	-1.3450	-1.2853	-1.2872	-1.2062	-1.2440	-1.3289	-1.3603	-1.3809
lnpropExLicL#lnEmployees	-1.8612**	-1.9121**	-1.9103**	-1.9102**	-1.9102**	-1.7994**	-1.8373**	-1.8870**	-1.8740**	-1.8525**	-1.7110**	-1.6657*	-1.6845*	-1.6631*	-1.5953*
dCaMed#c.lnEmployees	-0.0022	-0.0248	-0.0335	-0.0340	-0.0329	0.0004	-0.0070	-0.0223	-0.0349	-0.0451	0.0699	0.0879	0.0953	0.1082	0.1455
dCaNoMed#lnEmployees	0.3448	0.2685	0.1853	0.1838	0.1848	0.4480	0.5317	0.4215	0.4363	0.4589	0.4971	0.6600	0.6528	0.7525	0.8054
dUsNoMed#lnEmployees	0.8667**	0.8714**	0.8671**	0.8671**	0.8674**	0.8651**	0.8710**	0.8583**	0.8602**	0.8497**	0.8874**	0.8951**	0.8963**	0.9081**	0.9075**
dCaMed#lnPatentsDmD	-0.9620*	-0.9549*	-0.9235*	-0.9231*	-0.9235*	-0.9493**	-0.9385*	-0.8562*	-0.8424*	-0.8153*	-0.8869*	-0.8611*	-0.8432*	-0.8224*	-0.7866*
dCaNoMed#lnPatentsDmD	-1.0414*	-1.0260*	-1.0339*	-1.0343*	-1.0322*	-0.9049	-0.8714	-0.9590*	-0.9569*	-0.9557*	-0.9221	-0.8959	-0.9679*	-0.9524*	-0.8719
dUsNoMed#lnPatentsDmD	-0.8771**	-0.8738**	-0.8533*	-0.8534*	-0.8522**	-0.8447*	-0.8781**	-0.8909**	-0.9034**	-0.9194**	-0.8096*	-0.8388*	-0.8912**	-0.9147**	-0.8955**
lnpropLicLargeL	-0.5361	-0.2592	-0.1378	-0.1371	-0.1397										
lnpropLicLargeL(t-1)		-0.7648	-0.5997	-0.5974	-0.5977										
lnpropLicLargeL(t-2)			-0.5928	-0.5891*	-0.5911*										
lnpropLicLargeL(t-3)				-0.0142	-0.0191										
lnpropLicLargeL(t-4)					0.0214										
lnpropLicSmallL						1.3981**	0.9307**	0.6969*	0.6535	0.6131					
lnpropLicSmallL(t-1)							1.2746***	0.9332***	0.8684***	0.8371***					
lnpropLicSmallL(t-2)								1.1674***	1.0550***	1.0065***					
lnpropLicSmallL(t-3)									0.4090	0.2994					
lnpropLicSmallL(t-4)										0.4291					
lnpropLicStartupL											-1.3607**	-1.0650**	-0.8806**	-0.7852*	-0.7348*
lnpropLicStartupL(t-1)												-0.8473*	-0.6673*	-0.5257	-0.4680
lnpropLicStartupL(t-2)													-0.7778*	-0.6233*	-0.4308
lnpropLicStartupL(t-3)														-0.7723*	-0.5617
lnpropLicStartupL(t-4)															-0.8593**
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	1.8934	1.9858	2.0804	2.0837	2.0811	1.1376	0.6795	0.3532	0.3154	0.2535	1.9398	1.9425	1.9256	1.9504	2.0503
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.4718	0.4735	0.4746	0.4746	0.4746	0.4781	0.4833	0.4876	0.4882	0.4889	0.4756	0.4773	0.4787	0.4801	0.4820
Adj. R-Square	0.4597	0.4611	0.4618	0.4614	0.4611	0.4661	0.4711	0.4752	0.4754	0.4758	0.4636	0.4650	0.4661	0.4672	0.4687
F	13.8566***	13.5848***	13.266***	13.2272***	13.3042***	14.4446***	14.932***	14.2375***	13.7422***	14.0277***	13.955***	13.8912***	13.6473***	13.5521***	13.7511***
Log likelihood	-3234.2532	-3231.7091	-3230.1456	-3230.1446	-3230.1423	-3224.8438	-3216.9669	-3210.4489	-3209.6037	-3208.5904	-3228.5204	-3226.0152	-3223.8862	-3221.8021	-3219.0267
BIC	6733.2403	6735.5059	6739.7326	6747.0844	6754.4335	6714.4216	6706.0214	6700.3392	6706.0026	6711.3296	6721.7749	6724.1181	6727.2139	6730.3993	6732.2022
AIC	6540.5063	6537.4182	6536.2912	6538.2892	6540.2846	6521.6876	6507.9337	6496.8978	6497.2074	6497.1807	6529.0409	6526.0304	6523.7725	6521.6041	6518.0533

***p≤0.001, **p≤0.01, *p≤0.05

We observe significant associations of the proportion of licences to incumbent companies with both the number of licences generating royalty and the amount of royalty. On the one hand, the proportion of licences to large companies is negatively associated with the number of licences generating royalty (cf. reg. NbRoy1) but has no significant association with the amount of royalty (cf. reg. $Roy1). On the other hand, the proportion of licences to small companies has a positive effect on the dependent variables for both dependent variables, an effect that is sustained over the years as can be seen from the lagged variables' effect (cf. reg. NbRoy6-NbRoy10 and $Roy6-$Roy8). This positive association is also growing over the course of the first three (3) years which might indicate the importance of an implementation phase for the licensed technology (cf. reg. NbRoy8 and $Roy8). These effects might stem from the difference in absorptive capacities between the two groups. Smaller companies may need more collaboration with the licensor to implement the solution and hence lean towards more royalty-based payment schemes while large companies already have important absorptive and transformative capacities and would prefer secrecy. Furthermore, royalty is considered less efficient for both licensor and licensee (Kamien and Tauman, 1986; Savva and Taneri, 2014), large companies having the means to pay for upfront fees and being skilled negotiators might be avoiding the royalty-based payment schemes (Cebrián, 2009). Our results support our hypotheses H3a and H3b. The proportion of licences to small companies is positively associated with both the number of licences generating royalty and the amount of royalty. They also confirm hypothesis H2a that the proportion of licences to large companies is negatively associated with licences generating royalty. However, we fund no support for hypothesis H2b and showed that the proportion of licences to large companies has no significant association with the amount of royalty.

The number of FTE TTO employees is positively associated with the number of licences generating royalty and the amount of royalty (cf. table 4.2) . The positive effect is further enhanced for U.S. universities with no medical schools (cf. table 4.2). The other control variables have no significant association with the number of licences generating royalty except for U.S. universities without a medical school for which we observe a negative association of the amount of legal fees per licence and the number of licences with royalty (cf. table 4.2). Furthermore, the amount of legal fees per licence is positively associated with the amount of royalty (cf. table 4.3). These results are coherent with previous studies relating a negative impact of outside lawyers on the number of licences granted and their positive impact on the amount of income generated (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014). However, the positive association of the amount of legal fees with the amount of royalty is hampered for U.S. universities without a medical school. The number of issued U.S. patents is positively associated with the amount of royalty for U.S. universities with a medical school but becomes negative for the other groups (cf. table 4.3). The proportion of exclusive licences is positively associated with the amount of royalty. The positive association of the proportion of exclusive licences with the amount of royalty is consistent for all four (4) groups with a weaker coefficient for Canadian universities without a medical school (cf. table 4.3). This is interesting since, on the one hand, exclusivity is reported as being used in early stages of the research projects which would not generate any income (Thursby et al., 2001a), and, on the other hand, embryonic stage is reported as leading to more royalty-based payment schemes (Trombini, 2012). One plausible explanation for the positive association of the proportion of exclusive licences with the amount of royalty is that companies pursue exclusivity if they believe the technology is valuable (van Den Berghe and Guild, 2007). Hence, the association might be due to exclusive licences being more valuable and marketable than their non-exclusive counterparts.

4.5.2 Equity

Regression results are presented in table 4.4 (number of licences with equity) and 4.5 (amount of income from equity sales) for equities. As expected the proportion of licences to startups is positively associated with the number of licences with equity for the same year and the association is sustained over the first year (cf. reg. NbEqu12). However, the proportion has no significant association with the amount of income from equity sales, this might be related to universities keeping the equity for longer periods of time (cf. reg. $Equ11-$Equ15). Another explanation would be that most startups have a low value (Bray and Lee, 2000). Thus, having more startups does not affect the income since most of the income is generated by a small number of deals. The association of the number of licences with equity with the proportion of licences to incumbent companies is negative for both large and small companies (cf. reg. NbEqu2 and NbEqu7). The significant negative association is only observed for the same year when entering the first lag for the proportion of licences to large companies (cf. reg. NbEqu2). However, the AIC and BIC values suggest that we should not include the lagged proportion of licences to large companies (cf. reg. NbEqu1 and NbEqu2). The proportion of licences to small companies carries the negative effect further in time for a lag of one (1) year (cf. reg. NbEqu7) but the significance is questionable for this lag since the AIC value is better for the regression that does not include the lag (cf. reg. NbEqu6). Results are still coherent since incumbent companies giving equity in exchange of a licence is unheard of. They also indicate that when TTOs licence, they might compare small companies and startups while large companies are considered a completely different category. This might very well stem from different approaches to licensing as the size will determine explorative versus exploitative approaches (van Den Berghe and Guild, 2007; Bruneel et al., 2016).

Table 4.4 Results for regressions of the number of licences with equity.

lnnbLicEqu	NbEqu1	NbEqu2	NbEqu3	NbEqu4	NbEqu5	NbEqu6	NbEqu7	NbEqu8	NbEqu9	NbEqu10	NbEqu11	NbEqu12	NbEqu13	NbEqu14	NbEqu15
dCaMed	-0.2267	-0.2457	-0.2544	-0.2737	-0.3010	-0.3616	-0.3924	-0.4101	-0.4263	-0.4492	-0.1011	-0.0949	-0.0937	-0.0853	-0.0726
dCaNoMed	1.1664**	1.1280**	1.1022**	1.0755**	1.0592*	1.1785**	1.1887**	1.1433**	1.1625**	1.1698**	1.4346***	1.5396***	1.5256***	1.5624***	1.5802***
dUsNoMed	-0.8233**	-0.8195**	-0.8146**	-0.8056**	-0.8103**	-0.7876**	-0.7957**	-0.8014**	-0.7929**	-0.7992**	-0.6777**	-0.6846**	-0.6994**	-0.6977**	-0.6934**
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnEmployees	0.3526***	0.3471***	0.3466***	0.3462***	0.3443***	0.3674***	0.3668***	0.3652***	0.3687***	0.3708***	0.4315***	0.4419***	0.4410***	0.4430***	0.4468***
lnPatentsDmD	0.0360	0.0386	0.0400	0.0418	0.0398	0.0470	0.0460	0.0470	0.0455	0.0455	0.0453	0.0376	0.0353	0.0325	0.0347
lnLegalLdDM	-0.1238*	-0.1247*	-0.1260*	-0.1276*	-0.1275*	-0.1729**	-0.1829***	-0.1863***	-0.1857***	-0.1861***	-0.1828***	-0.1956***	-0.1970***	-0.1964***	-0.1973***
lnpropExLicL	-1.3629**	-1.3766**	-1.3758**	-1.3609**	-1.3577**	-1.3892**	-1.4485**	-1.4757***	-1.4413**	-1.4249**	-1.4020**	-1.4453***	-1.4708***	-1.4624***	-1.4471***
lnLegalLdDM#lnpropExLicL	-0.0316	-0.0333	-0.0322	-0.0300	-0.0303	0.0064	0.0192	0.0209	0.0132	0.0121	-0.0005	0.0234	0.0232	0.0182	0.0191
dCaMed#lnLegalLdDM	-0.1921	-0.1904	-0.1856	-0.1826	-0.1757	-0.1659	-0.1587	-0.1460	-0.1418	-0.1296	-0.1538	-0.1475	-0.1422	-0.1425	-0.1389
dCaNoMed#lnLegalLdDM	0.0028	0.0039	0.0046	0.0068	0.0026	0.0195	0.0304	0.0254	0.0308	0.0235	0.0563	0.0700	0.0586	0.0578	0.0529
dUsNoMed#lnLegalLdDM	0.1339	0.1332	0.1328	0.1328	0.1312	0.1318	0.1302	0.1286	0.1263	0.1227	0.1325	0.1302	0.1271	0.1247	0.1228
dCaMed#lnpropExLicL	-0.0756	-0.0557	-0.0486	-0.0374	-0.0222	-0.0273	0.0120	0.0083	-0.0058	-0.0075	-0.1695	-0.1571	-0.1723	-0.1834	-0.1954
dCaNoMed#lnpropExLicL	-0.2957	-0.2566	-0.2468	-0.2692	-0.2508	-0.1035	-0.0894	-0.0623	-0.1128	-0.0841	-0.2755	-0.3287	-0.3176	-0.3351	-0.3190
dUsNoMed#lnpropExLicL	0.7082**	0.7090**	0.7026**	0.6771**	0.6732**	0.6253**	0.6418**	0.6486**	0.6231**	0.6237**	0.5431*	0.5555*	0.5741*	0.5795*	0.5822*
lnpropExLicL#lnEmployees	1.0118***	1.0205***	1.0203***	1.0194***	1.0196***	0.9864***	0.9937***	0.9999***	0.9944***	0.9881***	0.8645***	0.8496***	0.8537***	0.8501***	0.8413***
dCaMed#c.lnEmployees	-0.0532	-0.0493	-0.0481	-0.0424	-0.0372	-0.0330	-0.0316	-0.0296	-0.0243	-0.0213	-0.0883	-0.0942	-0.0959	-0.0980	-0.1029
dCaNoMed#lnEmployees	-0.7621**	-0.7491**	-0.7378**	-0.7217**	-0.7173**	-0.8121***	-0.8282***	-0.8144***	-0.8207***	-0.8274***	-0.9224***	-0.9761***	-0.9745***	-0.9914***	-0.9982***
dUsNoMed#lnEmployees	0.1732*	0.1724*	0.1730*	0.1731*	0.1744*	0.1709*	0.1697*	0.1713*	0.1705*	0.1736*	0.1472	0.1447	0.1444	0.1424	0.1425
dCaMed#lnPatentsDmD	0.0647	0.0635	0.0592	0.0557	0.0539	0.0732	0.0711	0.0608	0.0549	0.0469	0.0139	0.0054	0.0015	-0.0020	-0.0067
dCaNoMed#lnPatentsDmD	-0.0759	-0.0785	-0.0775	-0.0733	-0.0635	-0.1438	-0.1502	-0.1392	-0.1401	-0.1405	-0.2086	-0.2172	-0.2014	-0.2040	-0.2145
dUsNoMed#lnPatentsDmD	0.0345	0.0339	0.0311	0.0320	0.0378	0.0364	0.0428	0.0444	0.0497	0.0544	-0.0050	0.0046	0.0161	0.0201	0.0176
lnpropLicLargeL	-0.1703	-0.2175*	-0.2342**	-0.2421**	-0.2545**										
lnpropLicLargeL(t-1)		0.1304	0.1078	0.0827	0.0812										
lnpropLicLargeL(t-2)			0.0811	0.0414	0.0319										
lnpropLicLargeL(t-3)				0.1533	0.1302										
lnpropLicLargeL(t-4)					0.0996										
lnpropLicSmallL						-0.6176***	-0.5277***	-0.4984***	-0.4799***	-0.4680***					
lnpropLicSmallL(t-1)							-0.2452**	-0.2024*	-0.1748	-0.1656					
lnpropLicSmallL(t-2)								-0.1462	-0.0983	-0.0841					
lnpropLicSmallL(t-3)									-0.1744*	-0.1422					
lnpropLicSmallL(t-4)										-0.1259					
lnpropLicStartupL											1.3630***	1.2655***	1.2251***	1.2089***	1.2024***
lnpropLicStartupL(t-1)												0.2792**	0.2397*	0.2157*	0.2082*
lnpropLicStartupL(t-2)													0.1707	0.1445	0.1194
lnpropLicStartupL(t-3)														0.1308	0.1034
lnpropLicStartupL(t-4)															0.1120
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	0.1437	0.1280	0.1150	0.0791	0.0671	0.3865	0.4746*	0.5155*	0.5316*	0.5498*	-0.0610	-0.0619	-0.0582	-0.0624	-0.0754
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.4033	0.4038	0.4040	0.4047	0.4050	0.4161	0.4179	0.4186	0.4195	0.4201	0.4487	0.4505	0.4512	0.4515	0.4519
Adj. R-Square	0.3896	0.3897	0.3895	0.3899	0.3898	0.4027	0.4042	0.4045	0.4051	0.4052	0.4361	0.4375	0.4378	0.4379	0.4378
F	18.0722***	18.1009***	17.7022***	17.4564***	17.0141***	18.7715***	18.1018***	17.6553***	17.355***	16.9481***	19.3335***	19.2145***	18.677***	18.1515***	17.7689***
Log likelihood	-1559.3344	-1558.7035	-1558.4544	-1557.4849	-1557.0567	-1542.4697	-1539.9654	-1539.0932	-1537.7870	-1537.0455	-1497.4778	-1494.9816	-1494.0416	-1493.4944	-1493.0640
BIC	3383.4027	3389.4947	3396.3502	3401.7649	3408.2623	3349.6735	3352.0185	3357.6278	3362.3692	3368.2398	3259.6896	3262.0510	3267.5247	3273.7840	3280.2769
AIC	3190.6687	3191.4070	3192.9087	3192.9697	3194.1134	3156.9394	3153.9308	3154.1864	3153.5740	3154.0909	3066.9556	3063.9632	3064.0832	3064.9889	3066.1280

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$

Table 4.5 Results for regressions of the amount of income from equity sales.

lnIncEqu	$Equ1	$Equ2	$Equ3	$Equ4	$Equ5	$Equ6	$Equ7	$Equ8	$Equ9	$Equ10	$Equ11	$Equ12	$Equ13	$Equ14	$Equ15
dCaMed	-0.1861	-0.2272	-0.3007	-0.4203	-0.5807	-0.1892	-0.2397	-0.3252	-0.4391	-0.4736	-0.2244	-0.1948	-0.1741	-0.1644	-0.1640
dCaNoMed	4.1579	4.0994	3.9233	3.7556	3.7033	4.1221	4.1570	3.9608	3.9572	3.9862	4.1742	4.4968	4.4540	4.4891	4.4899
dUsNoMed	-1.1289	-1.1175	-1.1015	-1.1156	-1.1545	-1.1332	-1.1333	-1.1475	-1.1643	-1.1737	-1.1287	-1.1327	-1.1585	-1.1538	-1.1536
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnEmployees	3.7127***	3.6981***	3.6881***	3.6716***	3.6562***	3.7017***	3.7021***	3.6984***	3.7025***	3.7063***	3.7107***	3.7528***	3.7593***	3.7624***	3.7625***
lnPatentsDmD	0.4220	0.4287	0.4403	0.4506	0.4387	0.4185	0.4160	0.4215	0.4159	0.4159	0.4238	0.3936	0.3829	0.3795	0.3796
lnLegalLdDM	0.7292	0.7286	0.7176	0.7057	0.7078	0.7400	0.7215	0.7049	0.7013	0.7010	0.7186	0.6705	0.6664	0.6670	0.6670
lnpropExLicL	1.6234	1.5997	1.5603	1.4918	1.4977	1.6481	1.5612	1.4658	1.4790	1.5110	1.6020	1.4626	1.4432	1.4578	1.4584
lnLegalLdDM#lnpropExLicL	-0.7657	-0.7749	-0.7652	-0.7427	-0.7491	-0.7649	-0.7451	-0.7423	-0.7590	-0.7620	-0.7513	-0.6616	-0.6685	-0.6740	-0.6740
dCaMed#lnLegalLdDM	-2.1614**	-2.1513**	-2.1034*	-2.0757*	-2.0220*	-2.1685**	-2.1449*	-2.0796*	-2.0607*	-2.0423*	-2.1542**	-2.1249*	-2.1150**	-2.1171**	-2.1170**
dCaNoMed#lnLegalLdDM	-0.6759	-0.6603	-0.6422	-0.6387	-0.6491	-0.6798	-0.6556	-0.6665	-0.6641	-0.6699	-0.6616	-0.6383	-0.6852	-0.6891	-0.6892
dUsNoMed#lnLegalLdDM	0.6770	0.6746	0.6693	0.6645	0.6530	0.6782	0.6758	0.6678	0.6539	0.6480	0.6756	0.6695	0.6596	0.6571	0.6570
lnpropExLicL#lnEmployees	-0.0996	-0.0739	-0.0599	-0.0304	-0.0169	-0.0883	-0.0740	-0.0508	-0.0534	-0.0642	-0.0996	-0.1616	-0.1685	-0.1753	-0.1756
dCaMed#lnEmployees	1.4363	1.4460	1.4577	1.4918	1.5246	1.4403	1.4427	1.4504	1.4811	1.4855	1.4439	1.4213	1.4097	1.4069	1.4067
dCaNoMed#lnEmployees	-0.7288	-0.7036	-0.6203	-0.5400	-0.5242	-0.7092	-0.7448	-0.6776	-0.6919	-0.7058	-0.7444	-0.9320	-0.9254	-0.9433	-0.9436
dUsNoMed#lnEmployees	0.3004	0.2984	0.3072	0.3165	0.3268	0.2987	0.2938	0.3001	0.3047	0.3096	0.2997	0.2860	0.2790	0.2761	0.2761
dCaMed#lnPatentsDmD	-0.2940	-0.2929	-0.3210	-0.3279	-0.3298	-0.2875	-0.2850	-0.3468	-0.3753	-0.3885	-0.2886	-0.3164	-0.3425	-0.3480	-0.3482
dCaNoMed#lnPatentsDmD	-0.6304	-0.6388	-0.6326	-0.6141	-0.5567	-0.6054	-0.6184	-0.5585	-0.5617	-0.5630	-0.6423	-0.6708	-0.6024	-0.6050	-0.6054
dUsNoMed#lnPatentsDmD	-0.2122	-0.2134	-0.2355	-0.2307	-0.1944	-0.2033	-0.1897	-0.1809	-0.1562	-0.1487	-0.2076	-0.1715	-0.1235	-0.1190	-0.1191
lnpropLicLargeL	-0.1723	-0.2962	-0.4333	-0.4743	-0.5523										
lnpropLicLargeL(t-1)		0.3357	0.1510	0.0308	0.0193										
lnpropLicLargeL(t-2)			0.6542	0.4605	0.4001										
lnpropLicLargeL(t-3)				0.7372	0.5944										
lnpropLicLargeL(t-4)					0.6093										
lnpropLicSmallL						0.2656	0.4516	0.6158	0.7030	0.7222					
lnpropLicSmallL(t-1)							-0.5082	-0.2692	-0.1426	-0.1281					
lnpropLicSmallL(t-2)								-0.8163	-0.5972	-0.5741					
lnpropLicSmallL(t-3)									-0.8069	-0.7566					
lnpropLicSmallL(t-4)										-0.1990					
lnpropLicStartupL											0.0755	-0.2920	-0.4616	-0.4802	-0.4804
lnpropLicStartupL(t-1)												1.0589	0.8907	0.8621	0.8619
lnpropLicStartupL(t-2)													0.7247	0.6934	0.6926
lnpropLicStartupL(t-3)														0.1542	0.1533
lnpropLicStartupL(t-4)															0.0035
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	-4.7767**	-4.8222**	-4.9077**	-5.0232**	-5.0903**	-4.9402**	-4.7730**	-4.5680**	-4.4323**	-4.4064**	-4.8161**	-4.8301**	-4.8497**	-4.8563**	-4.8568**
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.2411	0.2412	0.2415	0.2418	0.2421	0.2412	0.2413	0.2418	0.2422	0.2422	0.2411	0.2416	0.2419	0.2419	0.2419
Adj. R-Square	0.2253	0.2248	0.2246	0.2244	0.2242	0.2253	0.2250	0.2249	0.2248	0.2243	0.2252	0.2253	0.2250	0.2245	0.2240
F	7.8079***	7.8018***	7.6037***	7.3929***	7.2279***	7.8092***	7.6798***	7.4531***	7.2852***	7.1569***	7.8268***	7.7342***	7.5163***	7.3594***	7.3287***
Log likelihood	-4777.3281	-4777.2598	-4776.9958	-4776.6292	-4776.3686	-4777.2939	-4777.1228	-4776.6912	-4776.2455	-4776.2161	-4777.3449	-4776.8047	-4776.5500	-4776.5386	-4776.5386
BIC	9797.3290	9804.5462	9811.3719	9817.9925	9824.8249	9797.2607	9804.2721	9810.7627	9817.2249	9824.5199	9797.3626	9803.6360	9810.4802	9817.8111	9825.1648
AIC	9620.6562	9622.5196	9623.9916	9625.2585	9626.7372	9620.5879	9622.2456	9623.3824	9624.4909	9626.4322	9620.6897	9621.6095	9623.0999	9625.0771	9627.0771

***p≤0.001, **p≤0.01, *p≤0.05

These results confirm our hypothesis H1d that the proportion of licences to startups is positively associated with the number of licences with equity. However, we found no support for our hypothesis H1e that this proportion has a positive association with the amount of equity paid in the long run. This might be related to the time frame we use as we stop our lag at five (5) years but universities might theoretically keep these companies' actions indefinitely. More research could indicate the average time between the creation of the startup and the sale of equity by the university.

Both the number of licences with equity and the amount of income from equity sales are positively associated with the number of FTE TTO employees (cf. table 4.4 and 4.5). The positive association with the number of licences with equity is further enhanced for U.S. universities without a medical school while it is hampered for Canadian universities without a medical school (cf. table 4.4). We observe no other significant association between the amount of equity sales income and our control variables aside the significant negative association with the amount of legal fees per licence for Canadian universities with a medical school (cf. table 4.5). However, the amount of legal fee per licence has a significant negative association with the number of licences with equity (cf. table 4.4). This might be the result of outside lawyers being more interested in royalty than equity stakes. Lawyers would indeed not benefit from equity stakes and would prefer more tangible income streams instead since equity sales income is unreliable and equity can take a long time to bear fruits. This would be coherent with previous studies pointing to outside lawyers' preference for income generation over transfer success (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014). As was noted by others (see for instance Feldman et al. (2002)) and shown in Figure 4.3, equity sales income is highly dependent of the market, and income peaked during the 2000 dotcom bubble as most universities adopted a risk-averse strategy and scrambled to sell their stakes in startups. We observe a different attitude for the 2008 crisis which might be related to the crisis type or to TTOs learning and evolving their strategies. Furthermore, universities might be keeping equity stakes for longer periods of time than five (5) years which would explain the lack of correlation to the amount of income from equity sales. Nonetheless, equity sales income seems to be more related to market condition which catalyses the sale of equity than the university's intrinsic characteristics.

4.5.3 Other licensing income

Table 4.6 Results for regressions of the amount of other licensing income.

lnIncOther	$Oth1	$Oth2	$Oth3	$Oth4	$Oth5	$Oth6	$Oth7	$Oth8	$Oth9	$Oth10	$Oth11	$Oth12	$Oth13	$Oth14	$Oth15
dCaMed	0.6275	0.5472	0.542	0.5438	0.5937	0.8549	0.8248	0.8459	0.904	0.9792	0.7701	0.7645	0.7583	0.7218	0.6965
dCaNoMed	-0.6633	-0.7779	-0.7903	-0.7877	-0.7715	-0.6678	-0.6471	-0.5989	-0.597	-0.6603	-0.851	-0.9123	-0.8994	-1.0316	-1.0769
dUsNoMed	-1.9080***	-1.8856***	-1.8845***	-1.8842***	-1.8721***	-1.8893***	-1.8894***	-1.8859***	-1.8774***	-1.8568***	-1.9371***	-1.9363***	-1.9285***	-1.9463***	-1.9569***
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnEmployees	1.2155***	1.1869***	1.1862***	1.1865***	1.1913***	1.2455***	1.2457***	1.2466***	1.2445***	1.2363***	1.1984***	1.1904***	1.1884***	1.1766***	1.1680***
lnPatentsDmD	-0.0834	-0.0704	-0.0696	-0.0697	-0.066	-0.0895	-0.091	-0.0924	-0.0895	-0.0895	-0.0966	-0.0909	-0.0877	-0.0748	-0.0791
lnLegalLdDM	-0.1691	-0.1703	-0.1711	-0.1709	-0.1715	-0.1323	-0.1434	-0.1393	-0.1374	-0.1368	-0.093	-0.0839	-0.0826	-0.085	-0.0834
lnpropExLicL	-2.4170*	-2.4634*	-2.4662*	-2.4651*	-2.4669*	-2.3645*	-2.4162*	-2.3928*	-2.3996*	-2.4692*	-2.2334	-2.207	-2.2011	-2.2561*	-2.2948*
lnLegalLdDM#lnpropExLicL	0.3018	0.2837	0.2844	0.2841	0.286	0.2403	0.252	0.2514	0.2599	0.2663	0.2152	0.1981	0.2002	0.2209	0.2194
dCaMed#lnLegalLdDM	0.1582	0.1779	0.1813	0.1809	0.1642	0.1305	0.1446	0.1285	0.1189	0.0786	0.1109	0.1053	0.1023	0.1103	0.1068
dCaNoMed#lnLegalLdDM	-0.1682	-0.1378	-0.1365	-0.1366	-0.1333	-0.2242	-0.2098	-0.2072	-0.2084	-0.1957	-0.2616	-0.2661	-0.2519	-0.2372	-0.2316
dUsNoMed#lnLegalLdDM	0.2303	0.2256	0.2253	0.2253	0.2289	0.2356	0.2341	0.2361	0.2432	0.256	0.24	0.2412	0.2442	0.2536	0.2569
lnpropExLicL#lnEmployees	0.502	0.5523	0.5533	0.5528	0.5486	0.4671	0.4757	0.47	0.4713	0.4947	0.5507	0.5624	0.5645	0.5899	0.6103
dCaMed#lnEmployees	-0.9677**	-0.9488**	-0.9480**	-0.9485**	-0.9587**	-1.0167**	-1.0153**	-1.0172**	-1.0329**	-1.0424**	-0.9909**	-0.9866**	-0.9831**	-0.9723**	-0.9623**
dCaNoMed#lnEmployees	-0.8461*	-0.7967*	-0.7909*	-0.7921*	-0.7970*	-0.8134**	-0.8346**	-0.8511**	-0.8438**	-0.8136*	-0.7060*	-0.6703*	-0.6723*	-0.6048	-0.5897
dUsNoMed#lnEmployees	0.4926**	0.4887**	0.4893**	0.4892**	0.4860**	0.4921**	0.4891**	0.4876**	0.4852**	0.4745**	0.5011**	0.5037**	0.5058**	0.5166**	0.5168**
dCaMed#lnPatentsDmD	0.7055	0.7077	0.7057	0.7059	0.7064	0.6607	0.6622	0.6774	0.6919	0.7207	0.7032	0.7085	0.7163	0.7371	0.7487
dCaNoMed#lnPatentsDmD	0.3848	0.3686	0.369	0.3687	0.3509	0.4065	0.3987	0.384	0.3857	0.3884	0.4964	0.5018	0.4813	0.4911	0.5116
dUsNoMed#lnPatentsDmD	0.127	0.1246	0.1231	0.123	0.1117	0.0908	0.0989	0.0967	0.0841	0.0678	0.1216	0.1147	0.1003	0.0833	0.0882
lnpropLicLargeL	0.8679***	0.6255**	0.6158**	0.6164**	0.6407***										
lnpropLicLargeL(t-1)		0.6569***	0.6438***	0.6457***	0.6493***										
lnpropLicLargeL(t-2)			0.0462	0.0493	0.0681										
lnpropLicLargeL(t-3)				-0.0116	0.0328										
lnpropLicLargeL(t-4)					-0.1894										
lnpropLicSmallL						-0.0103	0.1005	0.0601	0.0156	-0.0264					
lnpropLicSmallL(t-1)							-0.3025	-0.3612	-0.4258*[1]	-0.4574**[1]					
lnpropLicSmallL(t-2)								0.2006	0.0888	0.0385					
lnpropLicSmallL(t-3)									0.4116*[1]	0.3018					
lnpropLicSmallL(t-4)										0.4341**[1]					
lnpropLicStartupL											-0.9108**	-0.8410**	-0.7900**	-0.7198**	-0.7072**
lnpropLicStartupL(t-1)												-0.2011	-0.1505	-0.0429	-0.0292
lnpropLicStartupL(t-2)													-0.218	-0.1003	-0.0518
lnpropLicStartupL(t-3)														-0.5806*	-0.5281*
lnpropLicStartupL(t-4)															-0.214
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	2.2074***	2.1183***	2.1123***	2.1141***	2.1349***	2.3819***	2.4814***	2.4311***	2.3619***	2.3052***	2.4460***	2.4487***	2.4546***	2.4796***	2.5080***
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.4975	0.5001	0.5001	0.5001	0.5004	0.4925	0.4931	0.4934	0.4946	0.4959	0.4969	0.4971	0.4973	0.4989	0.4992
Adj. R-Square	0.487	0.4893	0.489	0.4887	0.4886	0.4819	0.4822	0.4821	0.483	0.484	0.4864	0.4863	0.4861	0.4874	0.4874
F	23.4675***	23.9096***	23.346***	22.6715***	22.3023***	22.6681***	22.6313***	21.7333***	21.1384***	20.9191***	22.39***	21.8617***	20.8757***	20.2824***	20.5499***
Log likelihood	-2641.67	-2637.6322	-2637.6118	-2637.6104	-2637.2206	-2649.3693	-2648.4443	-2648.0466	-2646.2743	-2644.1339	-2642.6103	-2642.3106	-2641.9562	-2639.4665	-2639.103
BIC	5526.0129	5525.2909	5532.6038	5539.9548	5546.529	5541.4114	5546.9152	5553.4736	5557.2827	5560.3555	5527.8935	5534.6478	5541.2926	5543.6669	5550.2938
AIC	5349.3401	5343.2644	5345.2235	5347.2208	5348.4413	5364.7386	5364.8887	5366.0933	5364.5486	5362.2677	5351.2206	5352.6213	5353.9123	5350.9329	5352.206

[1] The symmetrical significant effect disappears when entered on its own;
***p≤0.001, **p≤0.01, *p≤0.05

The results for the amount of other licensing income presented in the table 4.6 show a positive significant association of the proportion of licences to large companies for the same year and a lag of one (1) year with the amount of other licensing income (cf. reg. $Oth2). These results combined with previous results for royalty income (cf. reg. NbRoy3 and $Roy1) indicates that large companies prefer to pay upfront fixed fees to minimise the royalty over the long term as was stated by Cebrián (2009). We also observe a significant negative association of the proportion of licences to startups with the amount of other licensing income (cf. reg. $Oth11). This is coherent with the common conception that startups are cash constrained (Lee et al., 2010). We find no other significant effect for proportions of licences to incumbent companies or startups. These results confirm hypotheses H1c and H2c that startups avoid fixed fees while large companies pay upfront fees to avoid royalty later. We found no support for hypothesis H3c that small companies avoid fixed fee payments schemes.

The amount of other licensing income is positively associated with the number of FTE TTO employees. The association is consistent for all four (4) types of universities (cf. table 4.6). We also observe a negative association of the amount of other licensing income and the dummy representing U.S. universities without a medical school (cf. table 4.6). Furthermore the amount of other licensing income is also negatively associated with the proportion of exclusive licences (cf. table 4.6) which is coherent with previous studies indicating that universities commercialise early stage inventions (Thursby et al., 2001a) and that embryonic inventions tend towards royalty type payment schemes (Trombini, 2012).

4.6 Conclusion

Our contribution to the literature is two-fold, first, we bring empirical evidence to the literature on licence payment schemes; second, we contribute to policy making by pointing out strengths and shortcomings of university research commercialisation related to company size. First, our results show that the choice of payment scheme for university research licences is associated with the partner size. While the theoretical literature emphasises the optimal payment scheme for both parties as being fixed fees, empirical data indicates that this strategy is not always feasible let alone desirable for licensors and licensees alike. The choice of payment scheme is tied to perceived risks and rewards as well as resources such as absorptive capacity and financial slack. Second, we show that by better coordinating the university-industry licensing market, governments and universities can increase the knowledge transfer between parties and pave the way towards innovation and commercialisation. This can be achieved by playing the strengths and bolstering the weaknesses of different partner size and payment schemes, and more importantly reconsidering the way these two factors are combined to enhance collaborations' outcomes.

Universities derive a major part of their licensing income from royalty. This type of income represents over 80% of the income generated for some years of the period we studied. This is despite the theoretical models of the literature showing the superiority of fixed fees over royalty. We impute these outcomes to multiple factors at play. Most of the licences are granted to small companies which represent half of the licences received. Our results show that small companies are associated with royalty-based payment schemes. This might be related to small companies being more risk averse and preferring an output based payment scheme. Furthermore, they might also need the collaboration of the licensor for a successful transfer incentivised by this type of payment, and lack the funding necessary to pay upfront fees to minimise subsequent royalty. Finally, asymmetric information and lack of market knowledge might lead researchers to over estimate the value of the technology they are transferring, hence pursuing royalty-based payment scheme.

The data shows that in a normal year fixed fees only represent a quarter of the licensing income generated by universities but can go higher when the university makes a big sale. Our results show that fixed fee payments are correlated with the proportion of licences to large companies which account for a third of all the licences granted. Once again, this correlation might stem from multiple sources. Large companies have more capacities and can invest more into deal drafting and negotiations to reduce the cost of the transaction. This also means that they have the resources to pay upfront fees and hedge against future royalty. Furthermore, as these companies have better absorptive capacities than smaller companies, they might be better at identifying promising licences. Hence, they might be better at minimising risk than their smaller counterparts when paying upfront fees. These capacities also mean that they would need less collaboration with the licensor to implement the newly acquired knowledge. Furthermore, large companies might be actively avoiding collaboration with outsiders to guard against knowledge leaks that might end up in the competitors' hands and cost them their competitive advantage. Finally, the licensor might be more inclined to charge a fixed fee for larger companies as they might see contract enforcement as more difficult.

Although the proportion of licences to startups is slowly growing, licensing income from equity sales only represent a few percent of the total licensing income generated by universities. This shows an increasing interest in entrepreneurship within North American universities. However, the income generated by these deals is sporadic and market dependent. This makes it difficult to compare this strategy to others since the income is delayed in an unpredictable manner, while some deals might take years to mature, others might be prematurely terminated due to the company closing.

These results show the need for North American governments to implement specific policies to increase university-industry collaboration linked with the commercialisation of the research results. On the one hand, small companies can benefit from investments that would minimise the amount of royalty they pay in the long run. Besides, innovation in small companies is reported as being hampered by lack of funding (Lee et al., 2010). This would give them access to funding that they could reinvest into other projects. On the other hand, large companies could be incentivised to pay more royalty to TTOs which would increase the income for the university. These companies could also be encouraged towards closer collaboration with university researchers. This would lead to better knowledge transfer between the two communities and could result in more commercialisable research projects. Finally, governments can improve the number of startups launched by universities and their survivability by investing into incubators that would increase their business acumen and deflate some of the financial pressure they experience by providing expertise and infrastructure.

Universities and TTOs have been reported in the literature as having different goals when it comes to commercialisation (Thursby et al., 2001a; Baglieri et al., 2018). For instance, the age and experience of the TTO can influence the strategy adopted and its effectivness. Experienced TTOs might be better at negotiating, drafting contracts and monitoring. Lacking this information, we are unable to differentiate between the different objectives the universities in our sample have set for themselves. These differences in objectives can not only influence the general amount of income generated but also the type of payments made to the university. One way for future studies to palliate this shortcoming would be to use previously used survey methodology to gather this missing information (Thursby et al., 2001a; Baglieri et al., 2018).

Furthermore, the field of the disclosure and the scientific activity domain of the university are also known to influence how the commercialisation process is tackled (Thursby and Kemp, 2002; Lach and Schankerman, 2004; Chukumba and Jensen, 2005). Scientific, technologic, and industrial fields can increase the need for investment and risk, it is relatively cheaper to develop a software than a new drug. This in turn can influence the choice of partner as startups and small companies might be priced out of certain fields. Subsequent studies could add publication, patent, and industry data to improve our results.

This study concentrates on three payment types that are royalty, equity and other types. Unfortunately, our data does not give more details about the content of "other licensing income" which represent an important part of licensing income; nor does it record the number of licences with other types of payment beside equity and royalty. Furthermore, due to the nature of our data, we are unable to account for mixed strategies that can include all three types. Our data does not differentiate between ad valorem and per unit royalty either which might give different results, nor does it take into account if the licence was granted following an auction.

As we are comparing two different countries our sample has a wide range of different political and economic landscape. We tried to capture these differences through our dummy variables. However the local differences might go deeper than that. Furthermore as we converted all monetary variable to Canadian dollars we are subject to this methodology's known shortcomings. The PPP conversion being based on prices can't take into account the short-term fluctuations of the market and is unsuitable to periods of crisis (Melchior et al., 2000; Di Matteo et al., 2016). Finally, as our data is sourced from a self-reported survey it is subjected to all known self-reporting biases.

The literature review showed that other factors could also affect the commercialisation process. For instance, the financial constraints or R&D expenditure of the partner firms (Cohen and Levinthal, 1990; Merz, 2019). However, the AUTM STATT database only reports aggregate data and makes it impossible to recoup information on partner firms through other databases or surveys.

CHAPITRE 5 ARTICLE 2: THE EFFECTS OF PATENT PORTFOLIO DIVERSIFICATION ON UNIVERSITY STARTUP CREATION.

This chapter was submitted to Economics of Innovation and New Technologies on the 21st June 2021 as an article with the same title by Arman Yalvac Aksoy, Davide Pulizzoto, and Catherine Beaudry. The article was sent back to the authors on 15 July 2021 for major revisions with a one (1) year deadline. The contribution of Davide Pulizzoto to the article was providing the necessary expertise to extract patent data from the USPTO databases. The article shows the association between university patent portfolio composition and university startup creation. Results show that technological diversification is positively associated with opportunity discovery. However, technological proximity to local patent holders is negatively associated with startup creation for non-diversified universities and positively associated with startup creation for diversified universities. The reasoning behind these effects is two-fold. Companies collaborating with non-diversified smaller universities can direct R&D efforts and capture all the spillovers while companies collaborating with larger diversified universities are unable to fully capture all knowledge spillover resulting from their collaboration.

5.1 Abstract

The growing interest for university entrepreneurship has created a fertile ground for spinoffs. Spinoffs are launched for the main purpose of commercialising university sourced patents and knowledge. Previous studies have underlined the importance of the university size and strategy for successful spinoffs. Yet, little is known about the effect of the patent portfolio composition of the university on the spinoff process. This study aims at bridging the literature gaps between university startups, and technological diversification and proximity. Our findings show that spinoff creation is positively associated with university patent portfolio diversification. Technological diversification also plays a role in determining the association of national expertise and technological proximity to the state with the number of startups created. Proximity and national expertise have a negative association to the number of startups create for less diversified universities. The relationship is inverted for diversified universities that benefit from national expertise and proximity to the local industry for startup creation. This indicates that universities should adapt their strategies to their idiosyncratic characteristics. This has important ramifications for university deans and policy-makers.

JEL Classification: O20, O32, O51

Keywords: university, spinoff, diversification, proximity, relatedness

5.2 Introduction

The recent policies aimed at improving university research commercialisation have brought the development of strategies and structures to improve the technology and knowledge transfer process. Universities can transfer their technologies to the market via various ways such as consulting, licensing and startups (Thursby et al., 2001a). In these last two decades, startups have been garnering increased interest in the scientific community as a more lucrative way to benefit from the technology transfer (Bray and Lee, 2000; Godfrey et al., 2020).

Early technology transfer offices (TTO) were considering startup creation as the last resort solution to commercialise technologies that could not be brought to the market otherwise (Swamidass, 2013). The more recent approach to innovation takes a Schumpeterian approach where the entrepreneur and the startup are seen as the lynchpin of socio-economic change. This approach is supported by the perception of startups being more lucrative in the long run, and is accompanied by the creation of support structures to increase the number of startups and improve their survivability (Franklin et al., 2001; Clayman and Holbrook, 2003; Prokop et al., 2019; Hunt et al., 2019). Furthermore, since TTOs have reported a recurrent lack of staffing (Swamidass and Vulasa, 2009), this strategy has the added benefit of employing outsiders to sift through the patent portfolio of the university and match potential technological solutions to existing socio-economic and technological problems in a techno-push manner. In the event of a failure, the TTO will not have expanded labour hours for the project, while in the event of success, it will benefit from the equity sales and other incomes the startups generate.

An important factor for the creation of startups is the opportunity discovery and creation (Boland et al., 2013; George et al., 2016). Previous studies have shown the path-dependent nature of innovation through technological trajectories (Dosi, 1982), and in the last decade, put forward the importance of relatedness for successful innovation and technology commercialisation (Hidalgo et al., 2018). This was also noted by the literature on entrepreneurship: in their extensive literature review George et al. (2016) reported the importance of prior knowledge, social capital, and environmental conditions as recurring factors influencing the opportunity discovery process for entrepreneurs.

Traditionally, research on technological trajectories and proximities has been conducted using patent and publication data. Researchers have studied the concepts with a focal point of the principal investigators, companies, and regions (Omobhude and Chen, 2019). However, universities have been absent as the focal point of previous studies on the subject of patent portfolio composition and innovation commercialisation.

This paper aims at studying the effects of patent portfolio diversification on university research commercialisation through the number of university startups. We organise the remainder of this paper as follows. Section 2 introduces relevant literature. Section 3 presents our framework. Section 4 explains the methodology used. The results are discussed in Section 5 and Section 6 concludes.

5.3 Literature review

5.3.1 University spinoffs

Established scholars of university research commercialisation have used a funnel model to study the process starting with R&D expenditure, followed by disclosure to the TTO and licensing to companies (Thursby and Thursby, 2002; Carlsson and Fridh, 2002; Godin, 2006; Cartaxo et al., 2013). Startup creation is part of the last phase of the commercialisation process as the technology is licensed to a company established with the specific goal of bringing the technology to the market (Hindle and Yencken, 2004). The funnel model was proven to be relatively accurate even though the commercialisation process is known to be iterative and to vary according to the innovation's idiosyncratic characteristics (FDA, 2004; Mankins, 2009; Bradley et al., 2013).

Studies have shown the positive association of the amount of inputs and outputs of different phases of the process. These studies can be interpreted as demonstrating the positive effect of the size of the institution on the number of licences and startups created. More specifically, in the case of university startup creation researchers have shown the positive association of the number of startups created with the total number of journal articles (Kim, 2011), R&D expenditure (Markman et al., 2004; Kim, 2011; Di Gregorio and Shane, 2003; Cartaxo et al., 2013), disclosures (Chukumba and Jensen, 2005; Di Gregorio and Shane, 2003; Cartaxo et al., 2013), patents (Cartaxo et al., 2013), number of licences (Feldman et al., 2002; Di Gregorio and Shane, 2003; Cartaxo et al., 2013), licensing revenue (Cartaxo et al., 2013), and the number of full-time equivalent (FTE) TTO employees (Siegel et al., 2008). These relationships are clearly apparent from universities data collected by the association of university technology managers (AUTM) (cf Fig. 5.1).

Another aspect of the university that was reported as influencing the commercialisation process

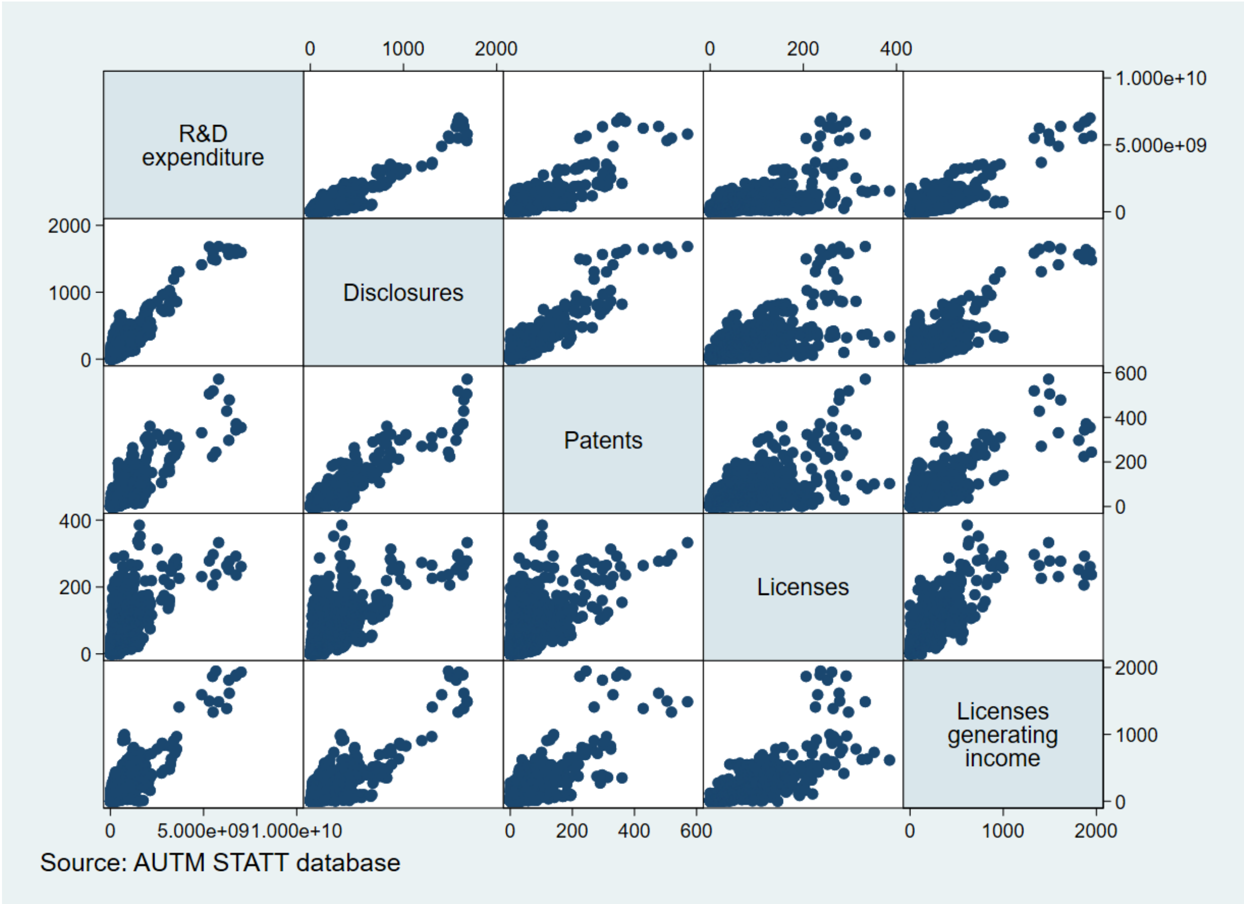

Figure 5.1 Relationship between the various phases of the commercialisation funnel.

is the age and experience of the TTO. However the literature on the subject is divided into those reporting a positive association of TTO's age with startup creation (Feldman et al., 2002; Friedman and Silberman, 2003; Chukumba and Jensen, 2005; Kim, 2011) and those reporting a negative association (Markman et al., 2004; Siegel et al., 2008). Furthermore, others have shown the positive association of the TTOs' previous experience with startup creation and the number of startups created (Di Gregorio and Shane, 2003). Di Gregorio and Shane (2003) report that TTOs which previously took equity stake in startups, and TTOs permitted to take equity in startups have a positive association with the number of startups created. The effect of age and experience is nonetheless difficult to quantify as TTOs are known to grow in size over the years, as such, both the age and size of the TTO are highly correlated (Castillo et al., 2016).

Other qualitative aspects of the universities aside the age and experience of the TTO can also play a role in the startup creation process. For instance, Siegel et al. (2008) reports a positive association of the presence of a medical school, while Kim (2011) reported a negative association of medical school's presence with the number of startups created. Others have reported positive effects of universities quality indicators on startup creation such as the Gourman graduate school score (Di Gregorio and Shane, 2003), the quality of graduate and engineering faculties (Chukumba and Jensen, 2005), and the average of Hospital, Medical, Science, and Engineering ranking (Kim, 2011).

The universities' strategy can also play a part in the commercialisation process and startup creation. For instance, Di Gregorio and Shane (2003) and Markman et al. (2004) both found a negative association between licensing revenue share to the scientist and startup creation. Furthermore, funding sources can also influence startup creation. Di Gregorio and Shane (2003) found that industry sponsored funding was positively associated with the number of startups. A similar result was shown by Chukumba and Jensen (2005) regarding the positive effect of the ratio of industrial to federal R&D funding on the number of startups. The positive effect of the proportion of research income from business was also supported by Siegel et al. (2008).

External factors outside of the universities' control can also affect the number of startups created. Friedman and Silberman (2003) reported the positive association between the number of startups with their local tech pole index. Chukumba and Jensen (2005) found a positive association between startup creation and venture capital funding in the state. Siegel et al. (2008) showed the positive effect of regional R&D on startup creation; and Belenzon and Schankerman (2009) found a negative impact of government constraints on entrepreneurship shown through the negative effect of local development objectives on the number of startups.

5.3.2 Co-creation and path-dependency

The co-creative path-dependent nature of innovation is well established (Kuhn, 1962; Porter, 1998; Etzkowitz and Leydesdorff, 2000; Geels, 2002; Boschma, 2005; George et al., 2016). This view of the innovation process is shared among many scientists approaching the subject from different angles such as innovation systems (Freeman, 1987; OECD, 1997), clusters (Porter, 1998), and proximities (Boschma, 2005). These were also accompanied by other frameworks on the nature of knowledge and its distribution in the population (Mokyr, 2002), interaction between institutional stakeholders such as government, industry, and universities (Etzkowitz and Leydesdorff, 2000), and socio-economic context leading to innovation (Geels, 2002).

In the last decade, researchers have put forward the concept of relatedness as a critical factor affecting innovation (Hidalgo et al., 2018). The concept builds on previous studies in various fields , and has been deployed by scientists to study different aspects of the actors and networks leading to innovation (Balland et al., 2019; Ceipek et al., 2019). Previous studies dealing with technological relatedness between actors have defined it as technological proximity. Technological proximity is known to have a curvilinear association to innovativeness. Too little or too much proximity between partners can have negative effects on the efficiency of the partnership. This is commonly known as the proximity paradox in the literature (Balland et al., 2015), R&D partnerships are more likely with partners similar to one-another but close proximity can create cognitive lock-ins hindering innovativeness. Other types of proximities have also been defined in the literature and are known to interact with one another. These proximities can be categorised into spatial and cognitive (Boschma, 2005; Knoben and Oerlemans, 2006; Balland et al., 2015). While spatial proximity is self-explanatory and refers to physical distance, cognitive proximity refers to ways of thinking and includes, techno-scientific knowledge, organisational forms such as company, university, or government, culture, and so on.

The diversity of the knowledge base used affects the type of innovation that is more likely to occur. A broader knowledge base is more conducive to radical innovation while depth of knowledge and expertise is better suited to incremental innovation. This is illustrated by Zhou and Li (2012) who reported that Chinese companies radical innovativeness is positively associated with internal collaboration for diversified companies and external collaboration for specialised companies. The relationship between knowledge base diversification and innovativeness is also reported by other researchers for industry (Quintana-García and Benavides-Velasco, 2008) and university alike (Acosta et al., 2018). Existing companies might find it easier to implement incremental innovation rather than radical innovation since incremental innovations are less likely to render previous investments obsolete or cannibalise market shares of existing products and services.

5.4 Conceptual Framework

Previous research on innovation and its commercialisation have studied the subject with different focal points such as the innovation itself (OECD, 1997), the creator (George et al., 2016), and the context (Ceipek et al., 2019). These studies have reported the recombinant nature of innovation and the co-creative aspect of the innovation process (OECD, 1997; George et al., 2016; Ceipek et al., 2019). We borrow from these literatures to develop our framework with the university as the focal point. Our framework considers that the intellectual property of the university is an indicator of the prior knowledge of its research personnel and potential entrepreneurs. The university itself is embedded into a larger context of regional capabilities. Hence, our model takes the university as the black box that creates the fertile environment for opportunity discovery and recognition which might ultimately result in startup creation (George et al., 2016). The process is influenced by the university's internal working regimes such as goals and strategies, as well as external factors related to the technological landscape in which the innovation evolves.

The recombinant co-creative nature of innovation implies the necessity for a large and diverse stock of prior knowledge. The necessity of a diverse knowledge base for innovation was exemplified in various contexts (George et al., 2016). Innocenti and Zampi (2019) showed that in the Italian context, local technological diversification was beneficial to the growth of startups. The positive effect of diversification on innovativeness has also been reported in the case of incumbent companies (Ceipek et al., 2019). However, the positive effect of technological diversification is disputed since studies found both linear and curvilinear effects on company innovativeness. Some have imputed this effect to the loss of efficiency tied to company size (Ceipek et al., 2019). University research funding and startup creation might not be linked in the same manner.

An important factor contributing to opportunity discovery is the prior knowledge of the entrepreneur (Shane, 2000a; Hindle and Yencken, 2004). The amount and diversity of the knowledge are contributing factors to opportunity discovery (George et al., 2016). A large university active in multiple fields is the ideal ground for exposing entrepreneurs to a large body of diverse knowledge. A common indicator used in measuring the knowledge stock of companies is the number of patents and the diversification of the patent portfolio. Patent portfolio is also important for universities. University technological diversification was shown to be positively correlated with the patenting activity of the university (Acosta et al., 2018), which in turn is related to licensing and licensing income. Although no direct links have been reported in the literature between university patent activity and the number of spinoffs, previous studies indicate the importance of patents for startups (Gonzalez, 2017). Hence, it follows that technological diversification should be positively associated with the number of startups created. Therefore, we posit:

Hypothesis 1*: University's patent portfolio diversification is positively associated with the number of startups*

Another important aspect that might influence the startup creation is the universities revealed technological advantage. Previous studies on companies have studied the concept by using the companies' revealed technological advantage (RTA) in its most active field (Chen and Chang, 2010a,b, 2012; Kim et al., 2016). Our hypothesis on the relationship of university revealed technological advantage and startup creation hinges on two (2) arguments.

First, expertise in a field is important for companies when they venture into university-industry collaboration (Santoro and Chakrabarti, 2002; Bercovitz and Feldman, 2007). Hence, university expertise could negatively impact startup creation by increasing the number of R&D partners and potential avenues for commercialisation through existing companies. The explorative versus exploitative nature of the R&D approach will play an important role in the type of innovation pursued by the company (Akcigit and Kerr, 2018). While an exploitative, incremental innovation focus might benefit from expertise, an explorative R&D strategy might yield more radical innovation due to the increased distance between the recombined knowledge Quintana-García and Benavides-Velasco (2008).

Second, from a Shumpeterian standpoint, incremental innovation might be less suited to startup creation compared to radical disruptive innovation. Startups are well suited to define new market and product categories but will struggle to compete with existing companies to commercialise improved versions of existing products and services. This relationship between the efficiency of explorative R&D activities and technological diversification was shown in the Swiss context. Arvanitis and Woerter (2015) reported that technological diversification is positively associated with exploration activities while it is exploitation activities that benefit the most from innovation performance. This indicates that companies' sales performance benefit more from technological expertise overall. This makes sense since companies use exploitation to increase their competitive advantage in existing markets while using exploration to enter net industries. This last point is also illustrated by Quintana-García and Benavides-Velasco (2008). The authors showed that for U.S. biotechnology firms, technological diversification is positively associated with firm innovativeness. They reported that the effect is stronger for explorative capabilities compared to exploitative ones. Thus, we propose:

Hypothesis 2*: University's revealed technological advantage has a negative association with the number of startups*

The third factor to consider is the technological proximity of the university to its local industry. This factor is important due to the co-creative path-dependency of innovation. For instance, Caragliu and Nijkamp (2016) suggested a positive correlation between technological proximities amongst regions and knowledge spillovers. This is also supported by Autant-Bernard (2001) who reported that in France, the number of patents in a region is related to the output of neighbouring areas and their technological proximity to each other. Ultimately the adoption of new knowledge and technologies is highly dependent on the absorptive capacity of the new host and the matching of its knowledge base to the knowledge base on which the innovation is built upon (Cohen and Levinthal, 1990). The relationship between technological proximity and startup creation is perhaps best illustrated by Acs et al. (2009). Using OECD data the authors found that the knowledge stock of incumbent firms positively affect entrepreneurial activities, while the incumbent firms efficiency in exploiting such knowledge decreases spillover and the entrepreneurial activity of the country. In essence, startups would benefit from unabsorbed knowledge spillovers since they are not plagued by the fear of cannibalising their existing products. Hence, they can exploit existing structural holes (Burt, 1993) even in the presence of similar or competing services and products. Thus, we postulate :

Hypothesis 3*: University's technological proximity with its province/state has a positive association with the number of startups created.*

5.5 Methodology

5.5.1 Data

We used the "The Association of University Technology Managers"'s (AUTM) Statistics Access for Technology Transfer Database (STATT) to access information about the universities. The data is gathered through a yearly survey and spans from 1991 to 2018. The survey encompasses a large section of U.S. and Canadian universities and is the most commonly used database in the literature (Rothaermel et al., 2007b). However, the survey is voluntary and as such has missing answers which yields an unbalanced panel. The STATT reports monetary values in the country's currency. Hence, we used the purchasing power parity obtained from the International Monetary Fund to convert U.S. dollars to Canadian dollars.

We complete the STATT by adding patent data from the USPTO. The reason for this is the absence of details about the patents in the STATT database. As such we used the USPTO database to gather information on the number of patents per classification categories. We used the Levenshtein distance to match the names of the universities from the STATT to the USPTO database and cleaned the results manually over multiple rounds taking the results of the previous round as the seed for the next round. We controlled the accuracy of our final results by regressing the numbers of patents per university and year reported in the STATT to the results obtained with our method. The regressions resulted in an R square of 0.95 between the two counts of patents.

5.5.2 Variables

Dependent Variables

We conduct our study on a single dependent variable extracted from the STATT [1]:

Startups represents the number of startups formed. Startup creation is a late stage commercialisation indicator used in the literature (Mendoza and Sanchez, 2018). Universities use this commercialisation strategy when they cannot find an incumbent firm to partner with (Markman et al., 2005). However, this strategy is on the rise in the U.S. and Canada as larger and older TTOs are using this path to market more often due to being perceived as more lucrative than licensing (Bray and Lee, 2000; Feldman et al., 2002).

Independent Variables

We use patent data from the USPTO database to build our independent variables. We use four (4) indicators related to the diversification, proximity, and revealed technological advantage. We use the subclass level of the International Patent Classification (IPC) to allow comparison with previous studies in the field using the same classification. [2]. This is also the reason behind the choice of the province/state level of geographical aggregation for our study. Furthermore, the choice of the level is motivated by previous studies indicating that while diversification effects are more easily observed with aggregate data, specialisation is more apparent with granular data. The effects are reported as crossing paths at the mid-level classification hence we choose the third level of the IPC and the state aggregation over postal code, city, regions or country levels (Beaudry and Schiffauerova, 2009).

TDU represents the overall technological diversification of the university. It is an adaptation of the entropy index (Shannon, 1948). This indicator was previously used to study company growth (Jacquemin and Berry, 1979) and efficiency (Chen and Chang, 2012; Chen et al., 2012; Kim et al., 2016; Kook et al., 2017). The maximum value of TDU depends on the number of categories in the

[1] A summary of the variables we use and their transformations can be found in the annexes table A1, statistical information about the variables can be found in table A2

[2] The IPC is composed of five (5) levels in descending order: Section, Class, Subclass, Group, and finally the Complete classification symbol.

classification [3]. TDU increases with diversification and reaches its maximum value for a perfect distribution. The diversification is associated with the size of the university as smaller universities are less diversified (see Fig. 5.2). The technological diversification is calculated using the following formula:

$$TDU = \sum_{i=1}^{I} P_i ln(\frac{1}{P_i}) \tag{5.1}$$

With P_i the proportion of patents in subclass i granted to the university that year.

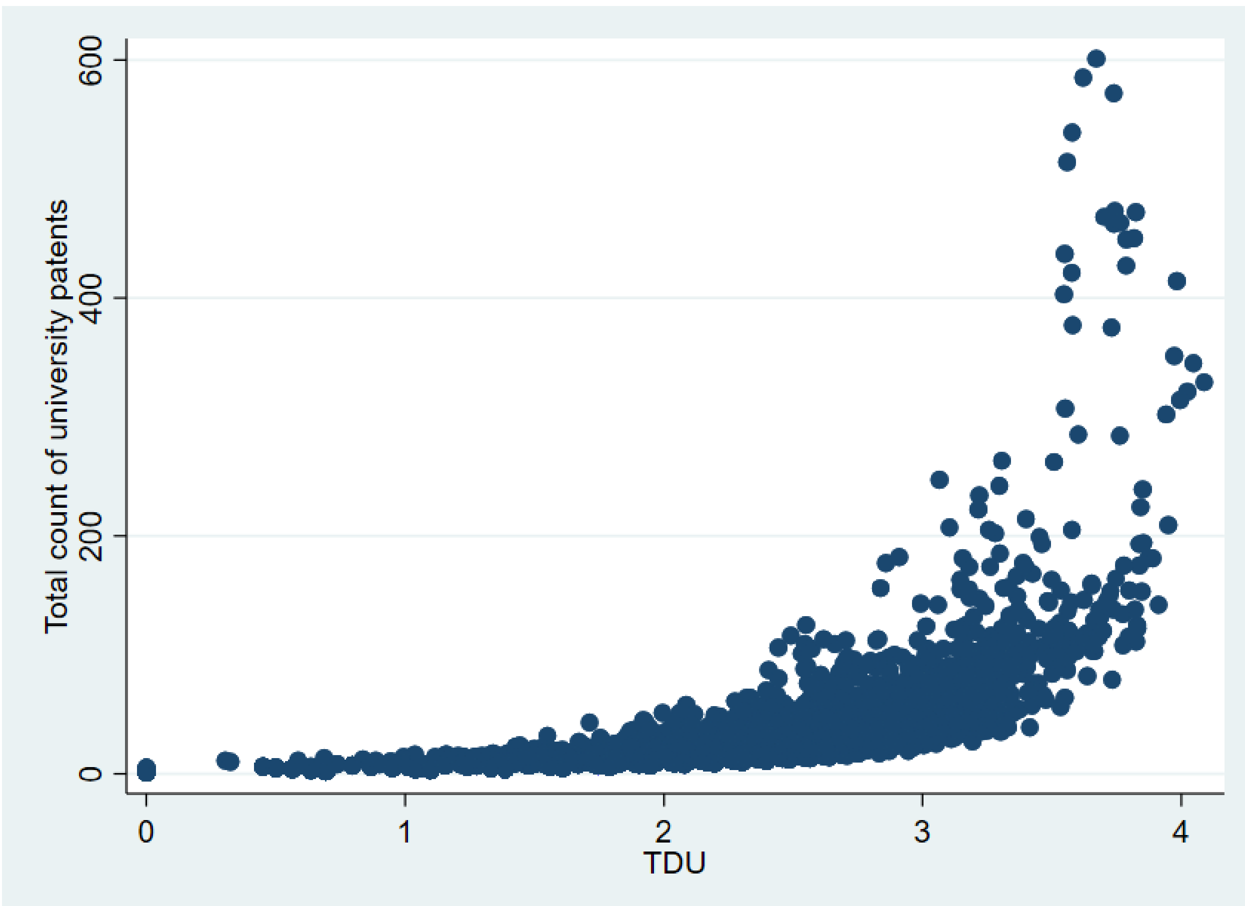

Figure 5.2 Patents and diversification relationship of North American universities, source: USPTO and STATT.

[3]This is due to the use of the inverted proportions of patents. As the number of patent class increases it reduces the denominator which increases the argument of the logarithmic part.

HHU is the Herfindahl-Hirschman index commonly used in the literature[4] (Ceipek et al., 2019) . We use this indicator to compare the results with the entropy based indicator to increase the validity of our results. HHU has an inverted correlation to TDU, it increases with specialisation. [5]. It has a maximum value of 1 for specialised universities and tends toward zero (0) for a perfect diversification. This indicator is less sensitive to the number of categories[6]. This can be illustrated by the figure comparing it to TDU (cf. Fig. 5.3) and is calculated as follows:

$$HHU = \sum_{i=1}^{I} (P_i)^2 \tag{5.2}$$

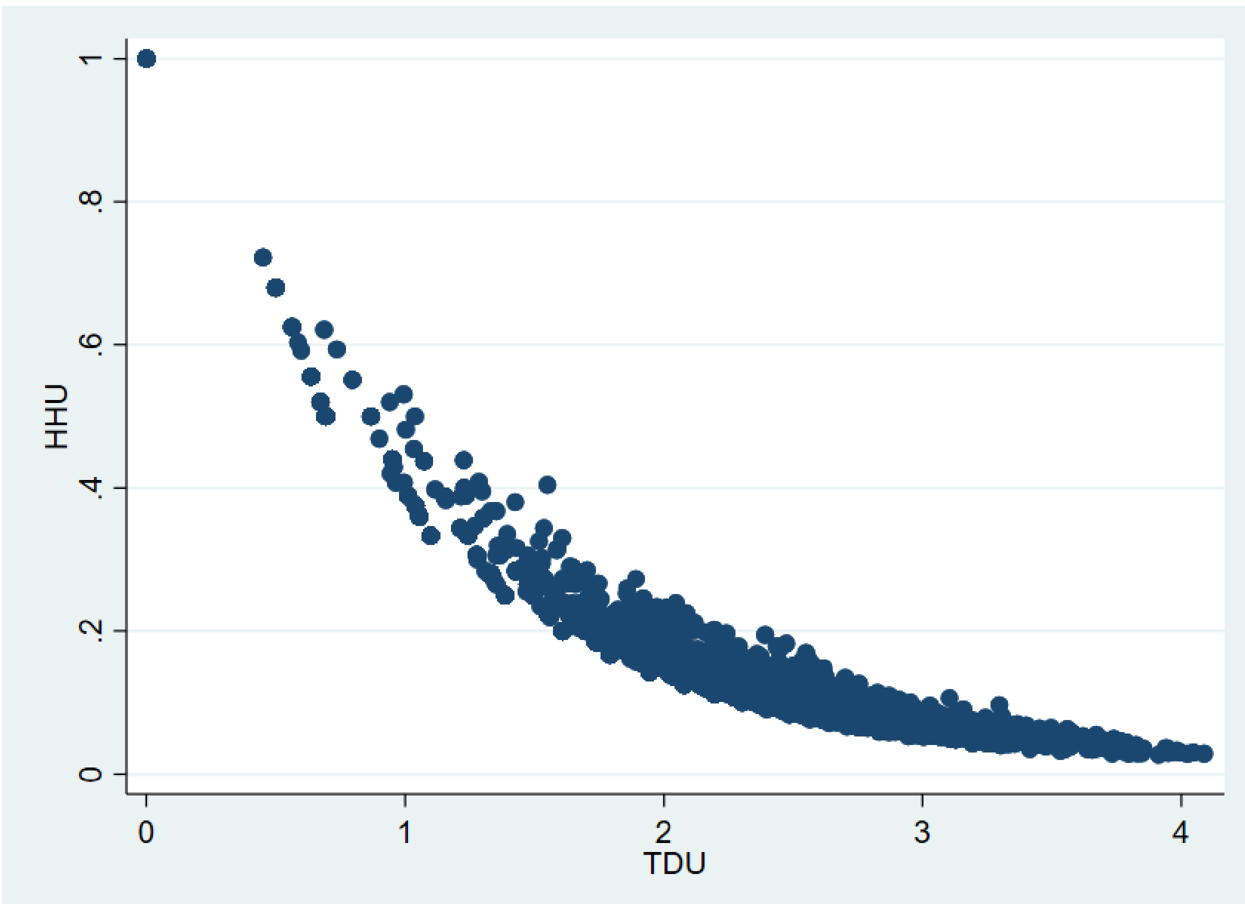

Figure 5.3 Comparison of HHU and TDU values, source: USPTO and STATT.

[4]We chose to use HHU instead of using the 1/HHU or 1-HHU due to the impossibility of normalising them.

[5]The correlation table of our variables can be found in the annexes table A3

[6]For instance, let's take two (2) universities with six (6) patents each, the first one has patents in four (4) categories with one (1) category having three (3) patents and the others having one (1) each, the HHU score would be 0.33 while the TDU would be 1.24. The second one has patents in three (3) categories distributed evenly giving it an HHU score of 0.33 too. However, its TDU in that case is 1.1 which is interpreted as lower diversification.

Prox represents the technological proximity between the university and the province it is located in. We use the cosine similarity to calculate the homogeneity between the patent vector of the university and the patent vector of the province. This method was developed by Jaffe (1986) and is fairly common (Knoben and Oerlemans, 2006). A value of one (1) indicates perfect match between the two vectors while a value of zero (0) no similarity. The formula used is as follows:

$$Prox = \frac{\sum_{i=1}^{i} NP_{i_{univ}} \sum_{i=1}^{i} NP_{i_{province}}}{\sqrt{(\sum_{i=1}^{i} NP_{i_{univ}})^2}\sqrt{(\sum_{i=1}^{i} NP_{i_{province}})^2}} \tag{5.3}$$

Where NP_i represents the number of patents in subclass i granted to the university that year.

MaxRTA is the highest revealed technological advantage of the university. We calculate the RTA of the university in each technological field and select the highest value. This methodology was previously used to identify company core technological competences and technological leadership (Chen and Chang, 2010a,b, 2012; Kim et al., 2016). The relationship between the number of university patents and MaxRTA is not linear like our other diversification indicators (cf. Fig. 5.4). Lower and higher values of the indicator are dominated by smaller universities active respectively in popular and niche patent subclasses. We add this variable as a way to increase the validity of our results and contrast our other diversification indicators with an expertise oriented indicator. The expertise of the university should play a crucial role in the existing companies' decision to partner with the university[7]. The formula used to calculate this variable is as follows:

$$MaxRTA = MAX\left(\frac{\frac{P_{iuniv}}{\sum_{i=1}^{i} P_{i_{univ}}}}{\frac{P_{i_{country}}}{\sum_{i=1}^{i} P_{i_{country}}}}\right) \tag{5.4}$$

Control Variables

The following paragraphs list our control variables sourced from the STATT.

[7]We use the national instead of the regional leadership indicator to account for competition for R&D funding and contracts between universities at the country level.

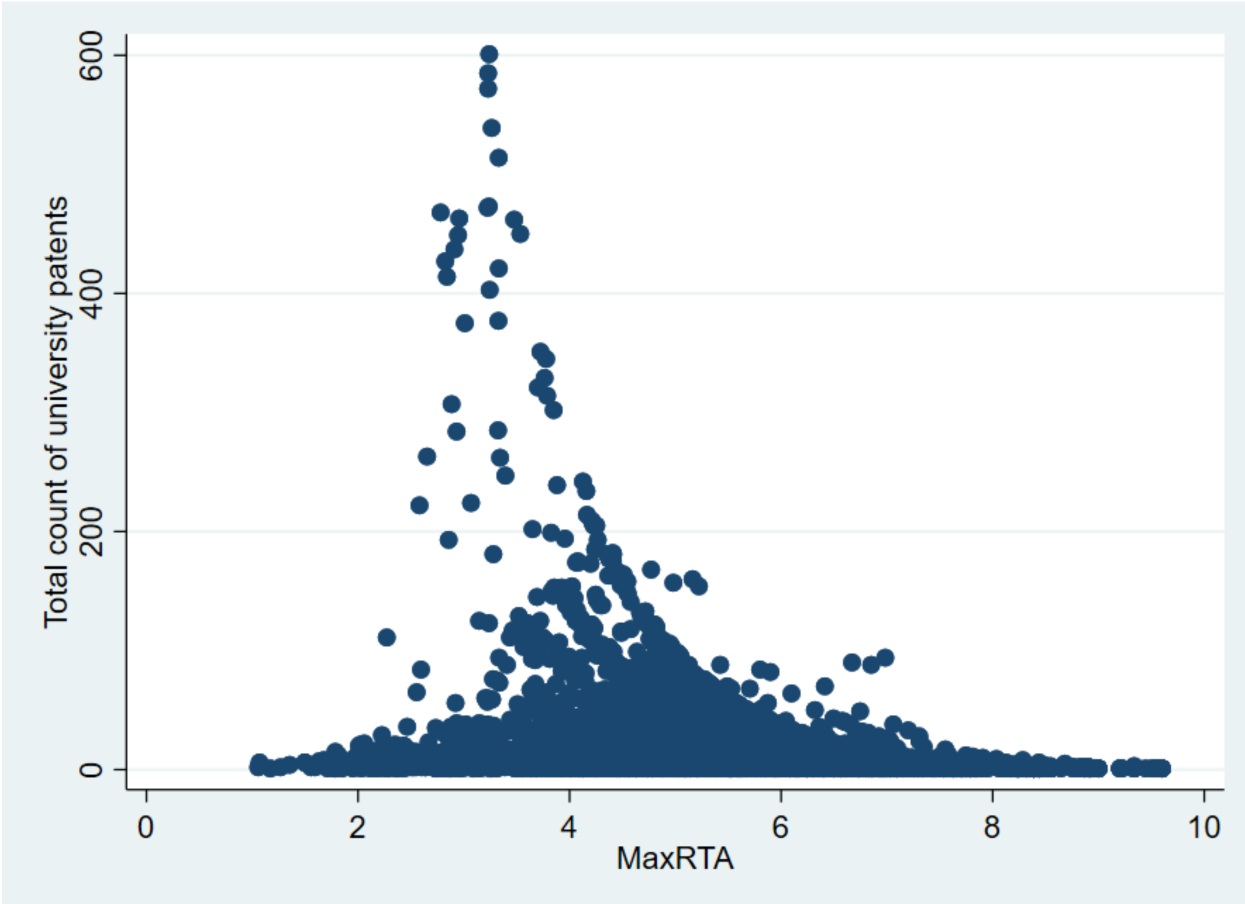

Figure 5.4 Patents and MaxRTA relationship of North American universities, source: USPTO and STATT.

RDExp is the total amount of R&D expenditure of the university. This indicator is frequently used in the literature to control for the size of the university. Previous studies have reported a strong correlation between the R&D expenditure and disclosures, patents, and licences (Rothaermel et al., 2007b). The relationship is also observable in our data (cf Fig. 5.1).

LegalL stands for the legal fees per licences. We use the ratio of the legal expenditure by the number of licences granted to account for the fact the former increases with the latter and vice versa. Previous studies have reported the effects of outside lawyers as having a negative impact on the number of licences but a positive one on the amount of licensing income (Sine et al., 2003; Siegel et al., 2003; Link and Siegel, 2005; Prets and Slate, 2014). We expect this variable to be negatively associated with the number of startups created.

PatentsD , the number of patents per disclosures, measure the effort put into patenting. Patenting only occurs in the last phases of the commercialisation process. It is not mandatory and not every university chooses to patent its disclosures in a systematic manner. Hence the number of patents has less predictive power on the number of licences and licensing income (Colyvas et al., 2002; Prets and Slate, 2014; Baglieri et al., 2018).

PropExclLic represents the proportion of exclusive licences. Previous studies have reported the importance of exclusivity for university startups (Thursby and Thursby, 2007). We expect the proportion of exclusive licences to be positively associated with the number of startups.

PatentState is the sum of all patents granted to patent holders in the province excluding the patents granted to the university. Economically developed provinces should have more patents and patent holders which could facilitate technology transfer toward incumbent companies.

IndRDT is the ratio of industry sourced R&D expenditure over the total amount of R&D expenditure. Industry sourced funding should be an indicator of university-industry collaborations and is expected to negatively affect the number of startups created as the research projects will be geared toward the direct needs of the partnering firm.

dCanada is the dummy variable we use to identify Canadian universities. We expect Canadian universities to behave differently than U.S. universities as they are parts of different socio-economic and education systems.

dMedSchl, is a dummy variable indicating the presence of a medical school. This indicator is commonly used in studies dealing with university research commercialisation with an overall positive impact on the number of licences and licensing income (Rothaermel et al., 2007b; Cardozo et al., 2011; Cartaxo et al., 2013).

5.5.3 Model

We estimate the Y_{it} number of university startups using an ordinary least square panel regression[8]. The J control variables are represented by Z_{ijt} and the K independent variables are represented by

[8] We used fixed effect models following the results of our Hausman tests not presented here.

X_{ikt}[9]. The full model is as follows:

$$Y_{it} = \alpha_{it} + \sum_{k=1}^{K} \beta_k X_{ikt} + \sum_{j=1}^{J} \gamma_j Z_{ijt} + \varepsilon_{it} \tag{5.5}$$

where i represents the university, α_{it} is the constant, the β_{kt}s are the coefficients of the independent variables and the $\gamma_j t$s are the coefficients of the control variables, t is the year, and ε_{it} is the error term.

5.6 Results and discussion

Our results show that technological diversification has an overall positive association with the number of startups created (cf. table 5.1 PnOLS6 & PnOLS8). We identify a small difference between TDU and HHU with HHU also showing a curvilinear association (PnOLS7)(cf Fig. 5.5). However we impute this difference to the curvilinear relationship between the two indicators (cf. Fig. 5.3). These findings are coherent with previous report on the effect of company's technological diversification (Ceipek et al., 2019), and confirm the necessity for a broad spectrum of prior knowledge to recognise opportunity (George et al., 2016). This indicates that university startup creation is not subjected to the same loss of efficiency companies can experience related to the increased cost of coordination (Ceipek et al., 2019). This was to be expected since entrepreneurs integrate knowledge from various sources to discover and recognise opportunities but are not necessarily dependent on each other or competing for resources like company departments and research projects (George et al., 2016; Ceipek et al., 2019).

[9] We normalise the distribution of our variables using a combination of natural logarithm: $lnX = ln(X+1)$, and factors of ten (10).

Table 5.1 Results of our panel regressions

	PnOLS1	PnOLS2	PnOLS3	PnOLS4	PnOLS5	PnOLS6	PnOLS7	PnOLS8	PnOLS9	PnOLS10	PnOLS11
Year dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
dMedschl	-0.1147	-0.1138	-0.1164	-0.1179	-0.1181	-0.1197	-0.1097	-0.1186	-0.1131	-0.1261	-0.127
RDExp	0.5259***	0.5241***	0.5276***	0.5260***	0.5258***	0.5254***	0.4899***	0.5313***	0.5121***	0.5197***	0.5327***
LegalL	-0.0891**	-0.0882**	-0.0891**	-0.0884**	-0.0885**	-0.0920**	-0.0841**	-0.0915**	-0.0836**	-0.0892**	-0.0864**
PatentsD	0.1315**	0.1270**	0.1169*	0.1301**	0.1288**	0.0973+	0.1032+	0.1147*	0.1211*	0.0936	0.1138*
propExLicL	0.6011***	0.6011***	0.6000***	0.6010***	0.5996***	0.6039***	0.6093***	0.6018***	0.6075***	0.6124***	0.6089***
PatentState	0.0654**	0.0643**	0.0505*	0.0659**	0.0662**	0.0625**	0.0622**	0.0642**	0.0643**	0.0642**	0.0650**
IndRDT	0.0009	-0.0013	-0.0025	0.0017	0.0029	0.0094	0.0046	0.0057	0.0008	0.0131	0.0082
dCanada x propExLicL	0.9074***	0.9186***	0.9015***	0.9093***	0.9013***	0.9170***	0.8839***	0.9185***	0.9082***	0.8562***	0.8529***
dCanada x IndRDT	0.5324***	0.5402***	0.5317***	0.5335***	0.5367***	0.5057***	0.5040***	0.5203***	0.5215***	0.5037***	0.5209***
LegalL x PatentsD	-0.0867***	-0.0874***	-0.0868***	-0.0871***	-0.0861***	-0.0865***	-0.0933***	-0.0856***	-0.0925***	-0.0868***	-0.0878***
MaxRTA		-0.022	0.1509**							-0.0680**	0.0504+
$MaxRTA^2$			-0.0154***								
Prox				0.0569	-0.1364					-0.4969**	0.3646*
$Prox^2$					0.3056						
TDU						0.0891***	-0.0776			-0.1403+	
TDU^2							0.0525***				
HHU								-0.0695*	-0.4384***		0.3542**
HHU^2									0.1350***		
MaxRTA x TDU										0.0302**	
Prox x TDU										0.2332**	
MaxRTA x HHU											-0.0581***
Prox x HHU											-0.3663**
Const.	0.4128*	0.5552**	0.2104	0.3953+	0.4122*	0.2777	0.3867+	0.4992**	0.7080***	0.7768**	0.107
Nb of obs.	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
Log likelihood	-1931.82	-1930.78	-1926.93	-1931.58	-1931.1	-1925.13	-1919.94	-1929.82	-1924.66	-1920.19	-1923.62
Log $likelihood_0$	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69	-2378.69
BIC	4117.518	4123.354	4123.6	4124.954	4131.941	4112.072	4109.623	4121.447	4119.053	4133.911	4140.769
AIC	3927.648	3927.551	3921.863	3929.151	3930.204	3916.269	3907.886	3925.643	3917.316	3914.374	3921.232
R^2_{within}	0.2742	0.2747	0.2767	0.2743	0.2746	0.2777	0.2803	0.2752	0.2779	0.2802	0.2784
$R^2_{between}$	0.3483	0.3395	0.3697	0.3544	0.3513	0.4458	0.453	0.3953	0.3978	0.4249	0.3753
$R^2_{overall}$	0.3664	0.3616	0.3788	0.3712	0.3705	0.4179	0.4364	0.3888	0.4033	0.4117	0.3852
$R^2_{adjusted}$	0.2052	0.2055	0.2073	0.205	0.205	0.2087	0.2113	0.206	0.2086	0.2102	0.2083
F	31.0242***	30.1253***	29.4944***	30.0625***	29.1761***	30.5698***	30.0298***	30.2004***	29.6683***	27.4778***	27.2369***

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

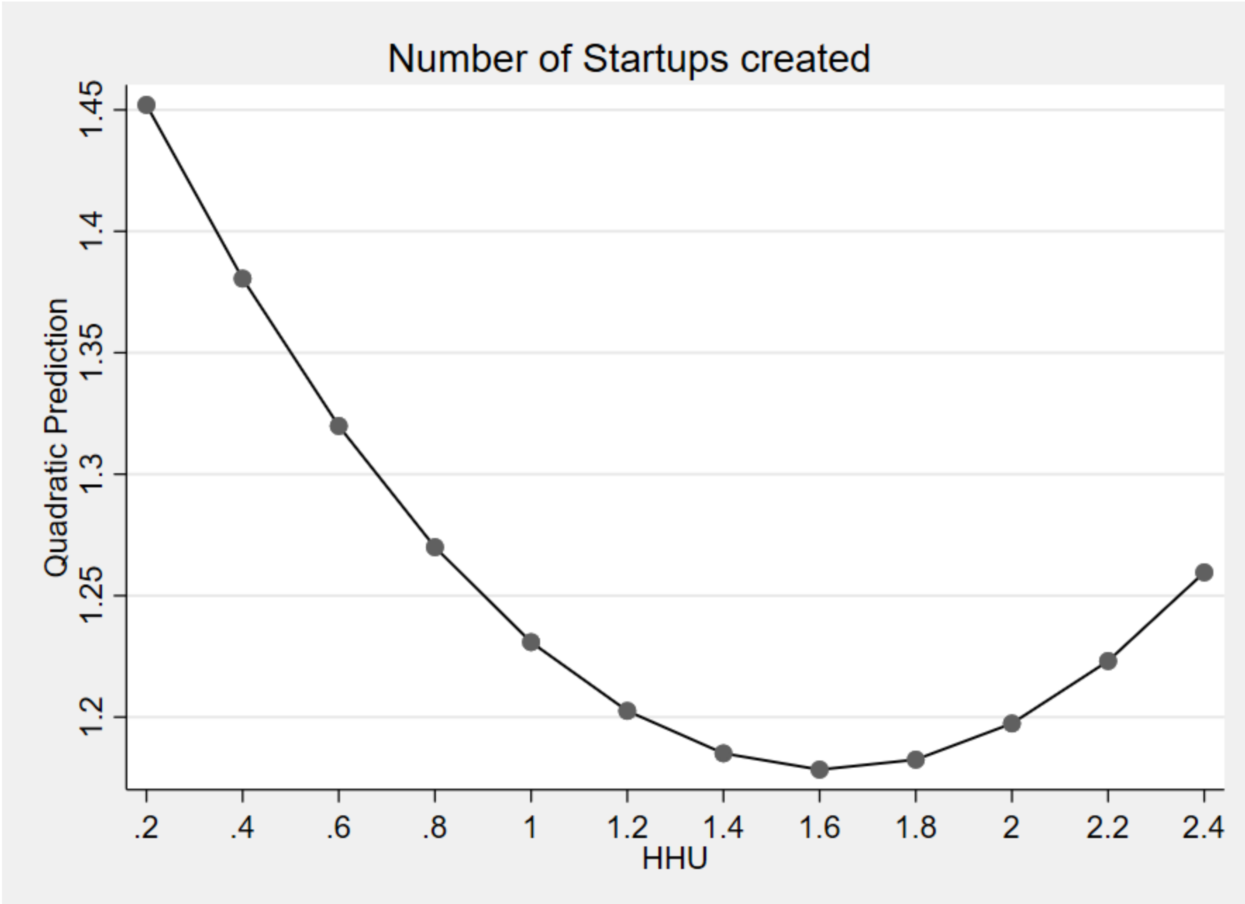

Figure 5.5 Marginal effect of HHU on the number of startups created

The positive relationship between diversification and startups creation can also be observed with MaxRTA (PnOLS3)(cf Fig. 5.6). The relationship is not a straight line due to the idiosyncratic characteristics of the indicator. MaxRTA is influenced not only by the diversification of the university patent portfolio but also by the popularity of the patent subclass. On the one hand, lower MaxRTA values are dominated by smaller universities active in common patent subclasses. These universities can increase the number of startups by either increasing their overall patent count or by diversifying into less popular patent subclasses. On the other hand, higher MaxRTA values are associated with smaller universities active in niche patent subclasses. Similar to universities with lower MaxRTA values, these universities can also increase their number of startups by either increasing their overall patenting activity or by or diversifying into more popular patent subclasses[10].

[10]These associations can also be observed for an alternative model with the number of patents as the size variable (UnivTotPatCount) on a subsample only taking universities with fewer than ten (10) patents. The results are presented in Table A4 in annex. We chose not to use the alternative model due to the high pairwise correlation of the number of patents with our independent variables reaching an r^2 value of 0.9 in some cases.

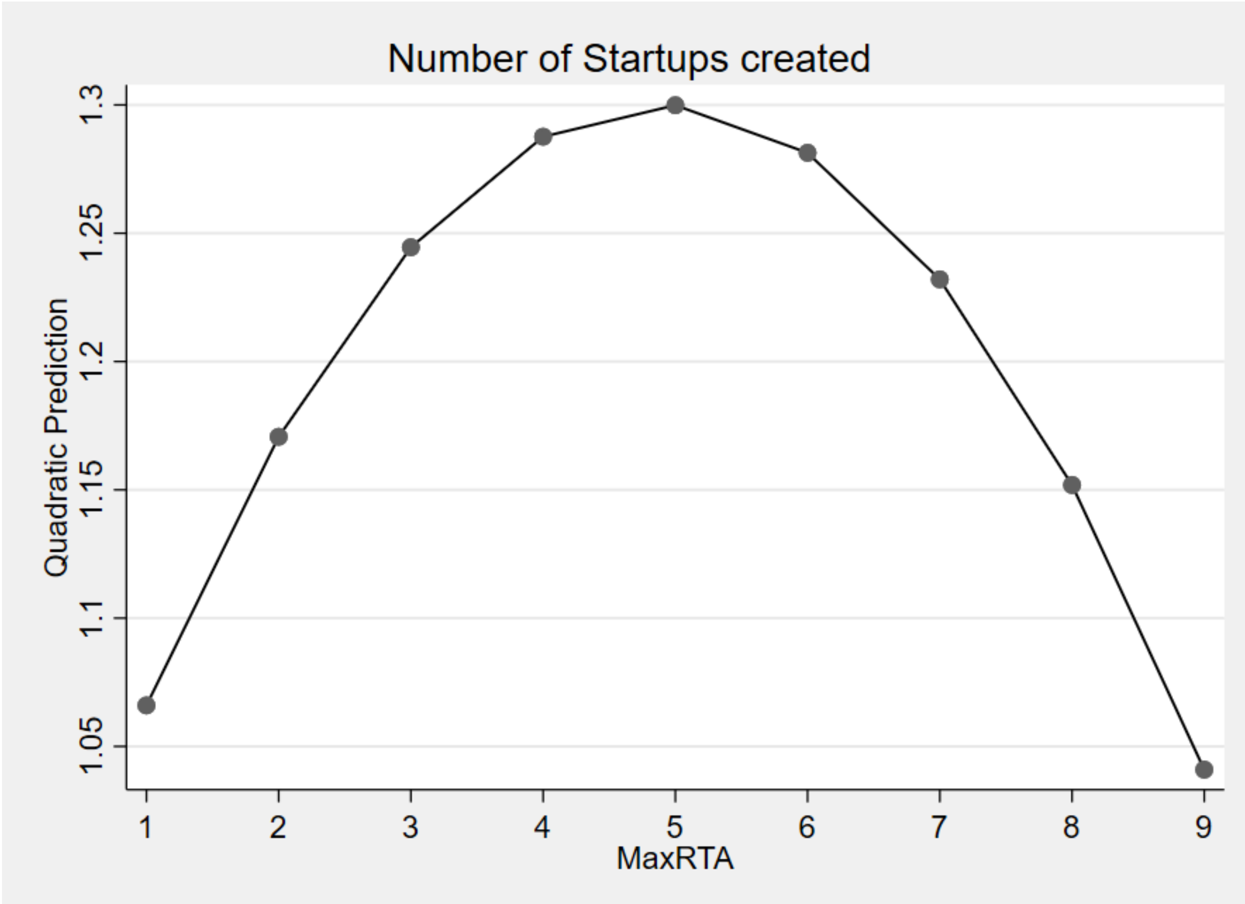

Figure 5.6 Marginal effect of MaxRTA on the number of startups created

Together, these results show that the broad knowledge base that technologically diversified universities confer to their researchers has a positive association with the number of startups created. This is also coherent with previous studies indicating the importance of university expertise for university-industry partnership (Santoro and Chakrabarti, 2002; Bercovitz and Feldman, 2007). Expertise increases the probability of having partnerships with incumbent companies and the probability of the incumbent absorbing any incremental innovation that might stem from the partnership, thus hindering startup creation. This confirms hypothesis H1 and H2.

We did not find any association of proximity with the number of patents on its own, be it linear or quadratic (PnOLS4 and PnOLS5). The relationship only became apparent when taking into account our other independent variables (PnOLS10 and PnOLS11). This further emphasises the importance of prior knowledge for opportunity discovery.

We found important interactions between our dependent variables. Results show that the effect of diversification is not straightforward and is influenced by both the national expertise level

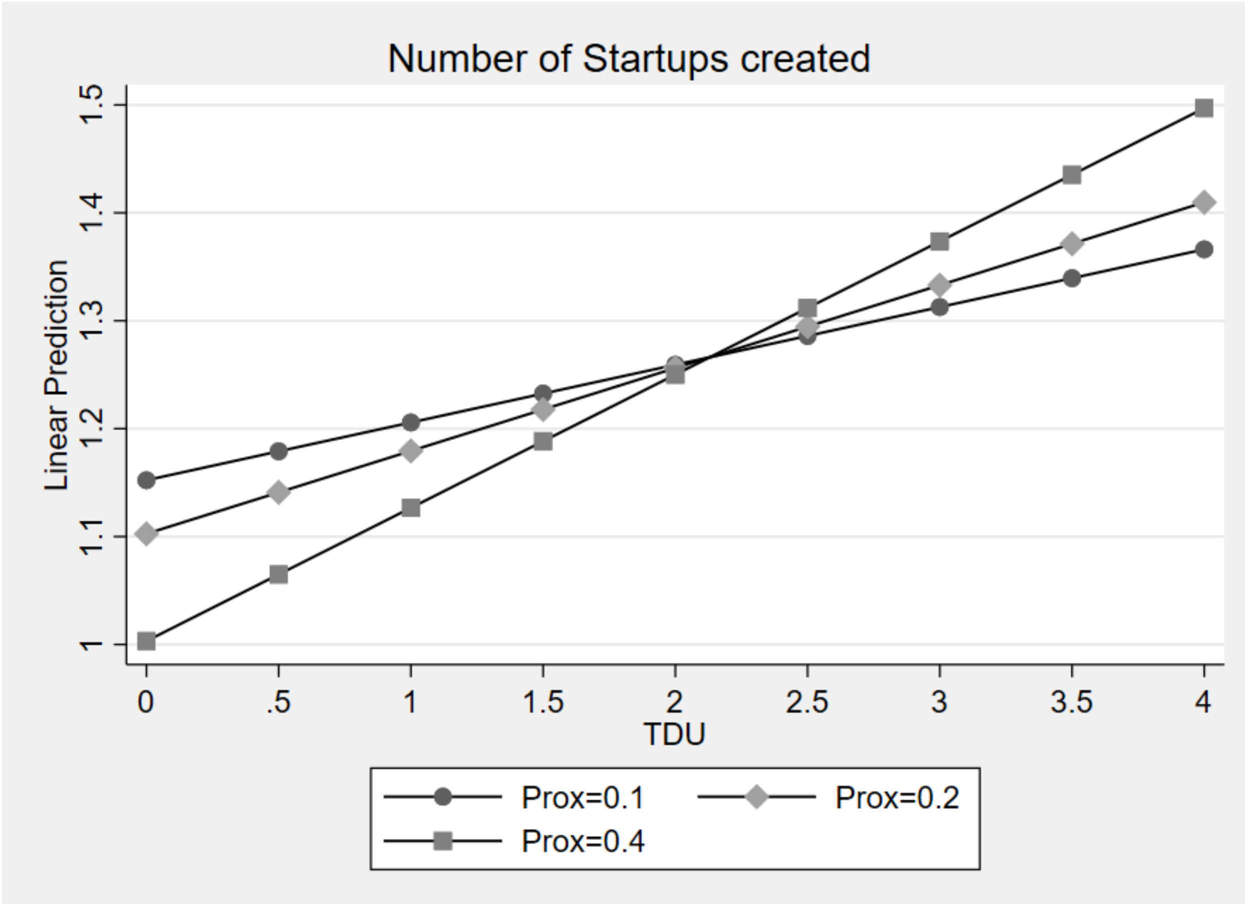

Figure 5.7 Marginal effect of proximity's and TDU's interaction on the number of startups created for the 25th, 50th, and 75th percentile values of proximity

(MaxRTA) and the similarity between the university's and the local state's patent portfolios (Prox)(PnOLS10 and PnOLS11)(cf Fig. 5.7, 5.8, 5.9, and 5.10). These findings are overall coherent with previous literature reporting the importance of university expertise (Santoro and Chakrabarti, 2002; Bercovitz and Feldman, 2007) and company absorptive capacity (Cohen and Levinthal, 1990) for university-industry partnerships. Furthermore, they also confirm that universities' commercialisation strategies need to be adapted to their research profiles.

The relationship between technological proximity to the local industry and the number of startups is mediated by the university's technological diversification (cf Fig. 5.7 and 5.8). Proximity has a positive association with the number of startups for diversified universities but has a negative association with startup creation for less diversified universities. Hence, we observe four (4) different cases for low and high values of diversification and proximity.

The lowest startup creation occurs in universities with high proximity and low diversification.

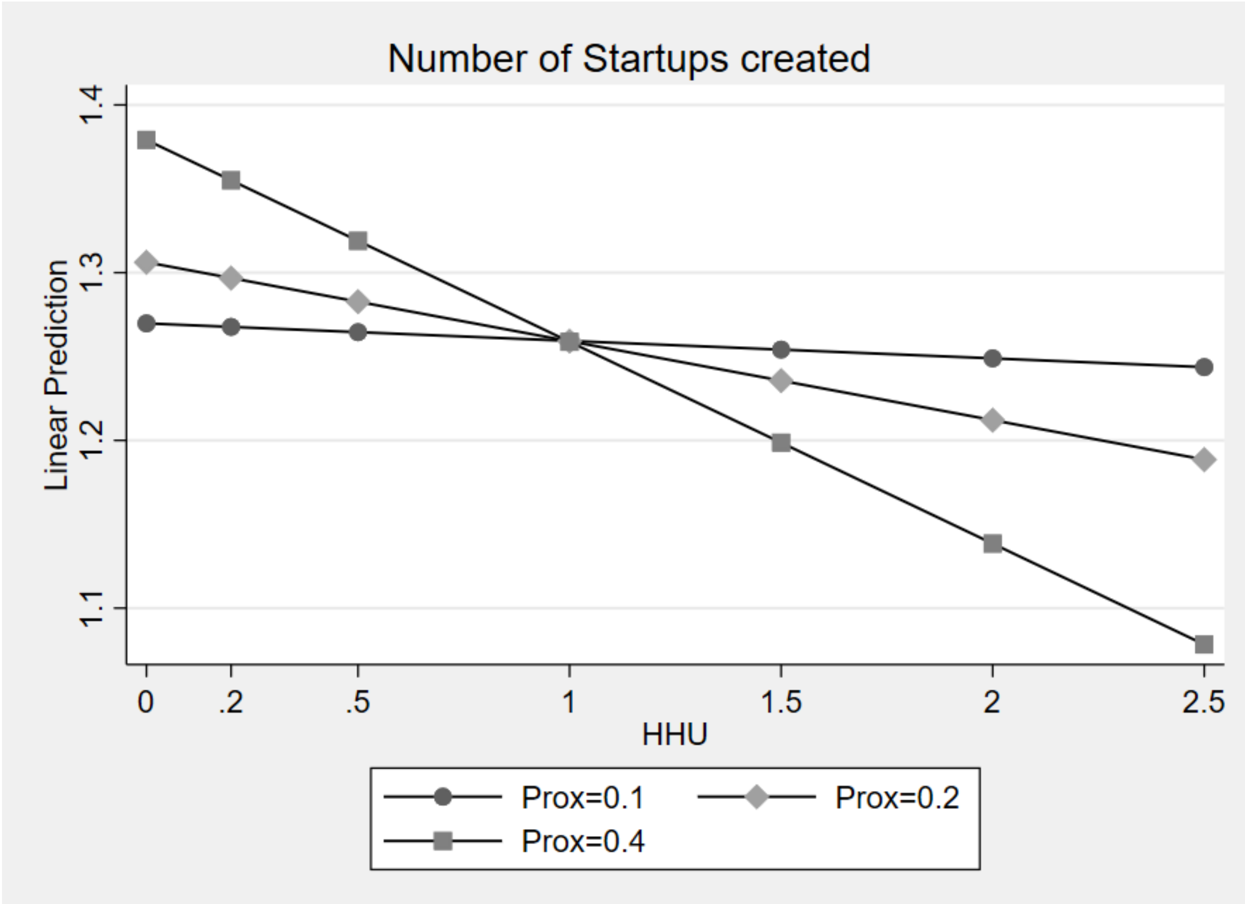

Figure 5.8 Marginal effect of proximity's and HHU's interaction on the number of startups created for the 25th, 50th, and 75th percentile values of proximity

These universities are specialised in the local trade; hence they might be working closely with local companies and easily find partners to bring their innovation to the market. The second-lowest value concerns universities with low diversification and low proximity. These are specialised universities that might find it difficult to find local partners to commercialise their licences and are forced to find alternative ways to do so. The third case exhibits low-proximity high-diversification. These universities have the internal diversification necessary to create a fertile ground for innovation and opportunity recognition; however, the entrepreneurs are not able to see how these innovations fit into the industrial network due to the disconnect with the local industry. The highest value of startup creation is found for universities with high proximity and high diversification. These universities create the ideal conditions for startup creation by providing a fertile ground for cross-fertilisation of ideas internally and being close enough to local industry to identify structural holes in the techno-industrial and scientific fabric.

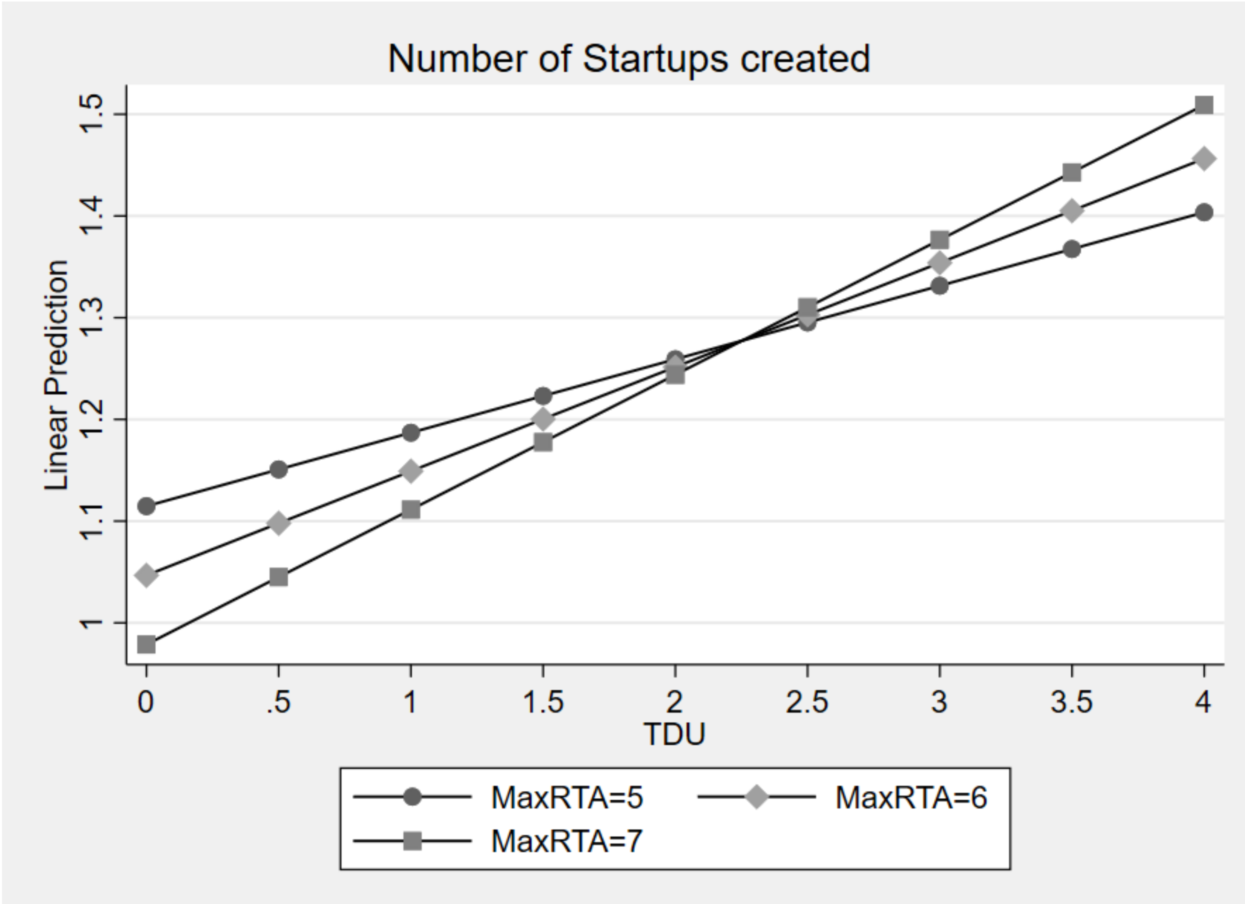

Figure 5.9 Marginal effect of MaxRTA's and TDU's interaction on the number of startups created for the 25th, 50th, and 75th percentile values of MaxRTA

National expertise (MaxRTA) is similarly influenced by the university's patent portfolio diversification (cf Fig. 5.9 and 5.10). The revealed technological advantage is negatively associated with the number of startups for less diversified universities and positively associated with spinoffs for diversified universities. Two (2) factors can be at the root of this phenomenon.

The first is related to the importance companies give to expertise in university-industry partnerships (Santoro and Chakrabarti, 2002; Bercovitz and Feldman, 2007). This indicates that expertise in a given field is all the more important for less diversified smaller universities if they want to partner with incumbent firms. The negative association of MaxRTA with the number of startups for less diversified universities indicates that national expertise in a niche field might attract more incumbent partners from far and wide due to the reputation effect that is related to the scarcity of players in the space. This is in contrast to less diversified universities with expertise in popular fields that might find it difficult to demarcate themselves in a crowded field and showcase their capabilities,

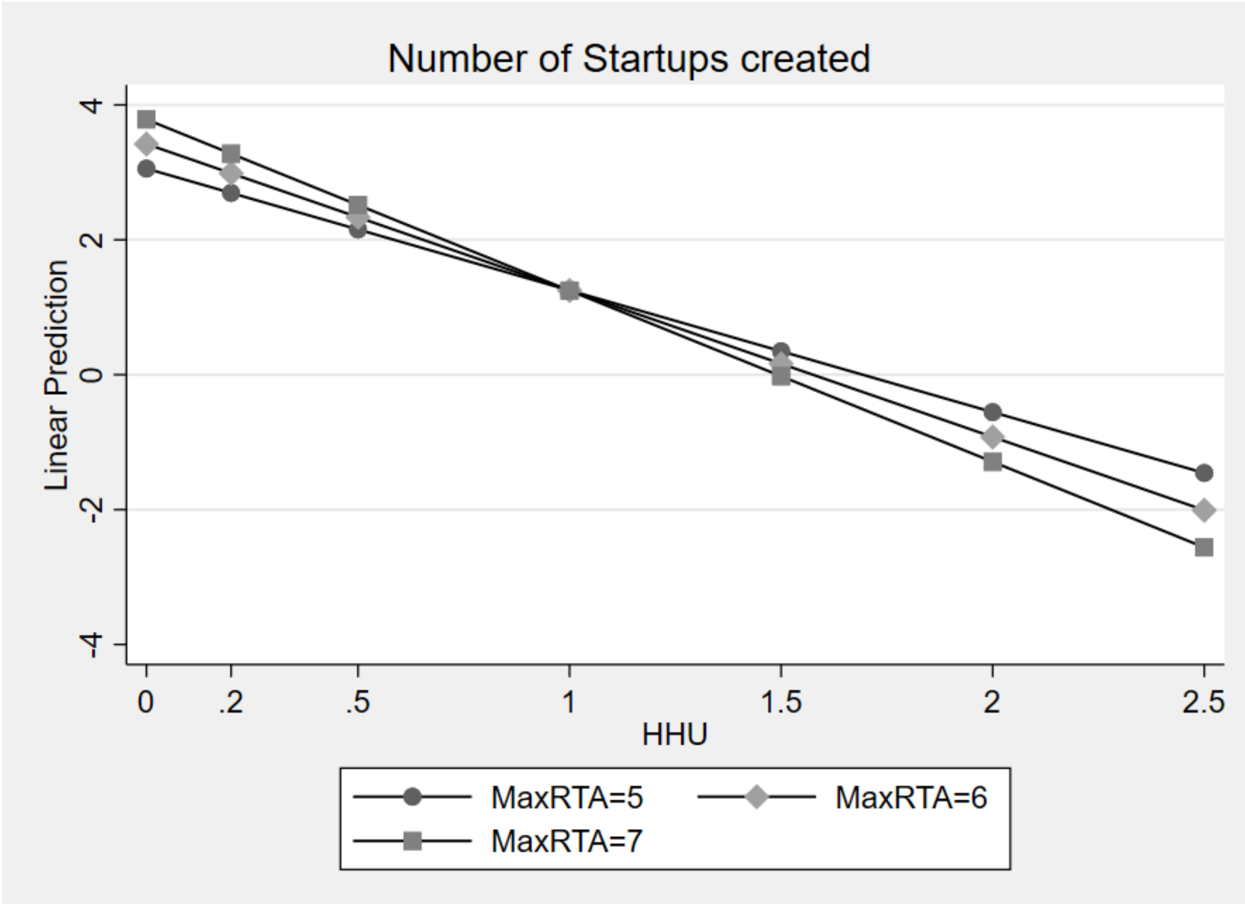

Figure 5.10 Marginal effect of MaxRTA's and HHU's interaction on the number of startups created for the 25th, 50th, and 75th percentile values of MaxRTA

hence turning toward startup creation instead.

The second argument is based on absorptive capacities (Cohen and Levinthal, 1990) and is more valid for large diversified universities. Similar to low proximity situations, a higher expertise level might make it difficult for incumbent firms to integrate the new knowledge into their operations. However, this negative effect might simply be counteracted by a large and more diversified knowledge base of the university increasing idea cross-fertilisation between different scientific and technological fields. The resulting innovation might simply be too radical, due to complexity and expertise, to be integrated into existing firms pushing the inventor to instead look for alternative commercialisation solutions.

This is coherent with previous research such as Baglieri et al.'s (2018) four (4) quadrant approach which emphasises the importance of local versus distant collaborations to commercialise innovation, and knowledge transfer versus value capture goals of the university. We distinguish two (2) major cases in our data. One the one hand, small universities specialised in niche markets with close ties to local industry create fewer startups. On the other hand, large universities with national expertise with close ties to local industry create more startups.

In the first case, the university is working with the local industry and behaves as a knowledge-intensive business service for incremental innovation. Hence, the innovations that stem from this collaboration can easily be absorbed by the local partners which is well versed in the field.

In the second case, the large university with close ties to local industry behaves as an idea incubator. The diversified knowledge base, expertise and ties with the industry makes for an ideal environment for radical innovation based on state-of-the-art knowledge and a recombination of knowledge from various sources. Of course this has the drawback of radical innovation which is harder to absorb for incumbent companies and thus generates more startups.

Furthermore, this also shows the importance of the local industry, universities in large and diverse agglomerations have an advantage when it comes to startup creation compared to their counterparts in less diversified areas. Universities located in different North American regions might well have different needs and strategies depending on their local industry. For instance, a university in a coastal state might behave differently than one located in the U.S. plains area or Canadian prairies. This echoes the findings of the innovation and agglomeration literature which emphasises the importance of proximity and centrality for innovation and commercialisation Autant-Bernard (2001); Acs et al. (2009). Hence, a positive association between proximity and the number of startups created for larger universities was to be expected. Our findings show the direct link between proximity and the number of startups for larger universities. This partly confirms our hypothesis H3 as the relationship is inverted for smaller universities.

Other factors also play a role in the startup creation process. The size of the university (RDExp) and the number of patents granted to assignees in the state (PatentState) are shown to have a positive association to the number of startups launched. This is understandable since larger universities have more experience and resources for technology transfer (Di Gregorio and Shane, 2003; Castillo et al., 2016) and developed states might create more opportunities for the entrepreneurs to discover. We found no association between the presence of a medical school (dMedSchl) and the number of startups. The proportion of exclusive licences (propExLicL) is also positively associated with startup creation which is coherent with previous studies reporting the importance of exclusivity for startups (Di Gregorio and Shane, 2003; Thursby and Thursby, 2007)and the positive association is even steeper for Canadian universities. We also identify a positive association between the number of patents per disclosures (PatentsD) and spinoffs which is coherent with previous reports of the

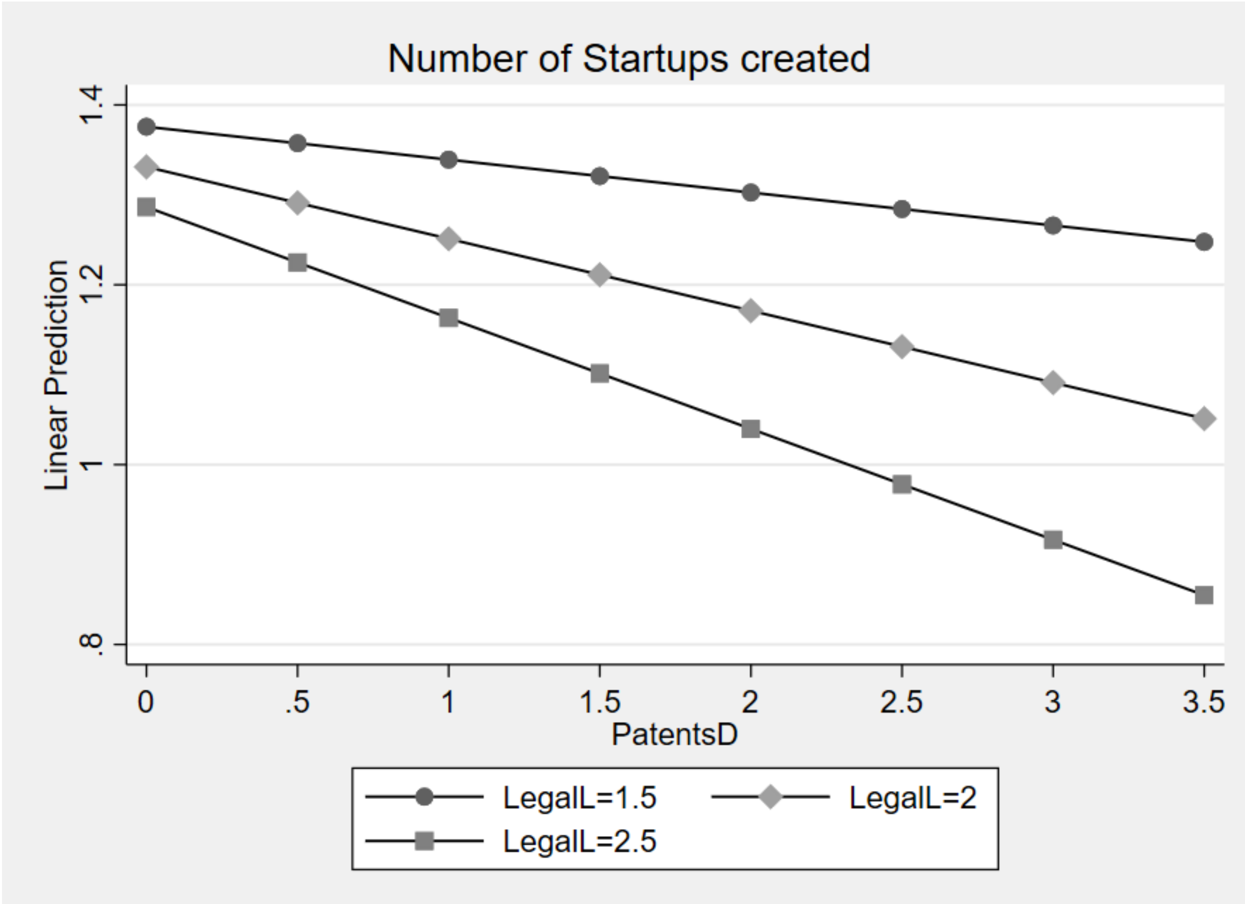

Figure 5.11 Marginal effect of LegalL's and PatentsD's interaction on the number of startups created for the 25th, 50th, and 75th percentile values of MaxRTA

importance of patents for startups (Di Gregorio and Shane, 2003; Thursby and Thursby, 2007). The relationship is mediated by the amount of legal fees per licences (LegalL) but holds true (cf Fig. 5.11). The amount of legal fees per licences is negatively associated with the number of startups indicating that incumbent companies might require more legal work per licence. Finally, we observe a positive association between the proportion of industry sourced R&D funding and the number of startups created for Canadian universities. This is interesting since closer ties to the industry seems to create more opportunities but are not necessarily absorbed by the partnering firm for Canadian universities.

5.7 Conclusion

This study is the first to evaluate the effect of university patent portfolio composition on the number of startups created. Our results show that technological diversification is positively associated with the number of startups. Furthermore, technological diversification also mediates the relationship between the university's revealed technological advantage and proximity with the number of startups. We find negative association of the university's revealed technological advantage and proximity with the number of startups for non-diversified universities. The situation reverses for diversified universities and the relationship becomes positive instead. We believe these effects to be related to the difficulty for incumbent companies to absorb radical innovations stemming from a more diverse and distant knowledge base while seeking university expertise to incrementally improve their existing offerings. This has important ramifications for policy-makers and university deans.

Our findings indicate that university startup creation behaves differently than licences to incumbent companies. Previous studies with the company as the focal point have shown the inverted-U shaped relationship between technological diversification with the innovativeness and efficiency of companies(Ceipek et al., 2019). University startup creation differs from these as the association is found to be linear and positive. We attribute this difference to the loss of efficiency of incumbent companies that stem from shared resources and the resulting competition between the different stakeholders. The competition between company research projects and products creates a zero-sum game which in turn can hinder the development and commercialisation of competing products and services. This curvilinear relationship is known as the proximity paradox and the law of diminishing returns (Balland et al., 2015). The relationship is different for startups as they do not necessarily share the same resources and thus do not compete with one another for dominance. Hence, startup creation benefit from increased diversity and proximity to a technologically diverse province as both these aspects contribute to the knowledge sourcing of the entrepreneur and his opportunity recognition.

The unyielding positive association of diversification with the number of startups also indicates that increased technological diversification could negatively impact collaborations with local incumbent companies. Increasing the technological diversification of the university could make it harder for the local companies to absorb the knowledge. This would be coherent with previous studies showing a positive association between the number of startups and the technological diversity of the provinces. Furthermore, while our findings show the positive relationship of diversification with the number of startups, we are unable to quantify the value and survival of these ventures. This is due to the important length of time between the creation of the startup and the eventual sales of the university's equity in the startup. Moreover, this would require more granular data on the startups that the AUTM survey does not gather.

Startups can be very beneficial to the university and the society through the value they create and the innovation they carry to the market. However, this requires the investment of resources by the university and the province to improve their chances of survival and success. Historical data on U.S. startups indicate that half the companies fail in their first five (5) years, the situation is a bit different for university startups, some universities report a survival rate over 80% after five (5) years for their spinoffs (Clayman and Holbrook, 2003; Prokop et al., 2019). However, there is ground to believe that these companies are not as lucrative as they are touted to be and the survival rate might be the result of zombie companies surviving thanks to market manipulations such as government and university resource allocation. These interventions, although increasing the survival rate of these companies, might simply be the result of a principal-agent problem where the TTO (agent) is signalling success through the number of startups and their survival to the principal (university or government) without actually creating economic or social value (Godfrey et al., 2020).

Two recommendations stem from this study. First, governments and universities should encourage if not dictate better record keeping on university startups by TTOs and other stakeholders. These records could include but should not be limited to: the number of jobs created, average salary of employees, revenues generated, their sources, and so on. This would allow to better identify the relationships between the incentive and reporting structures of TTOs, and the economic and social value creation of startups. This would solve the current principal-agent problem and would allow to better gauge the effectiveness of policies and resource allocation geared toward startup creation and survival.

Second, previous studies on researchers indicate that they might lack business acumen, while it can be tempting to improve their skills through programmes this would take away from their research time. Another solution would be to solicit the help of the local business community. Universities could use local angel investors and veteran entrepreneurs to screen and commercialise their research. This would ensure that the business plan and technology are properly vetted before more resources are allocated to the project. Such initiatives are already in place in some North American universities and have been deployed in the UK too (Franklin et al., 2001).

Another way to mobilise the business community could be through the use of spin-ins with incumbent companies (Hindle and Yencken, 2004). Such initiatives are also stimulating the interest of the business community that is dealing with the "M&A Paradox" which leads to value destruction for the acquiring firm (Hunt et al., 2019). This would be beneficial for the startup as it would have access to the incumbent's resources and expertise which would improve its survival and success odds. At the same time, the incumbent would have access to knowledge about the new technology and benefit from its success while hedging against the obsolescence of its existing technology. This would also create the opportunity to integrate the new technology and company into its own organisation without having to pay a premium related to information asymmetry between the parties (Hunt et al., 2019). Therefore, joint ventures would reduce the risk of the university, the startup, and the incumbent by distributing the risk over the stakeholders and improving the odds of success by increasing the resources available to the startup.

CHAPITRE 6 ARTICLE 3: UNIVERSITY-INDUSTRY PARTNERSHIPS IN THE SMART SPECIALISATION ERA.

This chapter was submitted to Technological Forecasting and Social Change on June 18 2021 as an article with the same title by Arman Yalvac Aksoy, Davide Pulizzoto, and Catherine Beaudry. The article is in the review process at the time of this thesis submission. It was accepted with minor modifications on the 5th October 2021. The contribution of Davide Pulizzoto to the article was providing the necessary expertise to extract patent data from the USPTO databases. The article shows the association between university patent portfolio composition and the number of licenses generating income. Results show that patent portfolio diversification is positively associated with the number of licenses generating income. However, technological proximity to local patent holders is negatively associated with the number of licenses generating income for diversified universities, and positively associated with the number of licenses generating income for non-diversified universities. The reasoning behind this is that technologic proximity for non-diversified universities allows local companies to more easily absorb university sourced knowledge while technological proximity to local companies for diversified universities is conducive to more outgoing spillovers.

6.1 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:

6.2 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.

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.

6.3 Literature review

6.3.1 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. These factors influence the number of opportunities created and the rate of capitalising on them. Capitalisation could further be separated into the will to transfer and the ease in doing so.

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. Size is also known to influence the outputs of the universities be it the number of publications or licences. 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, incubators, collaborative research centres, and university research parks. 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. 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).

6.3.2 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).

6.4 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.*

6.5 Methodology

6.5.1 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.

6.5.2 Variables

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.

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

[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

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. 6.1). It is the sum of related and unrelated diversification, and is calculated using the subclass of the patents with the following formula:

$$TD = \sum_{i=1}^{I} P_i ln(\frac{1}{P_i}) \tag{6.1}$$

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.

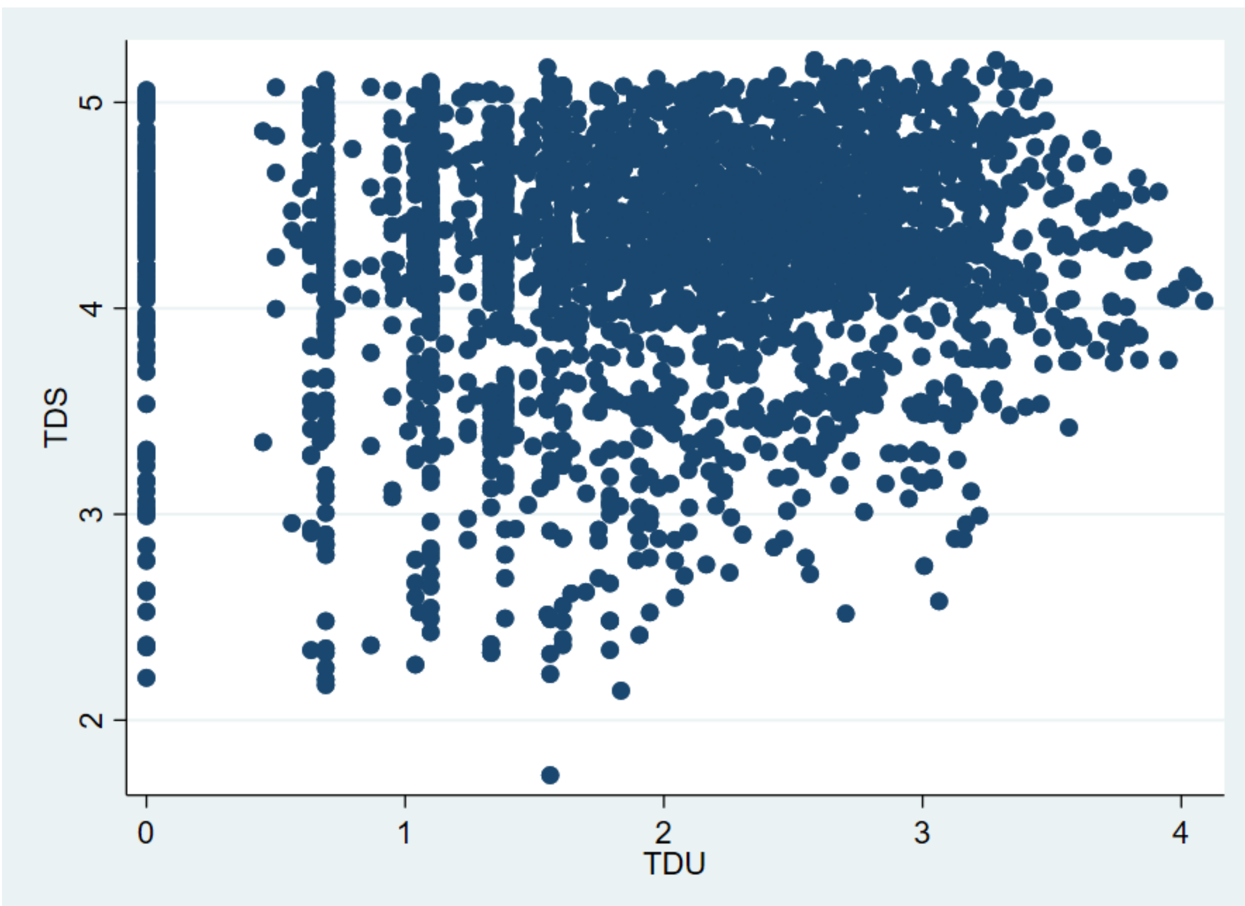

Figure 6.1 University and state diversification

[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).

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. 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:

$$TD_{UNREL} = \sum_{s=1}^{S} P_s ln(\frac{1}{P_s}) \tag{6.2}$$

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. We use the following formula to calculate it:

$$TD_{REL} = \sum_{i \in s} \frac{P_i}{P_s} ln(\frac{P_s}{P_i}) \tag{6.3}$$

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:

$$Prox = \frac{\sum_{i=1}^{i} P_{i_{univ}} \sum_{i=1}^{i} P_{i_{state}}}{\sqrt{(\sum_{i=1}^{i} P_{i_{univ}})^2} \sqrt{(\sum_{i=1}^{i} P_{i_{state}})^2}} \tag{6.4}$$

MaxRTA is the highest revealed technological 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:

$$MaxRTA = MAX(\frac{\frac{P_{i_{univ}}}{\sum_{i=1}^{i} P_{i_{univ}}}}{\frac{P_{i_{country}}}{\sum_{i=1}^{i} P_{i_{country}}}}) \tag{6.5}$$

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. 6.2). Hence, the indicator should help us account for the size difference between them.

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

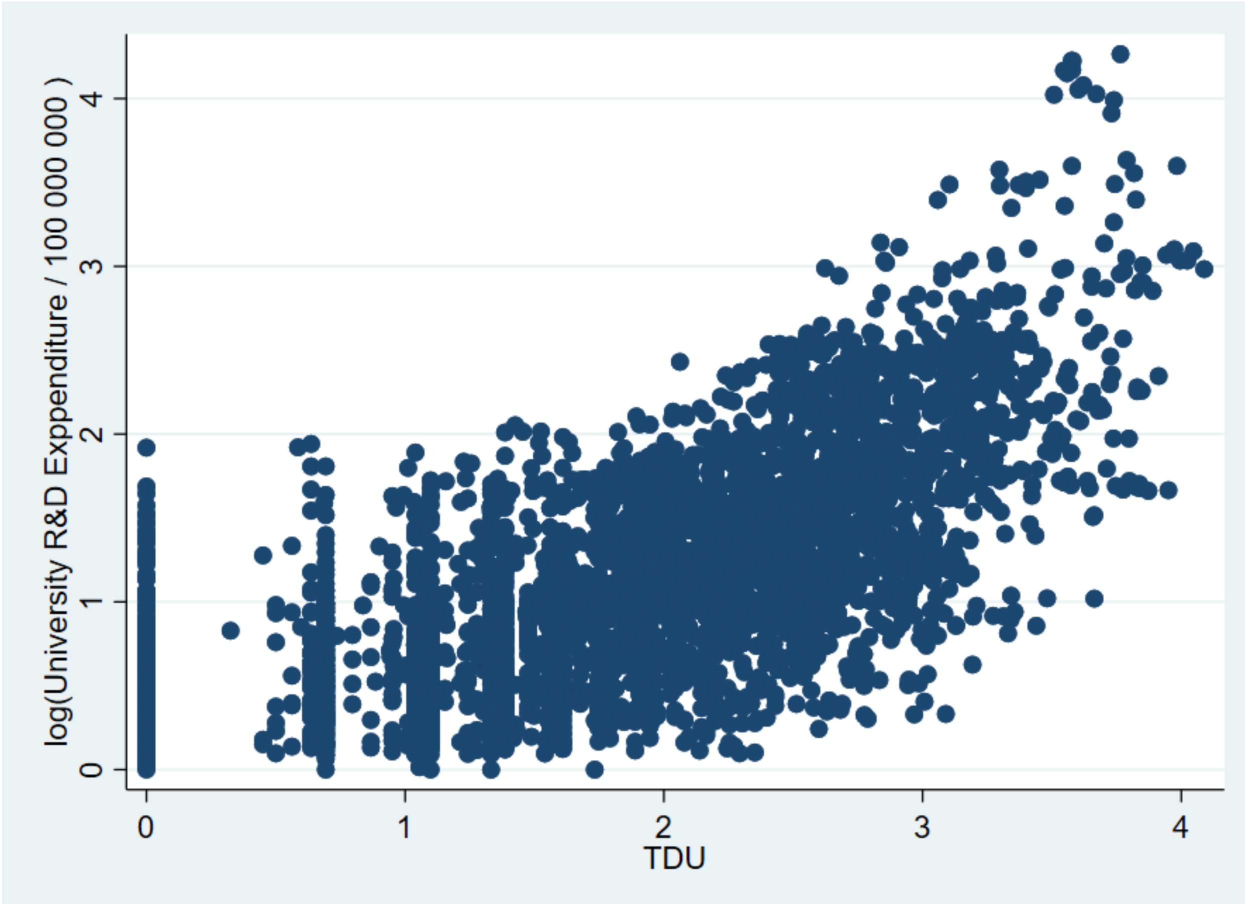

Figure 6.2 University size and technological diversification

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., 2001b).

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. 6.3). 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.

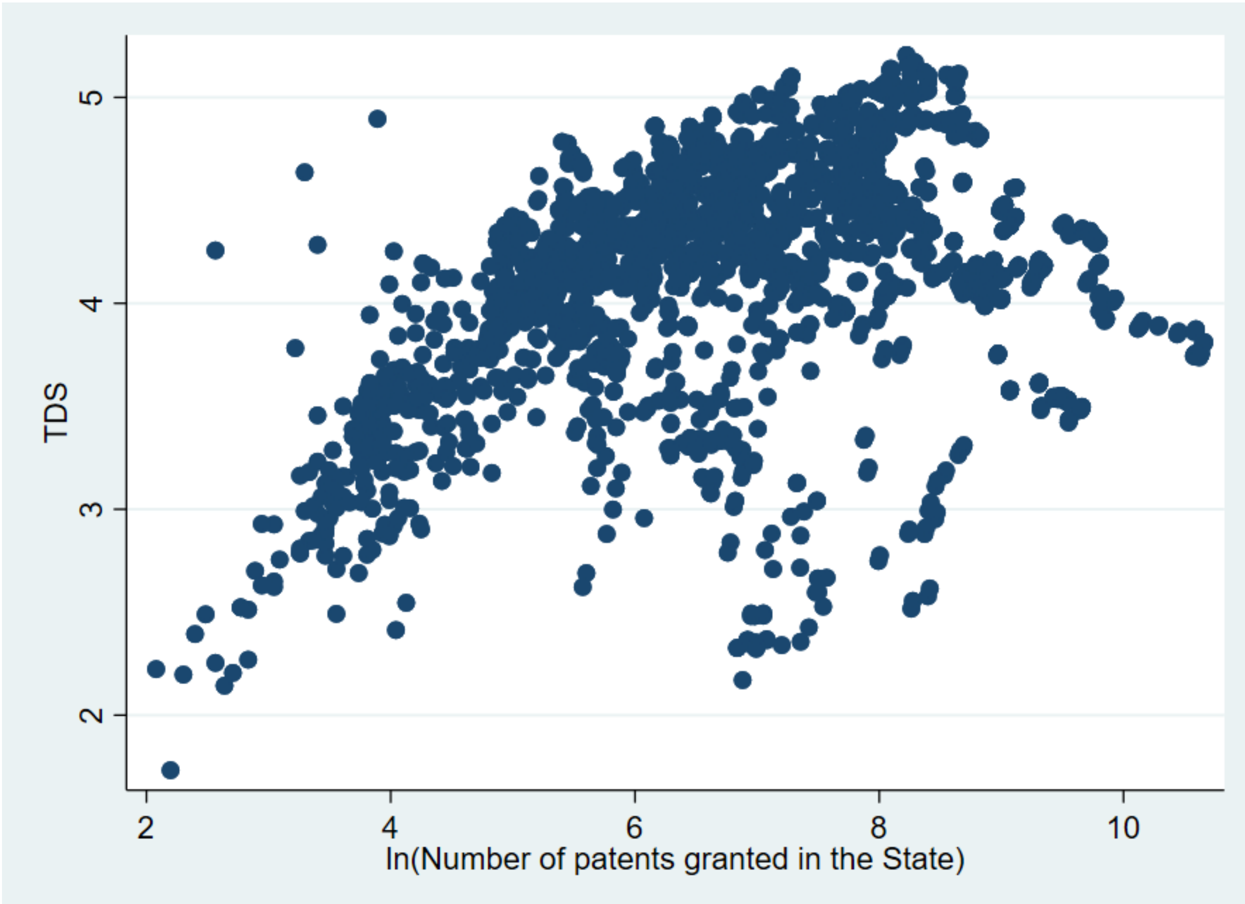

Figure 6.3 Patents granted in the local state and technological diversification

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).

6.5.3 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 :

$$Y_i = \alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \sum_{j=1}^{J} \gamma_j Z_{ijt} + \varepsilon_{it} \tag{6.6}$$

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.

6.6 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 6.1) 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; 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

[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

[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.

Table 6.1 Results of our panel regressions predicting the number of licenses generating income

	(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≤0.001, **p≤0.05, *p≤0.1 +p≤0.15

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.

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. 6.4 and 6.5). 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 number 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. Second, larger universities have started knowledge transfer and licensing earlier than their smaller counterparts, 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. 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-

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).

[7]We present alternative models taking age into account to illustrate our point in the annexes table A6 (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

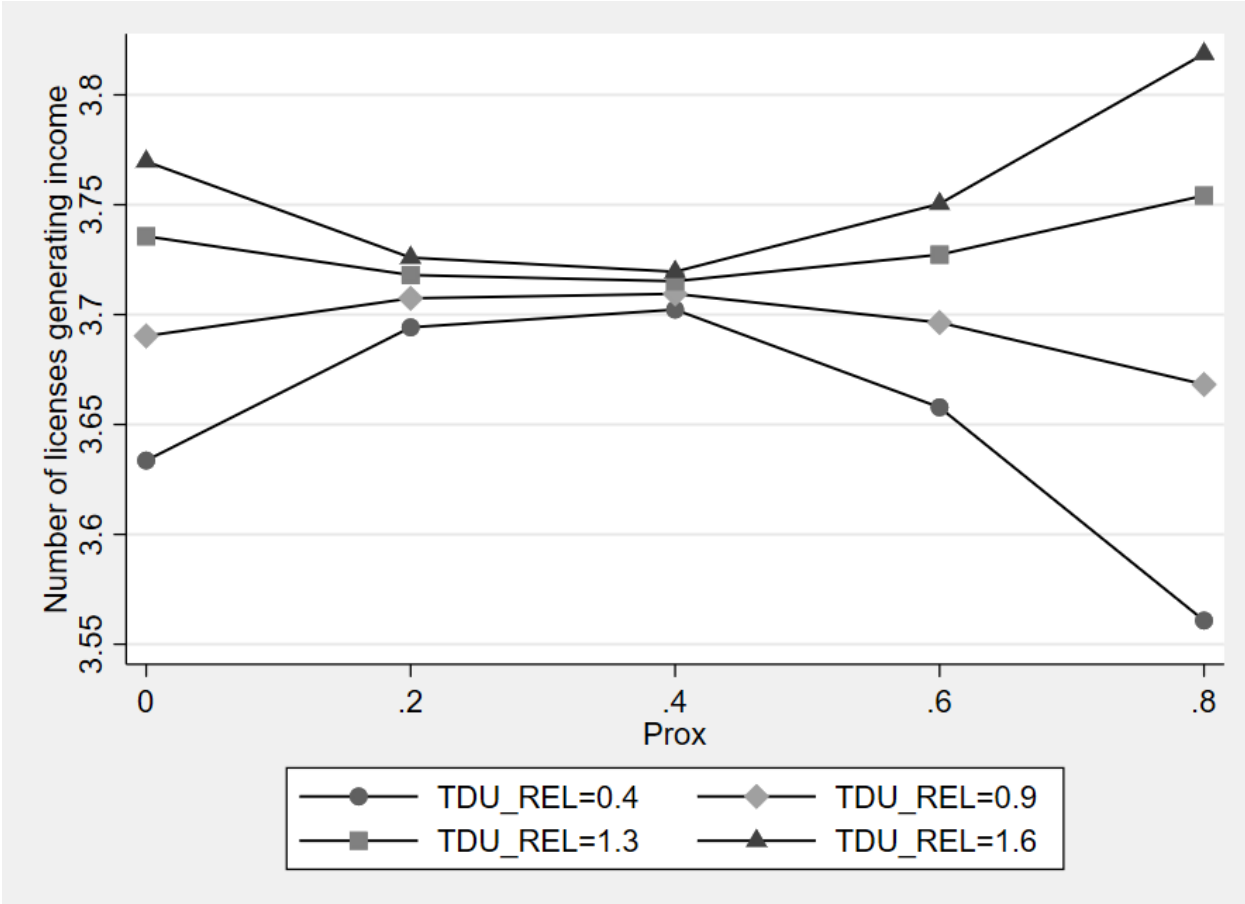

Figure 6.4 Marginal effect of diversification and proximity at 25% 50% 75% and 90% percentiles of TDU_{REL}

diversity, low proximity high diversity, and high proximity low diversity. A summary of can be found in fig 6.6.

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.

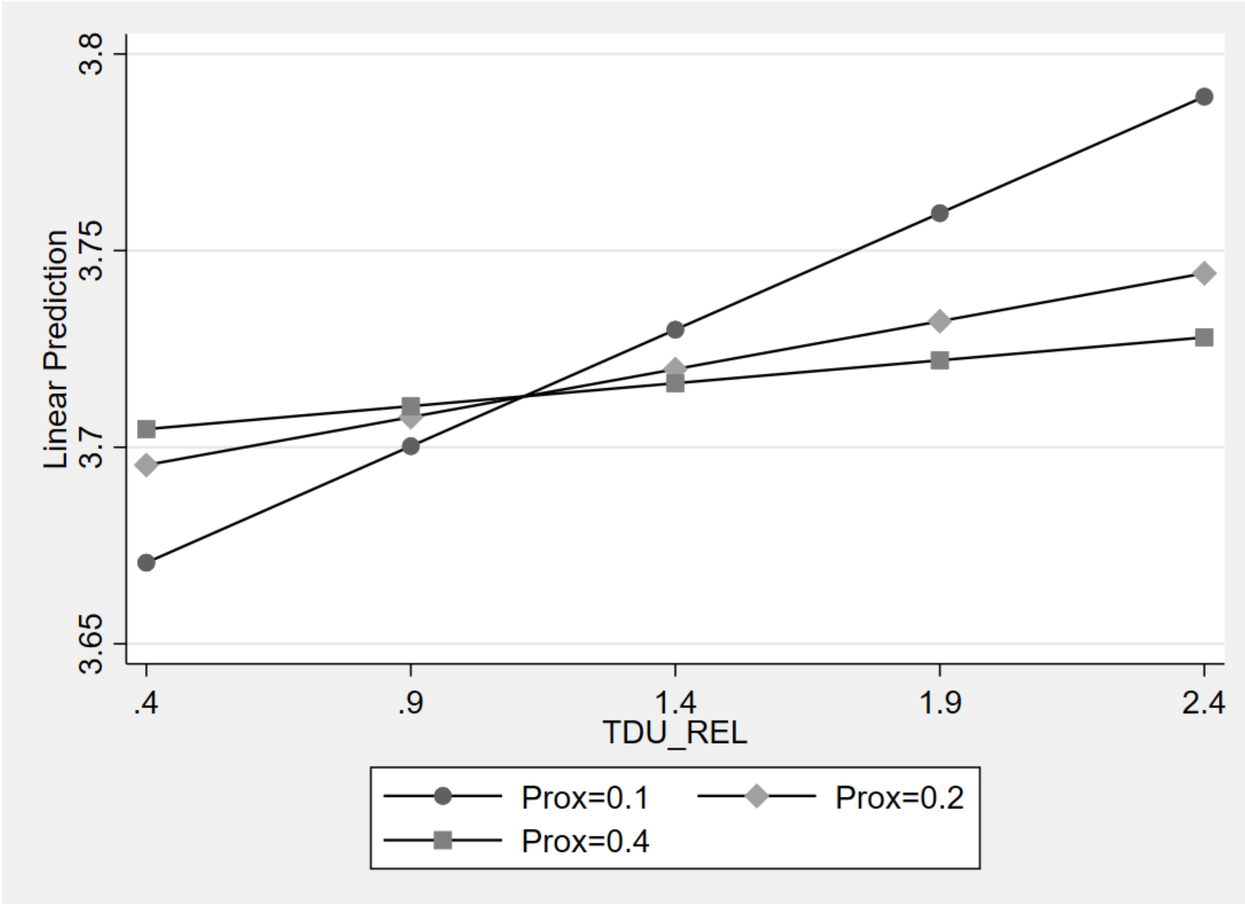

Figure 6.5 Marginal effect of diversification and proximity at 25% 50% and 75% percentiles of proximity

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., 2001b; 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.

Larger universities might have more time to transform the knowledge into licensable codified

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

Figure 6.6 Summary of the four (4) extreme scenarios

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., 2001b).

6.7 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 universities might have the upper hand when it comes to generating licenses and licensing income. We found a curvilinear inverted-

[8] We used subsamples in the annexes table A6. 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).

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.

6.8 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.

CHAPITRE 7 GENERAL DISCUSSION

This thesis contributes to the literature in two ways. The first article deals with licensing strategies and helps to explain the source of income from university licensing. The second and third articles show the effects of knowledge base diversification, relatedness, and technological proximity to local industry on university research commercialisation methods.

The studies presented here paint a picture of the licensing strategies universities deploy to commercialise their technologies. They identify differences between the two main types of licensees: incumbent and startups. They show that licences to incumbents are characterised by higher licensing income than those granted to startups which corroborate hypothesis H1a. Furthermore, licences generating income and startups are also associated with different university knowledge base diversifications and technological proximity to local industry. This is coherent with the Schumpeterian model which describes radical and incremental innovation as two distinct processes with their idiosyncratic characteristics (Schumpeter, 1942). The framework used in this thesis is a simplification of reality for the sake of argument. First and foremost, the framework is based on a linear model of commercialisation. However, the commercialisation process is far from being linear as the technology can reach the market via various ways and the process can be highly iterative with multiple loops (Bradley et al., 2013). Although sufficient for this thesis, the linear model can distort reality by omitting the importance of continuous R&D collaboration between parties. Second, although universities and TTOs can encourage commercialisation, commercialisation is still mostly driven by researchers' motivations (Perkmann et al., 2013). Therefore, taking a university and TTO perspective might give the wrong impression that the process is top-down driven. Of course, universities are still managing recruitments, investments and politics but the contribution of individual researchers is still central to commercialisation(Rothaermel et al., 2007a; Perkmann et al., 2013).

7.1 Company and Payment Types

Most of the literature on university-industry collaboration would let us believe that partnerships with universities are mostly the realm of large companies with deep pockets that can pay for their service and products be it R&D contracts or licences (Santoro and Chakrabarti, 2002). However, the first article shows that half of the university licences are granted to SMEs which are associated with higher royalty income over longer periods compared to their larger counterparts associated with a short burst of income in the first years of the licence. A plausible explanation is that these differences are the result of smaller companies having fewer financial resources to pay upfront fees to minimise subsequent royalties. This strategy also ensures the collaboration of the university in implementing the technology for which the company only pays for the usage of the license. This is also beneficial for the university which can stretch its income and partnership over a longer period rather than receiving a smaller immediate payment from an occasional deal. This indicates that universities can also fulfil the role of R&D subcontractors and consultants for local SMEs that might lack financial slack to conduct R&D projects on their own, and are coherent with hypotheses H1b and H1c.

This study also contributes to the discussion on the profitability differences of licences to incumbent and spinoffs. Some have argued that commercialisation through startups is more lucrative for universities in the long run. While this can be true for some spinoffs and universities (Bray and Lee, 2000; Savva and Taneri, 2014), these claims could not be verified with quantitative data and corroborate hypothesis H1a. This is likely the result of two (2) reasons: either the technology is perceived as very high value and the entrepreneur is not willing to share or the technology does not create commercial interest by incumbents. The lack of incumbent interest can further be subdivided and be related to either no real commercial value of the license, a lack of value recognition by the incumbent, or no current incubent with adequate absorptive capacities. **All in all these findings from the first article confirm hypothesis H1: the size of the university licensing partner influences payment scheme and outcome.**

This has implications for universities as the pressure to generate income could lead to specific strategic choices by the TTO. As observed by Feldman et al. (2002), the long delay between startup creation and income generation can lead TTOs, which are expected to be self-sufficient, to concentrate more on licensing to incumbents for royalty to stay afloat. Comparable concerns can arise for the university depending on the goal of commercialisation efforts, an emphasis on income generation might create incentives to license to incumbent over startups (Baglieri et al., 2018). However, opportunity discovery and the choice of licensee might not always be in the hands of the university. Tehnological diversification, relatedness, and proximity play a crucial role in defining the licensee type and commercilisation outcome as is shown in the subsequent articles.

7.2 Technological diversification and Opportunity Discovery

Both the second and third articles demonstrate the necessity of knowledge diversity for opportunity recognition as our diversification indicators are positively associated with the number of startups and the number of licences generating income. These findings are coherent with previous studies reporting the importance of knowledge base diversification for opportunity recognition. Entrepreneurs and scientists benefit from having a wide array of knowledge (Shane, 2000b; George et al., 2016). Previous studies on organisations have shown that the diversification of knowledge base is conducive to more opportunity discovery. The positive effect of outside knowledge was shown for both specialised companies benefiting more from collaboration and for university researchers being more prolific when collaborating with companies(Perkmann and Walsh, 2009; Cassia et al., 2014). The results of the study corroborate the literature on this point. Diversification is in fact conducive to more opportunity discovery.

This is related to the recombinant nature of innovation that requires to have prior knowledge to reorganise. Furthermore, the diversity of prior knowledge also allows these individuals to avoid myopia and source new ideas from other fields. Combined with the heterogeneous nature of university researchers and their interactions, this diversity yields increased opportunity discovery that translates into new products and processes that can be commercialised through new and existing companies.

These findings were corroborated by all our diversity indicators: the widely used Herfindahl index, the less popular entropy index, and the revealed technological advantage. Small variations were observed but were attributed to the mathematical differences between the indicators as the entropy index was more sensitive to the number of patent categories. Furthermore, the revealed technological advantage was also exhibiting a negative association with commercialisation, which was further proof of the negative effect of specialisation on commercialisation in the short term. **These results confirm hypothesis H2: technological diversification is positively associated with opportunity discovery.** They also raise questions about the policies that should be implemented to foster diversity and reconcile knowledge base diversification and regional specialisation. This is especially important for the recent Supercluster Initiative in Canada and the European Smart Specialisation Strategy.

7.3 Technological Diversification Relatedness and Licensing Income

These initiatives have of course important potentials to improve the economic activity of their respective geography and can have a major influence on society. A great deal of attention should be given to broadening the knowledge base while at the same time creating synergies. This is crucial if the aim is to generate direct income instead of just stimulating opportunity recognition as income generation is only associated with related diversification.

The results presented in the second and third articles show that the number of startups is positively associated with technological diversification and whether or not it is related is irrelevant. These companies might be the seed of future clusters and industries in their region but do not generate licensing income for the university and are hard to value in the short term. In contrast, the number of licenses generating income is positively associated with related diversification but is not associated with unrelated diversification. This is coherent with previous studies arguing about the difficulty for companies in absorbing distant knowledge (Cohen and Levinthal, 1990; Chen et al., 2012; Chen and Chang, 2012; Kim et al., 2016). **These results corroborate hypothesis H3: technological diversification relatedness is positively associated with licensing income.**

Policymakers and universities should aim at creating the appropriate environment to stimulate knowledge recombination between different fields while at the same time cultivating enough similarity between the participants to be able to communicate effectively and grasp opportunities to innovate. Failing to do so might still yield innovations and create new companies. However, these innovations and startups might have more difficulties in being integrated into the existing structures due to the various hurdles that the technological distance would create.

7.4 Technological Proximity and Opportunity Discovery

The argument put forward in the framework is that proximity will yield higher opportunity discovery. However, reality is more nuanced, which show the limits of the framework. he effect of technological proximity is different for diversified and non-diversified universities. On the one hand, non-diversified universities are benefiting from technological proximity to local industry through more licences generating income. Yet the association of technological proximity with the number of startups is negative. This shows that non-diversified universities benefit from technological proximity to find applications and incumbent licensees for their research. Hence, results show that technological proximity can help non-diversified universities by increasing the demand-side market-pull forces for their technology, leading to fewer startups and more licences to incumbents.

On the other hand, diversified universities exhibit a positive association of technological proximity with the number of startups instead of more licences generating income. This could indicate that technological proximity has a positive association with opportunity discovery through the synergy of the university's scientific and technical knowledge and the local industry's market knowledge, leading to more startups. Hence, for diversified universities, technological proximity seems to either: increase the value of the innovations which leads to lower willingness to license to incumbents, or to spillovers leading to the knowledge being transferred by other channels instead of creating licensing. Whichever the case, proximity is allowing these universities to have more startups and fewer licences to incumbents than their technologically more distant pairs.

These results are coherent with the notion that startups are more adapted to commercialise radical innovation, that commercial partnerships are the least preferred method of transfer by academics and industrials alike (Nsanzumuhire and Groot, 2020), and fits well with the observations of Savva and Taneri (2014) who noted that when the perceived value of the innovation is high the university will prefer to go for equity instead of royalty. Therefore, the number of startups is a context-dependent indicator that has a dual role of indicating failure to find customers for the university research and might at the same time hint at the higher value innovations of the university. It also shows that proximity to the local industry should be used strategically to gather knowledge to discover and recognise commercialisation opportunities for university sourced technologies. **These results partly confirms hypothesis H4: The technological proximity between the university and its local state is positively associated with opportunity discovery.**

7.5 Recomendations

These articles show that a parallel can be drawn between the case of firm innovations and university research commercialisation. Companies use different partners for knowledge sourcing regarding the type of innovation they are pursuing. Firms source market knowledge from their suppliers, customers and competitors, for incremental innovations (Belderbos et al., 2004). They use public research organisations to improve non-core competencies and to develop new technologies (Belderbos et al., 2004). A similar situation can be seen for universities that exhibit different profiles of commercialisation related to their diversification and technological proximity to local industry.

These results are coherent with the literature on entrepreneurship highlighting the necessity of technical and market knowledge for opportunity recognition. Less diversified universities with close ties to their local industries can more easily find venues to commercialise their technologies through existing companies. By contrast, diversified universities with close ties to their local industries can more easily create the right setting for researchers to recognise opportunities to capitalise on their knowledge and technologies through radical market propositions.

Ultimately spinoffs are an answer of the universities to the search problem imposed on them by stakeholders where they need to identify applications for their technologies. Universities can generate awareness and help opportunity discovery by showcasing their capabilities through startups and other means such as publications and patents. The equivalent knowledge transfer from industry toward university regarding their need are consulting and R&D contracts but do not have the same scope in presenting the information to multiple stakeholders at once. One solution to increase scientist awareness of industrial needs would be to encourage industrials to participate in networking events and conferences to present their value chains and challenges to which they need solutions. For instance, presenting a list of the top ten (10) challenges and their cost for an industry or a community could help identifying market needs and stimulate innovation.

Governments and universities should encourage research agenda diversification for it increases the commercialisation of university research through licences and spinoffs. One way of doing so is to increase the number of R&D partners. Universities and policy-makers should work together to increase the university-industry collaboration with SMEs and provide support for spinoff creation and establishment. Data shows that catering to SMEs is the most lucrative strategy for universities when it comes to licensing. Furthermore, by working in close collaboration with local companies, universities can gather market knowledge that could help in opportunity discovery and recognition, and tease out spinoffs to develop new technical capabilities. These capabilities can in some cases fill a structural hole in the existing global value chain network, and in others, even radically change the network configuration and give rise to new industries.

This also hints at the importance of collaboration and objective alignment between government and university. Universities must establish the right incentive system to tease out the right kind of innovation and partner, and governments must support the creation of organisations and programmes to help these actors thrive and cooperate. Startups and incumbents have different needs, companies might also diverge in their behaviours relative to their industry and environment. Past studies have found the effectiveness of boundary spanners such as TTOs, science parks, and incubators in improving the knowledge transfer from academia to society. These organisations alleviate the technological and knowledge base distance by increasing proximities in other forms such as geographical, social, and organisational. Furthermore, the knowledge necessary to a successful deployment is different for both incumbent and spinoff. Spinoffs might need more business acumen which would explain the interest for surrogate entrepreneurs and mentoring programmes while incumbents already possess this knowledge and would be better served by increasing technical and scientific knowledge. In a sense, spinoffs benefit from programmes aimed at developing business skills in technical individuals while incumbents benefit from programmes aimed at translating and inserting scientific and technical knowledge into business networks.

CHAPITRE 8 CONCLUSION AND RECOMMENDATIONS

Studies from a few decades ago would let us think that university-industry R&D partnerships are the domain of large companies with important R&D budgets (Santoro and Chakrabarti, 2002). Therefore, it is understandable that policies in the past were aimed at improving and fostering these partnerships. Nowadays, the focal point for university research commercialisation seems to be startups (Rothaermel et al., 2007b). However, the vast majority of companies are neither and the literature does not put enough emphasis on SMEs that are the startups of yesterday and the large companies of tomorrow. The importance of SMEs have been noted by U.S policymakers since the 1980s and gave birth to the SBIR program (Audretsch, 2003; Niosi, 2009). The program, considered a major success (Audretsch, 2003), was unfortunately not emulated by Canada to the desired extent. Researchers looking at the Canadian and Quebec ecosystems pointed this out as a weakness of the country and the province, and a major source of difference of innovation outcomes between both countries (Niosi, 2009; Deschamps et al., 2013). This lack of interest is even more alarming considering that R&D spending is persistent (Harris and Trainor, 2009) and that it is, therefore, crucial to establish the necessary culture and organisational framework early on to increase competitiveness, future collaboration with public research organisations, and resilience to technical change.

Partnerships with SMEs can be beneficial for both universities and firms. The companies get access to resources otherwise too costly and the university gets access to invaluable market knowledge that can help with opportunity discovery. It is a well-known fact that SMEs are usually financially constrained. Therefore, these companies can make use of all the help they can get, especially when innovating, an inherently unpredictable process. No wonder then that financial incentives are cited by so many as a reason to enter into partnerships with public research organisations. Partnering with SMEs is also beneficial for universities. Of course, from a financial standpoint, one good licensing contract with a large company can easily surpass the sum of multiple contracts with smaller firms and supporting multiple smaller contracts might be more complex than drafting a single patent transfer agreement. As was noted by Lihua Kuo et al. (2012) an important challenge for licensers is the oversight of royalty deals. However, there is a method to the madness and having a diverse range of smaller contracts with SMEs that cannot pay upfront can be more lucrative over time. This is based on two reasons, higher income over time and knowledge source diversification.

Judging the value of new technology is an arduous task due to the evolving market conditions and the information asymmetry between the licensing parties. Furthermore, the reason for licensing the technology can be different for large companies and SMEs. Large companies license technologies in non-core technological areas and buy licences right from universities for technologies that they already deem interesting or that they think they are infringing on. However, small companies license technologies in their core technological areas and use royalty to ensure the proper deployment of the technology (Santoro and Chakrabarti, 2002). These differences create a situation where the large companies reduce their total payment by paying a large sum upfront, while SMEs are generating smaller upfront fees but pay higher royalty to the university over time for licence use. This is perhaps best illustrated by our first article showing that a large share of licensing income of universities is derived from licences to SMEs.

Working with SMEs has the added benefit of multiplying the partners and increase the diversity of knowledge sources for the university. It can be argued that having multiple smaller partners instead of an equivalent larger one allows the university to cover a larger segment of the supply chains and probe more industries for valuable market knowledge. This increase of knowledge source diversity can in turn allow the university to discover more opportunities to deploy its technologies. Hence, the university can improve its opportunity discovery process by exposing its students and researchers to industry sourced knowledge. Furthermore, having access to a diverse range of market knowledge also allows the creation of startups that might otherwise not see the day due to the asymmetry of knowledge and the researchers' unawareness of the industry's technical challenges.

The importance of diversification for opportunity discovery and university research commercialisation cannot be overstated. Technological diversification increases both the number of startups created and licences granted by universities. It is even more important than being technologically close to the local industry. However, technological diversification is most efficient when done strategically, while overall diversification is effective at teasing out spinoffs, it is only related diversification that is effective at generating licensing income. This is most likely related to the difficulties incumbent firms experience in absorbing and transforming disparate knowledge that is outside of their core competencies into commercial offers.

The choice between diversification into related fields or matching the local industries needs through technological proximity should be weighted given current and future socio-economic and technological state. The right strategy to adopt depends on the type of technology and the objectives pursued by the university and policy-makers. The two strategies of meeting local demand and launching startups can feed each other.

Proximity for non-diversified universities is conducive to more licences generating income but reduces the number of startups. Therefore, these universities can be considered as R&D subcontractors for the local industry as they fill the important role of knowledge-intensive business services. Proximity in the case of diversified universities allows the university to leverage its capabilities by enhancing opportunity discovery thus allowing the launch of more startups.

On the one hand, pushing non-diversified universities toward servicing local companies R&D needs might be more adapted to an income generation strategy. However, this might be conducive to technological myopia. Therefore, diversifying even in the absence of local need can help build resilience in the face of change by helping spinoff launch that might become the seeds of the future local industry.

On the other hand, since codified knowledge is less influenced by geographical distance, increasing related diversification for diversified universities can help income generation by allowing licensing to non-local companies. However, close ties through technological proximity to local companies might be more beneficial for knowledge transfer and startup creation since informal relationships between academic and industrial researchers can help discover opportunities that cannot be grasped by existing companies.

The source of the knowledge and the aim are important aspects that should be considered when defining the R&D agenda and the innovation strategy. Universities have to balance the needs of multiple actors. Researchers have feared that the addition of the third mission would pervert the research agendas of the universities and steer them away from more basic science. These concerns have been brushed aside yet they are only the tip of the iceberg. Universities are not shielded from market forces. Companies will choose their R&D partners according to their innovation strategy and aim. Universities need to identify the partners they want to serve such as local industries or cross-national supply chains while not forgetting the glocal community and not-for-profits. The choice of partners will in turn define the challenges and needs that the university researchers and students will be exposed to and define the innovations that will result from these interactions in a path-dependent manner.

8.1 Limitation and futur research

The main limitation of this study is the use of secondary data. Both the STATT and the USPTO database were obtained from other sources. As such, the study had to make due with the granularity of the data and availability of other data sources. For these reasons, difficutlies were encountered when matching datasets. Furthermore, the collection process although documented by the providers might still lead to innacuracies and other biases.

A major difficulty encountered during this research was the identification of university patents. Missing details about the patent owner were a common occurrence and have dictated the pruning of some universities and patents. Examples of these included patent owners failing to indicate the university properly with many patents being granted to "the trustees of the university" without indicating which one in states with multiple universities. Difficulties also arise from having different granularity between the USPTO and STATT database where universities could report activity and apply for patents for only parts or the whole university such as reporting for one campus in the STATT but granting patents under the name of the university.

The literature on university knowledge transfer emphasises the importance of alternative indicators to financial gains due to the unpredictable time lag between investment and return. Startups are one of the indicators used when gauging the success of university knowledge transfer. They are believed to be a vital component of an innovation ecosystem as they play the role of boundary spanner between the university and the industry. They provide a technology showcasing opportunity for the university and build local capabilities at the same time. However, there is no quantitative data on university spinoffs that can prove these claims. The literature seems to lack more adequate indicators to measure the effectiveness of university spinoffs in creating long-term returns be it financial or social.

Further studies could look at the reason for startup creation and determine if it is due to the entrepreneur's willingness to spinoff due to high perceived value, the last resort effort due to a lack of commercial potential of the technology and misjudgment of the entrepreneur, or a lack of opportunity recognition by the incumbents.

Although university backed companies can enjoy a higher survival rate (Gonzalez, 2017; Prokop et al., 2019), income distribution for equity sales, similar to licensing income, is highly skewed with a handful of universities generating most of the gains (Thursby and Thursby, 2002). Of course, both strategies of spinoffs and licensing to incumbents are complementary in some regards. However, generating and maintaining these spinoffs have a cost. The training of the founders and the cost of maintaining adequate support structures can sometimes compete with the licensing to incumbent strategy. Time will tell whether governments are investing in unicorns or pies in the sky, the reality will probably be both with most startups failing to create value for society and others being home runs. Better record-keeping about the startups such as their founders, employees, finances, technologies, industries and activities could help in measuring the impact of government spending on ecosystem building and maintenance. This would ultimately help researchers better orient their efforts and avoid waste of resources.

More data about the startups could help in identifying the impact of startups. It could be argued that the time necessary for income from startups and equity is even longer than the dataset allowed to test in this thesis. The reason for the creation of these startups is also unclear. They could be the result of genuine interest in spinoff by the researcher due to high commercial value or an indication that the technology has no commercial value for incumbents. More studies on startups could identify the rationale behind these spinoffs and help stakeholders identify whether or not they are desirable. For instance, it would be interesting to study the differences between startups launched by technologically distant and close universities to identify how and if these companies differentiated from one another be it in their customer base, the market readiness of their technology, or the venture capital type they attract.

The time lag can also affect the results for expertise. Similar to startups, the revealed technological advantage might in the long term become the seed of new local capabilities and industries. Future studies could look at the long term effect of keeping such an advantage for the university and its local stakeholders. Arguably RTA would then wain as the local industry would develop capabilities in the same space.

Further studies could look at the difference between the two types of university strategy and establish if they are two separate strategies or the evolution of university research commercialisation from servicing the local need toward a spinoff and new local industry creation strategy. The longevity of the partnerships is also an important aspect of collaboration as it will impact trust between partners and can influence knowledge sharing and coordination. The data did not allow to verify if the licences were granted to different companies or the same companies be it in the same year or over time. Having this information could help in further establishing the importance of diversity of knowledge and trust for knowledge transfer. The geographical location of the licensees and their industries could also help to identify university strategic choices and their impact on knowledge transfer.

Last but not least, the literature on knowledge transfer is ill-equipped to measure the quantity of knowledge being transferred and more importantly, its direction. Identify who is learning more in these partnerships as both parties gather information on different subjects from one another is a complicated task. The university is providing technical and scientific knowledge in exchange for market knowledge from their more commercialisation partners.

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ANNEXE A TABLES ARTICLE 1

Table A1 Breusch-Pagan Cook-Weisberg tests' results for the first article.

Year	Chi2	Prob>Chi2
2002	0.52	0.4712
2003	3.90	0.0483
2004	0.71	0.4007
2005	0.05	0.8195
2006	1.13	0.2878
2007	0.36	0.5480
2008	0.26	0.6094
2009	0.06	0.8042
2010	1.39	0.2383
2011	0.00	0.9662
2012	0.66	0.4178
2013	4.29	0.0384
2014	1.91	0.1665

Table A2 Descriptive statistics of the variables used in our regressions.

	lnLegalLdDM	lnpropExLicL	lnEmployees	lnPatentsDmD	lnFedRDdMM	lnDisclosuresE
N	1562	1562	1562	1562	1562	1562
mean	1.8693	0.3683	2.2746	1.0658	5.0250	2.3651
sd	0.7327	0.1794	0.7495	0.4282	1.0470	0.5067
min	0	0	0.1823	0	0	0.2876
max	4.7634	1.4880	5.4156	3.5835	8.2168	4.374
skewness	0.2487	0.1765	0.4084	0.2569	-0.2782	0.0337
kurtosis	3.0347	3.2886	3.4303	4.3824	3.5364	4.2081
Transformation	ln(LegalL*(10^{-4})+1)	ln(propExLicL+1)	ln(Employees+1)	ln(PatentsD*(10)+1)	ln(FedRD*(10^{-6})+1)	ln(DisclosuresE+1)

	lnnbLicRoy	lnRoyaltiesdC	lnIncOtherdDM	lnnbLicEqu	lnIncEqu
N	1562	1562	1562	1562	1562
mean	3.2007	9.1303	4.0213	0.9215	3.8541
sd	1.2589	2.6408	1.8527	0.8503	5.9169
min	0	0	0	0	0
max	6.4676	16.1449	11.0977	3.8286	18.2138
skewness	-0.0759	-0.7570	-0.2138	0.5703	0.9502
kurtosis	2.7285	4.2855	3.0176	2.4439	2.0321
Transformation	ln(nbLicRoy+1)	ln(Royalties*(10^{-2})+1)	ln(IncOther*(10^{-4})+1)	ln(nbLicEqu+1)	ln(IncEqu+1)

	lnpropLicLargeL	lnpropLicSmallL	lnpropLicStartupL
N	1562	1562	1562
mean	0.2492	0.3844	0.1793
sd	0.1573	0.1689	0.1499
min	0	0	0
max	0.6931	0.6931	0.6931
skewness	0.2953	-0.3921	1.0865
kurtosis	2.7169	2.7218	4.1698
Transformation	ln(propLicLargeL+1)	ln(propLicSmallL+1)	ln(propLicStartupL+1)

Table A3 Regression results for the number of licences generating royalty income with the alternative model

lnnbLicRoy	NbRoy1	NbRoy2	NbRoy3	NbRoy4	NbRoy5	NbRoy6	NbRoy7	NbRoy8	NbRoy9	NbRoy10	NbRoy11	NbRoy12	NbRoy13	NbRoy14	NbRoy15
dCaMed	2.9089*	2.9880*	3.0537*	3.1434*	3.1799*	3.1068*	3.2428*	3.4715**	3.5569**	3.6641**	2.8600*	2.9060*	3.0180*	3.0234*	3.0333*
dUsNoMed	0.8812	0.8369	0.8375	0.8363	0.8382	0.9535	0.9284	89	82	94	184	455	1117	1109	104
dCaNoMed	-0.8113	-0.8735	-0.7588	-0.7176	-0.7379	-0.6674	-0.5652	-0.2248	-0.1061	-0.1412	-0.6841	-0.5388	-0.4347	-0.4006	-0.3924
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnFedRDdMM	0969***	1152***	1189***	1265***	1295***	0652***	0611***	0618***	0636***	0611***	0532***	0367***	0349***	0328***	0257***
lnDisclosuresE	-0.16	-0.1738	-0.1779	-0.1806	-0.1822	-0.1185	-0.1076	-0.0875	-0.0827	-0.0817	-0.0835	-0.0565	-0.0239	-0.0181	-0.0134
lnLegalLdDM	-0.1288	-0.1312	-0.1264	-0.1223	-0.1223	-0.0688	-0.0302	-0.012	-0.0087	-0.0066	-0.1018	-0.0674	-0.058	-0.057	-0.0548
lnpropExLicL	2.0753	2.1347	2.1583	2.2328	2.2433	2.176	2.2876	2.347	2.3959	2.3621	2.205	2.2344	2.237	2.2223	2.163
lnLegalLdDM#lnpropExLicL	-0.0192	-0.0019	-0.008	-0.0175	-0.0172	-0.0332	-0.0754	-0.0819	-0.0783	-0.0789	-0.0091	-0.0655	-0.0619	-0.0575	-0.0612
dCaMed#lnLegalLdDM	-0.2022	-0.2238	-0.2458	-0.2574	-0.2669	-0.2341	-0.2843	-0.3397	-0.3454	-0.3678	-0.1862	-0.1992	-0.2054	-0.2018	-0.2012
dCaNoMed#lnLegalLdDM	0.1551	0.1309	0.1046	0.091	0.0915	0.1617	0.1247	0.0848	0.0725	0.0878	0.1856	0.185	0.2083	0.2135	0.2296
dUsNoMed#lnLegalLdDM	-0.3692**	-0.3637**	-0.3597**	-0.3582**	-0.3571**	-0.3674**	-0.3695**	-0.3658**	-0.3626**	-0.3568**	-0.3708**	-0.3739**	-0.3737**	-0.3723**	-0.3686**
dCaMed#lnFedRDdMM	-0.4570**	-0.4762**	-0.4840**	-0.5003**	-0.5052**	-0.4706**	-0.4783**	-0.4952**	-0.5105**	-0.5200**	-0.4130**	-0.4034**	-0.4059**	-0.4052**	-0.4016**
dCaNoMed#lnFedRDdMM	-0.5225**	-0.4990**	-0.5116**	-0.5207**	-0.5146**	-0.4814*	-0.4407*	-0.4842**	-0.4970**	-0.4892**	-0.4925**	-0.4865**	-0.5054**	-0.5065**	-0.5140**
dUsNoMed#lnFedRDdMM	-0.2411	-0.2509	-0.2551	-0.2595	-0.2621	-0.2455	-0.2528	-0.2631	-0.2636	-0.2691	-0.2132	-0.2078	-0.2107	-0.2085	-0.2076
dCaMed#lnDisclosuresE	-0.0923	-0.0679	-0.0675	-0.0667	-0.067	-0.1285	-0.1355	-0.1585	-0.1554	-0.1671	-0.1926	-0.2261	-0.2586	-0.2618	-0.272
dCaNoMed#lnDisclosuresE	1835**	1858**	1643**	1686**	1672**	0603*	0.9622*	0.9201*	0.8941*	0.8925*	0724**	0.9943*	0.9938**	0.9780**	0.9820**
dUsNoMed#lnDisclosuresE	0.4122	0.4436*	0.4489*	0.4563*	0.4598*	0.3958	0.4201*	0.4068	0.4062	0.4126	0.3145	0.2963	0.2762	0.2715	0.2699
lnpropExLicL#lnFedRDdMM	-0.6319**	-0.6555**	-0.6586**	-0.6736**	-0.6765**	-0.6009**	-0.5976**	-0.5984**	-0.6087**	-0.6020**	-0.5785*	-0.5497*	-0.5425*	-0.5392*	-0.5254*
lnpropLicLargeL	-0.6805**	-0.4660**	-0.4011**	-0.3851**	-0.3720*										
lnpropLicLargeL(t-1)		-0.5906***	-0.5001***	-0.4521***	-0.4511***										
lnpropLicLargeL(t-2)			-0.3199*	-0.2434*	-0.2336*										
lnpropLicLargeL(t-3)				-0.2931*	-0.2690*										
lnpropLicLargeL(t-4)					-0.1028										
lnpropLicSmallL						2375***	0.8877***	0.7385***	0.7052***	0.6791***					
lnpropLicSmallL(t-1)							0.9768***	0.7546***	0.7051***	0.6858***					
lnpropLicSmallL(t-2)								0.7605***	0.6774***	0.6445***					
lnpropLicSmallL(t-3)									0.3122*	0.2388*					
lnpropLicSmallL(t-4)										0.2849*					
lnpropLicStartupL											-0494***	-0.8436***	-0.7001***	-0.6816***	-0.6655***
lnpropLicStartupL(t-1)												-0.6039***	-0.4560***	-0.4262***	-0.4103***
lnpropLicStartupL(t-2)													-0.6533***	-0.6214***	-0.5691***
lnpropLicStartupL(t-3)														-0.1603	-0.1009
lnpropLicStartupL(t-4)															-0.2416
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	-1398	-707	-324	-68	-0.9995	-9576**	-2.2961***	-2.5481***	-2.6251***	-2.6704***	-3494	-3706*	-4362*	-4383*	-4099*
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.5071	0.5116	0.513	0.5142	0.5144	0.5254	0.5389	0.547	0.5484	0.5497	0.513	0.5168	0.5212	0.5215	0.5222
Adj. R-Square	0.4968	0.5011	0.5021	0.5031	0.5029	0.5155	0.529	0.5369	0.538	0.539	0.5028	0.5064	0.5106	0.5105	0.5109
F	22.0833***	20.202***	18.9378***	17.9567***	17.9306***	24.4052***	23.4791***	23.3321***	23.176***	23.4736***	27.923***	25.5868***	26.4245***	24.9434***	24.8728***
Log likelihood	-2023.0509	-2015.8594	-2013.6924	-2017048	-2014503	-1993.4533	-1970.9315	-1957.23	-1954.7791	-1952.5406	-2013.6121	-2007.5401	-2000.3357	-1999.9046	-1998.8504
BIC	4288.7746	4287453	4284.765	4288.1437	4294.9884	4229.5793	4198895	4178403	4174.2922	4177.169	4269.897	4265.1067	4258.0517	4264.5432	4269.7886
AIC	4112.1018	4099.7188	4097.3848	4095.4097	4096.9007	4052.9065	4009.863	3984.46	3985581	3979.0812	4093.2241	4083.0801	4070.6714	4078092	4077008

***p≤0.001, **p≤0.01, *p≤0.05

Table A4 Regression results for the amount of royalty income with the alternative model

lnRoyalties	$Roy1	$Roy2	$Roy3	$Roy4	$Roy5	$Roy6	$Roy7	$Roy8	$Roy9	$Roy10	$Roy11	$Roy12	$Roy13	$Roy14	$Roy15
dCaMed	3.4432	3.5527	3.6949	3.7577	3.7789	3.8061*	4.0013*	4.3452*	4.4630**	4.6396**	3.5282	3.6018*	3.7226*	3.7389*	3.7672*
dUsNoMed	-1197	-1811	-18	-1807	-1797	-593	-953	-0.9741	-0.9751	-0.9732	-0.9403	-0.8971	-0.8256	-0.8281	-0.8479
dCaNoMed	-2.0169	-2.103	-855	-8262	-8379	-8089	-6623	-1503	-0.9865	-443	-7674	-5353	-423	-3206	-2971
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnFedRDdMM	2.0386***	2.0640***	2.0720***	2.0773***	2.0790***	2.0068***	2.0009***	2.0020***	2.0045***	2.0004***	9795***	9532***	9512***	9451***	9247***
lnDisclosuresE	-0.503	-0.5221	-0.531	-0.533	-0.5339	-0.4594	-0.4437	-0.4135	-0.4069	-0.4052	-0.3894	-0.3463	-0.3112	-0.2937	-0.2801
lnLegalLdDM	0.6258*	0.6225*	0.6328*	0.6356*	0.6356*	0.7211**	0.7765**	0.8039**	0.8084**	0.8120**	0.6992**	0.7541**	0.7644**	0.7672**	0.7736**
lnpropExLicL	7.2021**	7.2844**	7.3354**	7.3876**	7.3937**	7.3369**	7.4971**	7.5864**	7.6538**	7.5982**	7.4290**	7.4758**	7.4786**	7.4347**	7.2650**
lnLegalLdDM#lnpropExLicL	-0.7225	-0.6986	-0.7118	-0.7185	-0.7182	-0.7721	-0.8327	-0.8425	-0.8375	-0.8384	-0.7558	-0.8459	-0.842	-0.8289	-0.8394
dCaMed#lnLegalLdDM	-0.8600*	-0.8899*	-0.9375*	-0.9456*	-0.9511*	-0.9192**	-0.9913**	-0746**	-0825**	-1194**	-0.8610*	-0.8818*	-0.8885*	-0.8778*	-0.8758*
dCaNoMed#lnLegalLdDM	-0.382	-0.4155	-0.4725	-0.482	-0.4818	-0.3934	-0.4464	-0.5066	-0.5234	-0.4984	-0.3622	-0.3632	-0.3381	-0.3224	-0.2765
dUsNoMed#lnLegalLdDM	-0.6544*	-0.6468*	-0.6381*	-0.6370*	-0.6364*	-0.6510*	-0.6540*	-0.6484*	-0.6439*	-0.6344*	-0.6554*	-0.6603*	-0.6601*	-0.6557*	-0.6453*
dCaMed#lnFedRDdMM	-0.3119	-0.3385	-0.3554	-0.3668	-0.3696	-0.3525	-0.3635	-0.389	-0.4101	-0.4258	-0.2737	-0.2584	-0.261	-0.259	-0.2487
dCaNoMed#lnFedRDdMM	0.0535	0.0861	0.0588	0.0525	0.056	0.1143	0.1727	0.1073	0.0896	0.1025	0.1163	0.1258	0.1054	0.1021	0.0806
dUsNoMed#lnFedRDdMM	-0.0575	-0.0711	-0.0803	-0.0834	-0.0849	-0.0754	-0.0858	-0.1013	-0.1021	-0.1111	-0.0294	-0.0209	-0.0239	-0.0175	-0.0149
dCaMed#lnDisclosuresE	-0.2488	-0.215	-0.2142	-0.2136	-0.2138	-0.2737	-0.2838	-0.3183	-0.314	-0.3333	-0.3838	-0.4373	-0.4724	-0.4822	-0.5114
dCaNoMed#lnDisclosuresE	0.9331	0.9363	0.8897	0.8927	0.8919	0.763	0.6224	0.559	0.5232	0.5205	0.7286	0.604	0.6034	0.5558	0.5673
dUsNoMed#lnDisclosuresE	0.9581	0016*	0130*	0182*	0202*	0.9698	0047*	0.9846*	0.9837*	0.9943*	0.8447	0.8156	0.794	0.7797	0.7751
lnpropExLicL#lnFedRDdMM	-6217***	-6543***	-6611***	-6716***	-6733***	-5838***	-5791***	-5804***	-5946***	-5835***	-5349**	-4888**	-4810**	-4712**	-4319**
lnpropLicLargeL	-0.4454	-0.1483	-0.008	0.0032	0.0108										
lnpropLicLargeL(t-1)		-0.8182*	-0.6223	-0.5887	-0.5881										
lnpropLicLargeL(t-2)			-0.6917*	-0.6381**	-0.6324**										
lnpropLicLargeL(t-3)				-0.2053	-0.1914										
lnpropLicLargeL(t-4)					-0.0594										
lnpropLicSmallL						6169***	1150**	0.8906**	0.8447*	0.8018*					
lnpropLicSmallL(t-1)							4015***	0672***	0.9990***	0.9671***					
lnpropLicSmallL(t-2)								1437***	0291***	0.9749***					
lnpropLicSmallL(t-3)									0.4307	0.3099					
lnpropLicSmallL(t-4)										0.4692					
lnpropLicStartupL											-7920***	-4633***	-3085***	-2529***	-2068**
lnpropLicStartupL(t-1)												-0.9647**	-0.8051**	-0.7158*	-0.6702*
lnpropLicStartupL(t-2)													-0.7050*	-0.6090*	-0.4595
lnpropLicStartupL(t-3)														-0.4816	-0.3116
lnpropLicStartupL(t-4)															-0.6910*
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	0.1733	0.2689	0.3519	0.3698	0.3741	-0.8019	-2876	-6665	-7727	-8474	-0.0339	-0.0677	-0.1385	-0.145	-0.0637
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.4199	0.4219	0.4233	0.4234	0.4235	0.4289	0.4352	0.4394	0.44	0.4408	0.4276	0.4297	0.4309	0.4315	0.4327
Adj. R-Square	0.4078	0.4094	0.4105	0.4102	0.4098	0.417	0.423	0.4269	0.4271	0.4276	0.4156	0.4174	0.4182	0.4184	0.4193
F	10.6942***	10.5402***	10.7557***	10.4797***	10.2132***	13193***	12488***	10.7948***	10.8301***	10.5387***	10.6947***	10.6771***	10.6656***	10.6459***	13041***
Log likelihood	-3307.4212	-3304.7642	-3302.8191	-3302.632	-3302.6157	-3295.1668	-3286.4882	-3280.7673	-3279.9115	-3278.7998	-3297.0416	-3294.0516	-3292.4419	-329698	-3290.0482
BIC	6857.5153	6859.555	6863.0184	6869.9981	6877.3192	6833.0065	6823.003	6818.915	6824.5569	6829.6874	6836.756	6838.1298	6842.2641	6848.1299	6852.1842
AIC	6680.8425	6677.5284	6675.6381	6677.2641	6679.2315	6656.3336	6640.9764	6635347	6638229	6635997	6660.0831	6656.1033	6654.8838	6655.3959	6654.0965

***p≤0.001, **p≤0.01, *p≤0.05

Table A5 Regression results for the number of licences with equity with the alternative model

lnnbLicEqu	NbEqu1	NbEqu2	NbEqu3	NbEqu4	NbEqu5	NbEqu6	NbEqu7	NbEqu8	NbEqu9	NbEqu10	NbEqu11	NbEqu12	NbEqu13	NbEqu14	NbEqu15
dCaMed	0.6903	0.6806	0.6637	0.6178	0.5923	0.4885	0.4714	0.4447	0.3862	0.3383	0.5071	0.4958	0.4834	0.4778	0.4705
dUsNoMed	-0.4494	-0.444	-0.4441	-0.4435	-0.4448	-0.4418	-0.4386	-0.448	-0.4475	-0.4481	-0.5354	-0.5421	-0.5494	-0.5486	-0.5434
dCaNoMed	2.0480**	2.0556**	2.0262**	2.0051**	2.0192**	9644**	9516**	9118**	8305**	8462**	8490**	8132**	8017**	7666**	7606**
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnFedRDdMM	0.5154***	0.5132***	0.5122***	0.5084***	0.5063***	0.5180***	0.5186***	0.5185***	0.5173***	0.5184***	0.5456***	0.5497***	0.5499***	0.5520***	0.5572***
lnDisclosuresE	-0.039	-0.0373	-0.0362	-0.0348	-0.0337	-0.0447	-0.046	-0.0484	-0.0517	-0.0522	-0.1064	-0.113	-0.1166	-0.1226	-0.1261
lnLegalLdDM	-0.0977	-0.0974	-0.0986	-0.1007	-0.1007	-0.1423*	-0.1471*	-0.1493*	-0.1515*	-0.1525*	-0.1694**	-0.1778**	-0.1789**	-0.1798**	-0.1815**
lnpropExLicL	-0.0353	-0.0426	-0.0487	-0.0868	-0.0941	-0.0818	-0.0959	-0.1028	-0.1363	-0.1212	-0.1988	-0.206	-0.2063	-0.1912	-0.1475
lnLegalLdDM#lnpropExLicL	-0.0772	-0.0793	-0.0778	-0.0729	-0.0732	-0.036	-0.0307	-0.0299	-0.0324	-0.0322	-0.0169	-0.003	-0.0034	-0.0079	-0.0052
dCaMed#lnLegalLdDM	-0.1268	-0.1242	-0.1186	-0.1126	-0.106	-0.0935	-0.0872	-0.0807	-0.0768	-0.0667	-0.1054	-0.1022	-0.1015	-0.1052	-0.1057
dCaNoMed#lnLegalLdDM	-0.03	-0.027	-0.0202	-0.0133	-0.0136	-0.0102	-0.0056	-0.0009	0.0074	0.0006	-0.0203	-0.0202	-0.0227	-0.0281	-0.0399
dUsNoMed#lnLegalLdDM	0.1779**	0.1772**	0.1762**	0.1754**	0.1746**	0.1759**	0.1762**	0.1758**	0.1736**	0.1710**	0.1774**	0.1781**	0.1781**	0.1766**	0.1739**
dCaMed#lnFedRDdMM	-0.1113	-0.109	-0.107	-0.0986	-0.0952	-0.0798	-0.0788	-0.0769	-0.0664	-0.0621	-0.1112	-0.1135	-0.1133	-0.114	-0.1166
dCaNoMed#lnFedRDdMM	-0.5051***	-0.5080***	-0.5047***	-0.5001***	-0.5044***	-0.5306***	-0.5357***	-0.5306***	-0.5218***	-0.5253***	-0.5576***	-0.5591***	-0.5570***	-0.5559***	-0.5503***
dUsNoMed#lnFedRDdMM	-0.1775*	-0.1763*	-0.1752*	-0.1730*	-0.1712*	-0.1620*	-0.1611*	-0.1599*	-0.1595*	-0.1571*	-0.1830**	-0.1843**	-0.1840**	-0.1863**	-0.1869**
dCaMed#lnDisclosuresE	0.0262	0.0232	0.0231	0.0227	0.023	0.0163	0.0172	0.0199	0.0177	0.023	0.0947	0.1029	0.1065	0.1099	0.1174
dCaNoMed#lnDisclosuresE	0.0262	0.0259	0.0314	0.0292	0.0302	0.0888	0.1011	0.106	0.1238	0.1245	0.1807	0.2	0.2	0.2163	0.2134
dUsNoMed#lnDisclosuresE	0.4445**	0.4407**	0.4393**	0.4355**	0.4331**	0.4141**	0.4111**	0.4126**	0.4131**	0.4102**	0.4852***	0.4896***	0.4919***	0.4968***	0.4979***
lnpropExLicL#lnFedRDdMM	0.1638	0.1667	0.1675	0.1752	0.1772	0.1536	0.1532	0.1533	0.1604	0.1573	0.1059	0.0988	0.098	0.0946	0.0845
lnpropLicLargeL	-0.2113	-0.2376*	-0.2543**	-0.2624**	-0.2716**										
lnpropLicLargeL(t-1)	0.0723	0.049	0.0244	0.0238											
lnpropLicLargeL(t-2)		0.0821	0.043	0.0361											
lnpropLicLargeL(t-3)			0.1501	0.1334											
lnpropLicLargeL(t-4)				0.0715											
lnpropLicSmallL					-0.5257***	-0.4817***	-0.4643***	-0.4415***	-0.4298***						
lnpropLicSmallL(t-1)						-0.123	-0.097	-0.0632	-0.0545						
lnpropLicSmallL(t-2)							-0.0888	-0.0319	-0.0172						
lnpropLicSmallL(t-3)								-0.2138**	-0.1810*						
lnpropLicSmallL(t-4)									-0.1274						
lnpropLicStartupL										2607***	2100***	1942***	1751***	1633***	
lnpropLicStartupL(t-1)											0.1486	0.1323	0.1017	0.09	
lnpropLicStartupL(t-2)												0.072	0.0391	0.0006	
lnpropLicStartupL(t-3)													0.1652	0.1215	
lnpropLicStartupL(t-4)														0.1778	
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	-5733***	-5818***	-5916***	-6047***	-6098***	-3312**	-2886**	-2592**	-2064**	-1861**	-5380***	-5328***	-5255***	-5233***	-5442***
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.3872	0.3874	0.3876	0.3883	0.3884	0.3957	0.3962	0.3964	0.3979	0.3984	0.4255	0.426	0.4261	0.4267	0.4275
Adj. R-Square	0.3744	0.3741	0.3739	0.3742	0.374	0.383	0.3831	0.383	0.384	0.3842	0.4134	0.4136	0.4133	0.4135	0.4139
F	12.3456***	12.471***	12.1395***	16809***	14247***	12.6592***	12.3096***	12.6398***	12.2643***	18826***	14.0821***	13.7914***	13.8944***	13.6649***	13.6572***
Log likelihood	-1580.1139	-1579.9249	-1579.6755	-1578.7673	-1578.5526	-1569.246	-1568.6401	-1568.33	-1566.439	-1565.7038	-1529.7998	-1529.119	-1528.9583	-1528.1207	-1527.0762
BIC	3402.9007	3409.8764	3416.7313	3422.2686	3429.1929	3381648	3387.3067	3394.0402	3397.6119	3403.4953	3302.2724	3308.2645	3315.2968	3320.9753	3326.2401
AIC	3226.2279	3227.8498	3229.3511	3229.5346	3231052	3204.492	3205.2802	3206.6599	3204.8779	3205.4076	3125.5996	3126.2379	3127.9166	3128.2413	3128.1524

***p≤0.001, **p≤0.01, *p≤0.05

Table A6 Regression results for the amount of equity sales income with the alternative model

lnIncEqu	$Equ1	$Equ2	$Equ3	$Equ4	$Equ5	$Equ6	$Equ7	$Equ8	$Equ9	$Equ10	$Equ11	$Equ12	$Equ13	$Equ14	$Equ15
dCaMed	0.9576	0.9735	0.8674	0.7021	0.5921	618	611	0.835	0.5829	0.4953	0.8913	0.8347	0.7293	0.7108	0.6872
dUsNoMed	-2.6714	-2.6803	-2.6812	-2.6791	-2.6847	-2.6223	-2.6221	-2.7018	-2.6996	-2.7006	-2.5984	-2.6317	-2.6941	-2.6912	-2.6747
dCaNoMed	7.3029	7.2904	7.1054	7.0295	7.0906	7.3873	7.3868	7.0501	6.6996	6.7283	7.3482	7.1695	7.0716	6.9557	6.9361
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnFedRDdMM	3.5826***	3.5862***	3.5802***	3.5663***	3.5573***	3.5618***	3.5618***	3.5611***	3.5558***	3.5578***	3.5598***	3.5801***	3.5818***	3.5887***	3.6057***
lnDisclosuresE	-0.8594	-0.8622	-0.8555	-0.8504	-0.8456	-0.8325	-0.8326	-0.8525	-0.8667	-0.8675	-0.8223	-0.8555	-0.8861	-0.9059	-0.9172
lnLegalLdDM	0.7323	0.7318	0.7242	0.7166	0.7166	0.7662	0.766	0.7479	0.7383	0.7366	0.7364	0.6941	0.6852	0.682	0.6766
lnpropExLicL	9.0568*	9.0687*	9.0307*	8.8933*	8.8617*	9.1175*	9.1169*	9.0582*	8.9140*	8.9415*	9.1104*	9.0743*	9.0719*	9.1216*	9.2632*
lnLegalLdDM#lnpropExLicL	-0.6982	-0.6948	-0.6849	-0.6674	-0.6685	-0.7019	-0.7017	-0.6953	-0.7059	-0.7054	-0.6803	-0.6109	-0.6143	-0.6291	-0.6204
dCaMed#lnLegalLdDM	-2.1807*	-2.1851*	-2.1496	-2.1281	-2.0996	-2.1974*	-2.1972*	-2.1424	-2.1255	-2.1072	-2.1663	-2.1503	-2.1444	-2.1566*	-2.1582*
dCaNoMed#lnLegalLdDM	-0.1724	-0.1773	-0.1347	-0.1098	-0.1111	-0.1653	-0.1651	-0.1256	-0.0895	-0.1019	-0.1507	-0.1499	-0.1718	-0.1896	-0.2279
dUsNoMed#lnLegalLdDM	0.7983	0.7994	0.7929	0.7901	0.7867	0.7992	0.7992	0.7955	0.786	0.7813	0.7971	0.8009	0.8008	0.7958	0.7871
dCaMed#lnFedRDdMM	0.5659	0.5621	0.5747	0.6047	0.6194	0.5612	0.5613	0.578	0.6232	0.631	0.5946	0.5828	0.5851	0.5827	0.5742
dCaNoMed#lnFedRDdMM	-0.8759	-0.8711	-0.8508	-0.8342	-0.8525	-0.852	-0.8522	-0.8091	-0.7713	-0.7777	-0.8662	-0.8735	-0.8557	-0.852	-0.8341
dUsNoMed#lnFedRDdMM	-0.8082	-0.8102	-0.8034	-0.7953	-0.7876	-0.8091	-0.809	-0.7988	-0.7972	-0.7928	-0.7911	-0.7977	-0.795	-0.8023	-0.8045
dCaMed#lnDisclosuresE	4963	5012	5005	499	5001	4707	4708	4935	4843	4938	4439	4851	5157	5268	5512
dCaNoMed#lnDisclosuresE	-0.0173	-0.0168	0.018	0.01	0.014	-0.0908	-0.0904	-0.0487	0.028	0.0293	-0.0605	0.0355	0.0359	0.0898	0.0802
dUsNoMed#lnDisclosuresE	2.3900**	2.3963**	2.3878**	2.3741**	2.3637**	2.3750**	2.3748**	2.3880**	2.3899**	2.3847**	2.3341**	2.3565**	2.3754**	2.3915**	2.3953**
lnpropExLicL#lnFedRDdMM	-9392*	-9440*	-9389*	-9112	-9025	-9199	-92	-9191	-8887	-8942	-9154	-9509*	-9577*	-9687*	-2.0016*
lnpropLicLargeL	-0.4826	-0.4395	-0.5442	-0.5736	-0.6131										
lnpropLicLargeL(t-1)	-0.1187	-0.2647	-0.3532	-0.3562											
lnpropLicLargeL(t-2)		0.516	0.3751	0.3455											
lnpropLicLargeL(t-3)			0.5402	0.4679											
lnpropLicLargeL(t-4)				0.3091											
lnpropLicSmallL					0.7527	0.7544	0.9019	1	215						
lnpropLicSmallL(t-1)						-0.0048	0.215	0.361	0.3768						
lnpropLicSmallL(t-2)							-0.7521	-0.5068	-0.4799						
lnpropLicSmallL(t-3)								-0.9218	-0.8619						
lnpropLicSmallL(t-4)									-0.2328						
lnpropLicStartupL										-0.4455	-0.6985	-0.8336	-0.8966	-0.935	
lnpropLicStartupL(t-1)											0.7426	0.6034	0.5023	0.4643	
lnpropLicStartupL(t-2)												0.615	0.5065	0.3818	
lnpropLicStartupL(t-3)													0.5448	0.403	
lnpropLicStartupL(t-4)														0.5765	
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	-11.4012***	-11.3873***	-11.4492***	-11.4963***	-11.5184***	-11.9130***	-11.9114***	-11.6622***	-11.4348***	-11.3978***	-11.5309***	-11.5049***	-11.4431***	-11.4358***	-11.5036***
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.2398	0.2398	0.2399	0.2401	0.2402	0.24	0.24	0.2404	0.2409	0.241	0.2397	0.24	0.2401	0.2403	0.2404
Adj. R-Square	0.2238	0.2233	0.223	0.2227	0.2222	0.2241	0.2236	0.2235	0.2235	0.2231	0.2238	0.2236	0.2232	0.2229	0.2225
F	6.6167***	6.5282***	6.402***	6.257***	6.2226***	6.6316***	6.5232***	6.3966***	6.3766***	6.4273***	6.6206***	6.5714***	6.4158***	6.2845***	6.1939***
Log likelihood	-4778.7516	-4778.7431	-4778.5793	-4778.3837	-4778.317	-4778.4771	-4778.4771	-4778.1122	-4777.536	-4777.4958	-4778.8011	-4778.5358	-4778.3529	-4778.2109	-4778.0398
BIC	9800.1761	9807.5129	9814.539	9825013	9828.7218	9799.6271	9806.9808	9813.6046	9819.8059	9827.0793	9800.275	9807.0982	9814.086	9821558	9828.1674
AIC	9623.5033	9625.4863	9627.1587	9628.7673	9630.634	9622.9543	9624.9542	9626.2243	9627.0719	9628.9916	9623.6022	9625.0717	9626.7058	9628.4218	9630.0797

***p≤0.001, **p≤0.01, *p≤0.05

Table A7 Regression results for the amount of other licensing income with the alternative model

lnIncOther	$Oth1	$Oth2	$Oth3	$Oth4	$Oth5	$Oth6	$Oth7	$Oth8	$Oth9	$Oth10	$Oth11	$Oth12	$Oth13	$Oth14	$Oth15
dCaMed	2.7334	2.6474	2.6494	2.6868	2.765	2.9624	2.9288	3.0137	3.1198*	3.2766*	3.0461	3.065	3.1175*	3.1298*	3.1322*
dUsNoMed	-4457	-3975	-3975	-3979	-3939	-5124	-5062	-4763	-4772	-4755	-4339	-4228	-3917	-3936	-3953
dCaNoMed	0.4474	0.515	0.5185	0.5357	0.4922	0.4972	0.4719	0.5985	0.7459	0.6946	0.6351	0.6945	0.7433	0.8206	0.8226
dUsMed	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
lnFedRDdMM	2178***	1979***	1981***	2012***	2076***	2361***	2372***	2374***	2396***	2360***	2100***	2032***	2024***	1977***	1960***
lnDisclosuresE	-0.4506	-0.4356	-0.4357	-0.4369	-0.4403	-0.4703	-0.473	-0.4655	-0.4596	-0.458	-0.4153	-0.4042	-0.389	-0.3758	-0.3746
lnLegalLdDM	-0.2302	-0.2276	-0.2274	-0.2257	-0.2257	-0.1914	-0.2009	-0.1941	-0.1901	-0.1869	-0.1466	-0.1326	-0.1281	-0.126	-0.1255
lnpropExLicL	-0.5823	-0.6469	-0.6462	-0.6151	-0.5927	-0.5698	-0.5974	-0.5753	-0.5146	-0.564	-0.4495	-0.4375	-0.4363	-0.4695	-0.4836
lnLegalLdDM#lnpropExLicL	0.3687	0.3499	0.3497	0.3458	0.3466	0.3027	0.3131	0.3107	0.3152	0.3143	0.2708	0.2477	0.2494	0.2593	0.2584
dCaMed#lnLegalLdDM	0.4104	0.434	0.4333	0.4285	0.4082	0.372	0.3844	0.3639	0.3567	0.3239	0.3651	0.3598	0.3569	0.365	0.3651
dCaNoMed#lnLegalLdDM	0.2161	0.2424	0.2416	0.2359	0.2369	0.1747	0.1839	0.169	0.1539	0.1761	0.176	0.1757	0.1867	0.1985	0.2023
dUsNoMed#lnLegalLdDM	0.3780*	0.3721*	0.3722*	0.3728*	0.3752*	0.3804*	0.3809*	0.3822*	0.3863*	0.3947*	0.3802*	0.3789*	0.3790*	0.3823*	0.3832*
dCaMed#lnFedRDdMM	-0.9137**	-0.8929**	-0.8931**	-0.8999**	-0.9103**	-0.9622***	-0.9603***	-0.9666***	-0.9856***	-0.9995***	-0.9511**	-0.9472**	-0.9483**	-0.9467**	-0.9459**
dCaNoMed#lnFedRDdMM	-3833***	-4089***	-4092***	-4130***	-3999***	-3662***	-3762***	-3924***	-4083***	-3969***	-3308***	-3284***	-3372***	-3397***	-3415***
dUsNoMed#lnFedRDdMM	-0.2237	-0.213	-0.2131	-0.215	-0.2205	-0.2492	-0.2474	-0.2512	-0.2519	-0.2599	-0.2391	-0.2369	-0.2383	-0.2334	-0.2332
dCaMed#lnDisclosuresE	0.3863	0.3598	0.3598	0.3602	0.3594	0.4311	0.4329	0.4243	0.4282	0.4111	0.3695	0.3558	0.3406	0.3332	0.3307
dCaNoMed#lnDisclosuresE	6831***	6806***	6799***	6817***	6789***	6572***	6814***	6657***	6335***	6311***	5478***	5159***	5156***	4797***	4807***
dUsNoMed#lnDisclosuresE	0.6465	0.6123	0.6124	0.6155	0.6229	0.7146*	0.7086*	0.7036*	0.7028	0.7122*	0.6686*	0.6612*	0.6518	0.641	0.6406
lnpropExLicL#lnFedRDdMM	-0.3247	-0.2991	-0.2991	-0.3054	-0.3116	-0.3285	-0.3293	-0.3296	-0.3424	-0.3325	-0.2838	-0.2721	-0.2686	-0.2613	-0.258
lnpropLicLargeL	0.8876***	0.6542**	0.6562***	0.6629***	0.6909***										
lnpropLicLargeL(t-1)		0.6425**	0.6452***	0.6653***	0.6674***										
lnpropLicLargeL(t-2)			-0.0097	0.0222	0.0433										
lnpropLicLargeL(t-3)				-0.1223	-0.0709										
lnpropLicLargeL(t-4)					-0.2198										
lnpropLicSmallL						0.0702	0.1567	0.1012	0.0599	0.0218					
lnpropLicSmallL(t-1)							-0.2414	-0.3241	-0.3855	-0.4138*					
lnpropLicSmallL(t-2)								0.2827	0.1795	0.1314					
lnpropLicSmallL(t-3)									0.3878*	0.2806					
lnpropLicSmallL(t-4)										0.4165**					
lnpropLicStartupL											-0.9830**	-0.8989***	-0.8316***	-0.7896***	-0.7858***
lnpropLicStartupL(t-1)												-0.2469	-0.1775	-0.1101	-0.1063
lnpropLicStartupL(t-2)													-0.3065	-0.234	-0.2216
lnpropLicStartupL(t-3)														-0.3635	-0.3493
lnpropLicStartupL(t-4)															-0.0575
Year dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Constant	0.0541	-0.021	-0.0198	-0.0092	0.0066	0.2026	0.2863	0.1926	0.097	0.0307	0.1786	0.17	0.1392	0.1343	0.141
Nb of obs.	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562	1562
Nb of groups	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179
R-Square	0.4597	0.4622	0.4622	0.4623	0.4626	0.4546	0.4549	0.4555	0.4565	0.4577	0.4596	0.4599	0.4603	0.461	0.461
Adj. R-Square	0.4484	0.4506	0.4502	0.45	0.4499	0.4432	0.4432	0.4433	0.444	0.4449	0.4483	0.4482	0.4483	0.4486	0.4483
F	15.8186***	15.5233***	15.1118***	14.705***	14.3211***	15.4276***	14.971***	14.6602***	14.4394***	14.0541***	14.8038***	14.7824***	14.3973***	14.0609***	13.9574***
Log likelihood	-2698.3316	-2694.7552	-2694.7544	-2694.6098	-2694.124	-2705.7422	-2705.1972	-2704.4639	-2703.0121	-2701781	-2698.4953	-2698.0746	-2697.4225	-2696.5147	-2696.4902
BIC	5639.3359	5639.537	5646.8891	5653.9536	5660.3357	5654.1573	5660.421	5666.3081	5670.7582	5674.444	5639.6634	5646.1757	5652.2253	5657.7633	5665.0682
AIC	5462.6631	5457.5104	5459.5088	5462196	5462.248	5477.4845	5478.3944	5478.9278	5478.0242	5476.3563	5462.9905	5464.1491	5464.845	5465.0293	5466.9805

***$p \leq 0.001$, **$p \leq 0.01$, *$p \leq 0.05$

Table A8 Pairwise correlation of our variables.

	lnLegalLdDM	lnpropExLicL	lnEmployees	lnPatentsDmD	lnFedRDdMM	lnDisclosuresE	propLicLargeL
lnLegalLdDM	1						
lnpropExLicL	0.1595	1					
lnEmployees	0.0931	-0.2553	1				
lnPatentsDmD	0.2272	0.0465	0.0058	1			
lnFedRDdMM	0.1457	-0.2127	**0.7554**	0.0881	1		
lnDisclosuresE	0.0449	0.0726	-0.1452	-0.0738	0.2099	1	
propLicLargeL	0.0462	-0.1611	0.1547	-0.0449	0.1297	-0.0025	1
propLicSmallL	-0.2241	-0.1239	0.0625	-0.0201	0.0508	-0.0521	**-0.5976**
lnpropLicStartupLmC	0.1466	0.2195	0.0683	0.0705	0.1384	0.1938	-0.1704
lnnbLicRoy	-0.0966	-0.2838	**0.6708**	0.0457	**0.6329**	0.0987	0.0242
lnRoyaltiesdC	0.0887	-0.2041	**0.6169**	0.0893	**0.6033**	0.0634	0.0906
lnIncOtherdDM	0.1254	-0.2373	**0.6338**	0.0599	**0.6189**	0.0874	0.1874
lnnbLicEqu	0.0488	0.0126	**0.5446**	0.0736	**0.5588**	0.218	0.0337
lnIncEqu	0.0979	-0.085	**0.4574**	0.0457	**0.4112**	0.0474	0.072

	propLicSmallL	lnpropLicStartupLmC	lnnbLicRoy	lnRoyaltiesdC	lnIncOtherdDM	lnnbLicEqu	lnIncEqu
propLicSmallL	1						
lnpropLicStartupLmC	**-0.4697**	1					
lnnbLicRoy	0.2426	-0.0689	1				
lnRoyaltiesdC	0.1381	-0.0249	**0.7488**	1			
lnIncOtherdDM	0.0465	0.0078	**0.4974**	**0.4619**	1		
lnnbLicEqu	-0.0854	0.3428	0.3891	0.3665	**0.4761**	1	
lnIncEqu	0.0188	0.0459	0.3349	0.3325	0.3772	**0.4181**	1

Table A9 Pairwise correlation of our transformed variables (Continued).

	lnpropExLicL	lnEmployees	lnPatentsDmD	lnFedRDdMM	lnDisclosuresE	propLicLargeL	propLicSmallL
lnpropExLicL	1						
lnEmployees	-0.2553	1					
lnPatentsDmD	0.0465	0.0058	1				
lnFedRDdMM	-0.2127	**0.7554**	0.0881	1			
lnDisclosuresE	0.0726	-0.1452	-0.0738	0.2099	1		
propLicLargeL	-0.1611	0.1547	-0.0449	0.1297	-0.0025	1	
propLicSmallL	-0.1239	0.0625	-0.0201	0.0508	-0.0521	**-0.5976**	1
lnpropLicStartupLmC	0.2195	0.0683	0.0705	0.1384	0.1938	-0.1704	**-0.4697**
lnnbLicRoy	-0.2838	**0.6708**	0.0457	**0.6329**	0.0987	0.0242	0.2426
lnRoyaltiesdC	-0.2041	**0.6169**	0.0893	**0.6033**	0.0634	0.0906	0.1381
lnIncOtherdDM	-0.2373	**0.6338**	0.0599	**0.6189**	0.0874	0.1874	0.0465
lnnbLicEqu	0.0126	**0.5446**	0.0736	**0.5588**	0.218	0.0337	-0.0854
lnIncEqu	-0.085	**0.4574**	0.0457	**0.4112**	0.0474	0.072	0.0188

	lnpropLicStartupLmC	lnnbLicRoy	lnRoyaltiesdC	lnIncOtherdDM	lnnbLicEqu	lnIncEqu
lnpropLicStartupLmC	1					
lnnbLicRoy	-0.0689	1				
lnRoyaltiesdC	-0.0249	**0.7488**	1			
lnIncOtherdDM	0.0078	**0.4974**	**0.4619**	1		
lnnbLicEqu	**0.3428**	**0.3891**	**0.3665**	**0.4761**	1	
lnIncEqu	0.0459	**0.3349**	**0.3325**	**0.3772**	**0.4181**	1

Table A10 Variance inflation factor results

NbRoy1	VIF	1/VIF	NbRoy6	VIF	1/VIF	NbRoy11	VIF	1/VIF
y2002	1.46	0.684342	y2002	1.46	0.684419	y2002	1.46	0.684445
y2003	1.51	0.663284	y2003	1.51	0.663296	y2003	1.51	0.663294
y2004	1.51	0.660296	y2004	1.51	0.661206	y2004	1.51	0.661599
y2005	1.63	0.615065	y2005	1.61	0.619998	y2005	1.62	0.618869
y2006	1.7	0.589949	y2006	1.69	0.5921	y2006	1.7	0.588668
y2007	1.65	0.606928	y2007	1.64	0.608726	y2007	1.65	0.605853
y2008	1.69	0.591867	y2008	1.68	0.59394	y2008	1.69	0.59182
y2009	1.65	0.607469	y2009	1.64	0.610043	y2009	1.64	0.609144
y2010	1.64	0.610932	y2010	1.63	0.61273	y2010	1.64	0.609184
y2011	1.62	0.616097	y2011	1.61	0.621195	y2011	1.61	0.62002
y2012	1.67	0.598218	y2012	1.66	0.601591	y2012	1.68	0.595118
y2013	1.64	0.608419	y2013	1.65	0.607491	y2013	1.66	0.601502
y2014	1.68	0.595279	y2014	1.67	0.59815	y2014	1.69	0.590165
dCaMed	1.17	0.855296	dCaMed	1.17	0.854226	dCaMed	1.17	0.855526
dUsNoMed	1.32	0.760245	dUsNoMed	1.31	0.761847	dUsNoMed	1.31	0.760714
dCaNoMed	1.1	0.911435	dCaNoMed	1.1	0.909092	dCaNoMed	1.1	0.908457
lnEmployees	1.32	0.756075	lnEmployees	1.32	0.758668	lnEmployees	1.32	0.756913
lnPatentsDmD	1.28	0.783742	lnPatentsDmD	1.27	0.78714	lnPatentsDmD	1.27	0.787002
lnLegalLdDM	1.31	0.763857	lnLegalLdDM	1.36	0.734482	lnLegalLdDM	1.34	0.74893
lnpropExLicL	1.29	0.777846	lnpropExLicL	1.26	0.795303	lnpropExLicL	1.38	0.724469
lnpropLicLargeL	1.07	0.930302	lnpropLicSmallL	1.09	0.920042	lnpropLicStartupL	1.22	0.819765
Mean VIF	1.47		Mean VIF	1.47		Mean VIF	1.48	

ANNEXE B TABLES ARTICLE 2

Table A1 Description of variables

Variable name	Description	Value used in the regressions
Startups	The number of startups is transformed using the natural logarithm.	ln(Startups + 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)
RDExp	The total amount of R&D expenditure of the university.	ln(RDExp / 100 000 000 + 1)
HHU	The Hirshman-Herfindalh index of patents granted that year.	ln(HHU x 10 + 1)
TDU	The technological diversity index adapted from the entropy index (Shannon, 1948).	N/A
MaxRTA	The highest revealed technological advantage index value.	ln(MaxRTA / 10 + 1)
Prox	The proximity of the patent portfolio of the university and the state developed by Jaffe (1986).	N/A

Table A2 Statistics of variables

stats	Startups	LegalL	PatentsD	propExLicL	PatentState	IndRDT	RDExp	HHU	TDU	MaxRTA	Prox
min	0	0	0	0	2.079442	0	0.0006027	0.2396305	0	1.056922	0
max	4.553877	6.474895	3.433987	0.7884574	10.66109	1.980523	4.265032	2.397895	4.088879	9.598869	0.8478552
mean	1.261069	1.858581	1.136055	0.3775214	7.008806	0.5349209	1.275818	1.023167	2.006938	5.64686	0.2641235
skewness	0.2584035	0.3900714	0.2414617	-0.0038039	-0.364193	0.9733914	0.7031442	0.9857791	-0.3457696	-0.2455488	0.5499676
kurtosis	2.659498	3.427002	3.612264	2.216379	2.975275	4.141799	3.587334	3.550148	2.642254	2.993064	2.512267
N	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789	2789

Table A3 Pairwise correlation of variables

	Startups	LegalL	Patents	propExLicL	PatentState	IndRDT	RDExp	HHU	TDU	MaxRTA	Prox
Startups	1										
LegalL	0.01	1									
	(0.599)										
Patents	0.0589	0.1966	1								
	(0.0019)	(0.0000)									
propExLicL	-0.1212	0.1193	-0.0338	1							
	(0.0000)	(0.0000)	(0.0739)								
PatentState	0.3006	0.2216	0.1456	-0.1666	1						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)							
IndRDT	0.0106	-0.0199	-0.0932	0.1869	-0.0334	1					
	(0.5751)	(0.294)	(0.0000)	(0.0000)	(0.0778)						
RDExp	0.6848	0.0729	0.0529	-0.2731	0.3283	-0.0683	1				
	(0.0000)	(0.0001)	(0.0052)	(0.0000)	(0.0000)	(0.0003)					
HHU	-0.5022	-0.1609	-0.3006	0.164	-0.2978	0.1074	-0.5817	1			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
TDU	0.591	0.1844	0.3333	-0.1917	0.3669	-0.0972	0.6805	-0.9724	1		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
MaxRTA	-0.3127	-0.0627	-0.0263	0.0276	-0.3443	-0.1891	-0.3771	0.259	-0.3106	1	
	(0.0000)	(0.0009)	(0.1645)	(0.1449)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Prox	0.3322	0.1282	0.1711	-0.0764	0.3066	0.0171	0.3795	-0.414	0.4639	-0.3255	1
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.3672)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

p-values in parentheses

Table A4 Results of our panel regressions with an alternative model and smaller sample

	AltPnOLS10	AltPnOLS11
Year dummies	incl.	incl.
dMedschl	0.1871	0.1859
UnivTotPatCount	0.1703*	0.1812**
LegalL	0.0054	0.0054
PatentsD	0.2907***	0.2929***
propExLicL	0.6593***	0.6600***
PatentState	0.1302***	0.1308***
IndRDT	0.2796**	0.2798**
dCanada x propExLicL	0.4332+	0.4409+
dCanada x IndRDT	0.188	0.1944
LegalL x PatentsD	-0.1198***	-0.1200***
IndRDT x PatentsD	-0.2112**	-0.2136**
dMedschl x LegalL	-0.0271	-0.0263
MaxRTA	-0.0682**	0.1884***
Prox	-0.5956*	0.6519+
TDU	-0.6373***	
HHU		0.8667***
MaxRTA x TDU	0.0822***	
Prox x TDU	0.3956*	
MaxRTA x HHU		-0.1091***
Prox x HHU		-0.5308*
Const.	-0.0854	-2.1333***
Nb of obs.	1096	1096
Nb of groups	155	155
Log likelihood	-728.273	-727.391
Log likelihood$_0$	-837.898	-837.898
BIC	1729.524	1727.759
AIC	1534.546	1532.782
R^2_{within}	0.1813	0.1826
$R^2_{between}$	0.0088	0.008
$R^2_{overall}$	0.1035	0.1029
$R^2_{adjusted}$	0.0072	0.0088
F	5.2625***	5.3093***

***p≤0.001, **p≤0.05, *p≤0.1 +p≤0.15

Table A5 VIF values for PnOLS10

Variable	VIF	1/VIF
RDExp	2.86	0.349525
LegalL	1.37	0.731755
PatentsD	1.41	0.710928
propExLicL	1.35	0.739112
PatentState	1.52	0.659663
IndRDT	1.09	0.918267
MaxRTA	1.42	0.705223
Prox	1.5	0.664537
TDU	2.61	0.383339
TDS	1.45	0.691233
Mean VIF	1.88	

ANNEXE C TABLES ARTICLE 3

Table A1 Description of our variables

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 A2 Statistics of our transformed 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 A3 VIF values for PnlOLS18

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 A4 Pairwise correlation of our transformed variables

	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 A5 Pairwise correlation of our transformed variables (continued)

	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

Table A6 Alternative models

	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***

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